

AGRI-INTELLIGENCE

Artificial Intelligence Reflections in Agriculture

EDITOR
HUMAR KAHRAMANLI ÖRNEK



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Preface

One of the oldest and most important sectors in the world is agriculture. Today, agriculture is faced with many challenges and problems. These problems affect both production processes and environmental and economic sustainability. The problems experienced in agriculture require innovative solutions to make the sector more efficient, sustainable and environmentally friendly. Modern technologies, especially the Internet of Things and artificial intelligence, are frequently used to overcome these problems. Artificial intelligence provides a major transformation in agriculture and brings smarter, faster and more environmentally friendly solutions. Agricultural processes are being automated with artificial intelligence-supported tools such as spraying robots, automatic irrigation systems and harvesters. Plant diseases can be detected early using artificial intelligence-supported sensors. The use of artificial intelligence in agriculture is an important step to ensure food safety, protect natural resources, increase productivity, reduce agricultural drug use and predict future agricultural needs.

In recent years, the term Agri-intelligence has emerged as a developing concept related to the use of digital technologies such as artificial intelligence, data analytics and the Internet of Things in agriculture. Agri-intelligence refers to innovative solutions obtained by using artificial intelligence technologies in the digitalization process of agriculture. In this book artificial intelligence applications in agriculture are examined and applications are presented. I hope that the book will add a new perspective to your research on the future of agriculture. I would like to thank all the authors who contributed to the creation of the book and Çizgi Publishing House for its publication.

Humar KAHRAMANLI ÖRNEK

December, 2024

Contemporary Technologies and Application Areas in Smart Agriculture: Methods, and Case Studies from a 2024 Perspective

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Introduction

The use of artificial intelligence (AI) technologies in agriculture stands out as one of the most important innovations of our time. These innovative approaches, which replace traditional agricultural methods, increase efficiency, reduce costs and offer a sustainable agricultural model (Javaid et al., 2022). Advanced data analytics, machine learning algorithms and automation solutions provided by AI are used in many different areas of agricultural production; they find a wide range of applications from climate management to crop health, from animal tracking to smart greenhouses (Mana et al., 2024). In this way, farmers can manage their production processes more effectively and sensitively and support environmental sustainability by optimizing resource use. In this section, the concept of smart agriculture, the role of AI in agricultural practices and the latest developments in this field will be discussed under headings, along with artificial intelligence technologies. A representative illustration of this study is given in Figure 1.

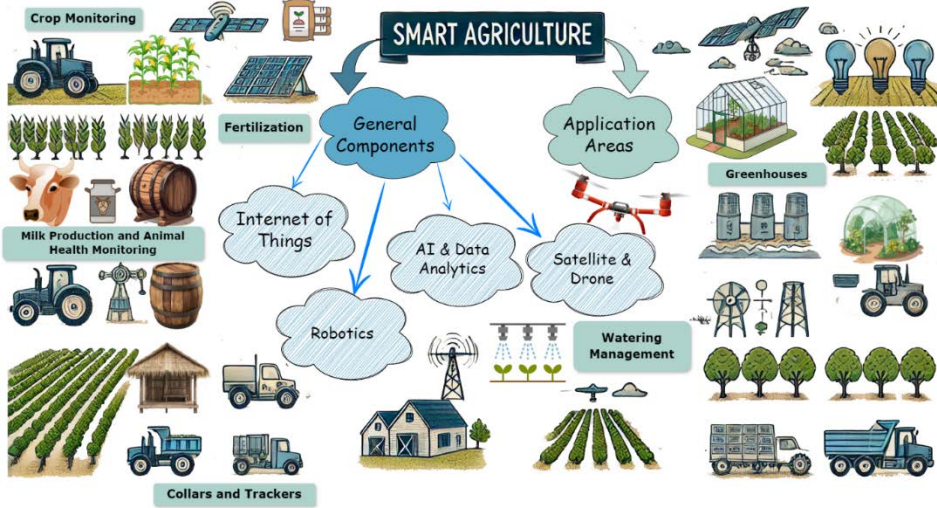


Figure 1. Representative Display of This Study

General Definition and Importance of Smart Agriculture

Smart agriculture is an innovative approach that optimizes agricultural production processes using modern technologies. This system, which is more sensitive and efficient than traditional methods, allows farmers to use resources in the best way. With the help of smart agriculture applications, factors such as soil moisture, weather conditions, and plant health are monitored and analyzed in real time. In light of this data, production processes can be managed at lower costs, in an environmentally friendly and sustainable manner. As the world population increases and natural resources decrease, the solutions offered by smart agriculture are of great importance for the future of the agricultural sector. Advantages such as efficient use of resources, increasing product quality, and minimizing agricultural risks are the main elements that distinguish smart agriculture from other methods (Janc et al., 2019; Magomadov, 2019; Mitra et al., 2022).

Core Components of Smart Agriculture

Smart farming applications are created by combining various technological components. Each of these components optimizes different aspects of agricultural production processes and makes them more efficient. A representative illustration of components of smart agriculture is given in Figure 2. The key components are:

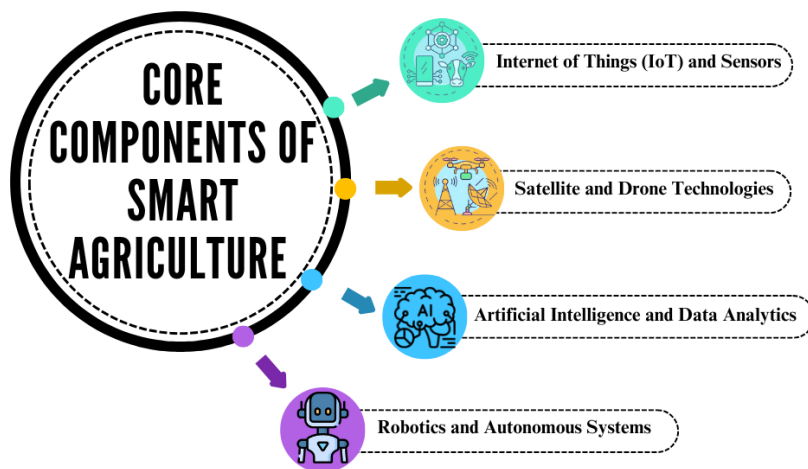


Figure 2. Core Components of Smart Agriculture

Internet of Things (IoT) and Sensors

IoT systems continuously monitor environmental factors such as soil moisture, pH level, and temperature with sensors placed in the fields. These data are instantly transmitted to the farmers and by means of automation systems, processes such as irrigation and fertilization are managed precisely (Ayaz et al., 2019; Mat et al., 2018; Sekaran et al., 2020). For example, irrigation systems can automatically activate when soil moisture is low, preventing water waste and helping plants grow in optimum conditions.

Artificial Intelligence and Data Analytics

Artificial intelligence and data analytics are important tools that strengthen the decision support systems of smart agriculture. Large datasets obtained from sensors, satellite images and other data sources are analyzed with AI algorithms, allowing farmers to make more informed decisions. For example, plant health data can be analyzed to detect early signs of crop diseases or pests and send early warnings to farmers. This prevents the spread of diseases and minimizes crop losses. AI algorithms also create predictive models in various areas such as plant growth, irrigation needs, weather forecasts and crop yield. These models help farmers better plan agricultural processes and minimize risks (Hamed et al., 2024; Ramesh et al., 2020; Tarik & Mohammed, 2020). For example, AI-powered forecasting

systems analyze pre-planting weather forecasts to suggest the most appropriate planting time to farmers.

Satellite and Drone Technologies

Satellite and drone technologies enable fast and effective monitoring of large areas in smart agriculture. Drones scan agricultural lands with high-resolution images and collect various data such as plant health, soil condition and water bodies. These images are analyzed by AI algorithms and provide farmers with information on which areas need more irrigation or fertilization. Satellite imaging plays an important role in monitoring large-scale agricultural lands. Multispectral satellite images provide important information about plant health by analyzing the reflections of plants at different wavelengths (Cancela et al., 2019; Kalamkar et al., 2020; Murugan et al., 2016). For example, satellite images enable farmers to intervene quickly by detecting plant stress symptoms (water deficiency, nutrient deficiencies) early.

Robotics and Autonomous Systems

Robotic and autonomous systems represent the automation dimension of smart agriculture. These systems automate processes such as planting, harvesting, fertilizing, weeding and spraying. Autonomous tractors can perform tasks such as plowing the field or planting seeds on their own with GPS-supported guidance systems. Similarly, robotic harvesters increase harvest efficiency by carefully collecting ripe crops. The use of autonomous systems reduces labor costs and increases efficiency, especially in large agricultural enterprises. In addition, these systems maintain product quality by performing precise and repetitive tasks without errors (Pearson et al., 2022; Srivastava & Raturi, 2022).

Application Areas of Smart Agriculture

Smart agriculture can be applied at almost every stage of agricultural production processes and can provide great benefits in various fields. Smart agriculture application areas and examples from the current literature of these areas are given as headings. A representative illustration of application areas of smart agriculture is given in Figure 3.

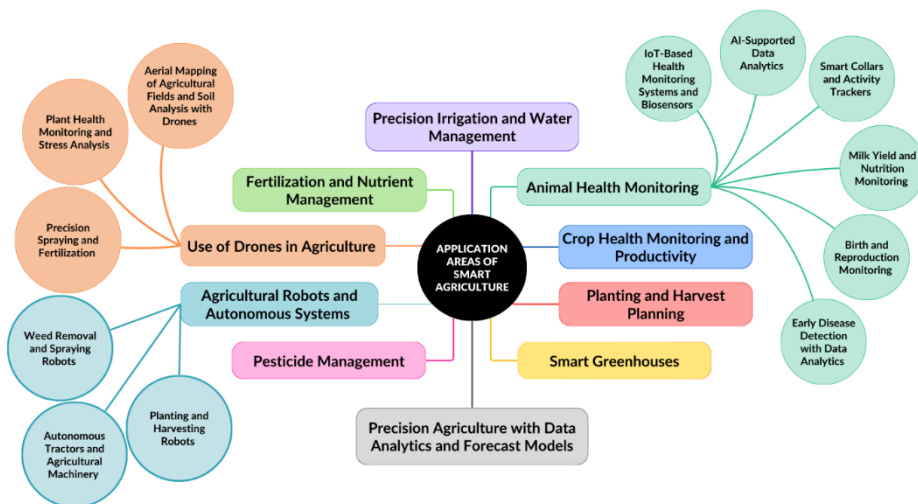


Figure 3. Application Areas of Smart Agriculture

Precision Irrigation and Water Management

Smart irrigation systems precisely manage the water needs of plants. Information obtained from soil moisture sensors and weather data is integrated into irrigation systems to ensure that the right amount of water is delivered only to the areas where it is needed. Especially in regions with water scarcity, smart irrigation technologies ensure that water is used efficiently and plants grow under optimum growth conditions (Bwambale, Abagale, et al., 2022; Bwambale, Naangmenyele, et al., 2022; Kamienski et al., 2019).

Kumar et al. developed a smart irrigation system for use in the agricultural sector in their study. For this purpose, they collected soil data using IoT based moisture and soil sensors and stored this data in a central cloud system. They managed to eliminate unnecessary data with the Correlation-based Feature Selection (CFS) algorithm for data processing. They used the K-means algorithm to group similar data and then created a classification model with Support Vector Machines (SVM), Random Forest (RF) and Naive Bayes (NB) algorithms. They trained, validated and tested the model with the collected data. As a result, they found that the K-means SVM hybrid classifier outperformed other methods with an accuracy rate of 98.5% and that this system saved up to 42% of fresh water by predicting water demand (Kumar et al., 2024).

In their studies, Amertet Finecomess, Gebresenbet and Alwan designed a smart irrigation system used in the agricultural sector. The system is equipped with IoT devices and measures parameters such as soil moisture, temperature and humidity and collects this data in a central cloud system. Using smart control algorithms on the collected data, the amount of water required for irrigation is determined and the irrigation valve is automatically opened. For this purpose, the authors first created mathematical models of agricultural tanks and developed fuzzy logic controllers based on these models. Then, the designed system was integrated into Cisco Packet Tracer and MATLAB/SIMULINK environments and simulation tests were performed. As a result, it was determined that the proposed system was successful in reducing water consumption by automatically regulating irrigation times. Outputs such as valve opening rate, water flow rate and pump performance were continuously monitored and they stated that the system was in compliance with the specified requirements (Amertet Finecomess et al., 2024).

In their study, Anand et al. developed a smart agricultural system to increase productivity in the agricultural sector. Using IoT technologies, they designed a system that continuously monitors field conditions through sensors that measure various parameters such as humidity, temperature, and pH. The data is stored in a cloud-based database and analyzed with machine learning algorithms. In the study, smart decision mechanisms were developed for automatic irrigation, appropriate crop recommendations, and fertilizer use. The system saved water by irrigating the right amount under the right conditions and increased yield by determining suitable crops. Resulting from the trials, it was determined that the K-nearest neighbor (kNN) algorithm gave the best results with a success rate of 98.3%. As a result, the authors provided farmers with appropriate crop and fertilizer recommendations with this smart agricultural system and achieved significant improvements in terms of water management and field productivity (Anand et al., 2024).

Ramasamy et al. have developed a smart irrigation system based on the IoT to increase efficiency and save water in agriculture. The system uses sensors to measure various environmental parameters such as temperature, humidity and soil moisture and transfers this data to a cloud-based database. The authors have developed a new algorithm called "Differential Water-flow Algorithm" (DWA) that analyzes this data and enables the irrigation motor

to start or stop automatically. The system automatically turns the motor on or off when certain threshold values are reached, thus preventing unnecessary water consumption. As a result of the trials conducted on a real agricultural field, they stated that this model optimizes irrigation management and provides 70% higher efficiency compared to existing methods (Ramasamy et al., 2024).

Thiagarajan and Sripriya, in their study, developed an irrigation management system based on IoT and machine learning for precision irrigation in agriculture. The system collects environmental data such as temperature, humidity, soil moisture via sensors and transmits it to the IoT platform, and this data is analyzed to determine irrigation needs. The authors provided real-time monitoring of environmental data using low-cost IoT technologies and used machine learning algorithms to estimate irrigation needs with this data. In the study, it was determined that the LDA (Linear Discriminant Analysis) algorithm, which has a high accuracy rate, gave the best result with an accuracy rate of 92%. As a result, it is stated that the proposed system optimizes irrigation processes, saves water and energy, and offers an effective solution for sustainable agriculture (Thiagarajan & Sripriya, 2024).

Fertilization and Nutrient Management

Smart farming technologies optimize fertilization plans using data from soil sensors and plant health analysis. This ensures that only the amount of fertilizer needed is applied, reducing costs and environmental impact. Precise fertilization techniques help plants better absorb nutrients, improving crop quality (Selim, 2020; Wu & Ma, 2015).

In their study, Anjaneyulu et al. developed an IoT-based plant nutrient control system for sustainable agriculture. The system uses NPK sensors to measure essential nutrients such as nitrogen (N), phosphorus (P) and potassium (K) in the soil and collects this data in real time. The collected data is transmitted to a cloud-based storage system such as Google Firebase and analyzed. The system allows farmers to receive recommendations according to the nutrient needs of the plants and prevents unnecessary fertilizer use. In addition, environmental parameters such as soil moisture and temperature are constantly monitored and farmers can be notified when irrigation is needed (Anjaneyulu et al., 2024).

Sakthipriya and Naresh, in their study, developed precision farming methods using a convolutional neural network (CNN) based on machine learning and genetic algorithm (GA) for nutrient management in rice production. The proposed system monitors and analyzes field conditions in real time using high-efficiency sensors and remote sensing technologies. They aimed to optimize plant development by analyzing nitrogen levels and other nutrients in the soil. They stated that genetic algorithms automatically optimize the CNN architecture, providing accurate and fast nutrient management. The results of the study show that the proposed system offers higher accuracy rates (99%) and lower costs than other existing methods. In addition, the authors stated that they aim to develop the model using wider datasets in different crop types in the future (Sakthipriya & Naresh, 2024).

Banu et al. developed a cloud-based and CNN-supported smart nutrient management system to optimize nutrient management in agriculture. The system monitors various soil parameters such as soil pH, nitrogen, phosphorus, potassium and moisture levels in real time with IoT-based sensors. The collected data is processed on a cloud-based platform and analyzed with advanced data analytics and machine learning algorithms. As a result of these analyses, farmers are provided with specific recommendations on the right fertilizer selection, application rate and time. The system continuously collects data with sensor networks installed in the field and dynamically updates nutrient management recommendations as conditions change. The authors stated that the system provides more efficient resource use and increases crop productivity after real-world trials. They also stated that it reduces fertilizer runoff and soil pollution by promoting environmental sustainability. They stated that the mobile application and web-based panels developed for farmers' use allow data to be easily monitored and decisions to be made effectively (Banu et al., 2024).

In their study, De Luna et al. developed a machine learning-based device to optimize fertilizer selection in agriculture. The device was evaluated with Neural Network (NN), RF, Decision Trees (DT), SVM and XGBoost algorithms to make appropriate fertilizer recommendations using soil analysis data. The device, integrated with Jetson Nano hardware, was developed with the Python programming language using NumPy, Pandas and Scikit-learn libraries for data processing. The researchers used a dataset containing 4513 samples to develop the device, applied the SMOTE method to eliminate data imbalance and optimized the hyperparameters of the

models with Optuna. The NN model exhibited the highest performance with 99% accuracy, followed by the DT and RF models with 98.30% and 97.82%, respectively. As a result, they stated that the device provides efficiency by increasing the accuracy of fertilizer recommendations and supports environmental sustainability (De Luna et al., 2024).

Sabharwal and Reddy developed a machine learning-based approach that combines environmental parameters and nutrient management to provide precise crop recommendations in agriculture. The study aimed to provide accurate crop recommendations using a dataset that included factors such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall. The authors analyzed two different scenarios: In the first scenario, all parameters were considered, while in the second scenario, only NPK nutrients were focused on. The models were trained and evaluated using RF, Decision Tree (DT), and SVM models with a dataset of 80% training and 20% testing ratio. The results revealed that the RF model performed best with 99.31% accuracy, and the scenario where all parameters were considered performed better than the one focusing only on NPK. These findings emphasized the importance of environmental factors for more accurate and sustainable crop management in agriculture (Sabharwal & Reddy, 2024).

Crop Health Monitoring and Productivity

Smart agriculture technologies use modern tools such as multispectral imaging, artificial intelligence (AI)-supported image analysis, machine learning (ML), drone technology, and IoT to monitor crop health and detect diseases early. With the help of these technologies, agricultural lands can be quickly scanned with drones or satellite images to obtain detailed information about plant health. Processes carried out with physical observations in traditional methods have become more efficient, faster, and more sensitive through modern technologies. Crop health monitoring regularly observes the health status of plants during the growth process, allowing early detection of adverse effects such as diseases, pests, nutrient deficiencies, and environmental stress. These proactive approaches are critical to increasing efficiency in modern agriculture and optimizing the production process (Niedbała et al., 2023; E. F. I. Raj et al., 2024; Shafi et al., 2019).

Bandla et al. examined the use of artificial intelligence (AI) in precision farming and crop monitoring applications in agriculture. The study examined the role of AI in areas such as yield estimation, disease and pest detection, and soil health assessment. They also explained how machine learning and computer vision techniques are used to monitor crop health through processing data from satellite images, drone data, and sensors. It was stated that AI technologies increase agricultural productivity by helping make decisions such as irrigation, fertilization, and pest control at the right time. The results showed that AI-based crop monitoring and yield estimation systems were more successful than traditional methods with 90-95% accuracy rates. The study revealed that AI technologies have great potential for optimizing agricultural processes, improving resource utilization, and promoting sustainability. However, it was noted that challenges such as high costs, lack of technical knowledge, and data access hinder widespread adoption. The authors emphasized that policy support and affordable AI solutions are needed to overcome these challenges (Bandla et al., 2024)

Nguyen-Tan and Le-Trung developed a smart farming system that integrates 5G private mobile network (PMN) and deep learning techniques for precision irrigation and plant health monitoring in agriculture. The proposed system works with real-time data obtained from IoT-based sensors and drones. The deep learning model creates automatic irrigation schedules based on environmental data such as weather and soil moisture. In addition, YOLOv8 models are trained to detect plant growth stage, health status, and nutrient deficiencies (nitrogen, phosphorus, potassium). It is stated that the system provides reliable data transmission using 5G connectivity while optimizing agricultural activities. The results show that the irrigation schedule model reaches 73% accuracy, the growth stage model 93.8%, the health status model 87%, and the nutrient status model 83%. It is stated that lightweight model architectures are preferred in the research to ensure that the system can be easily implemented in low-cost devices. The authors emphasize that the system has the potential to increase agricultural productivity with practical applications (Nguyen-Tan & Le-Trung, 2024).

Boni et al. developed a wireless biosensor node for real-time plant monitoring for precision agriculture. This system uses an organic electrochemical transistor (bioristor) placed on the stem of plants and monitors plant health by measuring the concentration of nutrients. It is stated that the wireless sensor node operates with ultra-low power consumption

and transmits data to a cloud-based server using NB-IoT/LTE-M radios. It is stated that the system allows long-term monitoring of seasonal crops that require continuous data tracking and can especially help optimize irrigation and fertilization strategies. The results indicate that the proposed biosensor node is suitable for wide-scale applications due to its low cost and long life. It is also stated that this system, which can detect early drought and nutrient deficiency in plants, aims to increase agricultural productivity and promote environmental sustainability (Boni et al., 2024).

Caselli et al. have developed a wireless biosensor node "W-Bioristor" for real-time monitoring of plants in precision agriculture. This system is placed on the plant stem using an organic electrochemical transistor (OECT) and measures ion concentrations in plant sap. This sensor, which is stated to operate with low power consumption, transmits data to a cloud-based server with wireless communication protocols such as NB-IoT or LTE-M and can be accessed remotely. It has been stated that in this way, the physiological conditions of plants can be monitored in real time and agricultural applications such as irrigation can be optimized. Due to the low power consumption of the system, the results provide battery life of up to three months for seasonal plants and over one year for perennial plants. It has also been stated that the sensor's wide-ranging wireless connection feature allows easy collection and analysis of data in agricultural operations (Caselli et al., 2024).

Planting and Harvest Planning

Planting and harvesting processes are one of the most important stages of agricultural production. Smart agricultural systems determine the most appropriate planting and harvesting times using soil analysis, weather forecasts and other datasets. In this way, farmers can plant during the optimum growth periods of plants and increase productivity by carrying out harvesting operations on time. In addition, harvesting robots optimize labor by quickly and carefully picking ripe products (Kasera et al., 2024; Kiani et al., 2022).

Mahdavamanshadi, Yao and Fan developed a multi-stage stochastic optimization model for guayule harvest planning and machine scheduling in semiarid regions. This model aims to optimize the harvesting process of products such as guayule, cotton and wheat under the uncertainty of drought scenarios. The model aims to minimize total costs by considering harvest

time, machine routes, product shortage and stock costs in different drought scenarios. In the research, the model was tested with case studies in agricultural fields in Arizona and optimal harvest plans were determined for each product. As a result, it was determined that guayule is more resistant to drought than other products and therefore has more advantages in reducing economic losses. It was stated that the proposed model can help farmers determine which product is more appropriate to plant according to drought conditions, thus ensuring long-term sustainability in agricultural production (Mahdavamanshadi et al., 2024).

Wang et al. developed a deep learning-based image processing method to assist in harvest planning for large-scale strawberry fields. An improved YOLOv8 model was used to detect ripe strawberries, unripe strawberries, and strawberry flowers using drone images. This model was optimized to increase identification accuracy and detection speed. Furthermore, the number of strawberry plant areas was estimated using region segmentation and edge extraction algorithms based on environmental stability. In the study, the growth map generated by drone images provided farmers with information on which areas should be harvested first by reflecting the maturity levels in different regions. They stated that the experiments successfully helped in harvest planning with an average accuracy rate of 80.53% (C. Wang et al., 2024).

Dhonju et al., in their study, developed a management information system (MIS) that predicts the optimum timing and crop load for mango harvest. The system makes predictions through a 'harvest prediction engine' using temperature, flowering and fruit maturity data. The developed system provides farmers with information on flowering rate, fruit size and maturity time using data obtained manually or by machine vision. It is stated that the data obtained throughout the day with advanced temperature sensors can be combined with heat accumulation measurements (Growing Degree Days - GDD) to optimize the harvest time. As a result, it is stated that the proposed system succeeded in predicting the harvest time and load with an accuracy rate of over 95% in different mango varieties. It is stated that this innovative approach allows farmers to make better harvest planning, optimize resource management and increase productivity. It is also stated that the study makes a significant contribution to the digitalization of agricultural production by demonstrating the effectiveness of modern sensor technologies and data analysis in harvest management (Dhonju et al., 2024).

Smart Greenhouses

Smart greenhouses are technological systems that optimize plant production in closed areas. These greenhouses automatically monitor and control the temperature, humidity, light and CO₂ levels that plants need. Thus, production can be done throughout the year regardless of seasonal and climatic conditions (Bersani et al., 2022; Maraveas, 2022).

Sadek and Shehata developed a smart greenhouse equipped with indoor hydroponic and aeroponic systems in Egypt. This system automatically monitors and controls environmental parameters inside the greenhouse using IoT technology. The designed system provides optimal plant growth conditions by measuring temperature, humidity, light intensity and total dissolved solids (TDS). The system also includes automatic pesticide spraying features to prevent pests. The IoT-based platform allows remote monitoring and control of parameters inside the greenhouse. In experiments conducted with this system where Batavia lettuce is grown, they stated that 80-90% of water and fertilizer savings were achieved compared to traditional methods, and the production period was reduced to 45 days and the yield was doubled. The authors also developed a dynamic website and mobile application to use renewable energy sources to reduce energy consumption of the system and to provide remote access (Sadek & Shehata, 2024).

Wang developed a smart agricultural greenhouse control system based on the IoT and machine learning in his study. This system aims to increase plant growth efficiency and reduce resource waste by monitoring and optimizing environmental parameters such as temperature, humidity, and light in the greenhouse in real time. The system collects data through sensors, transfers this data to the cloud, and analyzes it with machine learning algorithms. Thus, greenhouse conditions can be instantly adjusted, and environmental parameters can be adjusted according to the needs of different crops. Machine learning models can predict future greenhouse conditions based on past data and thus provide precise control of parameters in the greenhouse. As a result, it was stated that the system increased plant yield and provided more sustainable agricultural production by optimizing the use of energy, water, and fertilizer. The study also used advanced control strategies and algorithms (such as PID, Model Predictive Control, and fuzzy control systems) to reduce energy consumption and improve resource use (Wang, 2024).

Riskiawan et al., in this study, developed a smart greenhouse control system based on artificial intelligence (AI) and IoT. The system was designed to provide optimum growth conditions by monitoring temperature, humidity, light and gas levels for the cultivation of plants such as meloun. For this purpose, a microcontroller was used to collect sensor data, and the data was processed with a long short-term memory (LSTM) model. It was stated that the system provides automatic control via smart agents using a cloud-based platform and Laravel framework to remotely manage data collection and control processes. It was stated that the results showed that the system can optimize environmental parameters up to three minutes in advance by making more accurate predictions compared to traditional manual methods. It was stated that the study provides energy saving and increased efficiency by providing climate control based on sensor data, which reduces costs in greenhouse production (Riskiawan et al., 2024).

Rahman et al. developed a process management framework using digital twin technology for smart greenhouse management. They stated that this framework aims to optimize real-time data processing, remote monitoring and decision-making processes with the integration of new generation mobile networks (5G/6G) and IoT devices. They stated that the proposed system consists of physical, fog and cloud layers. They stated that the physical layer monitors the greenhouse environment with sensors and actuators; the fog layer provides low-latency processing of data; and the cloud layer provides data analytics and process management decisions using artificial intelligence (AI) and ML algorithms. As a result, they stated that the developed system creates a digital twin that simulates and controls the greenhouse environment in real time. They stated that this technology increases greenhouse efficiency, reduces energy consumption and minimizes manual intervention. They emphasized that the study contributes to the digitalization of agricultural processes by providing a strong data-driven control for smart greenhouse management (Rahman et al., 2024).

Morales-García, Terroso-Sáenz and Cecilia stated that they developed an integrated learning approach that combines multiple deep learning models in order to more accurately predict environmental variables in smart greenhouses. They stated that this approach focuses on predicting each environmental variable separately by combining different deep learning algorithms instead of using a traditional single model. In this way, decision support systems (DSS) in smart greenhouse environments can make more

accurate and balanced predictions. As a result, they stated that the proposed integrated learning model performed up to 8% better compared to single model approaches and allowed DSS systems to make more proactive and reliable decisions. They stated that the study made significant contributions to increasing agricultural productivity and optimizing resource use (Morales-García et al., 2024).

Precision Agriculture with Data Analytics and Forecast Models

Data analytics and forecasting models are used to increase efficiency in agricultural production, optimize resource use and improve decision-making processes using a big data approach. Artificial intelligence and machine learning algorithms process the collected data, allowing farmers to make better plans and take precautions in advance. In this way, processes such as weather forecasts, crop health monitoring, and irrigation planning are managed more precisely (Aditya Shastry & Sanjay, 2020; Farooqui et al., 2024).

In their study, Manikandababu et al. aimed to improve crop yield estimation using IoT and machine learning techniques in precision agriculture applications. IoT devices provide real-time monitoring by collecting environmental data such as temperature, humidity, soil moisture and crop health. The collected data is analyzed with machine learning algorithms, agricultural production estimations are made and can help farmers make data-driven decisions on issues such as irrigation, fertilization and pest control. The research indicates that algorithms such as regression models, decision trees and neural networks are effective in solving complex patterns and connections in agricultural data. As a result, it is seen that the proposed system achieves a higher success rate in crop yield estimation than previous studies with a 92% accuracy rate. It was stated that the system, which uses 100 IoT devices, managed to increase the sustainability and efficiency of agricultural operations by providing farmers with more accurate estimations with 24 daily data collection processes (Manikandababu et al., 2024).

Raj et al. developed a model using machine learning methods to predict crop yield in precision agriculture applications. The study examined the use of algorithms such as decision trees, random forests, support vector machines, and neural networks to accurately predict crop yield using various data sources such as soil properties, rainfall data, farming practice methods,

and remote sensing images. They stated that this approach will enable data-driven decisions to be made for efficient use of resources and increased agricultural productivity. The results revealed that the proposed models successfully predicted crop yield with 97.32% accuracy. The study showed that machine learning-based models offer potential for optimizing agricultural operations and sustainable agriculture. Going forward, it was stated that the integration of additional data sources such as satellite imagery, climate forecasts, and soil analysis could further increase the accuracy of the models (G. B. Raj et al., 2024).

Sravanthi and Moparthy developed an IoT-based crop disease prediction and product recommendation system for precision agriculture. The proposed system uses Multi-level Kronecker Guided Pelican Convolutional Neural Network (MKGPCNN) to make appropriate crop recommendations and Combined Graph Sample and Aggregate Attention Network (CGSAAN) to detect crop diseases. They collected soil and environmental data using IoT sensors and analyzed these data using machine learning algorithms. The results showed that the proposed system achieved 99% accuracy in crop recommendations and 98% accuracy in disease prediction. The study aimed to optimize agricultural production by providing farmers with appropriate crop selection, disease detection and appropriate fertilizer recommendations. It was stated that this two-way system helps farmers make data-driven decisions, thus increasing productivity and reducing manual labor (Sravanthi & Moparthy, 2024).

In their study, Ubaid and Javaid developed a computer vision and deep learning based method to count sugarcane plants in the tillering stage in precision agriculture applications. In the study, they compared YOLOv3 and Faster R-CNN models to detect and count sugarcane plants using images taken by drones and proposed a new modified Faster R-CNN model. In the modified model, feature extraction was performed using VGG-16 and Inception-v3 modules. Data augmentation techniques were applied to increase the diversity of the data. They stated that the results showed that the proposed modified Faster R-CNN model outperformed other models with an accuracy rate of 82.10%. It was also stated that the study provided a more accurate and faster solution compared to traditional manual counting methods, allowing farmers to optimize their agricultural management decisions (Ubaid & Javaid, 2024).

Pesticide Management

Pesticide management is one of the critical elements that directly affects the efficiency and sustainability of modern agriculture. In traditional methods, farmers applied extensive pesticides and fertilization throughout the field to combat pests and provide the nutrients that plants needed. However, these methods caused various problems such as unnecessary chemical use, high costs and environmental damage. Modern technologies, especially pesticide systems supported by artificial intelligence (AI), IoT, image processing and data analytics, minimize these problems and offer more efficient and sustainable solutions. Pesticides are used to protect plants from insects, weeds and diseases, while fertilizers support growth by providing plants with the necessary nutrients. Effective pesticide management increases crop productivity reduces production costs and reduces negative impacts on the environment. Traditional extensive pesticide methods often result in excessive chemical use, which both increases costs and harms the environment. Modern technologies, on the other hand, optimize the use of pesticides and fertilizers by making this process more precise (Kanwal et al., 2022; Katiyar, 2022; Shah & Razaq, 2020).

Li et al. stated that they developed a disease and pest prediction algorithm based on image processing and SVM as a solution to the problems of complexity and low accuracy of traditional methods. They stated that they first obtained the morphological features of pests with techniques such as image filtering and feature extraction. Then, they labeled and scientifically classified these features based on disease and pest data from previous years and created a dynamic prediction model to predict the possible spread of future pests. As a result, they stated that the prediction results of the developed model reached 90% accuracy and that this method offers high prediction accuracy. The authors stated that this approach can provide more effective protection against agricultural damages by predicting the spreading trends of pests more efficiently and scientifically (Li et al., 2020).

Ahuja et al., in their study, examined the role of artificial intelligence (AI) technology in precision pest management and water use optimization in modern agriculture. In the study, the use of AI-supported drones and sensors enabled the detection and monitoring of pests, thus aiming to reduce the use of pesticides and protect water quality. AI analyzed pest behavior and environmental factors, optimized pest management strategies and reduced pesticide use. At the same time, they evaluated data such as soil moisture and

weather conditions, optimized irrigation programs and prevented water waste. As a result, it was stated that the study revealed that AI-based precision agriculture applications support environmental sustainability while increasing production. The authors stated that these technologies offer the potential to increase agricultural productivity, reduce labor costs and improve product quality. They also stated that small-scale farmers have limited access to these technologies and that their more widespread use should be encouraged for sustainable agriculture (Ahuja et al.).

Agarwal et al. stated that they investigated the effects of agricultural chemicals on human health and investigated ways to better manage these interactions using artificial intelligence (AI) technologies. They drew attention to the negative effects of increasing agricultural intensity on human health and stated that they used AI-based deep neural network (DNN) techniques to minimize these effects. The study examined the negative health consequences of pesticides used during agricultural production and emphasized the goal of protecting human health by offering ways to optimize pesticide use. As a result, they stated that the developed DNN model reduces the use of agricultural chemicals, guides producers on safe application methods and minimizes health risks. They also stated that farmers should wear protective clothing and take certain safety precautions during chemical use. It was stated that these findings contribute to the adoption of sustainable agricultural methods, increase agricultural productivity, and reduce negative effects on the environment and human health (Agarwal et al.).

Agricultural Robots and Autonomous Systems

Agricultural robots and autonomous systems are innovative technologies developed to increase efficiency, reduce costs and optimize labor in the agricultural sector. Many processes in traditional agriculture require intensive labor and time; however, robots and autonomous systems have revolutionized agricultural production by automating these processes. These systems are used in many different areas, from planting to harvesting, from spraying to product classification. Agricultural robots are machines and systems designed to automate processes performed by human power on farms. These robots can perform various tasks such as seed planting, weeding, irrigation, fertilization, harvesting and even plant health monitoring. The use of agricultural robots increases efficiency, especially in

large-scale agricultural enterprises, and reduces dependence on labor. At the same time, in regions where agricultural labor is reduced, robots ensure the continuity of agricultural production by providing continuous and regular work. Robots can also perform tasks that are too delicate and detailed for humans to do; this increases crop quality and minimizes losses (Pearson et al., 2022; Rahmadian & Widyartono, 2020). A representative illustration of agricultural robots and autonomous systems is given in Figure 4.

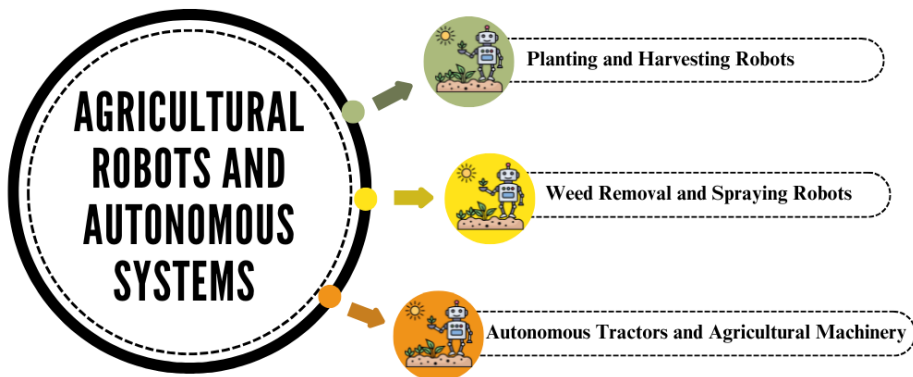


Figure 4. Agricultural robots and autonomous systems

Planting and Harvesting Robots

Planting and harvesting robots are one of the most common areas of use for agricultural robots. Planting robots ensure that seeds are planted at the right depth and distance in the field. While this process is done manually or with large machines in traditional methods, robots manage this process more precisely and efficiently. Equipped with GPS and sensors, these robots help place seeds in ideal growing conditions and ensure maximum use of the area. Harvesting robots are used to collect ripe products. Dependence on manpower is quite high, especially in fruit and vegetable harvesting; however, robots speed up this process and reduce costs. Robotic arms detect the maturity levels of the products and collect only the ripe ones, which increases product quality and prevents damage to the products during harvest. For example, strawberry or tomato harvesting robots can quickly

collect plants without damaging them and can do this process 24 hours a day without interruption (Mail et al., 2023; Pradhan et al., 2024).

In their study, Das et al. stated that they developed an agricultural rover equipped with deep learning algorithms for vegetable harvesting and soil analysis in modern agriculture. It was stated that the developed rover has the ability to perform autonomous vegetable harvesting and analyze soil health. The system detects ripe vegetables using image processing techniques with the YOLOv5 algorithm and harvests these vegetables with its robotic arm. It also evaluates field health by measuring soil nutrient values through NPK sensors. As a result, it was stated that the developed rover achieved high accuracy rates in vegetable detection and harvesting and offered farmers an efficient and sustainable agricultural experience with soil analysis functions. The authors stated that this robotic system has the potential to increase efficiency in agricultural production and reduce manual workload. It was also stated that this system can be expanded in future agricultural applications such as harvesting different types of vegetables and remote monitoring of fields (Das et al., 2024).

Prasanna et al. stated that they developed an IoT-based automatic tuber harvesting robot for precision agriculture. It was stated that the developed robot provides live video streaming by working integrated with the ESP32 camera and Arduino control unit, and the user can direct the robot via the browser. It was also stated that this system optimizes yield by automatically cutting, collecting and measuring the load of plants. The weight of the harvested plants is measured using a load cell, and this data is compared with estimates based on solar activity to predict the yield of the coming years. As a result, it was stated that the proposed system offers high yield estimation performance with an accuracy rate of 92%. The authors stated that this approach is an important step in increasing agricultural productivity and promoting sustainability by reducing manual labor. They also stated that in the future, solar energy-powered versions of this system can be developed and energy consumption can be optimized (Prasanna et al., 2024).

Li et al. stated that they developed a deep learning-based Selective Intelligent Seedling Collection Framework (SISPF) in order to increase the efficiency of seedling planting robots in modern agriculture. They drew attention to the problem that existing planting machines cannot distinguish weak or damaged seedlings in the seedling bed and therefore plant poor quality seedlings and reduce the yield. The developed SISPF system aimed

to solve this problem by using machine learning algorithms to select strong seedlings and eliminate weak ones. In the study, the health and quality of the seedlings were evaluated using a single-stage detection approach. As a result, it was stated that the SISPF model had an average accuracy (mAP) rate of 86.4% and a fast image processing time of 28.9 ms. This model increased the quality of seedlings during automatic seedling planting, making it possible to obtain 18.92% higher healthy seedling rate in the field and 9.91% less incomplete planting rate. The authors stated that this system has the potential to increase agricultural productivity and improve the quality of mechanized planting operations (Li et al.).

Begam et al. stated that they developed an IoT-based agricultural robot for multi-purpose use in agriculture. The developed robot is designed to collect environmental data such as soil moisture and temperature, to perform various tasks such as seed planting and pesticide spraying. Equipped with an ESP32 camera and a Bluetooth RC application, the robot allows users to remotely monitor and manage agricultural fields. The robot is enabled to move comfortably on rough terrain using the Rocker Bogie mechanism. As a result, it is stated that the robot performs agricultural operations faster and more efficiently compared to manual methods, reduces energy consumption and significantly eases the workload of farmers. The authors stated that this technology offers a practical solution for increasing productivity and promoting sustainability in agriculture. It is also stated that the robot can be developed to work with renewable energy sources such as solar energy in the future (Begam et al., 2024).

Wu et al. stated that they developed a deep learning-based crop harvesting robot grasping system in their study. The system uses a CNN to identify crops and determine the correct grasping points. First, it was stated that the diversity of the model's training data was increased by applying preprocessing and boosting techniques on the image data. It was stated that the CNN model was optimized with the stochastic gradient descent (SGD) algorithm and that crop types were identified with high accuracy. In addition, LiDAR and Time-of-Flight (ToF) sensors were used to obtain depth and location information, and clustering was performed with the AGNES algorithm in location determination. According to the experimental results, it was stated that the developed system had a low error rate in 3D coordinate calculations and the analysis time for a single image was only 0.000316 seconds. It was stated that the overall accuracy was 97.58%. It was stated that

this study has the potential to increase productivity in agriculture by providing reliable technical support in automatic crop harvesting processes (Wu et al., 2024).

Weed Removal and Spraying Robots

Weeds are one of the biggest problems that negatively affect crop productivity. In traditional methods, it may be necessary to manually weed or clean large areas with chemical pesticides. Weeding robots have been developed to solve this problem. Equipped with image processing and artificial intelligence (AI) technologies, these robots detect weeds in the field and mechanically clean them or destroy them using minimal chemicals. This offers an environmentally friendly approach and reduces the use of chemical pesticides. For example, a weed robot moving on the field recognizes weeds through its image analysis system and cleans these weeds with targeted mechanisms. Spraying robots, on the other hand, apply the drugs necessary for plant health with precision. While traditional spraying methods spray the entire field, spraying robots only apply drugs to the areas where they are needed. This significantly reduces chemical use and reduces costs. These robots analyze the health status of plants with sensors and imaging technologies and target only sick plants. For example, when a pest is detected, the robot quickly sprays the area where the pest is located and prevents it from spreading to other plants (Muchhadiya et al., 2024; Vijayakumar et al., 2023).

Ghimire, Shrestha and Pariyar stated that they developed an agricultural robot based on image processing techniques and IoT. They stated that the developed robot automatically performs various tasks such as disease detection, weed management and crop harvesting in tomato plants. The robot, controlled with an ESP32 microcontroller, can identify plant diseases with 95% accuracy using CNN models for image processing. In addition, the robot can perform tasks such as seeding, irrigation, fertilization and harvesting with its mechanical arms. As a result, they stated that the proposed system aims to reduce labor and increase efficiency by automating agricultural operations. It was stated that the robot showed high performance with 95.56% fruit detection and 95.14% plant detection accuracy. The authors emphasized that this technology can be expanded for other agricultural applications in the future and will contribute to sustainable agricultural solutions (Ghimire et al., 2024).

Azghadi et al. stated that they introduced the robotic point sprayer named "AutoWeed" developed for weed control in sugar cane fields in their study. The system detects weeds using computer vision and deep learning-based algorithms and reduces chemical use by spraying herbicide only in necessary areas. The researchers presented the results obtained during field trials, which show that the system can be integrated with existing agricultural machinery. As a result, they stated that AutoWeed uses 35% less herbicide compared to the common spraying method, which is the industry standard, and provides 97% effectiveness in weed control. It was also stated that point spraying technology has positive effects on water quality, reducing the average herbicide concentration by 39% and its load by 54%. The authors emphasized that this approach has the potential to both reduce costs and improve water quality by supporting environmental sustainability (Azghadi et al., 2024).

Lippi et al. reported that they developed a fully autonomous spraying robot architecture for the management of bottom shoots in large-scale hazelnut orchards. The system detects shoots using YOLO-based image processing algorithms, reconstructs them in 3D, and estimates the amount of herbicide required for each plant with a data-driven approach. The ground robot, equipped with an RGB-D camera and spraying system, aims to reduce chemical use and environmental pollution by applying local herbicide according to the needs of each plant. As a result, it was stated that the system gave successful results in real-world tests conducted in a hazelnut orchard in Caprarola, Italy, and achieved 97% weed control efficiency using 35% less herbicide than traditional methods. The authors stated that this autonomous solution increases efficiency in precision agriculture practices while supporting environmental sustainability (Lippi et al., 2024).

Balasingham et al. stated that they developed an autonomous precision agriculture robot called SPARROW. This robot is designed to detect weeds in agricultural fields and spray targeted herbicide only to the detected weeds. The system detects weeds with high accuracy using a YOLOv8-based image processing algorithm and uses this information to perform spot spraying with the herbicide spraying system. The movement and navigation of the robot were provided by an image-based detection system, thus providing a low-cost and efficient solution. As a result, it was stated that SPARROW detected weeds with a high accuracy rate of 93.99% with the developed algorithms and optimized the use of herbicide while reducing energy

consumption. The authors stated that this system has significant potential to increase productivity by reducing labor in agriculture and to support environmental sustainability (Balasingham et al., 2024).

Autonomous Tractors and Agricultural Machinery

Autonomous tractors are among the agricultural vehicles that farmers need the most. Unlike traditional tractors, autonomous tractors can operate without human intervention. Equipped with GPS, sensors and artificial intelligence algorithms, these tractors can be programmed to plow the field, sow seeds, fertilize and perform other agricultural tasks. These technologies provide great savings in labor and time, especially for large-scale agricultural enterprises. Autonomous tractors can move according to the needs of different areas in the field and optimize resource use by applying precision agricultural techniques. In addition, with the help of GPS and sensor systems, they operate safely by detecting obstacles and can perform multiple tasks at the same time. One of the biggest advantages of autonomous tractors is the ability of farmers to control these tractors remotely. This provides great convenience, especially for farmers working on large agricultural lands. The tractor moves on the programmed route and performs all operations independently, which saves a lot of labor (Alberto-Rodriguez et al., 2020; Baillie et al., 2017; Eaton et al., 2008).

Liu et al. stated that they developed a system that provides automatic identification of header boundaries and distance measurement for smart agricultural machines. The system aims to perform tasks such as turning operations when approaching header fields by using deep learning and dual vision technologies. In the study, header images were recognized and segmented using deep learning models such as MobileNetV3 and DeeplabV3+, and then distance measurement was performed with dual vision technology. Specially created datasets allowed the model to work with high accuracy in different fields and header environments. As a result, it was stated that the developed system provided successful segmentation with a MIoU value of 92.08% in field tests and worked with high precision with error rates ranging from 4.35% to 6.72% in header distance measurements. The system meets real-time detection requirements in the field and is designed to be compatible with various agricultural machines. The authors stated that this technology contributes to the digitalization of agricultural

processes by meeting environmental sensing needs in smart agricultural machines (Liu et al., 2024).

Wang et al. stated in their study that they developed an interactive image segmentation method and software to detect field boundaries for autonomous agricultural machines. This method is designed to accurately identify field boundaries, roads, exits, obstacles and other agricultural field features on high-resolution orthophoto images. The interactive segmentation model provides more precise segmentation of images with positive and negative signs added by the user. The study aimed to provide more accurate boundary detection in agricultural fields using the HRNet-18 based deep learning model. As a result, it was stated that the developed model provided high accuracy with 93.2% mean intersection over unity (mIoU) and met the real-time segmentation requirements with a fast inference time of 0.197 seconds per second. It was also stated that the developed software was successfully tested in different agricultural fields and that this method can be widely used in precise path planning and field management applications for agricultural machines in the future. The authors stated that this system contributes to the digital transformation process in agriculture and enables more efficient and optimized agricultural operations (H. Wang et al., 2024).

Xu and Rai stated in their study that they developed a low-cost, camera-based autonomous navigation system for the use of autonomous tractors in peach orchards. They stated that they aimed to provide a reliable navigation solution without the need for expensive equipment such as LiDAR by using a stereo camera and an inertial measurement unit (IMU). The proposed system consists of a multi-task detection network, a frame transformation algorithm, and motion planning modules. The multi-task detection network simultaneously detects tree trunks, obstacles, and passable areas from RGB images. The algorithm uses this information to determine the center of tree rows and create appropriate return paths. As a result, it was stated that the developed system provided object detection with 96.7% accuracy and passable area segmentation with 98.1% accuracy. The authors stated that this approach can efficiently perform autonomous navigation in peach orchards with both accuracy and fast detection time. They stated that in the future, this technology will be developed to be used in other agricultural areas and will enable wider adoption of autonomous agricultural machines to increase environmental sustainability (Xu & Rai, 2024).

Jeon et al. stated that they introduced an autonomous tractor system in which they developed a path planning algorithm that provides full coverage for mudding and leveling operations in rice fields. This system determines the optimal path sequence using genetic algorithm (GA) in order to muddy and level the field efficiently and aims to minimize turning distances. The tractor is equipped with a mudding rake with foldable wings and follows predetermined paths to level after mudding. As a result, simulation studies have shown that the developed algorithm reduces the turning distance from start to finish in pentagon, trapezoid and rectangular fields by 28.5%, 33.9% and 45%, respectively, compared to previous methods. In real field tests, the autonomous tractor covered 36% less distance and consumed 4.7% less fuel than manually controlled tractors. However, it was stated that the process took 30% longer due to the slower movement of the autonomous system during turns. The authors stated that this technology is an important step towards providing efficient and sustainable agricultural operations and that they plan to test the system on more complex field structures in the future (Jeon et al., 2024).

Xu stated in his study that he developed a vision-based autonomy stack for autonomous tractors and smart spraying systems in orchards. This system provided a low-cost alternative using a stereo camera and inertial measurement unit (IMU) and enabled the tractor to move autonomously in the field. The developed system simultaneously detects tree trunks, obstacles and passable areas using a multi-task sensing network; performs global path planning and route tracking tasks with a multi-feature fusion algorithm. In addition, a special spraying mode was developed for the system's real-time spraying operations in field conditions. Deep learning models were used to map the leaf and flower density of plants to provide more effective spraying. As a result, it was stated that the system achieved successful results with high accuracy rates in field tests and provided significant improvements in both autonomous navigation and precision spraying operations. Xu stated that this technology has the potential to reduce costs and reduce labor by increasing agricultural productivity while supporting environmental sustainability (Xu, 2024).

Hajiahmadi, Jafari and Reyhanoglu stated that they developed a ML based method for the control of autonomous vehicles (AVs) for cleaning solar panels in agricultural solar energy farms. The system aimed to ensure that AVs operate effectively in dynamic environmental conditions by using the

biologically inspired Brain Emotional Learning (BEL) model in order to reduce the difficulties and costs of traditional manual cleaning methods. The BEL-based controller helps AVs adapt to difficult terrain conditions, installation of panels at different angles, and environmental uncertainties. As a result, it was stated that the developed ML-based controller performed better than traditional PID control methods and provided superiority especially in reducing tracking errors, providing fast response times, and providing control without overshoot. The study results showed that smart technologies can be successfully applied to increase the efficiency of agricultural solar energy systems. The authors stated that these methods can be expanded and used for agricultural applications in the future and will contribute to increasing the efficiency of renewable energy infrastructures (Hajiahmadi et al., 2024).

Use of Drones in Agriculture

Drone use in agriculture has become an important part of modern agricultural techniques. Drones are aerial vehicles used in various stages of agricultural activities and are used to increase efficiency, optimize resources and manage agricultural processes more effectively. Since manual monitoring and management can be difficult, especially in large agricultural areas, drones perform these tasks quickly, precisely and cost-effectively. Below is comprehensive information about the details, advantages and different application areas of drone use in agriculture (Ahirwar et al., 2019; Dutta & Goswami, 2020; Pathak et al., 2020). The use of drones in agriculture allows farmers to monitor and analyze agricultural lands from a broad perspective. Drones quickly and effectively perform tasks that are difficult for farmers to perform manually. A representative illustration of drones in agriculture is given in Figure 5. The main advantages of this technology are: (Ahirwar et al., 2019; Dutta & Goswami, 2020; Pathak et al., 2020):

Fast and Wide Area Scanning: Drones can scan large agricultural lands in a short time and collect data on the general condition of these areas. In this way, farmers save time by performing field checks quickly.

Increased Productivity: Precise measurements of drones help farmers make more accurate and efficient decisions. For example, early diagnosis of pests or diseases minimizes crop losses.

Optimization of Resources: Operations such as irrigation, fertilization and spraying can be done on a point basis through drones. This prevents unnecessary use of resources and reduces costs.

Environmental Sustainability: With precision agriculture practices, drones optimize the use of water, fertilizer and pesticides. Thus, environmental impacts are reduced, and sustainable agricultural practices are encouraged.

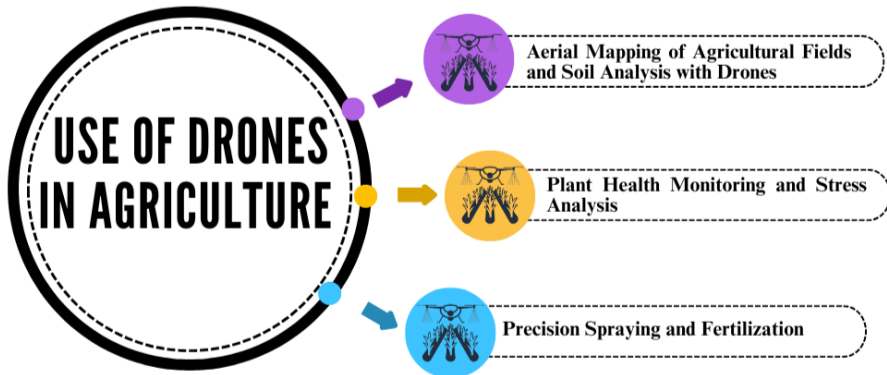


Figure 5. Drones in Agriculture

Aerial Mapping of Agricultural Fields and Soil Analysis with Drone

Drones provide high-resolution images to determine the general condition of agricultural lands and to perform productivity analysis. Critical information such as vegetation, soil condition and water bodies can be obtained with aerial scanning. In particular, pre-planting soil analysis provides farmers with information about the nutrient status and structure of the soil, and this data helps to make correct planting plans. Drones equipped with multispectral and hyperspectral cameras can reveal even details that the human eye cannot perceive (Huuskonen & Oksanen, 2018; Meivel & Maheswari, 2021).

Otto et al. stated that they obtained high-resolution data using unmanned aerial vehicle (UAV)-based remote sensing techniques for digital mapping of soil organic carbon (SOC). The study aimed to estimate SOC content by evaluating topographic and spectral variables in three different agricultural fields (vineyard, kiwi orchard and peach orchard). UAV data were analyzed with topographic modeling and multispectral imaging

techniques. It was stated that soil organic carbon was estimated to use three different models and that the models in which topographic and spectral variables were integrated had an explanatory power of 81%. As a result, it was stated that this approach can be used for precise estimation of SOC content and soil health assessments. The study predicts that UAV data is an effective tool for digital soil mapping and that machine learning approaches can be applied more widely in such analyses in the future. The authors stated that this method can contribute to sustainable agricultural management strategies by supporting data-driven decision-making processes in precision agriculture applications (Ottoy et al., 2024).

Ubben, Pukrop and Jarmer reported that they investigated the effect of different spatial resolutions on classification accuracy for UAV (unmanned aerial vehicle) based weed mapping in soybean fields. In the study, both pixel and object-based approaches were evaluated using four different resolutions (0.27, 0.55, 1.10, 2.19 cm) obtained at altitudes of 10, 20, 40 and 80 meters. It was stated that pixel-based classification outperformed object-based classification at all resolutions and that the accuracy was statistically significantly higher especially at altitudes of 10 and 20 meters. It was stated that the accuracy decreased significantly as the resolution decreased, but the flight and processing times decreased exponentially depending on the resolution. As a result, it was stated that the highest accuracy (93%) was obtained at an altitude of 10 meters in pixel-based classification and that there was a significant decrease in accuracy with decreasing resolution. However, it was stated that the flight and processing times took 75% less time at 20 meters compared to 10 meters, so flying at this height saved time. The authors stated that these results should be confirmed by further research on different plant species and growth stages in the future (Ubben et al., 2024).

Rathore et al. stated that they presented a method and framework design that they developed using drone images for area calculation of agricultural lands. In order to overcome the difficulties and high costs of traditional methods, they aimed to obtain high-resolution images with drones and to provide more accurate and faster area calculations by processing these images. The study focused on determining the boundaries of agricultural fields in images obtained with drones and calculating their areas using Gauss's area formula. As a result, it was stated that the proposed method achieved successful results with 97% accuracy compared to manual area measurement methods. The authors stated that this approach offers an

efficient and low-cost solution for agricultural field management with the integration of drone technology and image processing techniques. It was stated that this method can be expanded by trying more agricultural applications and different regional conditions in the future (Rathore et al., 2024).

Reyes et al. stated that they developed a method aimed at monitoring soil organic carbon (SOC) content in a long-term experimental area using multispectral UAV (unmanned aerial vehicle) images. Various machine learning models (CUBIST, MARS, linear regression) were used for the estimation of SOC, and it was aimed to increase data accuracy by applying image processing techniques. The best results were obtained using the CUBIST algorithm and the model performance was optimized with a 2-meter pixel selection strategy. The model created spatial distribution maps showing the effects of organic fertilization on SOC. As a result, the CUBIST algorithm showed better performance than other methods with 54% R-squared and 1.9 g/kg RMSE values. The authors emphasized the potential of multispectral UAV images for SOC monitoring and stated that these methods can be used to improve agricultural management and support environmental sustainability. It is stated that the study is planned to be applied to larger agricultural lands in the future and to be expanded with different data processing techniques (Reyes et al., 2024).

Frid and Frid stated that they addressed the integration of ground-based and drone-based ground penetrating radar (GPR) technologies in archaeological research. The research examined the advantages and difficulties of detecting underground remains in various environmental conditions, such as the difficult clay-containing soil structure in the Hulata region of Israel. The ground penetrating radar unit was designed to identify objects below the surface using electromagnetic waves, and data was collected at different depths with both drones and ground equipment. In particular, it was stated that the precise coordinate mapping of drone flights was provided using RTK technology, thus increasing the accuracy of the subsurface data. As a result, it was stated in the tests conducted that the combination of these technologies allowed the detection of underground structures with high accuracy rates even in clay-containing soil conditions. The research showed that drone-based GPR offers a time saving, economical and effective solution, especially in large areas. The authors stated that these technologies could have wider applications in geophysical research and

engineering projects outside of archaeology. It was stated that future studies are planned to increase the effectiveness of the system in more complex and different environmental conditions (Frid & Frid, 2024).

Plant Health Monitoring and Stress Analysis

One of the most common uses of drones is plant health monitoring and stress analysis. Drones equipped with multispectral and thermal cameras can monitor the health of plants and detect any problems early. These cameras can provide rapid warnings to farmers by detecting color changes, temperature differences and other signs of stress in plant leaves. Drones can be used to determine vegetation and plant diversity, thus playing an important role in determining biodiversity (Abbas et al., 2023; Barbedo, 2019).

Samborski et al. stated that they developed a method using unmanned aerial vehicle (UAV) images to remotely assess maturity class (MC) in potato breeding trials. The study aimed to accurately estimate maturity classes of potato clones using different vegetation indices (VIs). Multispectral images obtained with UAV were used to calculate various vegetation indices such as NDRE, NDVI, MCARI2. The data obtained were compared with the visual assessments and it was stated that NDRE gave the best results in MC estimation with the lowest error rate (MAE). As a result, it was stated that NDRE provided the highest accuracy in remote MC estimation with 0.81% MAE, especially for B clones. However, it was stated that factors such as irregularity of vegetation and damage to plants by tractor wheels reduced accuracy. The authors stated that these methods have the potential to be further developed with machine learning algorithms in the future, increasing agricultural productivity and improving breeding processes (Samborski et al., 2024).

Tavilla et al. reported that they investigated the use of unmanned aerial vehicles (UAVs) to monitor plant diversity in Natura 2000 protected areas in Sicily. They emphasized the advantages of drone technology in order to collect high-resolution images quickly and cost-effectively in areas that are inaccessible or difficult to reach with traditional methods. The study examined the plant diversity in the Rocca di Novara region and analyzed the spatial distribution of the vegetation using drone images. In addition, the presence of rare species such as *Saxifraga callosa* subsp. *australis* was confirmed after 140 years. As a result, it was stated that this method makes an important contribution to the development of biodiversity monitoring and

conservation strategies. It was stated that drones offer the opportunity to monitor plant communities more quickly and efficiently in areas that are difficult to access and that this approach can be applied in other areas. The authors stated that the use of drones as an effective tool in environmental monitoring studies can democratize scientific research and increase the participation of the broad public (Tavilla et al., 2024).

Ecke et al. stated that they developed a deep learning-based system for species identification and crown condition assessment using unmanned aerial vehicles (UAV) for forest health monitoring. High-resolution multispectral images were obtained from 235 different forest monitoring points in the Bavarian region of Germany between 2020 and 2022, and these were combined with the data to classify the crown health of the main tree species. Using the EfficientNet CNN architecture, models were created that aimed to distinguish between healthy and stressed trees, and classification was performed at five tree species and three genus levels. As a result, it was stated that the system managed to classify 14 different classes with an average F1-score of 61% and provided an accuracy of 97%, especially in dead trees. It was also stated that the proposed methods could complement existing ground-based monitoring studies and reduce operational costs. The authors stated that these methods have the potential to modernize forest management, increase efficiency and sustainability, and can be widely applied across Europe (Ecke et al., 2024).

Raniga et al. stated that they developed a method that aims to monitor the fragile vegetation of Antarctica using unmanned aerial vehicles (UAV), multispectral imaging, and artificial intelligence (AI). The research aimed to compare two different ML models, Extreme Gradient Boosting (XGBoost) and U-Net, using high-resolution image data to monitor the health of Antarctica, especially moss and lichen species. The study was supported by images obtained in the data collection campaign conducted in the ASPA 135 region near Casey Station, and five classes were determined according to plant health: Healthy Moss, Stressed Moss, Dying Moss, Lichen, and Non-Vegetation Areas. As a result, the XGBoost model achieved over 85% precision, recall, and F1-score, while U-Net showed significant performance improvements, especially in the classification of healthy and stressed mosses. In particular, the second method of the U-Net model provided significant increases in accuracy and precision metrics. The authors stated that these technologies provide an effective solution for monitoring fragile ecosystems

and supporting conservation efforts. It was stated that in the future, the methods could be improved by applying them to larger areas and different environmental conditions (Raniga et al., 2024).

Precise Spraying and Fertilization

Drones are also frequently used in precise spraying and fertilizing operations. While traditional spraying methods spray pesticides over large areas, drones can only do this in the necessary areas and with precision. This can help reduce both chemical use and costs. Drones can target only sick plants by analyzing the health status of plants with sensors and imaging technologies. Thus, chemical residues in agricultural areas can be kept to a minimum level while ensuring environmental sustainability (Hanif et al., 2022; Mogili & Deepak, 2018; Spoorthi et al., 2017).

Singh et al. stated that they developed an autonomous drone system integrated with image processing and machine learning techniques for smart agriculture applications. The study addressed a drone system designed specifically to detect pineapple, papaya and cabbage plants and to perform precise spraying on these plants. The developed system performed real-time image processing using EfficientDetLite models trained to work with TensorFlow Lite. The drone sprays different amounts of pesticide according to the plant type with various spraying modes and performs these operations autonomously. As a result, it was stated that EfficientDetLite models achieved high accuracy rates, and the model processing speed was increased with the use of Edge TPU. The developed system optimizes chemical use in agriculture and increases efficiency by providing a cost-effective and energy-efficient solution. The authors stated that this approach can be improved with more powerful hardware and advanced algorithms in the future and expanded to different agricultural applications (Singh et al., 2024).

Azghadi et al. reported field trials with the robotic point spraying system "AutoWeed" used in sugar cane fields in the Burdekin region of Australia. The system detects weeds using deep learning-based image processing techniques and aims to control weeds by spraying chemicals only in necessary areas. The study analyzed the weed control effectiveness, chemical use and water quality effects of the point spraying system compared to traditional wide area spraying methods. The trials showed that AutoWeed achieved 97% effectiveness in weed control in sugar cane fields, while reducing herbicide use by 35%. This rate was up to 65% in areas with low

weed density. As a result, post-irrigation water quality analyses revealed that point spraying reduced herbicide concentration by 39% and load by 54% compared to traditional wide-area spraying. The authors stated that this technology could reduce farmers' costs while significantly reducing harmful effects on the environment. In the future, it is aimed to adapt this system to different agricultural crops and regions and expand it (Azghadi et al., 2024).

Li and Wu stated that they developed a comprehensive model using computational fluid dynamics (CFD) to increase the efficiency of pesticide spraying operations performed by drones in agricultural areas. The study created a multiphase flow model to understand how the airflow generated by drone propellers affects the evaporation and adhesion rates of droplets to the target. The effects of propeller speed on droplet impact speed and number, environmental factors (temperature, humidity) and surface slope were analyzed with CFD simulations. As a result, it was stated that the model successfully predicted droplet distribution with high accuracy under different propeller speeds and environmental conditions and was consistent with the experimental results. The benefits of using adjuvants to increase spraying efficiency by reducing droplet evaporation were revealed and suggestions were made. The authors stated that the model they developed will allow the optimization of operational parameters for drone use in agriculture and can be widely applied in the future (Li & Wu, 2024).

Wang et al. reported that they developed an autonomous drone spraying control system based on the coefficient of variation (CV) in spray distribution in order to increase the efficiency of agricultural pesticide spraying operations. The system is low-cost, modular and adaptable and includes a ground-based station and a control assistant unit on the drone. A regression forest model-based spraying control algorithm was used to optimize the CV, and environmental data was collected in real time and the drone's spraying strategy was adjusted accordingly. As a result, it was stated that the system successfully completed the spraying tasks of the targeted areas with high accuracy by keeping the CV values below 30% in the indoor and outdoor tests. In particular, CV values below 30% were obtained in 65% of the 23 indoor trials, which is consistent with the model's prediction results. The authors stated that this system reduces costs in agriculture and increases the accuracy of pest control applications by adding precision spraying capabilities to traditional agricultural drone models. They stated that in the

future, the system is planned to be used in wider agricultural applications and its performance is further improved (P. Wang et al., 2024).

Rayamajhi, Jahanifar and Mahmud stated that they developed a system based on unmanned aerial vehicles (UAV) and self-monitoring Segment Anything Model (SAM) to measure tree crown features for precise spraying applications of ornamental plants. The research was carried out by processing drone images to measure features such as tree height, crown area and volume. The obtained crown volume information was used to precisely calculate the amount of pesticide required for ornamental trees. As a result, it was stated that drone-based measurements showed high agreement with manual measurements and had average error rates ranging from 2.43% to 12.58%. The SAM-based method provided a faster and more cost-effective solution compared to traditional methods, allowing accurate measurement of crown features, especially in areas where trees are dense. The authors stated that this approach optimizes chemical use by supporting precision agriculture applications in agriculture and ornamental plant cultivation and can be adapted to different plant species and regions in the future (Rayamajhi et al., 2024).

Akdoğan, Özer and Oğuz stated in their study that they developed an artificial intelligence (AI) controlled spraying drone system integrated with advanced image processing techniques to increase productivity in agriculture. The study used YOLOv5, YOLOv7 and YOLOv8 deep learning models to detect cherry trees and perform point spraying applications. Two different approaches were adopted in the study: In the first approach, models were trained without preprocessing techniques; in the second approach, performance was improved by applying preprocessing techniques such as Gaussian, wavelet transform (WT) and histogram equalization (HE) to increase image quality. As a result, 98.6% F1 score and 98.9% accuracy were obtained in the second approach, and it was stated that pesticide use could be reduced by 53% and energy consumption could be reduced by 47% with the AI-supported spraying system. In real-time tests, it was stated that the system successfully detected and sprayed trees by 66% to 77%. The authors stated that these methods could be expanded in different agricultural applications in the future (Akdoğan et al., 2024).

Kovalev et al. stated that they developed a precision agriculture system based on the use of unmanned aerial vehicles (UAVs) for spraying pesticides and fertilizers. They stated that UAVs offer a more cost-effective,

environmentally friendly and flexible solution due to the access difficulties and high costs of traditional methods. The study emphasizes that dry product protection agents and biological pesticides and fertilizers can also be applied with UAVs. As a result, it was stated that the widespread use of UAVs in agriculture will spread further in the future and that the use of "drone swarms", where multiple drone groups are controlled by a single operator, has significant potential. The authors stated that these technologies will be developed with higher battery life, wider spraying capacities and obstacle avoidance features in the future. It was also emphasized that such systems should be supported by legal regulations and technological advances (Kovalev et al., 2024).

Animal Health Monitoring

Animal health monitoring plays a critical role in increasing efficiency, preventing and controlling diseases in modern livestock farms. In traditional animal husbandry methods, the health status of animals was monitored through observation, manual checks and veterinary examinations. However, these methods can be both time-consuming and costly, especially on large farms. Today, with the use of technologies such as artificial intelligence (AI), IoT, biosensors and data analytics, the health status of animals can be monitored continuously and in real time. This process is carried out for the purpose of early diagnosis of diseases, monitoring the birth process, optimizing the diet and improving the general well-being of animals. Animal health monitoring systems provide farmers with fast and accurate information, both protecting the health of animals and reducing operating costs (Ali & Al-Zu'bi, 2023; Gowthamii et al., 2023). A representative illustration of animal health monitoring is given in Figure 6.

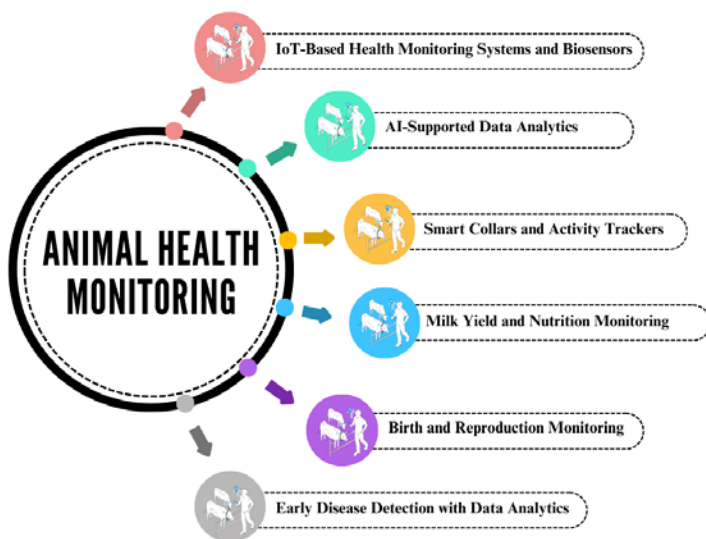


Figure 6. Animal Health Monitoring

IoT Based Health Monitoring Systems and Biosensors

IoT technology is one of the most important components used in animal health monitoring. IoT-based systems can continuously monitor biological data such as body temperature, heart rate, respiratory rate, mobility and feed consumption of animals through biosensors placed on animals. These sensors are designed as small devices that can be attached to the ears, neck or skin of animals. These devices can record the behavior and health status of animals in real time. Biosensors provide early diagnosis of disease symptoms. In addition, they can detect whether there is a change in the feeding habits of animals by monitoring their feed and water consumption. Such monitoring is important for the healthy growth process of animals (Karthick et al., 2020; Neethirajan, 2017; Neethirajan et al., 2017).

Lakshmi et al. stated that they developed a system that uses wireless sensor networks (WSN) to monitor the health status of cattle. The system is equipped with sensors that measure basic health parameters of animals such as temperature and heart rate. Data from the sensors are collected in real time and transmitted to a central server, where health problems are detected at an early stage using machine learning algorithms. The system provides efficient herd management by tracking the locations of animals with the help of the GPS module and warns users with instant notifications when necessary. As a result, it was stated that the developed system provides early detection of

diseases and increases animal welfare. It was also stated that the system increases the efficiency of farm operations by reducing the need for manual control. The authors stated that this technology can be further developed in the future with energy efficiency, data analytics and integration with IoT platforms (Lakshmi et al., 2024).

Mukhametova et al. reported that they developed synthetic oligosaccharide-based biosensor tracers using the fluorescence polarization test (FPA) for the detection of brucellosis in animals. In order to overcome the difficulties in traditional serological methods, synthetic fluorescently labeled trisaccharide tracers were used to detect antibodies against *Brucella* bacteria. These tracers target immunologically important regions of *Brucella* lipopolysaccharide (LPS) and reveal the presence of antibodies with high sensitivity and specificity. The study tested the performance of these tracers on samples taken from different serums. As a result, it was stated that the trisaccharide tracer gave similar accuracy results to classical serological methods (e.g., Rose Bengal test, complement fixation test) with 87% sensitivity and 88% specificity. The authors stated that this method offers a faster, more economical and more reliable alternative to traditional culture and biochemical tests. The fact that the developed FPA system provides fast and accurate results using compact equipment increases its usability in field conditions. The authors stated that this method has the potential for wider application in monitoring animal health and preventing epidemics (Mukhametova et al., 2024).

Nithisha et al. stated that they developed an IoT-based system to detect plastic waste in livestock facilities and to protect animals from consuming these harmful substances. The system performs real-time object identification using the YOLO (You Only Look Once) algorithm to detect wastepaper and plastic bottles, especially in agricultural areas. Detected waste prevents animals from consuming these wastes by sending audible warnings through a buzzer system connected to a control unit. IoT sensors were strategically placed in livestock facilities and visual data was collected and processed instantly. As a result, it was stated that the system can perform fast and accurate waste detection in real time and is more cost-effective and efficient compared to other traditional methods. The authors stated that this technology has significant potential in protecting animal health and encouraging environmentally friendly agricultural practices. It was also

stated that the system could be used in larger agricultural areas and to detect different types of waste in the future (Nithisha et al., 2024).

Tran et al. stated that they developed an IoT-based system that uses accelerometers to recognize the behaviors of cattle in real time. The system detects behaviors such as feeding, lying down, standing and walking using accelerometers mounted on the neck and legs of the animals and uses the DT algorithm to analyze this data. In particular, effective classification was achieved using short data windows (3 seconds) and high performance was achieved with low computational complexity. As a result, it was stated that the system was successful in behavior classification with 94% accuracy, 91% sensitivity and 90% positive predictive value. It was stated that this dual accelerometer-based approach offered much higher performance compared to traditional methods. The authors stated that this system has significant potential to improve animal welfare and can be applied to different animal species in the future and used in a wider range (Tran et al., 2024).

AI Supported Data Analytics

Artificial intelligence (AI) and machine learning algorithms play a major role in the analysis of animal health monitoring data. Large datasets collected from IoT sensors are analyzed with AI algorithms to extract important information about the health status of animals. Machine learning algorithms learn from past data to recognize early signs of a certain disease and send alerts to the farmer. Such proactive measures provide a great advantage in terms of protecting the health of animals and increasing productivity. AI can also monitor changes in animal behavior. For example, it can detect that an animal is moving less than normal or is not eating and analyzes the reasons for this situation. This is especially important in monitoring the individual health status of animals in the herd. AI-based systems also analyze general health trends in the herd with data analytics used in herd health management, predicting future risks and allowing farmers to take precautions in advance (Ali & Al-Zu'bi, 2023; Ezanno et al., 2021).

Jeong et al. stated that they developed a YOLO-v8 based IoT system to monitor animal behaviors in large cattle farms 24 hours a day. The system aims to detect the mounting behavior of animals in real time in both day and night conditions. Day and night images were captured using RGB and infrared (IR) cameras, and these images were processed with the YOLO-v8 model to detect mounting behavior instantly. It is stated that the system

provides high efficiency by working with the same model under different lighting conditions. As a result, it was stated that the system successfully detected mounting behaviors with 96.90% daytime accuracy and 93.80% nighttime accuracy. It was stated that the model provides farmers with the opportunity to intervene by sending instant notifications, thus increasing animal welfare. The authors emphasized that this technology can be expanded to detect other health-related behaviors and has the potential to increase efficiency in livestock management (Jeong et al., 2024).

Kim and Kim stated that they developed a "Health Score" using an artificial intelligence (AI)-based disease prediction algorithm to evaluate the health status of dogs. In the study, the daily behavior patterns of the dogs (itching, licking, swallowing and sleeping) were monitored with the help of sensors for nine months and the data obtained was analyzed with the AI algorithm. The AI detected abnormal behaviors and determined them as a numerical "Health Score". The scores were categorized as healthy conditions between 6 and 10 and conditions requiring treatment between 1 and 5. In the comparative analysis conducted with veterinarians, it was stated that the system provided 87.5% accuracy. As a result, it was stated that the developed AI-based Health Score allows dog owners to quickly and accurately evaluate the health status of their dogs. The authors stated that this method makes it easier to monitor pet health even for individuals without veterinary knowledge and that it can be developed and spread with more sensor technology and data analytics in the future (Kim & Kim, 2024).

Pandey and Mishra stated in their study that they developed a mobile application-supported system that integrates artificial intelligence (AI) and IoT technologies for monitoring both cows and crops in dairy farms. This system aims to monitor the health and behavior of animals in real time using AI and edge computing and to detect health problems such as lameness at an early stage. The deep learning-based VGG16 model was used to detect cow behaviors, and the Bi-LSTM model was applied to define temporal relationships of behaviors. As a result, it was stated that the developed system exhibited superior performance with 96.65% accuracy, 97.04% sensitivity and 96.67% recall rates compared to other methods. It was stated that this integrated approach has the potential to improve animal welfare in dairy farms while also optimizing crop productivity. The authors stated that this technology could be used in different agricultural areas with further development in the future (Pandey & Mishra, 2024).

Schork et al. stated that they developed an artificial intelligence (AI)-based system to monitor and analyze dogs' sleep behaviors. This system, called BlyzerDS, uses convolutional neural networks (CNN) to detect dogs' sleep patterns and measure sleep duration. The research tested the accuracy and effectiveness of the AI-based system by conducting comparative analyses with traditional observational methods. The system detected the sleep and wakefulness states of dogs by working on video footage taken with low-quality cameras and was trained on a total of 13,688 videos. As a result, it was stated that the system provided an 89% accuracy rate in detecting sleep behaviors and achieved similar results with manual observations. The system was able to record more sleep duration than human observers, which revealed the difficulties brought by manual examinations. The authors stated that such AI-based systems allow for more accurate and faster monitoring of animal behaviors and can be applied to different animal species and behavior types in the future (Schork et al., 2024).

Mon et al. have developed an artificial intelligence-supported system for real-time tracking and identification of cattle in various environments. They stated that this system analyzes overhead images of cattle using an RGB image-based camera against the risk of loss or damage of traditional identification methods (radio frequency or ear tag). The YOLOv8 model was used to identify cattle, and unique local identities were assigned to each individual and the images were recorded. Then, cattle identities were determined with the Visual Geometry Group (VGG) feature extractor and SVM. As a result, it was stated that the developed method is highly accurate and cost-effective. The system increases animal welfare and reduces the need for manual work since it provides non-contact identification, unlike traditional methods. The system, which was tested on three different farms, was able to prevent the problem of ID change by monitoring the unique back patterns of cattle and provided 98.90% identification accuracy. It was stated that this study emphasizes the importance of advanced technologies for sensitive animal husbandry in the agricultural sector (Mon et al., 2024).

Smart Collars and Activity Trackers

Smart collars and activity trackers developed for animal health monitoring are used to monitor physical activities, feed consumption and even birth processes of animals. These devices are worn around the neck of the animals and are equipped with equipment such as GPS, speedometers

and biosensors. Smart collars can detect abnormal activities by following the daily movements of animals. Smart collar systems facilitate herd management. Especially on large farms, it can be difficult to continuously monitor the individual health status of animals. Smart collars automatically record and analyze the health data of each animal, making herd management more effective. These devices also allow the tracking and finding of lost animals, because they are integrated with GPS and can instantly report the location of the animal to the farmer (Durán López et al., 2019; Helwatkar et al., 2014; Mao et al., 2023).

Miller et al. stated that they developed an IoT system consisting of wearable sensors to monitor the health and activities of horse herds. The system consists of photoplethysmography (PPG) sensors that measure heart rate, GPS modules, and motion-detecting accelerometers and gyroscopes. The sensors are mounted on the tails of the horses and connected to each other using LoRa technology for long-distance data communication. This technology provides a better understanding of herd behavior by tracking the heart rate, movements, and locations of horses. As a result, it was stated that the system can measure heart rate with 95% accuracy and determine the effects of environmental stress factors on horses. The study aims to increase animal welfare by monitoring herd behavior and optimizing the living conditions of horses according to their natural behavior. The authors stated that this system can be adapted to other animal species and can be used extensively in the field of agriculture and animal husbandry in the future with more advanced data analytics techniques (Miller et al., 2024).

Versluijs et al. stated that they developed a system that analyzes accelerometer data using a virtual fence collar to classify the behaviors of free-ranging cattle. In the study, common behaviors of cattle such as feeding, resting, walking and rare behaviors (scratching, head-butting, self-grooming) were observed using three-axis high-resolution accelerometers. These behaviors were classified using various features and modeling techniques, and analyzed by taking into account data distortions that may arise from the orientation of the virtual fence collar. As a result, it was stated that the models reached 99.8% accuracy, 99.1% precision and 98.9% recall rates. High performance was achieved especially with a 20-second data processing interval, and it was shown that the data could be classified correctly depending on the location of the virtual fence collar. The authors stated that this technology contributes to sensitive animal husbandry practices in

agriculture by providing better monitoring of cattle in free-ranging areas and may allow the development of early warning systems against situations such as stress factors or predator attacks in the future (Versluijs et al., 2023).

Sharma et al. stated that they developed an advanced GPS tracking system to prevent pets from getting lost and to monitor their health. The system includes an Arduino-based microcontroller, GPS module, GSM module and pulse sensor. These components track the animal's location and heart rate and send this data to the animal's owners in real time. The system sends alerts when the pet goes outside a specified geographical area, allowing the animal to be found quickly in case of loss. As a result, it was stated that the developed GPS tracking system provides peace of mind to pet owners by providing a low-cost and reliable solution and increases the rate at which lost animals are found. The authors stated that in the future, the system can be equipped with more sensors to increase the capacity to monitor animal health and provide more comprehensive security solutions for pets (Sharma et al., 2024).

In this study, the authors stated that they developed an artificial intelligence (AI) and wearable sensor-based system to monitor the health status and activities of assistance and rescue dogs. The developed system collects vital data such as heart rate, movement and body temperature with sensors placed on the necks and bodies of the dogs. The collected data is transferred wirelessly to a computer via Raspberry Pi and analyzed here to provide information about the health status and stress levels of dogs. It is stated that the system was developed to improve training processes and objectively evaluate the behavior of dogs. As a result, it was stated that the system provided accurate and reliable data in the tests and that this data helped dog trainers understand the stress levels of the dogs. The authors stated that this technology can be further developed with real-time analysis in the future to improve the performance of the dogs and to be expanded by adapting to different animal species (Chi-Pérez et al., 2024).

Watanabe et al. stated that they evaluated the effectiveness of different locations and time intervals using accelerometer data to predict the behavior of young bulls in the fattening system. The study was based on placing accelerometers in two different locations, the halter and the neck collar, and collecting data at time intervals ranging from 6 seconds to 600 seconds. These data were analyzed using machine learning algorithms such as RF, SVM, multilayer perceptron (MLP), and Naive Bayes (NB) to determine eating,

drinking, and other activities. As a result, it was stated that all models except NB reached high accuracy rates. It was stated that accelerometers placed on the neck collar were more practical and effective, and that even analyses with fewer observations provided sufficient performance. It was emphasized that using fewer observations in the dataset reduced computational costs and extended the battery life of the devices. The authors stated that this approach could increase efficiency in the field of monitoring animal behavior and could be used in other applications in the future (Watanabe et al., 2024).

Milk Yield and Nutrition Monitoring

In dairy farms, the milk yield and diet of cows are critical indicators for understanding their overall health. Biosensors and smart devices continuously monitor the cows' feed intake, milk production amount and milk quality. If a cow starts to give less milk than normal, this could be a sign of nutritional problems, stress or illness. The system detects this situation and sends early warnings to the farmer. Nutrition monitoring also monitors the animals' feed consumption behavior. Abnormalities in feed consumption can indicate digestive problems, dental problems or other health issues. This information helps veterinarians treat animals better and create appropriate nutrition plans. In addition, milk productivity can be increased and feed costs can be optimized with correct nutrition plans (Gehlot et al., 2022; Neethirajan, 2023).

Alwadi et al. stated that they developed a smart dairy farm system for milk production estimation using machine learning and artificial intelligence (AI) techniques. In the study, data collected from approximately 4000 cows over a 14-month period was used. The data included milk production records, environmental factors and genetic profiles, and short-term daily and long-term monthly milk production estimation models were created based on these data. The system was developed using machine learning models including support vector regression (SVR) and various deep learning algorithms. In addition, classification and regression models that estimate different milk yield levels (low, medium, high and very high) were also applied. As a result, it was stated that deep learning models outperformed traditional machine learning algorithms and contributed to early detection of diseases, nutrition and reproduction management by increasing operational efficiency in dairy farms. The authors stated that such AI-supported estimation systems help farmers make the right decisions and can be

improved with more data in the future. They offered suggestions for the creation of new generation breeding programs that will further increase milk production by combining systems with genetic analyses in the future (Alwadi et al., 2024).

Guevara-Escobar et al. aimed to predict first lactation milk yield using growth curve derivatives of female calves. The study analyzed body weight data of 78 female calves raised on pasture between 3 and 21 months of growth period. Prediction models were developed with machine learning algorithms using body weight (P), first derivative (1D) and second derivative (2D) values of calves modeled with Fourier function. The study investigated the effects of these derivatives on milk yield and better prediction results were obtained especially in the 6-month period. The results showed that the prediction performance increased with the inclusion of 1D and 2D derivatives in the model. 1D derivatives stood out as important variables in the 6- and 9-months period, and 2D derivatives in the 3- and 12-months period. It was also stated that these models could help in selecting calves at an early age and making management decisions. Thus, it was stated that it could contribute to the reduction of financial and environmental costs (Guevara-Escobar et al., 2024).

Bhavsar et al. conducted a study on milk quality prediction using machine learning techniques. The study included measuring the properties of milk samples such as pH, temperature, odor, taste, fat content, color and turbidity with the help of various sensors. Data was taken from the Kaggle database and milk quality was graded. RF and SVM were used among machine learning models. The results showed that the RF model performed best with 92% accuracy, while SVM was lower with 57% accuracy. It was stated that RF has the ability to make better generalizations by creating multiple decision trees and combining their results. It was stated that the system proposed in this study provides higher accuracy than machine-based systems, allowing fast and accurate assessment of milk quality. It is stated that this technology can be used to provide better quality control in milk production processes (Bhavsar et al., 2024).

Cassimiro et al. developed a low-cost milk weighing system using machine learning techniques. With the help of sensors and cameras monitoring milk flow, the actual milk weight was estimated. The study was conducted with data obtained from 250 cows for 12 days, and a total of 8,601 milk flow records were examined. Prediction models were developed using

RF and Deep Neural Network (DNN) algorithms, and it was stated that the RF model exhibited the best performance in MSE, RMSE and MAPE metrics (2.81, 1.29 and 10.26%, respectively). The results indicated that the RF model can predict milk weight with high accuracy and can be applied to improve milk production processes of small-scale farms. It was also stated that the data collection process can be easily integrated into other milking systems. It was stated in the study that future research may aim to increase the generalization capacity of the model and estimate milk content using larger datasets (Cassimiro et al., 2024).

Mhapsekar et al. discussed the use of deep learning (DL) methods in milk quality analysis and proposed a Hybrid Mixed Deep Learning (HyBDL) model to evaluate milk quality with spectral data taken from milk samples. HyBDL model was developed to classify different impurities that may be present in milk samples by combining classical DL algorithms such as CNN, LSTM and GRU. In the study, the performance of the model on different edge devices was evaluated and training time, energy consumption and accuracy were analyzed. The results indicated that HyBDL model provided higher accuracy (98.03%), and lower errors compared to traditional DL algorithms. It is stated that this study demonstrates how DL techniques can be used in applications such as milk impurity detection and how they can be applied on different devices (Mhapsekar et al., 2024).

Birth and Reproductive Monitoring

Another important area in animal health monitoring is the monitoring of birth and reproductive processes. Especially in large and small cattle farms, birth processes need to be managed carefully. Smart sensors and biosensors can detect birth signs and send early warnings to the farmer. This allows for the early detection of complications that may occur during birth and the necessary precautions to be taken. In addition, reproductive cycle monitoring is also important for animal health. Especially in large cattle farming, the reproductive periods of cows are accurately monitored, and the most appropriate mating times are determined. When these processes are automated with biosensors, they help farmers increase productivity and increase the likelihood of healthy offspring (Gordon, 2017; Saint-Dizier & Chastant-Maillard, 2018).

Marques et al. reported that they developed a machine learning-based model that integrates farm data with automatic activity monitoring (AAM)

systems for pregnancy prediction in dairy cows. In the study, AAM data such as activity, rumination and estrus scores of cows were combined with farm data such as age, parity, body condition, postpartum health status and environmental factors. Using these data, six different machine learning models (logistic regression, support vector machines, random forest, linear discriminant analysis, AdaBoost and Bagged Classification Tree) were evaluated to predict pregnancy success. As a result, it was stated that random forest and logistic regression models achieved the highest accuracy rates (up to 87%) and that the integration of AAM data and farm data gave 3-4% more successful results compared to predictions made using only AAM data. It was stated that this approach helps to make correct decisions in the artificial insemination (AI) process in farm management and especially ensures more efficient use of high-value semen. The authors stated that these methods can be increased in applicability in farm management strategies and can be combined with other reproductive technologies such as embryo transfer in the future (Marques et al., 2024).

Laplacette et al. investigated the effects of a targeted reproductive management (TRM) program using automatic estrus detection (AEA) on the reproductive performance of lactating cows. The study compared a TRM program that prioritized estrus-detected cows (AIE) with a program that only applied timed artificial insemination (ALL-TAI). The study included 1,260 Holstein cows and monitored their estrus behavior using neck sensors. The results indicated that although the TRM program was less successful at first service than ALL-TAI, overall pregnancy rates were similar in both programs. Pregnancy rates were high in estrus-detected cows and estrus behavior was considered an important indicator of cow reproductive performance. The authors demonstrated that automatic estrus detection is an effective tool for estimating reproductive potential and that such targeted management strategies can increase productivity (Laplacette et al., 2024).

Nagahara et al. developed a diagnostic method to predict the optimal artificial insemination time using artificial intelligence in cows. In the study, a pregnancy probability diagnosis model (PPDM) was developed that analyzes external images of the cervix in order to increase pregnancy rates in dairy and beef cows. In the first stage, images obtained during artificial insemination were trained with the AI model, then the sensitivity of the model was improved by increasing the image set. In addition, a web application that can perform real-time evaluation for use in practical field

conditions was developed. The results showed that PPDM has high accuracy rates when it predicts a pregnancy probability of 70% or higher. The model achieved 76.2%, 76.2% and 100% results in accuracy, precision and recall rates, respectively; the F-score was calculated as 0.86. This showed that AI-based tools provide a reliable method for determining the optimal artificial insemination time. The authors stated that such systems can provide significant advantages in improving breeding operations (Nagahara et al., 2024).

Wang et al. introduced the E-YOLO model, which they developed to detect the estrus period of cows quickly and accurately in modern dairy farms. In the study, an improved model named E-YOLO was developed based on the YOLOv8n model to overcome the low accuracy and efficiency problems of traditional methods. The model was optimized with new methods such as normalized Wasserstein distance (NWD) loss and contextual information augmentation module (CIAM) to determine estrus behaviors. In addition, the triple attention module (TAM) was added to ensure that the network focuses on individual estrus cows. The results showed that the E-YOLO model provided 93.9% estrus average accuracy (AP_{estrus}) and 95.7% estrus behavior accuracy (AP_{mounting}). These accuracies were 5.4% and 3.3% improvements over traditional methods. In addition, it was stated that the model is suitable for real-time monitoring conditions with its low computational cost and fast detection speed. The authors stated that this developed model will be an important tool in increasing the efficiency of dairy farms by facilitating the detection of estrus in complex agricultural environments (Z. Wang et al., 2024).

Early Diseases Detection with Data Analytics

Artificial intelligence and data analytics are one of the biggest advantages of animal health monitoring systems. Large datasets collected from sensors and smart devices are analyzed with artificial intelligence algorithms to detect signs of disease. For example, early signs of a certain disease can be detected by examining biometric data such as respiratory rate, body temperature and feed consumption. Machine learning algorithms recognize such abnormalities based on past data and can send early warnings to the farmer. Such early detection systems provide a great advantage in terms of protecting the health of animals. Diseases are detected and treated before they spread and affect other animals. This improves the overall health

of the herd and reduces treatment costs (Ali & Al-Zu'bi, 2023; Neethirajan, 2020; Zhang et al., 2021).

Scharre et al. compared a deep learning tool developed for diagnosing eye diseases in horses with the diagnostic accuracy of veterinarians. The study aimed to evaluate whether the artificial intelligence (AI)-based tool could assist veterinarians in diagnosing diseases that require urgent intervention, especially uveitis. The study compared the diagnoses of the deep learning tool and veterinarians from different specialties using photographs of 40 horse eyes. The results showed that the deep learning tool was able to detect diseases with 93% accuracy. In contrast, equine veterinarians made 76% and other veterinarians made 67% correct diagnoses. The authors stated that these findings indicate that the AI-based tool can be used as a support tool in identifying emergency situations and in the decision-making processes of veterinarians. However, it was stated that the system should not replace clinical examinations, but should only be used as an auxiliary tool (Scharre et al., 2024).

In his study, Saha stated that he developed a model using deep learning and machine learning techniques for the diagnosis of nodular skin disease (LSD) seen in dairy cows. In the study, different CNN models were tested and diseased areas were determined using image processing and segmentation techniques. Models such as MobileNetV2, DenseNet201, Xception and InceptionResNetV2 were tested. Among these models, MobileNetV2 exhibited the best performance with 96% accuracy and 98% AUC score. As a result, it was stated that the developed system can diagnose nodular skin disease with high accuracy and offers a reliable method for early diagnosis. It was stated that this approach can help veterinarians make faster and more accurate decisions, and it was suggested that the system can be developed with larger datasets and advanced techniques in the future. It was also emphasized that such models have the potential to improve animal health in the agricultural sector and reduce farmers' financial losses (Saha, 2024).

Eerdeken et al. developed an automatic diagnosis system to detect colic signs in horses early. In the study, data was collected from the leg movements of horses using accelerometer devices and this data was analyzed with machine learning algorithms. In the experiments, a temporary colic state was induced by applying prostaglandin injection to eight mares and during this process, the horses' behaviors were observed, and their pain scores were

determined. Using the accelerometer data obtained, 10 different behaviors related to normal behavior and pain were classified and an activity index was calculated. The results showed that the model could detect colic with 91.2% accuracy and distinguish colic levels (level 1 and level 2) with 93.8%. The authors stated that this system could detect colic signs earlier than manual observations. The system enables continuous monitoring and early diagnosis, allowing veterinary intervention to be accelerated. It was stated that this study is an important step in horse health and care and is open to future development (Eerdeken et al., 2024).

Conclusion

Smart agricultural technologies have become one of the most important tools of digital transformation in agricultural production processes. These technologies fulfill many critical functions such as monitoring soil health and plant development in real time, optimizing resource use and labor planning, predicting weather conditions, and automating agricultural activities. For example, while water resources are not consumed unnecessarily with precision irrigation systems, fertilization processes are carried out only at the rate required by the plants, thus minimizing the damage to the environment. Similarly, field and crop status can be monitored remotely with drones and satellite imaging systems, and the spread of pests or diseases can be detected at an early stage and rapid intervention can be provided.

Advanced sensors and IoT devices continuously monitor the moisture, pH, and temperature values of the soil and provide data to automatic irrigation and air conditioning systems to provide the conditions that the plants need. Machine learning and artificial intelligence algorithms analyze this data and make predictions about the most appropriate planting, irrigation, and harvesting timing for producers. With these predictions, farmers can minimize unpredictable risks and achieve maximum efficiency.

In addition, planting, spraying, and harvesting processes have been largely automated with autonomous agricultural machines. These autonomous machines move around the field without the need for human intervention and perform tasks more quickly and efficiently. Thus, labor costs are reduced, and faster production can be achieved in large-scale agricultural areas. Smart agriculture not only increases efficiency, but also plays an important role in combating climate change. For example, precise

fertilization techniques that reduce nitrogen emissions contribute to reducing the carbon footprint.

Smart agricultural technologies play a critical role in sustainable and efficient production in the agricultural sector of the future. The rapid development and spread of these technologies will both increase food security and protect environmental resources, enabling important steps to be taken for a sustainable future. These new generation agricultural practices, which go beyond traditional agricultural methods, are emerging as an indispensable solution in the modern world to meet global food demand.

In the future, smart agricultural technologies will revolutionize agricultural production, and production will be carried out with much more integrated, autonomous and intelligent systems than today. In the coming years, with the further development of artificial intelligence-supported prediction and decision-making mechanisms, farmers will not only be able to monitor current conditions, but also proactively manage production processes. For example, algorithms that can predict weather events due to climate change can determine how best to adapt crops to changing conditions. In this way, water and energy consumption will be minimized and productivity will be further increased. In addition, highly efficient, environmentally friendly agricultural areas can be created within cities with innovative applications such as soilless agriculture and vertical farming. Future agriculture will be integrated with fully automated systems to ensure sustainable food production both at the field level and in urban areas; through the collaboration of technologies such as artificial intelligence, IoT, biotechnology and genetic engineering, unprecedented progress will be made in food security and environmental sustainability.

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The Role of Data Science in Revolutionizing Agriculture

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Introduction

As we move forward in the vast sea of technological development called Industry 4.0, developments and innovations are being offered to service in every field without slowing down, and solutions are being developed for many problems encountered in daily life. While production-oriented sectors benefit from the blessings of this new technology, perhaps the sector that needs these innovations the most is the agricultural sector. Because the agricultural sector must find new ways to combat drought, climate problems, energy shortages, medicine, fertilizer, labor supply problems and many other problems. On the other hand, the greatest support in this solution-finding process comes from science, which is again the most advanced ability of mankind.

In this context, precision agriculture, which combines innovations from areas such as artificial intelligence, data science and the Internet of Things, stands out as a rapidly growing high-tech field that offers solutions to the agricultural sector (Lachman & López, 2019).

Today, the reflection of scientific developments called Industry 4.0 in the agricultural sector is expressed with the concept called "Precision Agriculture". The most basic component of this concept is information, because decision support systems, mathematical models, robotic technologies, spraying, fertilizing and irrigation systems used in precision agriculture are developed based on information and the digitization of information.

Precision agriculture is not only focused on crop farming but also on other agricultural production systems such as animal husbandry, aquaculture and agroforestry. The advancement of remote sensing technologies such as satellites, drones, ground-based sensors, and teams have enabled farmers to collect high-resolution data on their fields, allowing them

to make informed decisions about crop management. (Karunathilake et al., 2023)

However, the status of precision agriculture also presents some issues, such as unsustainable resource utilization, long-term monoculture, intensive animal farming, environmental compromises, uneven distribution of digitization, food safety issues, inefficient agri-food supply chain, and lack of awareness of and inertia toward novel changes. These issues prevent achieving efficiency, productivity, and sustainability from agricultural production and escalate unintended impacts on ecosystems (Lachman & López, 2019).

The diffusion of these new technologies not only leads to a more sustainable expansion of agricultural production but also to the emergence of local suppliers of knowledge-intensive equipment and services in countries specialized in agriculture.

The growing integration of advanced technologies into agriculture has not only revolutionized farming practices but also fostered an ecosystem that thrives on innovation and collaboration. This technological shift has enabled the seamless generation and utilization of data across various agricultural domains, from monitoring crop health to optimizing resource use. By creating an interconnected network of tools, sensors, and platforms, these innovations have laid the groundwork for a data-driven approach that empowers both individual farmers and industry leaders to make informed decisions. Consequently, the demand for robust, well-structured databases and datasets has surged, serving as a bridge between cutting-edge technology and practical agricultural applications.

The development of comprehensive databases and data sets has become increasingly important in supporting research, policymaking, and industry-driven initiatives. These data sets provide invaluable insights into the geographic distribution of crop areas, yields, and other key agricultural metrics, enabling researchers and practitioners to better understand the complexities of modern agriculture (Monfreda et al., 2008) (Molin et al., 2020). Moreover, the interpretation and integration of information from different sources of data allow enhancement of agricultural management due to its capacity to predict attributes of the crop and soil using advanced data-driven tools.

The synergy between comprehensive datasets and emerging technologies has paved the way for more efficient and innovative approaches in agriculture. While data sets provide the foundation for understanding and

optimizing agricultural systems, the integration of robotics enhances the practical application of these insights. By bridging data analytics with automation, researchers and practitioners can transition from theoretical models to real-world solutions. This convergence enables precise interventions in farming processes, ensuring that the insights derived from data are effectively translated into actionable practices, such as targeted crop management and efficient resource allocation.

In this concept the application of robotic technologies in precision farming has also gained significant traction in recent years. Robotic systems can perform various tasks such as crop monitoring, local application of inputs, and disease detection using cloud-based systems in digital platforms (Molin et al., 2020).

The importance of these agricultural data sets extends far beyond the research community, as they are crucial for understanding the impact of crops on water use, evaporative fluxes, and energy fluxes, as well as for evaluating the local variation in agricultural GDP and other economic metrics (Monfreda et al., 2008) (Grogan et al., 2022). While the availability of these comprehensive data sets has been a boon to agricultural research and industry, the collection and aggregation of such data is not without its challenges. As noted in a study on estimating local agricultural GDP, the geographic unit of interest may not align with administrative boundaries, and access to data capture and reporting in fragile, conflict, and violence-affected regions may be limited, posing significant hurdles to achieving complete geographic coverage (Blankespoor et al., 2022).

Recognizing the pivotal role that agricultural databases and data sets play in various domains, it is evident that the continued development and refinement of these resources will be crucial in driving advancements in agricultural research, policy, and industry.

Data mining techniques play a crucial role in extracting valuable insights from the collected data. Various algorithms, such as clustering, classification, and regression analysis, are employed to identify patterns and correlations within agricultural datasets. For example, clustering techniques are used to segment agricultural fields based on soil properties and crop types, enabling site-specific management practices that enhance yield and reduce input costs (Saifuzzaman et al., 2019; D'Accolti et al., 2018). Moreover, classification algorithms are utilized for predicting crop yields based on historical data, allowing farmers to anticipate market demands and adjust their planting strategies accordingly (Ismael et al., 2021; Pantazi et al., 2016).

The data obtained is very difficult to use in its pure form. Therefore, cleaning and analyzing this data, extracting information from the data, creating data-based models and detecting anomalies are of great importance in terms of precision farming technologies.

Machine learning algorithms, a subset of AI, have gained prominence in precision agriculture due to their ability to process large datasets and improve prediction accuracy over time. Techniques such as neural networks and support vector machines are employed to analyze complex agricultural data, leading to more precise yield predictions and better pest management strategies (Pantazi et al., 2016; Morota et al., 2018). In Turkey, researchers have applied these techniques to various crops, including wheat and cotton, demonstrating significant improvements in yield forecasting and resource allocation (Pantazi et al., 2016; Ngo & Kechadi, 2020).

The application of data mining and machine learning extends beyond crop management to include livestock monitoring and management. For instance, advanced data analytics are used to track animal health and productivity, allowing for timely interventions that enhance overall farm efficiency (Morota et al., 2018; Lindblom et al., 2016). The integration of big data analytics in animal agriculture has been shown to improve decision-making processes, leading to increased productivity and sustainability (Morota et al., 2018; Ngo & Kechadi, 2020).

Furthermore, the use of data fusion techniques, which combine data from multiple sources, has proven beneficial in precision agriculture. By integrating satellite imagery with ground-based sensor data, farmers can obtain a comprehensive view of their fields, leading to more accurate assessments of crop health and soil conditions (D'Accolti et al., 2018; Melgar-García et al., 2020). This holistic approach enables farmers to implement targeted interventions, such as variable rate irrigation and precision fertilization, which optimize resource use and minimize environmental impact (D'Accolti et al., 2018; Neubauer, 2021).

In this context, many scientific publications and data sources contribute to the literature to help researchers. It is possible to produce new models, develop methods and make designs by using these sources. In addition, thanks to the evaluation of these resources that are open to the whole world, it becomes possible for our researchers to develop joint studies integrated with the whole world. In this study, it is aimed to make a compilation of studies conducted on the subject in the world and to give researchers a starting point.

Method for Article Discovery

A preliminary investigation was conducted to understand the distribution of existing publications. For this purpose, a scientometric analysis was performed. The Scopus database was utilized for the study, and the following query was executed:

“(TITLE-ABS-KEY (" agricultur* ") OR TITLE-ABS-KEY (" data AND min* ") OR TITLE-ABS-KEY (" data AND analyt* ") AND TITLE-ABS-KEY ("machine lea*") AND TITLE-ABS-KEY ("dataset"))”

This query aimed to directly identify articles related to agricultural data and its processing. Using the "Analyze search results" feature, the graph presented in Figure 1 was obtained.

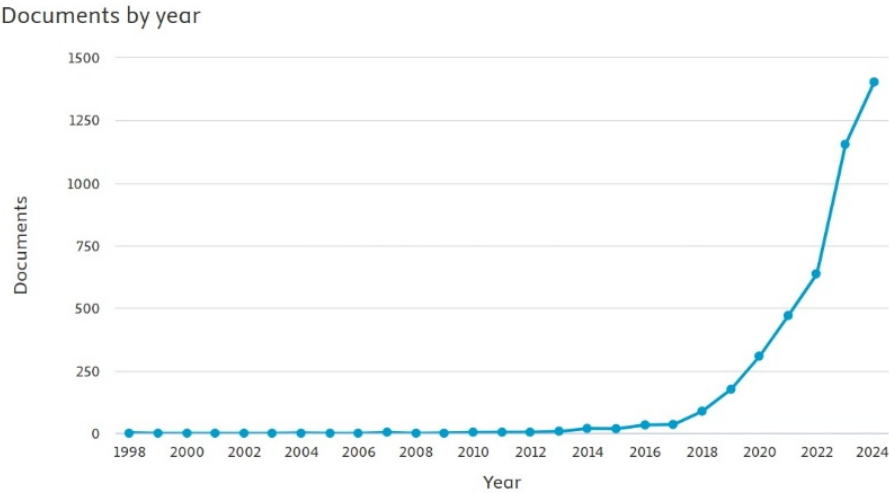


Figure 1. Distribution of the number of publications in the field by year.

When we examine the graph in Figure 1, it is possible to say that the graph is in an increasing direction. Thus, we can say that the subject attracts more attention, and more publications are made every year. In addition, considering that the first article in the field was published in 1988, it is seen that the field is relatively young. The distribution of the results “by country or region” is as shown in Figure 2.

Documents by country or territory

Compare the document counts for up to 15 countries/territories.

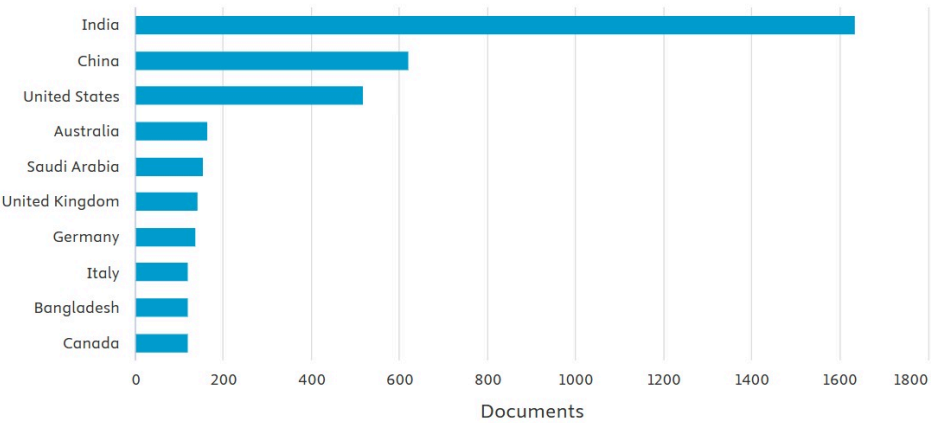


Figure 2. Distribution of publications by country

In the graphic it can be clearly seen that the leading country in the field is India with 1633 articles, followed by China and the USA with 618 and 516 articles, respectively.

This impressive output reflects the growing interest and investment in utilizing artificial intelligence and data science within the agricultural domain. Understanding the contributions from leading nations provides a foundation for analyzing the methodologies and tools driving this progress. Building on this context, the research delves deeper into the specific approaches and resources employed in the field.

The research process centered on two key areas. First, the study examined the methodologies employed in applying data science techniques to agriculture, along with their outcomes. Second, it reviewed currently available databases to provide researchers with resources for developing their own methods and conducting analyses, while also detailing the contents and scope of these databases.

Methods And Applications

Since the subject of the study is data-oriented, the most basic approach is to organize agricultural data based on a certain standard framework. These efforts have produced comprehensive agricultural databases that cover a range of metrics such as crop areas, yields, and economic indicators. These

These expressions in Figure 3 express the database structure and the field names are the special names given by the designer. The figure is taken as is from the publication. As can be seen, in this proposed model, agricultural data are analyzed from various perspectives, and they are designed to include sales and order management without limiting the perspective to only the botanical or biological side of agriculture.

While publicly available designs provide a general framework to facilitate data analysis, on the other hand, targeted studies also have a very important place in literature. For example, RN Izah and his colleagues, who focused on the satellite images of rice fields used convolutional network methods in the study “Classification of Paddy Growth Phase Based on Landsat-8 Image with Convolutional Neural Network Algorithm” (Izah et al., 2021) to predict a stage in rice production. According to the article, “Paddy Stage” is a very important stage for rice production. They developed a model using the data collected from Landsat-8 satellite to detect this stage and make predictions about it. They tried different epoch numbers to achieve the best accuracy and achieved the best performance by reaching 80.37% accuracy, 78.60% sensitivity and 90.75% specificity values with 50 epochs.

There are many benefits to satellite data analysis, one of which is the study titled “Monitoring and Modeling of Abandoned Farmlands Based on Multi-Source Data Integration”. In the study, Yang T. et al. combined multiple data sources to determine the reasons for abandonment of farmlands (Yang et al., 2020). They used data from Sentinel-2A, Resources-3, Gaofen-1 and Gaofen-2 satellites. In the study, they used high-resolution remote sensing data from these satellites and two different surveys, namely land use data and farmland conversion data, respectively. They have 8 factors (village distance, elevation difference, highway distance, parcel area, fractal dimension index, shelter forest, irrigation status and neighborhood characteristics, respectively). As a result, it was found that all 8 parameters except village distance have significant effects on abandonment.

Another targeted study is the method developed by Marthindill and his colleagues to detect areas where water amounts are decreasing. Both water and energy use are very important elements in agricultural production. Especially when it is considered that water is a limited resource and a vital resource for almost all living things, being able to manage water use reveals its importance. In this article, Jonathan R. Marthindill and his colleagues examined this area to create a prediction model that takes energy use as input

and estimates groundwater use (Martindill et al., 2021). In the article, the “efficiency lift method” was used to estimate use. And they developed a model that will make accurate predictions with an average error rate of 5% at the individual well level and 3.3% for well collections. This article shows that ELM (efficiency lift method) is a suitable method for such predictions.

It is also necessary to mention the use of AI in water is the study by Band et al. “Comparative analysis of AI models for accurate estimation of groundwater nitrate concentration”. In this study, they used different AI methods in the analysis of groundwater nitrate concentration. Methods “Support Vector Machine” (SVM), “Cubist”, “Random Forest” (RF) and Bayesian artificial neural network (Bayesian-ANN). They made the analysis on 11 independent variables. They used the data collected by measuring from 67 wells as dependent variables (Band et al., 2020). The data was divided into 70% training and 30% test. They evaluated the results under several headings. These are R^2 mean absolute error (MAE), root mean square error (RMSE) and Nash - Sutcliffe efficiency (NSE). As a result, random the forest algorithm was determined as the best algorithm among them.

In the research "Classification of Rice Varieties with Deep Learning Methods,"(Koklu et al., 2021) investigated the application of deep learning techniques for classifying different rice varieties. Features were extracted from rice grain images using image processing techniques and analyzed with deep learning models. The study reported excellent classification accuracy, highlighting the effectiveness of deep learning in the agricultural sector. The dataset included images of rice grains, encompassing their morphological characteristics.

The study "A CNN-SVM Study Based on Selected Deep Features for Grapevine Leaves Classification" (Koklu et al., 2022) involved the classification of grapevine leaves using deep feature extraction combined with Support Vector Machines (SVM). Image processing techniques were employed to extract features from leaf images, which were then used for classification. The results showed high accuracy in identifying grapevine varieties, providing a reliable approach for plant species identification. The dataset consisted of images of leaves from different grapevine varieties, focusing on shape and texture features.

In the study named “Implementation of K-Means Algorithm for Clustering Corn Planting Feasibility Area in South Lampung” (Aldino et al., 2021), a method has been developed for site specific treatment. To handle the

lands according to their needs, effective methods are needed to understand the sub-areas in a large area. There are many studies on site specific management or management area definition. In this study, Aldino AA and his colleagues used K- Means algorithm on 2 years of corn crop data from South Lampung region. They aimed to create clusters with field data with this algorithm. As a result of the studies, 17 areas were determined. 8 of them were determined as high and 9 as low feasibility.

Similarly, Mojenzi succeeded in obtaining results on the energy estimation of wheat production using data mining technique in Iran. To understand the energy use in Iran, Monjezi N used data mining techniques from a field data ranging from 2014 to 2018 (Monjezi, 2021). Monjezi used IBM SPSS and Standard CRIPS for this study and as a result, it was determined that chemical fertilizer, machinery and diesel variables had the highest effect on the output variable (productive energy) with coefficients of 0.2987, 0.2064 and 0.1527, respectively. In addition, the study managed to obtain a linear correlation of 0.92 and 0.88 between the actual data and the estimated values, respectively.

In addition to these methods data mining techniques play a crucial role in extracting valuable insights from the collected data. Various algorithms, such as clustering, classification, and regression analysis, are employed to identify patterns and correlations within agricultural datasets. For example, clustering techniques are used to segment agricultural fields based on soil properties and crop types, enabling site-specific management practices that enhance yield and reduce input costs (Saifuzzaman et al., 2019; D'Accolti et al., 2018). Moreover, classification algorithms are utilized for predicting crop yields based on historical data, allowing farmers to anticipate market demands and adjust their planting strategies accordingly (Ismael et al., 2021; Pantazi et al., 2016).

Moreover, the economic implications of adopting precision agriculture technologies are significant. Studies have shown that the implementation of data-driven practices can lead to substantial increases in agricultural productivity and profitability (Bahşi & Çetin, 2020; Abukari et al., 2016). By leveraging data mining and AI, farmers can optimize their operations, reduce waste, and improve crop quality, ultimately contributing to food security and economic sustainability in Turkey (Lee et al., 2021; Abukari et al., 2016).

Despite the promising advancements in precision agriculture, challenges remain in the widespread adoption of these technologies. Barriers such as

high initial costs, lack of technical expertise, and concerns over data privacy hinder the integration of data-driven practices in traditional farming systems (Sanders et al., 2022; Lee et al., 2021; Lowenberg-DeBoer & Erickson, 2019). Addressing these challenges requires collaborative efforts among stakeholders, including government agencies, research institutions, and the agricultural community, to create supportive policies and frameworks that facilitate technology adoption (Sanders et al., 2022; Lee et al., 2021).

The foundation of precision agriculture lies in the collection and analysis of vast amounts of data generated from various sources, including sensors, satellite imagery, and weather stations. These data sources provide critical insights into soil health, crop conditions, and environmental factors, enabling farmers to make informed decisions. For instance, the integration of Internet of Things (IoT) technologies allows for real-time monitoring of agricultural parameters, which is essential for effective resource management and yield optimization (Aishwarya & Ma, 2022; Ferrández-Pastor et al., 2016; Özdoğan et al., 2017). The utilization of sensor networks has been particularly prevalent in Turkey, where they facilitate the collection of data on soil moisture, temperature, and nutrient levels, thereby informing irrigation and fertilization strategies (Dung, 2023; Özdoğan et al., 2017).

The most important parameter in the success of the methods is the data obtained correctly and regularly. Many databases have been created to be used in studies and continue to be created every day. There are many databases available for researchers. In the compilation study, these databases can be examined as follows.

Datasets

Artificial intelligence algorithms designed for precision agriculture require datasets for training and learning. These databases can have very different contents and, depending on their content, are used in research such as product identification and classification, product detection, segmentation, crop disease and pest recognition. In addition, there are advanced databases for climate change monitoring with data collected from various points over many years. In precision agriculture applications, datasets, databases and big data applications are important both in terms of creating predictive models and provide many advantages in terms of developing an effective and healthy production methodology. (Bronson & Knezevic, 2016; Kamilaris et al., 2017).

Among these, databases containing images have a large place. The integration of computer vision applications plays a critical role in precision agriculture applications. Phenotypic characteristics are generally taken into consideration in data collection based on plant images. Appropriate imaging platforms and methods are used when creating datasets; cameras, smartphones, UAVs (Unmanned Aerial Vehicles) and synthetic data created in a virtual environment are also used in these databases (di Cicco et al., 2017). In addition, the quality and quantity of images play an important role in training the algorithms; Shooting from different angles and environmental lighting conditions may affect the quality of images taken.

It is possible to design a wide variety of architectures for training and modeling processes using these types of databases. One of the most important of these databases is the MARS database which is publicly available from the Joint Research Centre (JRC). The MARS database covers a wide thematic area. The scope of the database includes topics such as Agricultural Monitoring, Crop Yield Estimation, Global Food Security, Agrobiodiversity, Rural development, Climate change, and Earth Observation. One of the most recent studies using this database is “Machine learning for regional crop yield estimation in Europe” by Paudel et al.(Paudel et al., 2022)

The databases contain both real data and synthetic data created using real data. One of these is the “Synthetic Sugar Beet” dataset. This dataset is different from the others in terms of content creation. This dataset was created by the computer using the procedural dataset generation technique. Therefore, the images in this dataset are synthetic and make this study unique. As stated in the related study; by generating synthetic training datasets, human intervention was removed during the labeling phase, which reduced the time and effort required to train a visual inference model. The system trained using synthetic data showed similar performance to the system trained with real-world human-annotated images (di Cicco et al., 2017). The dataset contains 8518 RGB images with a size of 480 x 360 pixels. From the results of the tests, it is concluded that this dataset can reduce the human effort required for data collection and labeling. Two human images of the database are given in Figure 4.

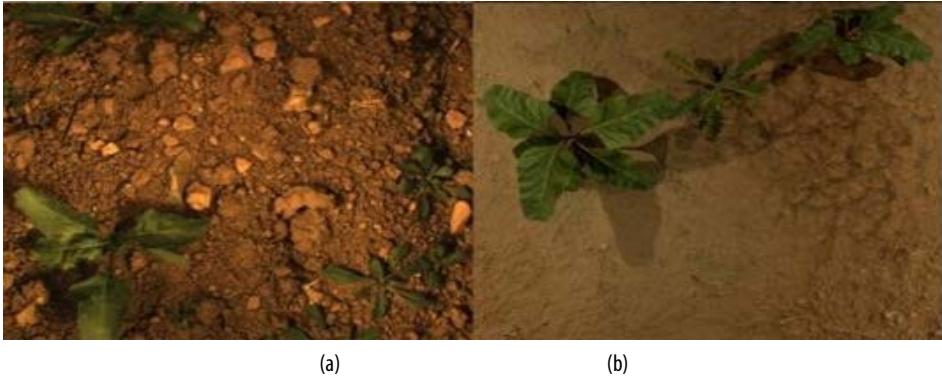


Figure 4 Sugar beet image (a) Real image, (b) Synthetic image

Another dataset prepared for Sugar Beet is the sugar beet database prepared by the University of Bonn. To create this dataset, the researchers used a robot equipped with different types of sensors not only for dataset creation but also for robot localization and mapping applications in agricultural areas. At the time of publication of this study, no comparable public dataset is available (Chebrolu et al., 2017). The dataset consists of 12,340 RGB and NIR images at 1296×966 pixels.

Detection of weeds in fields is also of utmost importance in agricultural studies. Powerful databases are required to produce models on this subject, and for this purpose the weedNet database was created. This dataset was obtained to be used in the study described in the article itself (Sa et al., 2018). Multispectral camera-equipped UAVs were used to create this dataset. Images obtained from 3 different field types, including only crops, only weeds, and crops and weeds together. The dataset contains 375 NIR+Red+NDVI training images distributed equally. 132 of them belong to only the crop area, 243 to only the weed area, and there are also 90 test images belonging to the crop and weed area. Examples of images used to create the dataset are given in Figure 5.

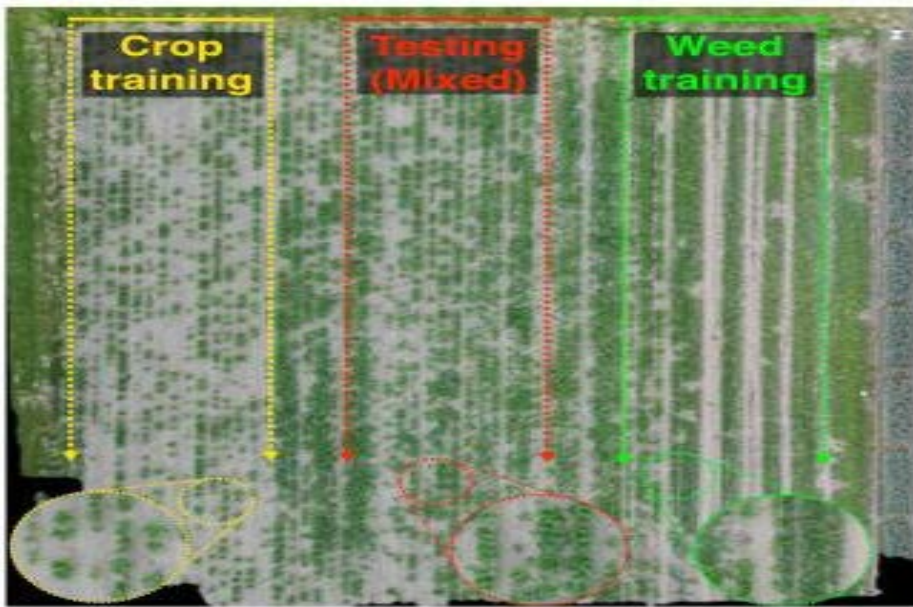


Figure 5 weedNet Dataset example

The link to access the database is as follows:

<https://github.com/inkyusa/weedNet>

Developing machine learning and data mining models can be problematic for users who do not have access to the same hardware for daily use. Therefore, data sets collected with easily accessible hardware are becoming important. An example of such databases is the “Leaf Counting” data set. This data set was created using smartphones and consumer cameras. It consists of 9372 RGB images for 18 weed species or families. The main reason for creating this data set is to reduce herbicide use. It was used to observe the growth stages of weeds by counting their leaves, and it is aimed to spray the herbicide optimally by considering these stages (Teimouri et al., 2018).

In production, the place of garden plants and fruits is very important as well as field crops. Databases are also required for studies to be carried out on this subject. For example, the KFujii RGB-DS database is a database consisting of images of Fuji apples. Data collection was carried out on Fuji apple trees. The RGB-D sensors used are two Microsoft Kinect v2 , an RGB camera and a time-of-flight (ToF) depth sensor . The dataset consists of 967 images and each image contains information from 3 different modalities:

color (RGB), depth (D) and range-corrected IR intensity (S). There are a total of 12,839 apples labeled in the entire dataset (Gené-Mola et al., 2019). An example of the images in this database is given in Figure 6.

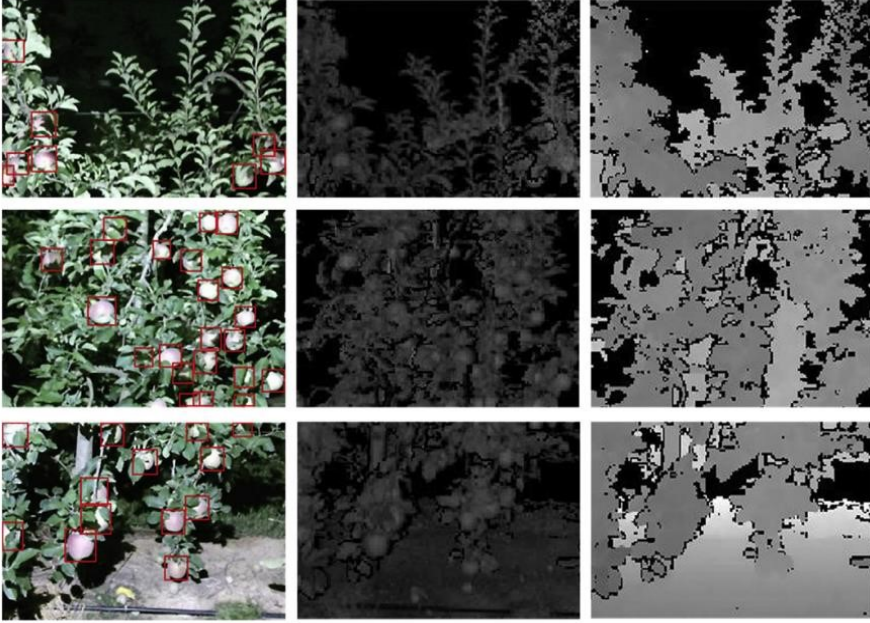


Figure 6 Three different multimodal (RGB, B and D) images and corresponding fruit positions

Dr. Murat Köklü, a faculty member at Selçuk University's Department of Computer Engineering, has made notable contributions to agricultural sciences by developing and sharing datasets for the classification and analysis of various agricultural products. These datasets have been employed in numerous studies, highlighting their utility in applications such as automated quality control and product identification.

The Rice Varieties Dataset includes morphological attributes of rice grains, facilitating classification tasks with 75,000 instances and 106 features. This dataset was employed in Köklü and Çınar's (2019) study, where artificial intelligence methods were used to classify rice varieties. The research demonstrated the dataset's potential for developing deep learning models, achieving high classification accuracy rates (Çınar & Köklü, 2019). Such studies emphasize the applicability of advanced computational techniques in enhancing agricultural productivity.

Another significant contribution is the Dry Bean Dataset, which comprises 13,611 instances and 16 attributes, capturing the physical

characteristics of various bean types. Köklü and Özkan (2020) utilized this dataset to classify dry beans using machine learning and computer vision techniques, achieving a high accuracy rate of over 90% in distinguishing between bean varieties. Their findings underscored the potential of this dataset for automating quality control processes in agriculture (Köklü & Özkan, 2020).

The Pumpkin Seeds Dataset, featuring 2,500 instances and 12 attributes, focuses on the classification of seed varieties based on size, shape, and color. Köklü et al. (2021) explored the use of this dataset in classifying pumpkin seeds with machine learning methods. Their study demonstrated the effectiveness of machine learning in analyzing morphological features and achieved substantial classification performance, providing a robust tool for agricultural analysis (Köklü, Sarıgil, & Özbek, 2021).

The Date Fruits Dataset includes 898 instances and 34 attributes, detailing the genetic variety of date fruits. In a study by Köklü and Kurşun (2021), this dataset was employed to classify genetic varieties using image analysis techniques. The research achieved high classification accuracy and demonstrated the dataset's applicability for genetic diversity studies and quality control in the fruit industry (Köklü & Kurşun, 2021).

The Raisin Dataset contains 900 instances with seven features, focusing on the classification of raisin grains. Çınar and Köklü (2020) utilized this dataset in their study to classify raisin grains using machine vision and artificial intelligence methods. The study achieved high accuracy, highlighting the dataset's importance in automating the identification and assessment of raisin quality (Çınar & Köklü, 2020).

Recent advancements in unmanned aerial vehicles (UAVs) have revolutionized data collection in precision agriculture. UAVs facilitate high-throughput phenotyping by capturing detailed spectral data that can be analyzed to assess various plant traits, including growth metrics, biochemical content, and stress responses (Shi et al., 2016; Yang et al., 2017). The use of spectral indices, as highlighted by Tayade et al., enhances the ability to monitor crop health and productivity, providing critical insights for precision breeding and pest management (Tayade et al., 2022). These technologies enable breeders to make informed decisions rapidly, thus accelerating the crop improvement process (Shi et al., 2016; Yang et al., 2017).

Moreover, the standardization and integration of genotype and phenotype data are crucial for maximizing the utility of these datasets in

agricultural sciences. Deng emphasizes that the effective utilization of large-scale data is essential for identifying genetic markers and facilitating genomic selection, which can lead to improved crop yields and sustainability (Deng, 2023). However, the integration of heterogeneous data sources poses significant challenges, as noted by Deng, which can hinder the effective application of these technologies in real-world scenarios (Deng, 2023).

In addition to UAVs, the application of imaging sensors for disease detection is another critical aspect of precision agriculture. Mahlein discusses how sensor-based analyses can detect plant diseases early, allowing for timely interventions that can mitigate crop losses (Mahlein, 2016). This capability is particularly important in the context of invasive pests, which can rapidly threaten agricultural production. For instance, the work by Campos et al. highlights the challenges posed by invasive pests like *Tuta absoluta*, which necessitate robust pest management strategies informed by accurate phenotypic data (Campos et al., 2014).

Furthermore, the role of phenotypic data in pest resistance breeding is underscored by Graham et al., who illustrate how architectural traits can be utilized to identify pest resistance in crops (Graham et al., 2014). This approach aligns with the broader goals of precision agriculture, which aims to enhance crop resilience through data-driven breeding strategies. The integration of phenotypic and genotypic data allows for the identification of quantitative trait loci (QTL) associated with pest resistance, thereby facilitating targeted breeding efforts (Deng, 2023; Akash, 2023).

As precision agriculture continues to evolve, the development of new tools and methodologies will be essential. The research conducted by Young et al. on ground robots for high-throughput phenotyping exemplifies the innovative approaches being explored to enhance data collection in field settings (Young et al., 2018). These advancements not only improve the efficiency of data acquisition but also contribute to a more comprehensive understanding of plant responses to environmental stressors and pest pressures.

In conclusion, the harnessing of comprehensive pest and phenotype databases through advanced technologies such as UAVs and imaging sensors is crucial for the future of precision agriculture. By integrating these data sources, agricultural practitioners can enhance crop management practices, improve pest resistance, and ultimately contribute to sustainable agricultural production.

Conclusion

The concept of precision agriculture stands at the crossroads of technological innovation and global necessity, presenting an unprecedented opportunity to transform traditional farming practices into a model of efficiency, sustainability, and productivity. At its core, precision agriculture encapsulates the integration of artificial intelligence, data science, the Internet of Things (IoT), and robotics to address the multifaceted challenges faced by the agricultural sector. From mitigating the effects of climate change to optimizing resource use, this paradigm shift not only promises to enhance agricultural yields but also to ensure the long-term viability of our natural ecosystems.

As reviewed throughout this study, the journey of precision agriculture is characterized by the increasing reliance on advanced methodologies such as machine learning, data mining, and computer vision. These tools have proven to be highly effective in tackling specific challenges, including crop management, pest detection, irrigation optimization, and yield prediction. For instance, the successful application of convolutional neural networks (CNNs) for rice growth stage detection, or the use of k-means clustering to identify feasibility zones for maize cultivation, highlights the versatility of these technologies in solving real-world agricultural problems.

Another significant aspect explored in this study is the critical role of datasets and databases in enabling and accelerating research in precision agriculture. Datasets such as the MARS database, Synthetic Sugar Beet dataset, and weedNet not only provide access to vast amounts of agricultural data but also democratize research by enabling researchers without high-end equipment to develop and test models. These resources have facilitated groundbreaking advancements, from modeling groundwater use with high accuracy to monitoring nitrate concentrations in irrigation systems using AI algorithms. The availability of such datasets is fundamental to the growth of this field, fostering a collaborative environment for innovation across geographies and disciplines.

In addition to datasets, the role of unmanned aerial vehicles (UAVs), imaging sensors, and other advanced data collection tools has been transformative. High-throughput phenotyping, disease detection, and pest management have benefited immensely from these technologies, enabling researchers and practitioners to gain deeper insights into plant health, stress responses, and productivity. For example, the integration of multimodal

imaging techniques, such as RGB, depth, and infrared sensors, in databases like the KFuji RGB-DS dataset, demonstrates the potential of leveraging diverse data sources for precision agriculture.

The field is not without its challenges. Issues such as the uneven adoption of technologies, gaps in data collection in fragile or conflict-affected regions, and the complexities of integrating heterogeneous data sources persist. Moreover, concerns about the environmental impact of long-term monoculture, intensive animal farming, and unsustainable resource utilization call for a more holistic approach to precision agriculture. To address these challenges, fostering interdisciplinary collaboration and enhancing global accessibility to agricultural technologies and datasets will be crucial.

Furthermore, the study underscores the potential of precision agriculture to catalyze broader societal benefits. By addressing critical issues such as food security, resource conservation, and climate resilience, precision agriculture has the capacity to create a sustainable agricultural framework that aligns with global development goals. The diffusion of these technologies is not merely a matter of agricultural advancement but also an opportunity to drive economic growth and social equity, particularly in regions heavily reliant on agriculture.

This compilation of research and case studies offers a starting point for future exploration in precision agriculture, emphasizing the need for continuous innovation and adaptability. As new datasets, tools, and methodologies emerge, the boundaries of what is achievable will continue to expand. Researchers are encouraged to not only build on existing work but also to explore novel applications of data-driven technologies in areas previously untouched by such advancements.

In conclusion, precision agriculture represents more than a technological revolution; it is a vision for a future where agriculture is smarter, more sustainable, and deeply connected to the needs of both humanity and the planet. By leveraging the power of data, robotics, and collaborative innovation, precision agriculture has the potential to redefine the agricultural landscape and address some of the most pressing challenges of our time. As this field grows, so too will its capacity to contribute meaningfully to the well-being of societies and the sustainability of our environment, ensuring a harmonious balance between productivity and conservation. This study serves as a testament to the remarkable progress made thus far and as an invitation to further advance this critical and exciting field.

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Artificial Intelligence Applications in Cherry Farming

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Introduction

The agricultural sector is undergoing a significant transformation with the rapid advancement of technology, with one of the primary driving forces behind this change being artificial intelligence (AI) technologies. Compared to traditional farming methods, AI-supported applications offer substantial advantages in terms of increasing efficiency, reducing costs, and ensuring environmental sustainability. Cherry farming is one of the areas benefiting from these technological advancements.

The cherry is a fruit widely consumed worldwide, known for its delicious taste and nutritious qualities. With its sweet and juicy nature, the cherry is a staple of summer fruits, appreciated not only for its flavor but also for the health benefits it offers.

- Belonging to the Rosaceae (rose) family and classified under the *Prunus* genus, cherries are botanically divided into two main types (Hussain et al., 2021):

- **Sweet Cherry (*Prunus avium*):** Typically consumed fresh, this variety is sweet and has large fruits. Its color ranges from red to deep purple.

- **Sour Cherry (*Prunus cerasus*):** Smaller in size with a tart taste, this type is commonly used in the production of jam, marmalade, and juice.

Cherry trees generally grow between 4 and 10 meters in height and bloom with pink or white flowers in spring. The fruit matures and is harvested in the summer months.

Cherries are a low-calorie fruit that contain significant amounts of vitamins and minerals. The average nutritional value of 100 grams of cherries is as follows (USDA, 2022):”

Calories: 63 kcal

Carbohydrates: 16 g

Fiber: 2 g

Protein: 1 g

Vitamin C: 16% of daily requirement

Potassium: 5% of daily requirement

- Cherries are also rich in antioxidants. Due to compounds such as anthocyanins, flavonoids, and melatonin, they provide numerous health benefits. The positive effects of cherries on health have been scientifically proven. Some of the health benefits of cherries include the following (Kelley et al., 2018):“

- *Source of Antioxidants:* Due to its high antioxidant content, cherries protect the body from the harmful effects of free radicals and help delay aging.

- *Reduces Inflammation:* The anthocyanins in cherries help reduce inflammation, offering protection against joint disorders and osteoarthritis in particular.

- *Improves Sleep Quality:* The melatonin content in cherries may aid in improving sleep patterns.

- *Supports Heart Health:* The potassium content in cherries helps regulate blood pressure and supports heart health.

Cherries can be consumed not only fresh but also in various other forms:

- *Fresh Consumption:* Cherries are often enjoyed fresh, especially during the summer months.

- *Dried:* Dried cherries can be used as snacks or in breakfast dishes.

- *Jam and Marmalade:* Jams and marmalades made from sour cherries are commonly enjoyed at breakfast.

- *Juice and Wine:* Beverages like cherry juice and cherry wine are also popular.

Turkey holds a prominent position in cherry production, playing an important role in both domestic and international markets. Agricultural policies, the use of technology, and market strategies are critical to sustaining Turkey’s success in this field.

In Turkey, certain provinces, such as Aydın, İzmir, Isparta, Bursa, Konya, and Manisa, stand out in cherry production.(Çelik et al., 2023)”

Cherry cultivation is carried out across various regions in Turkey, yet the most productive and large-scale production is typically concentrated in the following areas:

- *Aegean Region:* Aydın and İzmir are significant centers for cherry production.
- *Marmara Region:* Bursa and Çanakkale are prominent provinces in terms of cherry production.
- *Mediterranean Region:* The regions of Isparta and Antalya are also known for cherry production.
- *Central Anatolia Region:* Konya is recognized as an important area for cherry cultivation.

Turkey is also a key player in cherry exports, with a significant portion of its production shipped to regions such as Europe, the Middle East, and Russia. Turkish cherries are in demand in international markets due to their quality and taste. Turkey holds an important global position in cherry cultivation, ranking among the top five cherry-producing countries. The country plays a notable role in the global production of sweet cherry varieties in particular. Approximately 82,729 hectares in Turkey are devoted to cherry cultivation (Çelik et al., 2023).

Global Cherry Production Rankings (2022)

- **Turkey** - Turkey holds the position as the largest cherry producer worldwide, accounting for over 19% of global production (Çelik et al., 2023).
- **Chile** - Positioned strategically in the Southern Hemisphere, Chile ranks second, supplying cherries during the off-season for Northern Hemisphere producers.
- **Uzbekistan** - Uzbekistan has steadily increased its production in recent years, placing it third in global rankings.
- **United States** - The United States is known for cherry production, particularly in the states of Washington and California.
- **Spain** - Spain completes the top five with an approximate production of 116,070 tons, showing a slight decline compared to previous years.

Table 1. Global Cherry Production (by Tonnage)(FAO, 2022)

Country	Production (Tonnage)
Turkey	656,040
Chile	443,070
Uzbekistan	216,870
United States	210,190
Spain	116,070

The data in Table 1 were obtained from the United Nations Food and Agriculture Organization (FAO) database. Turkey's prominent position in cherry production is attributed to the country's extensive agricultural land, favorable climatic conditions, and advanced agricultural practices.

While cherry cultivation in Turkey is traditionally carried out using conventional methods, recent years have seen an increased adoption of modern agricultural techniques and technological advancements. Technological solutions, including artificial intelligence, are being utilized in areas such as cultivation of high-yield varieties, improvement of irrigation systems, pest control, market analysis, and demand forecasting.

Deep Learning in Cherry Cultivation

Deep learning is a technology within the fields of artificial intelligence (AI) and machine learning, characterized by its ability to process data through multi-layered structures similar to the functioning of the human brain. Deep learning is particularly effective in tasks such as learning from large datasets, pattern recognition, classification, and prediction. This technology is increasingly applied in the agricultural sector and plays a significant role in cherry cultivation.

Deep learning typically operates through algorithms known as neural networks, which consist of multiple layers. These neural networks process data at different levels in each layer and learn from data to identify complex patterns. In cherry cultivation, this technology can be effectively used in the following areas:

- **Image Analysis and Classification:** Deep learning is widely used in image processing applications within cherry cultivation. For instance, drone or satellite images can be utilized to gather information about the condition of cherry orchards. Deep learning algorithms can recognize patterns in these

images to detect the health status of trees, signs of disease, or pest presence, providing critical data for early intervention.

- **Disease and Pest Detection:** Deep learning employs trained models to detect diseases or pests in cherry trees. For example, a deep learning model can analyze lesions on leaves or abnormalities in the fruit. Using this data, the model can predict which diseases or pests may be present, providing early alerts to producers.

- **Yield Prediction:** Deep learning can be applied to predict cherry yields by learning from historical data. Analyzing various factors such as climate conditions, soil characteristics, irrigation, and fertilization, deep learning models can generate yield forecasts. This assists producers in optimizing harvest timing and planning market strategies.

- **Automated Harvesting:** In cherry cultivation, deep learning can also be utilized in robotic systems. Specifically, automated harvesting machines can use deep learning algorithms to identify ripe cherries and harvest them at the optimal time. This accelerates the harvesting process and minimizes human errors.

The application of deep learning in cherry cultivation may encounter challenges such as the requirement for high-quality data, the time and resource investments needed for training algorithms, and the dependency on a workforce with technological expertise for widespread adoption in the agricultural sector.

However, as deep learning technology continues to evolve and becomes more widely adopted in agriculture, it is anticipated that its applications in cherry cultivation will expand in scope. In particular, further advancements in data collection and analysis processes are expected to enable more efficient use of deep learning in cherry cultivation.

In their study, Chelpinski et al. (2019) examined how skin color measurement can be utilized to determine the ripeness level of sweet cherries. The study evaluated whether color measurement, as a non-destructive method, is suitable for assessing the ripeness of cherries.

In this research, the skin colors of cherries at different ripeness stages were analyzed, and the feasibility of using these colors as an indicator of ripeness was investigated. The findings indicate that skin color can be a reliable indicator for determining cherry ripeness. This method can aid

cherry producers and suppliers in selecting the optimal time for harvesting and marketing their products.

The methods used in the study to determine the ripeness of sweet cherries are as follows:

1. **Spectrometric Measurements:** The skin color of cherries was measured using a spectrometer, which analyzes how light reflects off the cherry surface to determine color components. Color was typically defined in terms of red, green, and blue (RGB) values.

2. **Visual Assessment:** In addition to spectrometric measurements, the ripeness of cherries was also visually assessed. This ensured accurate identification of color changes and validation of the data obtained from the spectrometer.

3. **Data Analysis:** After collecting spectrometric and visual data, statistical methods were used to analyze the data. The goal was to determine the relationship between skin color and ripeness and to assess whether it is a reliable ripeness indicator.

Details of the study are as follows:

1. **Location and Materials:** The research was conducted at the Departments of Horticulture and Multimedia Systems at the West Pomeranian University of Technology. The experiment took place in a commercial orchard near Szczecin. The cherry trees used were of the Burlat variety, planted with 3.5 x 4.0 m spacing.

2. **Measurements:**

- **Physical Properties:** Measurements were taken of firmness, skin puncture resistance, and soluble solids content (extract) in fresh fruits. Firmness and puncture resistance were measured using a FirmTech2 device, and fruit mass was weighed with an electronic scale. Soluble solids content was determined using a refractometer.

- **Color Measurement:** Fruit color was measured with a Konica Minolta CM-700d spectrophotometer in the CIE SCI/SCE Lab* system.

3. **Data Analysis:**

- **Dimensionality Reduction:** Dimensionality reduction was applied in MATLAB using principal component analysis (PCA). A feature vector consisting of 39 components was reduced to five main components.

- **Classification:** Various classification methods were employed to predict physical parameters, including Naive Bayes Classifier, Support Vector Machines, Multilayer Perceptron, Nearest Neighbor Classifier, Random Forest, Random Tree, and CART Classifier. Classification was performed using the WEKA data mining software.

4. Cross-Validation:

A 10-fold cross-validation method was used to evaluate the accuracy of the model, balancing training and test sets to objectively assess the model's performance.

5. Evaluation of Results:

The quality of the models was assessed using True Positive and False Positive rates. The highest accuracy (close to 80%) was achieved in predicting extract content, while the accuracy for other parameters was around 60%.

These methods encompass various physical and color measurements used to evaluate cherry ripeness. Color changes serve as a key indicator of fruit ripeness, and this study details how these changes can be monitored through optical methods. By combining these methods, an effective strategy was developed for accurately determining the ripeness level of sweet cherries and making informed decisions about harvest timing.

In their study, Momeny et al. (2020) aimed to classify cherry fruits based on their physical appearance using an enhanced Convolutional Neural Network (CNN) based on deep learning techniques.

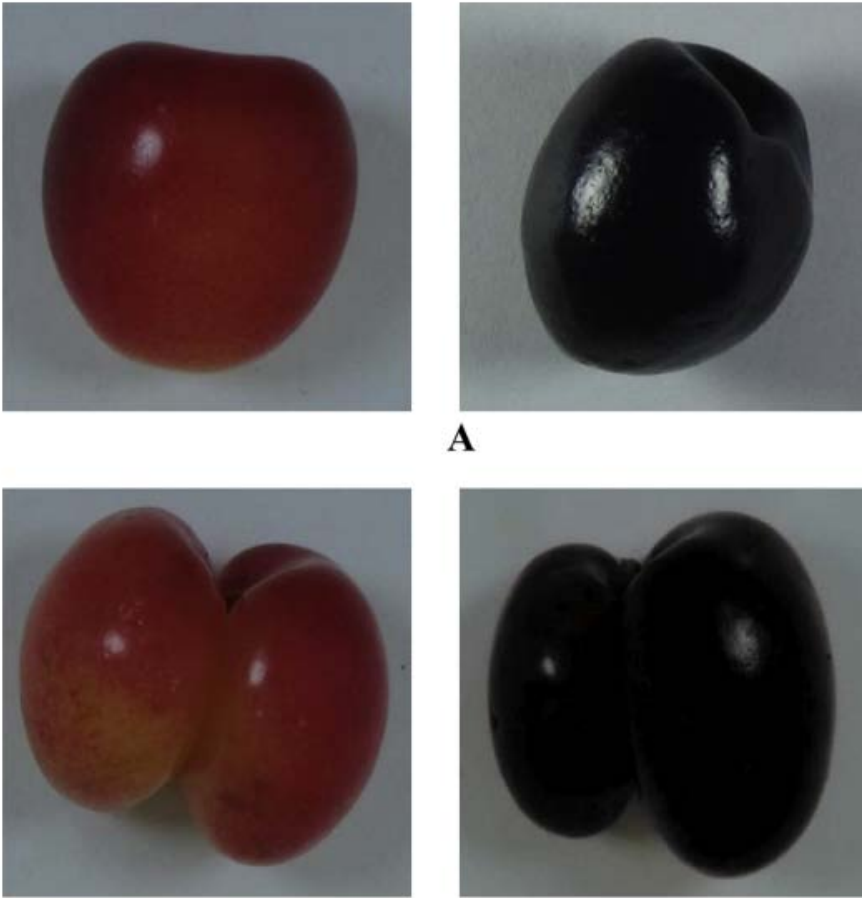


Figure 1 - Cherry samples of different forms (Momeny et al., 2020)

The study aimed to develop an efficient classification system by dividing cherry fruits (Figure 1) into two main categories: a) regular (single cherry) and b) irregular (double and multiple cherries).

Methods Used in the Study:

1. **Image Collection and Processing:**

- o A total of 719 cherry samples from two varieties (red and black) were selected, consisting of both regular and irregular-shaped cherries. Irregular-shaped cherries were typically classified as double or multiple cherries.

- o The images were captured in the RGB color space, and their backgrounds were subsequently removed using MATLAB software. The Otsu thresholding method was applied.

Details of the Otsu Thresholding Method:(Momeny et al., 2020)

- This method analyzes pixel intensities in the image, separating cherry and background pixels into two distinct categories: cherry pixels, which are generally darker, and background pixels, which are lighter.
- An optimal threshold value (T) is selected to distinguish cherry pixels from background pixels. The Otsu method determines this threshold by optimizing the two distributions within the image.
- After background removal, **mathematical morphology** was used to fill gaps in the cherry images, completing the image processing stage.

2. Data Augmentation:

- o Data augmentation techniques were applied to enhance the diversity of the training data. These techniques included image rotation, mirroring, and color manipulation. Through data augmentation, a total of 14,380 images were generated from the initial 719 images.

3. Enhanced CNN Model:

The CNN was employed to classify cherries into two categories (regular and irregular shapes). The CNN model comprised three main components:(Momeny et al., 2020)

- o **Convolution Layer:** This layer applies convolution to the input image using various kernels, learning local features.

- o **Hybrid Pooling Method:** Following the convolution layer, this layer was used to reduce the model's parameters. In this study, a **hybrid pooling** method combining both max pooling and average pooling techniques was used to improve the model's generalization ability.

- o **Batch Normalization and Activation Functions:** Batch normalization layers were used in the CNN model to accelerate training and reduce sensitivity. Additionally, the **ReLU (Rectified Linear Unit)** activation function was applied after each layer to capture non-linear relationships.

The ReLU activation function is a widely used non-linear activation function in neural networks. ReLU sets the output to zero for negative inputs and leaves positive values unchanged. Mathematically, it is defined as: $f(x)=\max(0,x)$ (Krizhevsky et al., 2012)

In the study, the proposed CNN model was compared with feature extraction methods such as **Histogram of Oriented Gradients (HOG)** and

Local Binary Patterns (LBP). The features extracted by these methods were evaluated using classifiers such as **KNN, MLP, Fuzzy, and EDT.**

HOG is a feature extraction method used for defining edges and textures of objects in an image. It analyzes the gradient orientations of pixels and creates a histogram of these orientations.

HOG is noted for its effectiveness in edge detection and texture analysis.

Study Results;

- The CNN model achieved accuracy rates of 99.4% at 16x16 pixel resolution, 98.7% at 32x32 pixel resolution, and 99.1% at 64x64 pixel resolution.

- The hybrid pooling method used with CNN produced higher accuracy rates compared to traditional pooling methods. Notably, in classifications performed with the **HOG** feature extraction method, CNN outperformed other algorithms.

- The results demonstrated that the proposed CNN model is an effective method for the fast, accurate, and non-destructive classification of cherry fruits.

The study highlighted that hybrid pooling and CNN-based image processing methods offer a modern approach that could replace traditional methods in the classification of agricultural products.

In their study, Chaschatzis et al. (2022) focused on the detection and characterization of diseased tissues in sweet cherry trees using artificial intelligence and machine learning techniques. Specifically, they aimed to detect diseased leaves and branches using YOLOv5 and ResNet deep learning architectures. These diseased leaves and branches were considered indicators of stress in the trees.

The study focused on root rot pathogens such as *Armillaria*, which cause significant losses in sweet cherry trees. Detection of *Armillaria* often occurs only after the tree has died, making early intervention challenging. Therefore, the study aimed to develop a methodology for the early detection of diseases like *Armillaria*.

This study represents a significant advancement in agricultural technology and plant health, especially by addressing the application of artificial intelligence (AI) and deep learning techniques in agriculture. Key aspects and details of the study are as follows:

1. *Dataset (ERICA)*: The study created a new dataset called ERICA, which included images of leaves and branches from healthy and diseased sweet cherry trees at various stages. The ERICA dataset provided a valuable resource for developing deep learning models related to plant health.

2. *YOLOv5 and ResNet50*: YOLOv5 and ResNet50 were the two main deep learning architectures at the center of this study. YOLOv5 was used for object detection, while ResNet50 was used for image classification. Both models demonstrated high accuracy in distinguishing between healthy and diseased trees.

YOLOv5 is a single-stage object detection model used to quickly and efficiently detect objects within images. Developed by Ultralytics, this model represents the fifth version of the open-source YOLO algorithm and is optimized using the PyTorch framework.

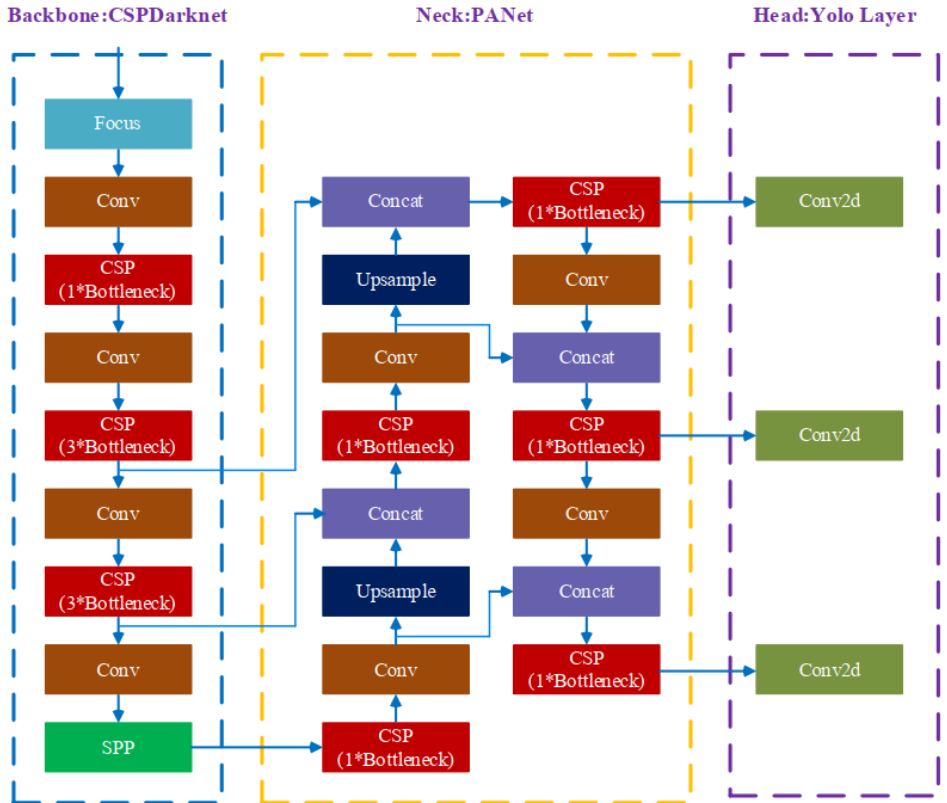


Figure 2 - YOLOv5 Architecture Model (Fang et al., 2021)

Figure 2 illustrates the YOLO (You Only Look Once) architecture, an object detection model. YOLO has a three-part structure:

- **Backbone:** Extracts different features from the input image. Enhanced Spatial Attention (ESA) layer allows multi-scale analysis to obtain detailed information about objects in the image.

- o **Focus layer:** Reduces input data by four times to obtain feature maps at a lower resolution, decreasing data volume and enhancing model efficiency.

- o **Conv layers:** Perform feature extraction, playing a crucial role in extracting meaningful features from the image.

- o **CSP (Cross Stage Partial) layers:** Use partially shared pathways to enrich information flow, facilitating more efficient learning with “bottleneck” blocks and processing data volume more effectively.

- o **SPP (Spatial Pyramid Pooling):** Uses windows of varying scales to enable the model to understand objects from broader and diverse perspectives.

- **Neck:** Processes the features extracted by the backbone, creating a feature map containing information about the object’s position and size. It combines multi-scale features, enhancing the model’s ability to recognize small objects.

- o **Concat:** Allows feature fusion from different layers.

- o **Upsample:** Enlarges feature maps, enabling re-analysis at varying resolution levels.

- **Head:** In the final stage, information from the neck is used for object detection, allowing classification and localization of objects.

This structure helps YOLOv5 achieve high accuracy and speed in real-time object detection tasks. Optimizing the backbone and neck of the model provides a significant advantage for applications requiring low latency.(KIVRAK & GÜRBÜZ, 2022)

ResNet-50 is a commonly used neural network architecture in deep learning and is part of the Residual Neural Network (ResNet) family. Introduced by Microsoft Research in 2015, this model was designed to overcome challenges associated with training deeper neural networks, particularly the degradation of performance as network depth increases. The

ResNet architecture addresses this issue with a technique known as “residual connections”.

Key Features of ResNet-50:

- **Depth:** Composed of 50 layers, including successive convolutional, pooling, and fully connected layers.(Krizhevsky et al., 2012)
- **Residual Connections:** These connections allow the input signal to bypass certain layers, adding it directly to the output of subsequent layers. This helps to mitigate the vanishing gradient problem that can occur in deep networks.(Szegedy et al., 2017)
- **1x1 Convolution:** Used to adjust channel width, this feature is essential for reducing computational load and decreasing the number of parameters.(Szegedy et al., 2017)
- **Global Average Pooling:** Replaces fully connected layers, reducing model complexity and lowering the risk of overfitting.(He et al., 2016)

3. *Detection of Diseased Tissues:* The study focused on early detection of serious diseases in sweet cherry trees, particularly root rot pathogens like *Armillaria*, which can be fatal to trees. The study outlined a roadmap for the early detection of such diseases.

4. *Applications:* The methods proposed in the study can be adapted for various plant species in agriculture. Disease detection in fruit trees and other agricultural products is critical for improving efficiency and preventing losses.

The study's findings demonstrate that AI and deep learning methods can be effective tools for the early detection of diseases in sweet cherry trees. This approach aims to improve agricultural productivity and reduce losses caused by disease.

In their study, Özer et al. (2022) developed an algorithm based on the YOLOv5 model using deep learning to detect cherry trees. Cherry trees were identified using drone-captured images in Afyonkarahisar, and a dataset was created from these images. This dataset was trained using three different versions of YOLOv5 (YOLOv5m, YOLOv5s, YOLOv5x), and the performance of the models was compared.

The methods and technologies used in the study are as follows:(Ozer et al., 2022)

1. Deep Learning and YOLO Algorithm:

- o **Convolutional Neural Network (CNN):** A CNN is capable of processing multi-dimensional data and is particularly useful in object recognition and classification tasks. It extracts features from input images and performs classification.(Sun et al., 2020)

- o **YOLO Algorithm:** The YOLO (You Only Look Once) algorithm is a fast, high-accuracy model that detects objects through a single network pass. It divides the image into SxS cells and predicts whether each cell contains an object.

2. Dataset and Training Process:

- o The dataset was created from 889 cherry tree images taken from different angles in Afyonkarahisar and was divided into 80% training and 20% test sets.

- o Training was completed over 100 epochs for each version of the YOLOv5 model (YOLOv5s, YOLOv5m, YOLOv5x).

- o **Feature Extraction and Optimization:** Stochastic Gradient Descent (SGD) and Adam optimization algorithms were used, with a learning rate of 0.01. SGD is a machine learning algorithm that efficiently finds optimal settings by sampling randomly and adjusting parameters incrementally.(Walker, 2024)

3. Model Performance and Evaluation:

- o The models' success was evaluated using metrics such as Precision, Recall, and F1 Score. It was observed that the YOLOv5s model achieved the highest performance, outperforming the other models in terms of F1 Score, Precision, and Recall.

- o The YOLOv5s model achieved the best performance with 98.3% Precision, 97.8% Recall, and a 98.0% F1 Score.

This study demonstrates that cherry trees can be detected with high accuracy, supporting automation in agriculture.

In their study, Bozcu et al. (2023) explored the application of deep learning techniques for detecting leaf diseases to enhance crop yields in plant production. Study Details:

1. *Disease Detection in Agriculture:* Early detection of plant diseases is crucial in agricultural production. Cherry leaf diseases, in particular, have a

direct impact on product quality and yield. Diseased leaves lead to slower plant growth and lower-quality fruit production.

2. *Use of Deep Learning:* The use of deep learning methods in detecting plant diseases contributes to agricultural economics and reduces chemical pesticide use, thus protecting the environment. This study investigated how transfer learning techniques can be applied for this purpose.

Methods Used in the Study:

1. **Dataset:** Two primary datasets were used: the PlantVillage dataset and a newly collected dataset from Kozlu Village in Eskişehir. These datasets include diseases such as powdery mildew and potassium deficiency on cherry leaves. For training, 3,509 leaf images were used (1,826 healthy and 1,683 diseased), and 877 images were used for validation (456 healthy and 421 diseased).

2. **Image Preprocessing:** The images were resized to 224x224 pixels and normalized using the OpenCV library. Additionally, image processing techniques such as color thresholding and histogram equalization were applied.

3. Transfer Learning Models:

- **AlexNet:** Developed in 2012, this model contains 5 convolutional layers and 3 fully connected layers. In this study, it was adapted for a binary classification problem.

- **VGG-16:** A convolutional neural network architecture consisting of 16 layers. A pre-trained VGG-16 model was retrained for classifying cherry leaves.

- **MobileNet-V2:** A model that reduces the number of parameters and provides higher accuracy. It stood out as the most successful model in this study.

- **Inception-V3:** A model known for achieving high accuracy on large datasets, utilizing multiple Inception modules in parallel.

- **ResNet-50:** Comprising 50 layers, this model aims to increase depth while minimizing overfitting. It is particularly effective in achieving high accuracy on large datasets.

Study Results:

- **Data Augmentation:** Various data augmentation techniques (rotation, shifting, brightness adjustment, etc.) were applied to the dataset. These techniques were used to enhance the model's generalization ability and prevent overfitting.

- **Performance Evaluation:** Different deep learning models (MobileNet-V2, Inception-V3, CNN, CNN + LSTM, CNN + BiLSTM) were tested, and each model's performance was evaluated using metrics such as accuracy, precision, recall, and F1 score. The results showed that the MobileNet-V2 model achieved the highest accuracy rate (99.03%).

- **Visual Results:** The MobileNet-V2 model accurately classified both healthy and diseased leaves. In the ResNet-50 model, the accuracy rate improved from 59% to 99% after applying the color thresholding technique.

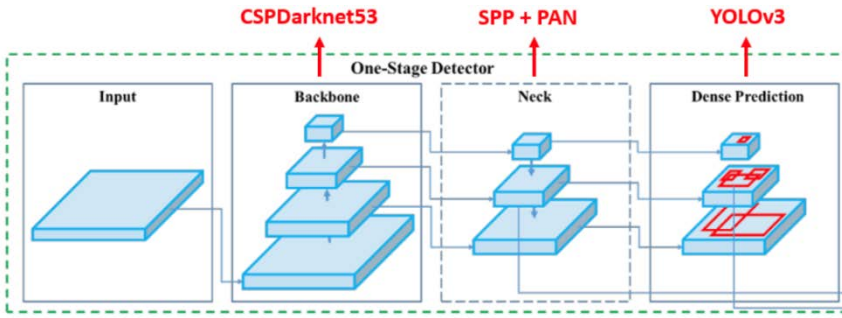
- **Conclusions:** The best results were obtained with the MobileNet-V2 and CNN + LSTM models. MobileNet-V2 was identified as the most effective model for detecting diseases on cherry leaves, offering a lower loss rate and higher accuracy compared to other models. The study suggests that model reliability could be further improved by using more datasets and testing different deep learning methods to enhance detection success.

This study demonstrates how transfer learning methods can be applied to detect plant diseases in agriculture and effectively shows how these methods can be implemented.

In their study, Gai et al. (2023) focused on an algorithm using an improved YOLO-V4 model to detect cherry fruits. In digital agriculture, the rapid and accurate detection of agricultural products is crucial to increase productivity. However, detecting small-volume fruits like cherries is challenging due to environmental factors such as shading and dense growth. The study proposed a method to improve the YOLO-V4 model to address these issues.

The backbone of the YOLO-V4 model, the CSPDarknet53 network, was replaced with DenseNet. Additionally, to make the model better suited for the round shape of cherries, anchor boxes were made circular. These enhancements strengthened the model's feature extraction, deepened the network structure, and increased detection speed. Compared to YOLO-V3, YOLO-V3-Dense, and YOLO-V4 models, the enhanced YOLO-V4-Dense model showed a mean Average Precision (mAP) value that was 0.15 higher.

The YOLO-V4 model is designed to provide high speed and accuracy in object detection. The fundamental principle of YOLO is to use a regression model to predict all objects in an image in a single step. (Wang et al., 2020)



$$\text{YOLOv4} = \text{YOLOv3} + \text{CSPDarknet53} + \text{SPP} + \text{PAN} + \text{BoF} + \text{BoS}$$

↓
Path Aggregation Network

Figure 3 – YOLOv4 Architecture Model (Wang et al., 2020)

According to Figure 3, the YOLOv4 model is an optimized architecture for object detection and consists of three main components:(Wang et al., 2020)

1. **Backbone - CSPDarknet53:** Allows the model to extract features from the image. It is used to enhance the Darknet53 backbone network in YOLO-V3, increasing the model's depth and accuracy.

2. **Neck - SPP (Spatial Pyramid Pooling) and PAN (Path Aggregation Network):** Architectural enhancements like SPP and PAN enable the model to detect objects at various scales more effectively.

3. **Head) - Mish Activation Function and BoF (Bag of Freebies)** Techniques such as the Mish activation function and BoF improve the model's accuracy by predicting the classes and locations of detected objects.

DenseNet, or Densely Connected Convolutional Networks, is a network structure derived from ResNet. In ResNet, shortcut connections between layers address the vanishing gradient problem, which can hinder learning in deep neural networks. DenseNet takes this principle further by connecting each layer directly to all preceding layers. This approach promotes feature reuse and accelerates information flow.(Huang et al., 2017)

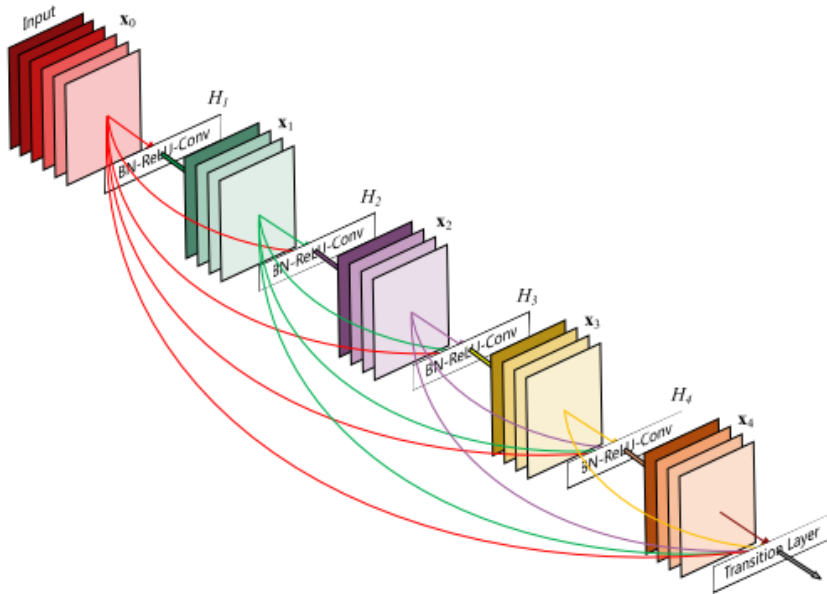


Figure 4 – DenseNet Architecture Model (Huang et al., 2017)

In the DenseNet architecture shown in Figure 4, each layer is connected to all other layers, hence the name Densely Connected Convolutional Network. For each layer, the feature maps from all previous layers are used as input, and its own feature maps are used as input for every subsequent layer.

By integrating DenseNet into YOLO-V4, the model's density and feature transfer between layers are enhanced, allowing for more accurate detection of small objects, such as cherries.

Study Results:

- Training with larger datasets improved detection accuracy.
- Detection performance was noted to decrease in distant views and images without cherries; however, the model's overall performance remained strong.
- In cases of shading and overlapping cherries, the YOLO-V4-Dense model outperformed other models.
- The model demonstrated high accuracy in detecting ripe, semi-ripe, and unripe cherries.

The YOLO-V4-Dense model enables rapid and accurate detection of cherry fruits, enhancing the efficiency of agricultural robots in fruit-picking tasks. This model aims to reduce labor, particularly by facilitating the harvesting of cherries based on their ripeness level.

In their study, Yang and Wang (2023) developed an innovative cherry appearance detection method for the rapid and accurate classification of different cherry ripeness stages and disease conditions. The appearance of cherries is a crucial indicator for consumer purchases and robotic harvesting, closely linked to ripeness classification and disease monitoring. Accurate determination of overall appearance quality is essential. Fruit appearance quality detection has been continuously enhanced through advanced deep learning techniques.

In the study, a method was applied to enable the rapid and accurate classification of cherries at various stages by extracting deep features and transferring these features to nine different classifiers.

Method and Techniques Used

1. **Dataset:** The study used 4,669 cherry images divided into five categories (unripe, semi-ripe, ripe, overripe, and diseased). Images were resized to a 224x224 resolution and split into training and test sets.

2. **Data Augmentation:** Seven data augmentation methods were applied to increase the number of images, especially in the diseased cherry category.

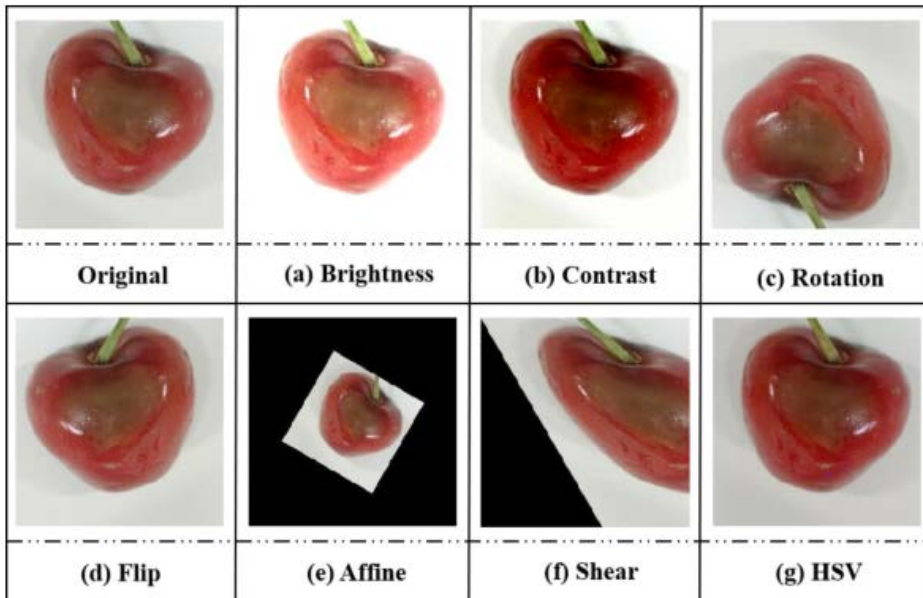


Figure 5 – Original and seven different types of enhanced images (Yang & Wang, 2023)

These techniques (Figure 5) included brightness and contrast adjustments, rotation, mirroring, cropping, and geometric transformations.

3. **Feature Extraction:** Deep features of the images were extracted using six convolutional neural network (CNN) models (VGG13, VGG16, VGG19, GoogleNet, ResNet101, and MobileNet_v2). These features were then prepared in vector form for classifier training.

4. **Classifiers:** Nine algorithms were used for classification:

- o Support Vector Machine (SVM)
- o Extra Trees (ET)
- o Random Forest (RF)
- o K-Nearest Neighbors (KNN)
- o Multilayer Perceptron (MLP)
- o Gaussian Naive Bayes (GNB)
- o Linear Discriminant Analysis (LDA)
- o XGBoost
- o Decision Tree (DT)

5. **Evaluation Metrics:** Classifier performance was evaluated using criteria such as accuracy, precision, recall, specificity, and F1 score.

Findings and Conclusions Combination

- **MobilNet_v2 + SVM Combination:** Transferring features extracted by MobileNet_v2 to the SVM classifier achieved an accuracy rate of 98.3%. This combination showed the best performance with the highest accuracy and shortest training time. Comparisons

- **Comparisons:** Compared to traditional transfer learning models, the proposed model achieved a 3.48% higher accuracy and shorter training time.

This study highlights the effectiveness of combining deep learning models and classifiers for rapid and precise classification of cherry ripeness stages and disease status, offering potential for improved decision-making in agricultural processes.

In his study, Kayaalp (2023) used deep learning methods and ensemble learning approaches to classify different cherry varieties. A dataset was created to classify seven cherry varieties grown in the Isparta region.

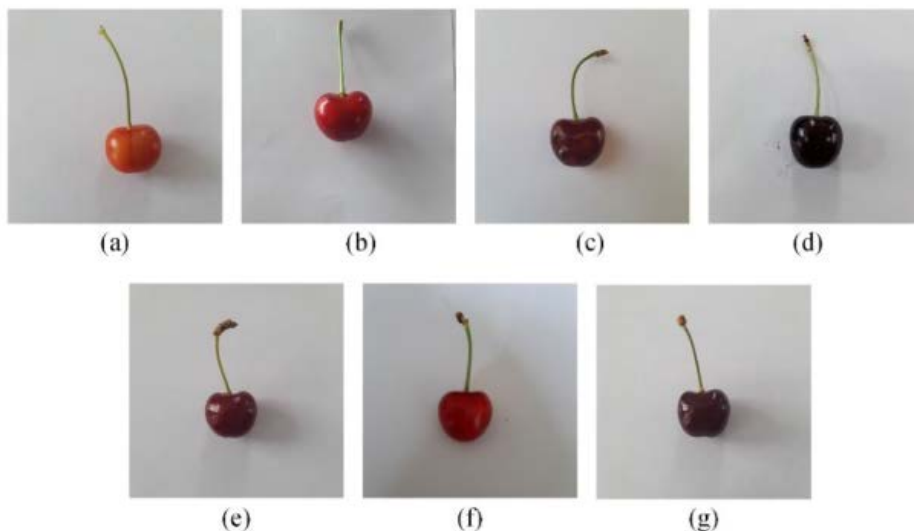


Figure 6 – Images of cherry varieties in the dataset (Kayaalp, 2024)

The cherry varieties classified in this study (Figure 6) are:

- a) Alyanak
- b) Lambert

- c) North Wonder
- d) Regina
- e) Stella
- f) Sweetheart
- g) Ziraat900

Methods Used in the Study:

1. **Image Data Collection:**

- o A dataset of 3,570 images was collected from various cherry orchards in Isparta.
- o The images, initially at a 3456x3456 resolution, were resized to 224x224 pixels.

2. **Data Augmentation:**

- o To increase the number of images and improve the model's generalization ability, various data augmentation techniques were applied, including rotation, shifting, zooming, and mirroring.

3. **Deep Learning Models:**

- o Six different CNN models were used for feature extraction and classification of cherry images:

- **DenseNet169:** Achieved the highest accuracy at 99.57%

DenseNet (Densely Connected Convolutional Networks), is a neural network that uses dense connections between layers. In this model, each layer takes the feature maps of all preceding layers as input and passes its own feature maps to all subsequent layers. This structure allows the model to learn more efficiently with fewer parameters.(Kayaalp, 2024) One advantage of DenseNet is its ability to reduce information loss in deeper layers and enhance feature sharing, resulting in more efficient learning. This approach enables the model to achieve better results, especially on large datasets.

- **MobileNet**

MobileNet is a lightweight model developed specifically to run deep learning models on devices with limited hardware resources, such as mobile and embedded devices.(Kayaalp, 2024) Its ability to function on low-power devices makes it highly advantageous for classification applications in the agricultural sector using mobile devices or robotic systems, enabling classification tasks to be performed on portable devices.

MobileNet uses depthwise separable convolutions, which are more efficient computations compared to traditional deep convolutional filters. This design allows the model to achieve similar performance with fewer parameters. Among the models used in the study, MobileNet achieved one of the highest accuracy rates (98.12%).

- **VGG19**

VGG19 is a neural network model with a total of 19 layers. The VGG architecture typically uses 3x3 convolutional filters.(Kayaalp, 2024) By employing smaller filters instead of the large ones used in previous models, VGG19 reduces computational load. Its deeper structure allows it to extract finer details from images, making it particularly effective for image classification tasks. In this study, the VGG19 model achieved an accuracy of 98.12%.

- **InceptionV3**

InceptionV3, developed by Google, is widely used in image classification.(Obinguar, 2023) This model reduces computational load and generates richer feature maps by using filters of various sizes in parallel within the same layer. By combining both larger and smaller convolution filters, InceptionV3 extracts more features from images, often achieving higher accuracy rates. In this study, however, InceptionV3 demonstrated the lowest performance among the models, with an accuracy rate of 94.81%.

- **ResNet152**

ResNet (Residual Networks), was developed to address issues that arise during the training of deep networks. The core feature of ResNet is the use of "residual connections," or skip connections, which help prevent the accumulation of errors in deep layers during learning.(He et al., 2016)

By leveraging these skip connections, ResNet152 enables the training of much deeper neural networks. Compared to earlier models like VGG, ResNet achieves higher performance with fewer parameters. In this study, the ResNet152 model achieved an accuracy rate of 97.40%.

- **NASNet**

NASNet (Neural Architecture Search), is a neural network architecture developed by Google Brain. This model uses an algorithm that automatically optimizes neural network architecture and employs reinforcement learning to improve the design of deep learning models.(Kayaalp, 2024)

NASNet is an optimized model that has been tested across different configurations, achieving high performance even on limited datasets. It also reaches high accuracy rates with fewer parameters. In this study, the NASNet model demonstrated one of the highest performances, achieving an accuracy rate of 98.56%.

4. Ensemble Learning:

o The two best-performing models (DenseNet169 and NASNet) were combined using the Maximum Voting method, an ensemble learning approach.

Maximum Voting is one of the simplest methods for combining predictions from multiple machine learning algorithms and is commonly used for classification problems. Through this combination, an accuracy of 100% was achieved. (Sarkar & Natarajan, 2019)

Study Results;

- The DenseNet169 model alone achieved an accuracy of 99.57%.
- The combination of DenseNet169 and NASNet models reached an accuracy of 100%.

This study demonstrates that deep learning and ensemble learning methods provide highly accurate and effective results for the classification of cherry varieties.

Cherries, being a delicate fruit that requires high maintenance, demand careful planning and management in their production processes. Various factors, such as climatic conditions, irrigation, and pest and disease management, directly impact cherry production. While managing these processes through traditional methods can be time-consuming and costly, AI-based solutions present new opportunities to overcome these challenges. This section discusses how artificial intelligence applications are utilized in cherry agriculture, the advantages these technologies offer, and potential future developments.

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Future Technologies in Hazelnut Agriculture: Artificial Intelligence Approaches

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Introduction

The agricultural sector is experiencing a major transformation driven by rapidly advancing technologies. Traditional farming methods are evolving to become more efficient, sustainable, and precise. At the forefront of this change are artificial intelligence (AI) applications, which play a key role in modernizing agriculture. AI is used in crucial stages of agricultural production, such as data collection, analysis, and the development of decision-support systems. This enables farming activities to be conducted more efficiently and at a faster pace (Shaikh et al., 2022; Zhai et al., 2020). In the face of global challenges like climate change, scarce water resources, and rising food demand, artificial intelligence holds immense potential to support the sustainability of the agricultural sector.

Artificial intelligence applications offer automation in key areas such as plant health monitoring, pest detection, irrigation, and fertilization, while also enhancing farmers' decision-making processes (Li & Wang, 2024; SS et al., 2024). For example, image processing techniques can detect plant diseases early and estimate crop yields, enabling more efficient use of resources. This helps prevent waste in agriculture and reduces costs. The rapid adoption of artificial intelligence in agriculture is seen as just the starting point of a broader transformation in the industry (Ali et al., 2024; Mana et al., 2024). In the future, AI-driven agricultural solutions will enhance the sector's ability to address global food security challenges by making production processes more sustainable, efficient, and precise.

Artificial Intelligence in Modern Agriculture

Agriculture serves as a primary source of food and income for many countries and forms one of the essential pillars of their economies. Additionally, the sector plays a vital role in driving economic growth by supplying raw materials to various industries (El Hoummaidi et al., 2021). However, agricultural production is increasingly challenged by issues such as climate change and diminishing water resources, posing significant threats to global food security (Dwivedi et al., 2023). These challenges make it even more critical to manage agricultural land sustainably, and this process requires detailed spatial information about soil, water and plants (Herrera-Franco et al., 2023). Sustainable agricultural management can be achieved by monitoring, controlling and evaluating agricultural systems using advanced technologies such as artificial intelligence (AI). These technologies have the potential to provide solutions to existing problems and increase agricultural productivity (Ahmad et al., 2023)(Figure 1).



Figure 1. Leveraging Artificial Intelligence for Sustainable Agriculture (Free, 2024)

Looking at the development processes of today's developed countries, it is clear that agriculture has been a foundational element of their growth. As quality and sustainable agriculture are among the key goals of nations, it is essential to apply modern agricultural techniques at every stage of production. In the past decade, food quality has become a growing concern, increasingly capturing the attention of societies around the world (Liu, 2018).

As in other sectors, technology is advancing rapidly in agriculture and is being widely adopted for the quality classification of crops.

Advances in computer technologies have paved the way for innovative methods in product classification. Key factors driving technological progress in this area include the increased processing power of computers and the use of graphics cards in image processing tasks. The widespread adoption of computer vision has sparked a revolution in classifying products into various categories. Techniques such as clustering, dimensional analysis of objects, product type identification, and quality-based classification are commonly applied. These methods play a crucial role in enhancing the efficiency and quality of agricultural products (Erbaş et al., 2022).

Artificial Intelligence for Hazelnut Farming

Türkiye is the global leader in hazelnut production, accounting for 65% of the world's total supply. It is followed by Italy, Spain, and the USA in production levels. Anatolia, the region where the genetic origins of hazelnuts can be traced, is a key source of both wild species and cultivated varieties. Hazelnuts play a significant role in Türkiye's economy, contributing approximately 12% of the country's foreign trade revenues. As a result, hazelnuts are not only a strategic agricultural product but also a vital export item for Türkiye (Köksal et al., 2006).

Since 2017, global hazelnut production has reached 1 million tons, with Türkiye maintaining its dominant position, accounting for 65.3% of the total production. It is followed by Italy at 13.1%, Azerbaijan at 4.3%, and the United States at 2.9%. In 2017, Türkiye's hazelnut yield was reported to be 154 kg per hectare. Hazelnuts are a key agricultural product in Türkiye, not only as one of the country's most exported items but also as a major source of foreign exchange. With its high-quality hazelnut production, Türkiye plays a crucial role in setting prices and influencing market dynamics globally, continuing to uphold its strategic position in the international hazelnut market (Gencturk et al., 2024).

Hazelnuts go beyond being just an agricultural product in Türkiye and create employment opportunities and contribute to the efficient use of resources. Hazelnuts are used as raw materials, semi-finished and finished products in various industries. In particular, they are used as raw materials in products such as hazelnut paste and hazelnut oil, as well as in the

confectionery, chocolate, bakery, dairy products, cosmetics and pharmaceutical industries. This versatile use provides added value to Türkiye's agricultural economy (Manterola-Barroso et al., 2024). In hazelnut production, growing high quality, uniform and well-filled hazelnuts is of great importance in order to compete in the market. Characteristics such as hazelnut size, shape, flawlessness, flavor, oil and protein content are the main factors in evaluating hazelnut varieties. These factors are closely related to environmental and cultural factors and play a critical role in determining the market position of producers (Mehlenbacher & Molnar, 2021).

Since 2017, global hazelnut production has reached 1 million tons, with Türkiye maintaining its dominant position, accounting for 65.3% of the total production. It is followed by Italy at 13.1%, Azerbaijan at 4.3%, and the United States at 2.9%. In 2017, Türkiye's hazelnut yield was reported to be 154 kg per hectare. Hazelnuts are a key agricultural product in Türkiye, not only as one of the country's most exported items but also as a major source of foreign exchange. With its high-quality hazelnut production, Türkiye plays a crucial role in setting prices and influencing market dynamics globally, continuing to uphold its strategic position in the international hazelnut market (Talebi et al., 2024).

In recent years, deep learning algorithms have become widely used in the classification of agricultural products such as fruits, vegetables, and grains. As a key subfield of machine learning, deep learning can learn complex, non-linear processes in both supervised and unsupervised manners across multiple layers. This technology plays a crucial role in automating quality control, production, and distribution processes within the food industry. It allows for the quick and accurate classification of products by type, quality, and size. As a result, production efficiency is enhanced by enabling the early detection and removal of undesirable or low-quality products, ultimately leading to higher-quality, safer food products for consumers (Saleem et al., 2021).

Computer Image Applications in Hazelnut Agriculture

Hazelnut farming is an economically valuable sector that is increasing its importance in the global market and offers significant advantages in achieving quality, productivity and sustainability goals when supported by modern technologies. Computer image processing technologies represent an innovative approach in hazelnut production as one of the most striking

examples of digitalization in agriculture. These technologies are used in a wide range from hazelnut quality assessment to precise classification of varieties. Image processing techniques provide great benefits especially in disease diagnosis by making visual analyses that are limited to the human eye more sensitive, fast and reliable.

Methods Used in Classification of Hazelnut Quality

One of the biggest problems of the hazelnut sector, which has a large market in the world, is that the quality and durability of the products cannot be determined correctly. In recent years, the safe and high-quality production of food products has gained great importance (Öztürk & Arıcı, 2017). Visual appeal and durability, key indicators of quality, are crucial factors influencing consumers' product preferences (Kalkan et al., 2007). Therefore, correctly classifying the quality of products in the hazelnut sector is of critical importance for both consumer satisfaction and market sustainability.

While cracked, crushed or rotten hazelnuts are generally not preferred by consumers, hazelnuts that are intact and have different textural characteristics are more popular. Therefore, the image-based quality classification of food products is a critical stage in the sales process. However, nowadays, farmers still do this classification manually, which is both time-consuming and makes it difficult to correctly separate products into different quality categories. Manual classification can also negatively affect the process by increasing labor costs.

The role of technology is crucial at this point. Agricultural products such as hazelnuts can be classified according to their quality using artificial intelligence technology (Kamilaris & Prenafeta-Boldú, 2018). Due to its high-precision algorithms, artificial intelligence is increasingly being used in agricultural applications and has the potential to improve quality and ensure sustainability. Artificial intelligence's importance in the digital world of the future will increase, so its use in agriculture will be vital in the years to come (Di Caro et al., 2019). Thus, traditional hazelnut classification methods are being replaced by modern AI-based techniques, allowing hazelnuts to be separated more quickly and accurately according to their quality. Considering these conditions, an AI-based hazelnut quality classification system will provide the following benefits:

- Artificial intelligence-based automatic systems will replace manual classification in agriculture to create a faster and more efficient classification process.

- Agricultural production will be made easier and more accessible for farmers by simplifying the classification process.

- Costs will be reduced and efficiency will be increased by classifying products economically.

- Saving time and space will allow manufacturers to manage their production processes more effectively.

- The profitability of farmers will increase as labor and production costs are reduced.

- There will be a fair price for products based on their quality, and a market will be available for them.

- A correct classification and pricing of quality products will facilitate exports.

- Market products will be of higher quality and will meet consumer needs better.

Producing high-quality products is essential if you want to meet the demands of the international market. Before reaching the end consumer, hazelnuts must be sorted and cleaned. Without mechanization, these processes, especially in large facilities processing a large amount of hazelnuts, create a significant labor requirement. Recently, hazelnut shelling machines have developed, but mechanical force breaking leads to quality loss because of damage to the hazelnut interior (Delprete & Sesana, 2014). Consequently, the high-quality products must be carefully separated after shell cracking.

It is crucial to ensure the careful separation of high-quality products at the conclusion of the shelling process. In industrial-scale hazelnut processing, standard procedures are typically followed. These include drying shelled and whole hazelnuts to achieve a commercial moisture content of less than 6% and subsequently storing them under these controlled conditions (Giraudo et al., 2018). However, before the shelling process, the moisture content must be increased from 6% to approximately 10% in order to minimize the rate of damaged and broken hazelnut kernels (Özdemir, 1999). As another measure to reduce quality loss, hazelnuts are graded according to their diameter to ensure balanced mechanical pressure is applied to all samples (Delprete & Sesana, 2014).

After the cracking process, the crushed hazelnuts are separated by a pneumatic system and transported to different compartments as kernel and shell (Selvi, 2018). If all hazelnuts were uniform in size and shape, the process would operate seamlessly. However, despite being sorted by diameter before shelling, variations in size persist, leading to challenges in the process. Larger hazelnuts crack as intended, but smaller ones may pass through undamaged. Consequently, both cracked and uncracked hazelnuts, along with the kernels, end up collected in the same compartment (Özdemir, 1999). These kernels, including damaged and small-sized hazelnut kernels, are sorted manually by workers standing on both sides as they move along the belt. Owing to developing technology, this process has been automated with laser sorting machines (Selvi, 2018); However, due to the high error rates in automatic systems, manual sorting is still widely preferred (Moscetti et al., 2015).

To enhance hazelnut processing efficiency and minimize quality loss, various technological innovations are being implemented. Traditional manual sorting, limited by the speed and capacity of human labor, is increasingly being supplemented by automatic laser sorting systems. These automated systems enable faster and more systematic separation of kernels from shells. However, despite reducing labor requirements, such systems still experience high error rates, necessitating the continued use of manual methods, particularly for separating small and damaged kernels from intact hazelnuts.

Advancements in image processing technologies hold great promise for accurately detecting hazelnut sizes and conditions. These methods facilitate consistent and efficient classification of products based on size and quality criteria. As research into hazelnut separation and classification continues to grow, significant progress has been made, particularly in the classification of hazelnuts of varying sizes.

In a study by Solak and Altınışık (2018), a system was developed to detect hazelnut fruits in real-time and classify them by size using image processing and clustering techniques. The system comprises three stages. The first stage involves pre-processing images captured by a camera, applying filtering, graying, and morphological operations to prepare the images for analysis. In the second stage, the hazelnuts in the environment are detected using image processing techniques. This process extracts information about their area, size, and position within the image plane. In the final stage, the collected data is stored in an information database, and the hazelnuts are

classified into three size categories—small (K1), medium (K2), and large (K3)—using average-based classification and K-means clustering methods. The study achieved 100% success in detecting hazelnut fruits with image processing techniques. When comparing the classification performance of the average-based method and K-means clustering, the results showed a high similarity, with accuracy ranging between 90% and 100% (Solak & Altınışık, 2018).

Taner et al. (2021) introduced a convolutional neural network (CNN)-based model designed to provide a fast, reliable, and non-destructive classification system for commercial hazelnut production, offering a more efficient alternative to traditional methods. Accurate species identification in agricultural product classification is critical for producers, industrialists, and consumers. However, existing methods primarily rely on expert visual inspections, which are labor-intensive, time-consuming, and prone to significant error margins. The study addressed the need for classifying 17 common hazelnut varieties grown in Turkey by developing a comprehensive dataset of 4,250 images. These images were sourced from hazelnuts provided by the Hazelnut Research Institute of the Ministry of Agriculture and Forestry and captured under controlled lighting and distance conditions during two seasons. The dataset was split into training (3,485 images), validation (255 images), and testing (510 images) sets. Five CNN models were employed in the study: a custom-designed Lprtnr1 model and four pre-trained models (VGG16, VGG19, ResNet50, and InceptionV3). The Lprtnr1 architecture featured an input layer, four convolutional layers, a smoothing layer, a fully connected layer, and an output layer. These models were evaluated using metrics such as accuracy, precision, recall, and F1-score, and all were trained with the same optimization algorithm on the dataset. While pre-trained models served as feature extractors, some exhibited overfitting due to the dataset size, highlighting the influence of data quantity and model depth on classification performance. The custom Lprtnr1 model achieved superior results, with an impressive accuracy rate of 98.63%. Moreover, the alignment of the loss and accuracy curves between the training and validation sets confirmed the absence of overfitting and demonstrated well-optimized parameters. This study underscores the potential of deep learning models to achieve high accuracy in hazelnut variety classification, significantly outperforming traditional methods (Taner et al., 2021).

Ünal and Aktaş (2023) developed a deep learning-based classification model to improve the efficiency of hazelnut sorting by distinguishing between "whole kernel" and three undesirable classes: "damaged kernel," "shell," and "skinny," which are typically sorted manually after mechanical processing. To create datasets for these four classes, an experimental setup was established under industrial conditions, resulting in the recording of 2,094 images. For each class, 1,466 images were allocated for training, 314 for validation, and 314 for testing. The study trained various network architectures from scratch, including EfficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, and InceptionV3. Among these, the highest test accuracy was achieved with the InceptionV3 model, at 97.85%. To further enhance performance, transfer learning was applied using pre-trained weights from the ImageNet dataset. With this approach, EfficientNetB2 and EfficientNetB3 models demonstrated superior accuracy, achieving a remarkable 99.28%. The classification's accuracy is particularly critical for correctly identifying the "whole kernel" class, as misclassifications in this category can lead to economic losses. The confusion matrix analysis revealed that EfficientNetB3 is four times more efficient than EfficientNetB2 and InceptionV3 in correctly classifying the "whole kernel" class. Furthermore, the study noted that misclassifications among the undesirable classes ("damaged kernel," "shell," and "skinny") have a minimal economic impact, reinforcing the primary objective of accurately identifying "whole kernel" hazelnuts. The exceptional performance of EfficientNetB3 in distinguishing "whole kernel" hazelnuts highlights its potential as an effective solution for enhancing hazelnut quality and reducing economic losses in industrial applications. This success underscores the applicability of deep learning models like EfficientNetB3 for solving similar classification challenges in industrial environments (Ünal & Aktaş, 2023).

Giraud et al. (2018) developed an automatic system to detect hazelnut defects, proposing a method for fast and objective identification of defective kernels using RGB images. The study utilized digital RGB images, which were transformed into colorgrams to serve as input for the PLS-DA (Partial Least Squares Discriminant Analysis) algorithm. The dataset comprised 2,000 half-cut hazelnut kernels, classified as either intact or defective. These samples were imaged using a Nikon D7000 digital camera within a controlled setup—a 40 x 50 cm field of view under consistent lighting. A fixed blue grid was used to organize 100 hazelnuts per session, and images were saved in

TIF format with a 24-bit color depth and a resolution of 4928 x 3264 pixels. The color information from the images was converted into one-dimensional signals, known as colorgrams, and initially analyzed using Principal Component Analysis (PCA). Subsequently, classification models based on PLS-DA and Interval-PCA-DA (iPLS-DA) algorithms were developed. A two-stage hierarchical tree model was employed for classification. In the first stage, the model distinguished intact kernels from defective ones. In the second stage, defective kernels were further classified as either rotten or pest damaged. The model demonstrated impressive performance, correctly identifying 97% of defective samples and achieving 92% accuracy in distinguishing between rotten and pest-damaged hazelnuts during the test set analysis. This approach highlights the potential of integrating imaging techniques and advanced algorithms to enhance the efficiency and objectivity of hazelnut defect detection (Girauda et al., 2018).

Sasso et al. (2024) conducted a comparative study of various machine learning algorithms to detect and map hazelnut orchards using optical and radar data. The research utilized Sentinel-1 and Sentinel-2 satellite data, analyzing a total of 62,982 labeled samples from Viterbo, Italy. Of these, 16,561 samples represented the "hazelnut" class, while 46,421 belonged to the "other" class. The study employed nested 5-fold cross-validation to evaluate algorithm performance and conducted an additional assessment by training the models in one area and testing them across seven other regions. Machine learning algorithms included Random Forest (RF), Support Vector Machines (SVM), Decision Trees, K-Nearest Neighbor (KNN), and Artificial Neural Networks (ANN). Among the tested algorithms, Random Forest outperformed the others, achieving 96% accuracy and excelling in delineating the boundaries between hazelnut orchards and other land types. In contrast, SVM exhibited the lowest performance, with an accuracy of 78%, struggling particularly in regions with heterogeneous and complex landscapes. KNN and Decision Trees delivered moderate performance, with accuracy rates ranging between 80% and 85%. This study highlights the superior effectiveness of the Random Forest algorithm in hazelnut orchard detection, demonstrating its ability to handle large-scale remote sensing data and complex spatial structures. Conversely, the limitations observed with SVM underline the challenges of generalization in areas with diverse land characteristics (Sasso, 2024).

Erbaş et al. (2022) developed a deep learning-based model for quality classification of hazelnuts using images from the MVTec Anomaly Detection dataset. The dataset included 514 hazelnut images with a resolution of 1024 x 1024, categorized into five quality classes. To enhance the dataset, data augmentation techniques were applied by rotating the images 90° clockwise, 90° counterclockwise, and 180°, effectively increasing the sample size. The model utilized the AlexNet CNN architecture with a transfer learning approach. The augmented dataset was split into 85% for training and 15% for testing. During training, the ReLU activation function and Adam optimization algorithm were employed. Additionally, the optimal learning rate was identified using the Learning Rate Interval Test (LRIT). The model demonstrated exceptional performance in hazelnut quality classification, achieving 99% accuracy, 98.7% sensitivity, and 99.6% recall. These results highlight the effectiveness of the AlexNet model as a reliable and precise method for hazelnut quality control. The study underscores the potential of deep learning techniques to significantly enhance quality control processes in the agricultural sector (Erbaş et al., 2022).

Classification of Hazelnut Varieties

Hazelnut is a product that is widely grown worldwide due to both its nutritional value and economic importance. Hazelnut, which has various types that have emerged by adapting to different climate and soil conditions, offers differences and richness in agricultural production owing to this diversity. Correct classification of hazelnut varieties is of great importance in terms of optimizing production processes, combating diseases and increasing productivity. In addition, differences between hazelnut varieties vary depending on factors such as taste, nutritional values and market demand. Therefore, classification of hazelnut varieties is becoming a critical issue for both producers and consumers. This section will focus on the definition, characteristics and classification criteria of hazelnut varieties.

Koç et al. (2020) classified 50 samples of pointed, black and plump hazelnut varieties with Gradient Boosting, Random Forest and DL4J (DeepLearning4J) and used physical properties such as maximum length, width, pressing resistance and weight of hazelnuts in this process. Classification accuracy was determined as 94% for Gradient Boosting, 100% for Random Forest and 94% for the deep learning model created with DL4J. Classification of hazelnuts is an important process that increases the

marketability and profitability of its production. Although traditional classification methods are widely used, machine learning and deep learning algorithms are also applied to improve and optimize hazelnut classification processes. In the study, Gradient Boosting, Random Forest and DL4J framework from traditional machine learning algorithms were used. The dataset was divided by 10-fold cross-validation method and the classifier performance criteria were accuracy, error percentage, F1 Score, Cohen's Kappa, recall, precision, true positive (TP), false positive (FP), true negative (TN) and false negative (FN). The results revealed that the Random Forest algorithm performed best with 100% accuracy, followed by the model built with Gradient Boosting and DL4J, each with 94% accuracy (Koç et al., 2020).

Gençtürk et al. (2023) conducted a study to classify hazelnut varieties using deep learning algorithms. A dataset was created using images obtained from hazelnut varieties belonging to Giresun, Ordu and Van provinces. Classification was performed with a total of 3627 images consisting of 1165 images belonging to Giresun, 1324 images belonging to Ordu and 1138 images belonging to Van. This classification was performed using the InceptionV3 and ResNet50 models. In order to combine the classification capabilities of these two models, the InceptionV3+ResNet50 model was developed with the data fusion method. The feature reduction process was performed owing to the convolutional layer added to the data fusion model to reduce the number of features. 100% classification accuracy was obtained for all images. The data fusion model, in which the number of features was reduced to 1024, provided the fastest classification time and was selected as the most successful model (Gençtürk et al., 2024).

Keles and Taner (2021) examined the optical, physical and mechanical properties of 11 different hazelnut varieties grown in Samsun Province and created artificial neural network (ANN) and discriminant analysis (DA) models with these data. Within the scope of the study, analyzes were made on three main axes (X, Y, Z) in order to classify hazelnut varieties. In this modeling process, physical properties of hazelnuts such as geometric mean diameter, sphericity, grain volume, surface area, shell thickness, grain weight and mechanical properties such as rupture force, rupture energy and deformation were used in each axis. In the study, 11 different hazelnut varieties, including 'İncekara', 'Kalınkara', 'Kan', 'Kuş', 'Okay28', 'Palaz', 'Sivri', 'Tombul', 'Uzunmusa', 'Yassı Badem' and 'Yuvarlak Badem', were tested and 50 samples were randomly selected from each variety to

determine these properties. The classification success rates performed with artificial neural networks and discriminant analysis were found to be 89.1% and 92.7% for the X-axis, 92.7% for the Y-axis, and 86.8% and 88.7% for the Z-axis, respectively. The results obtained show that the classification performances of ANN and DA models are very close to each other. The devices used in the study included a biological material testing device (Lloyd Instrument LRX Plus) to analyze the mechanical properties of hazelnut varieties and a colorimeter (Minolta, model CR-400) for optical analyses, while Adobe Photoshop and MATLAB software were used for image processing processes. This study proves the applicability and effectiveness of the proposed models in the classification of hazelnut varieties and shows that classification methods such as artificial neural networks and discriminant analysis provide significant contributions to the classification of agricultural products (Keles & Taner, 2021).

Stella et al. (2013) evaluated the applicability of Near Infrared (NIR) spectroscopy in the classification of hazelnut varieties. Within the scope of the study, spectra obtained from 600 hazelnut samples were analyzed by taking two spectra from opposite surfaces of each sample. Spectral data were converted from transmittance to absorbance and various spectral pre-processing was applied. The most appropriate variable set was selected for feature extraction with Iterative Linear Discriminant Analysis (LDA), and the highest success in classification was obtained with Partial Least Squares Discriminant Analysis (PLS-DA). The 1980-2060 nm range stood out as the region providing the lowest error rate in terms of classification accuracy. The study showed that NIR spectroscopy is effective in the classification of hazelnut varieties with high accuracy and especially the 1150-1650 nm, 1800 nm, 1980-2060 nm and 2120-2180 nm bands are important in classification. The classification results obtained with the Savitzky-Golay filter applied to smooth the spectral data and reduce noise showed excellent performance with 0% false positive, 2% false negative and 1% total error rate (Stella et al., 2013).

Various studies have shown that the classification accuracy of hazelnuts according to variety or quality classes can be improved with computer vision and new scanning techniques. These studies highlight the effectiveness of artificial intelligence and deep learning methods in classifying agricultural products, while revealing that different types of hazelnuts can be classified with high accuracy.

Disease Detection on Hazelnut Leaves

Detection of leaf diseases plays an important role in the economic well-being of countries (Sarkar et al., 2023). Leaf disease is a condition that negatively affects the natural growth of plants, poses a barrier to agricultural trade, and can disrupt a country's agricultural production. These diseases are the result of the life cycles of various types of bacteria, fungi, viruses, and other infectious organisms (Damicone & Brandenberger, 2015). Machine learning and deep learning techniques play an important role in solving the food problems faced by the agricultural industry. Various diseases in plants negatively affect agricultural production by reducing the quantity and quality of the product. Early detection of leaf diseases determines the types of infection by controlling the spread of the disease and thus provides important support for farmers to make effective interventions (Sarkar et al., 2023).

Detecting plant diseases in large agricultural areas is a complex and demanding task. Inspecting individual leaves in the field is not only time-consuming but also prone to errors, resulting in lower accuracy rates for manual identification. Furthermore, the process of identifying diseased regions can be lengthy, which delays timely interventions. Adverse weather conditions and recurring plant diseases significantly impact producers and can have widespread economic repercussions at both the local and national levels. Among these, powdery mildew stands out as a critical concern. This disease, prevalent both domestically and globally, has long been recognized as a major threat to agricultural productivity. Its widespread occurrence underscores the urgent need for efficient, accurate, and scalable detection methods to mitigate its adverse effects (Boyar & Yıldız, 2022).

Various methods have been developed to detect and classify different types of leaf diseases. The first and most traditional approach involves direct observation with the eye, but this method lacks clarity and systematic precision. Another approach involves examining leaf stress either manually or with the assistance of machine learning algorithms. However, visual or microscopic observations are often slow and fail to enable timely interventions before the disease spreads further. As a result, machine learning techniques have become the preferred method for early detection of plant leaf diseases. Early-stage detection is particularly challenging, making the task a critical area of research in fields such as image processing (IP), machine learning, and computer vision. These technologies offer the

potential to automate and enhance disease identification, enabling more effective and proactive disease management (Arribas et al., 2011; Harakannanavar et al., 2022; Martinelli et al., 2015).

The challenges faced by image processing in detecting leaf diseases can be summarized as follows:

Problems with Image Processing Algorithms: Although various image processing algorithms have been developed for the identification and classification of leaf diseases, almost every image processing technique faces some fundamental problems (Khirade & Patil, 2015; Singh & Misra, 2017).

Noise Problems: Electronic devices and light sources can create various types of noise in images, such as Gaussian and pulse, which can reduce efficiency. Noise is a major obstacle that complicates the disease prediction process.

Unfocused Images: Blur caused by out-of-focus capturing hinders the clear observation of diseases. Images captured by electronic devices that are out of focus pose a significant challenge in accurately detecting leaf diseases.

Dataset Limitations: While most researchers rely on existing datasets, capturing images of infected leaves directly from agricultural fields remains a challenging task. The image collection process is further complicated by several technical obstacles, such as varying lighting conditions, weather effects, and the need for precision in capturing detailed features of the leaves.

Shooting Conditions and Technical Difficulties: During the image capture process, factors such as weather conditions, shooting angle, distance of the device to the leaves and occlusion in the image create challenging tasks for researchers.

Device Selection: Different devices such as mobile phones and digital cameras each present limitations in terms of image focus and clarity. Blurring is especially common in images taken with mobile phones, while digital cameras may face limitations such as shooting distance and angle.

Large Image Selection: It is also difficult to select large images for analysis because factors such as blur can negatively impact the analysis of leaf diseases.

Shooting with Drone Cameras: Drone cameras are widely used to image infected leaves in agricultural fields, but these cameras have limitations such as short flight time and exposure to weather conditions. Drone footage was not used in this study (Sarkar et al., 2023).

These difficulties encountered in the detection and classification of leaf diseases are being overcome with technological developments. Today, the combination of image processing, machine learning and computer vision techniques makes it possible to overcome these obstacles and obtain more accurate and faster results.

One of the most common diseases on hazelnut leaves is powdery mildew. Powdery mildew is a fungal disease that occurs in plants, especially in organs such as leaves, flowers and fruits. This disease usually occurs in hot and humid weather conditions and can cause serious damage to agricultural products.

Powdery mildew is typically caused by fungi from the genera *Erysiphe*, *Sphaerotheca*, and *Podosphaera*, which spread the disease by producing spores within plant tissues. The most noticeable symptom is the appearance of a white or gray powdery layer on the upper surface of the leaves, resulting from the accumulation of fungal spores. As the disease advances, affected leaves turn yellow, dry out, and eventually fall.

This disease poses a significant threat to crops with high economic value, such as hazelnuts, as it reduces product quality and leads to yield losses. Powdery mildew can spread easily through wind and water, and the use of contaminated plants or soil further facilitates its transmission to healthy plants.

To manage the disease, various fungicides can be applied, but they must be used correctly and at the right time. Implementing good agricultural practices, such as improving air circulation, managing irrigation effectively, and using resistant plant species, can significantly reduce the spread of powdery mildew. Employing these preventive and control measures can mitigate its impact on agricultural productivity (Sezer & Şahin, 2022).



Figure 2. Powdery Mildew Disease in Hazelnuts (https://duzce.tarimorman.gov.tr/Belgeler/YAYIN/Kulleme_Liftlet.pdf)

Boyar and Yıldız (2022) applied the YOLOv5 model for the early diagnosis of powdery mildew, a major issue in hazelnut cultivation in Türkiye. Their study focused on detecting disease in images of hazelnut leaves. The dataset was compiled from various online sources, including Google and YouTube, to ensure diversity and quality. Images sourced from Google were carefully selected based on their quality and uniqueness, and those suitable for analysis were included in the dataset. To further enrich the dataset, videos of hazelnut fields from YouTube were processed, extracting frames to generate additional images. The final dataset consisted of 424 images, comprising 224 diseased leaves and 200 of healthy leaves, maintaining a balanced representation of both classes. The images were resized to 224x224 pixels to align with the YOLOv5 model's requirements. Each image was annotated, with class and location details saved in corresponding '.txt' files. This labeling ensured that the network learned effectively from the balanced dataset. The YOLOv5 model achieved a 90% accuracy rate in detecting diseased leaves and maintained an accuracy of 85% for images with complex backgrounds. These results highlight the model's potential for reliable disease detection in agricultural contexts, even under challenging visual conditions (Boyar & Yıldız, 2022).

Conclusion

This study explores the potential of artificial intelligence (AI)-based technologies in hazelnut farming, focusing on their applicability to critical agricultural challenges such as hazelnut classification and the detection of powdery mildew disease. The findings indicate that, when implemented effectively, AI can enhance production efficiency while enabling early

detection and intervention for diseases. In particular, image processing and machine learning algorithms offer substantial advantages in monitoring plant health across large agricultural areas by saving time and labor. Looking ahead, the broader adoption of AI applications is expected to facilitate the development of rapid and cost-effective solutions for widespread diseases like powdery mildew. Furthermore, AI's advanced data processing capabilities will enable systematic identification and classification of resilient hazelnut varieties that can adapt to diverse climatic conditions. In conclusion, AI's integration into hazelnut farming promises not only to address current challenges but also to promote sustainable agricultural practices and elevate quality standards, contributing to the long-term viability and success of the industry.

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Intelligent Agriculture Technologies on Apple and Apple Orchards

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Apple is considered a fruit in both botanical and nutritional classifications. Apple is one of the most common and most consumed fruits worldwide. It has great importance due to both its health benefits and agricultural production. Apple is a fruit that adapted from cold places such as the North of China and Siberia to very hot places such as Colombia and Indonesia (Hampson, 2000).

China carried out approximately 54.2% of the world's apple production. The USA, Poland, India, and Turkey followed China. There are more than 6000 apple varieties worldwide, but only a few of them are commercially important. The most commercially produced varieties are Golden Delicious, Red Delicious, Gala groups, Fuji, and Granny Smith. These five varieties account for 60% of the total apple production. Production of new varieties such as Delblush (Tentation®), Cripps Pink (Pink Lady®), Scifresh (Jazz®), Honeycrisp (Honeycrunch®), Corail (Pinova® or Pinata®), Civni (Rubens®), and Ariane is increasing (Hampson, 2000; O'Rourke, 2003; Anonymous, 2003; Atay, 2010).

The Latin names of apple varieties are generally based on the parent species, *Malus domestica*. However, commercial and local names may vary from region to region. Modern varieties are named according to the regions where they are produced or their characteristics. The most common apple varieties and their characteristics are given in Table 1.

In Türkiye, 84.9 million tons of apples were produced in 2022. When Figure 1 is examined, it shows that it is an important plant product and that research should be done on it (FAO, 2022).

Table 1. Apple Varieties and Characteristics

Varieties	Characteristics
Amasya	Small, sweet, and aromatic variety, native to the Amasya region of Türkiye.
Crispin (Mutsu)	Sweet and hard apple originating from Japan.
Gala	Sweet apple variety with red, and yellow tones
Fuji	. Sweet, juicy, and crispy texture.
Granny Smith	Green, sour, and hard apple.
Golden Delicious	Yellow, sweet, and crisp apple variety.
Hurymez (Türkiye)	A local species known for its durability and aromatic properties.
Jonathan	An apple with a balance of sour and sweet, which is often used for cooking.
Pink Lady	Pink apple with a sweet and sour taste.
Rome Beauty	A red apple which is often used for cooking.
Red Delicious	Dark red, sweet, and slightly juicy variety.
Starking (Starkrimson Delicious)	Known for its bright red skin and sweet flavor.

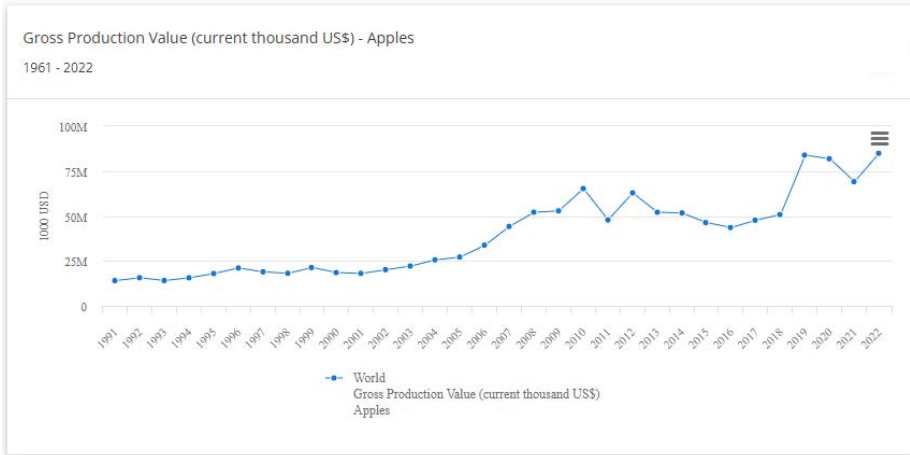


Figure 1. FAO 2022 Yılı Gross Production Value (Thousand US\$) (FAO, 2022)

Türkiye ranked third in the world in apple production in the 2023-24 season, producing 5.8% of the world's apple production. As of 2023, Türkiye produced 4.6 million tons of apples. It is estimated that 4.4 million tons of apples will be produced in 2024. (TurkStat, 2023). 84% of Turkey's apple production is concentrated in just 10 provinces. The highest production is provided by provinces such as Isparta (25.4%), Karaman (15.5%), Niğde

(12.6%), Antalya (9.7%), and Kayseri (5.6%). (TurkStat, 2024, Republic of Türkiye Ministry of Agriculture and Forestry, 2024). There are 460 types of apples grown in Turkey. Among these, the ones that are high in quality and yield and are commercially cultivated are very few. The most productive apple varieties are Golden, Starking, Starkrimson, Starkspur, Gronny Smith, Jonathan, Beacon, Black Stoyman Improved and Amasya apples. Starking, Golden, Starkrimson and Amasya apples are commercially produced (Republic of Türkiye Ministry of Agriculture and Forestry, 2024).

Apple (*Malus domestica*) is an important agricultural crop worldwide and a fruit that requires constant monitoring for quality control and harvest efficiency. There are some difficulties in ensuring the efficiency and quality of apple production with traditional agricultural methods. In this process, with the increasing use of technology, studies on apple fruits have also increased. Artificial intelligence (AI) and image processing (IP) technologies, drone technology, agricultural robots provide great benefits in solving these problems. In apple cultivation, these technologies are revolutionizing critical areas such as fruit health monitoring, disease detection, quality classification and harvest timing. IP is used to analyze various characteristics of the apple fruit, its physical parameters such as color and shape. In this way, apple producers can objectively evaluate product quality and make more efficient decisions. Traditional agricultural methods face limitations in critical processes such as quality control, disease detection, and harvest timing in fruit production. In this context, the integration of AI and IP technologies into apple farming in recent years has great potential to make production processes more efficient and to develop decision support systems, to examine their contributions in areas such as determining apple quality, classification, early diagnosis of diseases, and optimizing harvest time.

Recent studies have shown that IP techniques, machine learning (ML), especially deep learning (DL) algorithms have achieved significant success in fruit farming, in terms of increasing harvest efficiency, improving product quality, and diagnosing diseases, and are rapidly gaining application. These methods play a major role in apple cultivation and quality assessment. IP techniques are used to digitally analyze fruit characteristics, and these characteristics include elements such as fruit health, quality classification, harvest time determination, and disease diagnosis. Deep learning-based algorithms, in particular, can recognize the size, color, shape, and surface defects of apple fruits with the capacity to learn from images. Such analysis

allows apple producers to perform quality classification more accurately and quickly. DL models, especially convolutional neural networks (CNN), are highly effective in classifying apple images and detecting anomalies. These networks achieve high accuracy rates in recognizing defects or disease symptoms on the fruit surface. In addition, techniques such as image segmentation and feature extraction are used in the process of assessing fruit health and detecting diseases at early stages. Virtual image processing and 3D reconstruction methods help optimize quality control processes by detecting the size and shape defects of the apple fruit.

Tools such as robotic systems and drone technology used in every stage of apple production play an important role in collecting visual data. These tools accelerate the visual data collection process and allow analysis to be performed with artificial intelligence algorithms on real-time data. Artificial intelligence-based decision support systems provide significant contributions to increasing efficiency and reducing costs by enabling apple producers to optimize their production processes.

Research on academic studies on apple fruit and IP with AI can be grouped under the titles of image processing and quality assessment, anomaly detection and disease diagnosis in apple agriculture with ML and DL, apple production monitoring with robotic and autonomous systems in agriculture, apple production monitoring systems with virtual reality (VR) and 3D imaging methods, productivity with artificial intelligence and image processing and creation of data-based decision support systems.

In this study, the difficulties in the production process of apple fruit, how AI and IP technologies are used in these processes and what these technologies can bring to the future of the agricultural sector are summarized. It is aimed to provide an assessment of how current practices can transform in the future.

The studies are grouped under six headings below.

a)Quality Assessment in Apple Farming with Image Processing, Machine Learning, Deep Learning

There are studies on the use of ML, DL methods and IP techniques for the quality control of apple fruit. Studies have been conducted on topics such as surface defects, color analysis, size and shape classification, and yield determination.

b) Finding Fruits on Apple Trees and Determining Their Locations

Finding and locating fruits on apple trees is of critical importance for the automation and efficiency of agricultural production. Finding the location, quantity, and type of apples is a very important issue. It also allows harvesting robots and drones to accurately detect and collect target fruits. Precise positioning not only reduces labor but also increases quality by minimizing fruit damage.

c) Artificial Intelligence Productivity and Data-Based Decision Support Systems in Agriculture

It provides support in increasing productivity in agriculture, developing decision support systems, and optimizing agricultural management processes by using artificial intelligence and image processing.

d) Anomaly Detection and Disease Diagnosis in Apple Farming with Machine Learning and Deep Learning

Deep learning models are used in the early detection of diseases and disorders in apple fruits, in many areas such as location, and type. In addition, research is being conducted on the effects of artificial intelligence algorithms on fruit diseases, spoilage, and rot detection.

e) Apple studies with Robotic and Autonomous Systems based on Unmanned Aerial Vehicles in Agriculture

Studies are being carried out to examine the image collection and analysis processes carried out with robotic systems, drones, and autonomous machines in apple farming and to provide real-time decision support by analyzing image data with artificial intelligence systems.

f) Monitoring Apple Production with Virtual Reality and 3D Imaging Methods

Apple production processes are monitored with 3D imaging and VR technologies, fruit surface defects are detected and volumetric analyses are performed.

The articles examined are about some striking studies on apples and apple trees, conducted between 2010-2024 and mainly between 2023-2024. Articles on a wide range of topics from apple trees and apple cultivation to harvesting and classification, including AI, ML, DL, image processing techniques, and the use of drones and robots, were examined according to their fields. In some articles, more than one method was used in combination. Examples include image processing and the use of drones, deep learning techniques and drones, or disease, quality assessment, etc. Although

attempts have been made to provide these under these headings, it is also seen that some articles can fall under more than one heading.

a) Quality Assessment in Apple Farming with Image Processing, Machine Learning, Deep Learning

The images used in the studies are grouped under the headings of monochrome (black and white images), color images (RGB), and thermal images. When the general color of apples is considered, red apples come to mind. In the studies, images taken with a filter designed to capture the red wavelength were mostly used (Parrish and Goksel, 1977)

Zhang et al. (2020) conducted studies by using additional filters with monochrome cameras to obtain fewer faulty images. They also minimized errors caused by sunlight by obtaining images at night. The detection accuracy varies between 75% to 88%. Black and white images were used to identify and merge edges. The brightness values obtained from each edge were analyzed to recognize the general shape of convex or non-convex apples. They achieved satisfactory results in apple detection with 94% accuracy in black-and-white image datasets. They stated that color cameras exhibit distinct colors and that colour is a critical indicator for most fruits. Therefore colour cameras can be used to determine fruit ripeness and detect fruits successfully (Zhang et al., 2020).

Ji et al. (2012) reported that they achieved 89% accuracy in identifying apples on trees. First, they extracted texture and colour features from colour images. Support Vector Machine (SVM) was used for classification purposes. They demonstrate that colour features extracted from colour images have a significant impact in apple recognition tasks and these features can be used in apple-harvesting robots (Ji et al., 2012).

In conventional imaging, it requires a light source to create an image. If the area to be imaged is dark or inadequate lighting, object identification may be significantly hindered. In thermal imaging, however, the process is not influenced by lightening. Instead, the principle that all objects have electromagnetic radiation as a temperature signature is used. Therefore, based on differences in absorption or emission values between non-fruits (e.g. leaves and branches) and fruits, thermal sensors can be successfully used to detect fruits (R. Vadivambal, 2011)

Azizi et al. (2024) used a matching algorithm derived from color indexing, shape features, and epipolar geometry to find apples in an orchard

using images taken from stereo cameras, and as a result, they stated that 89.5% of the apple fruits could be recognized correctly. The authors stated that in the field of IP, feature extraction methods are important to analyze and understand image content. According to them the most commonly used features in fruit identification include texture, color, and shape, which are completed with image segmentation. These techniques and the features used to extract them are listed in Table 2. For classification, they first performed preprocessing and feature extraction processes. In the preprocessing phase, a series of operations and transformations such as denoising, thresholding, and global segmentation are performed on the images to make them ready for feature extraction. Then, texture, color, etc. features were extracted from the objects in the visuals. Finally, these features were passed to machine learning algorithms to be trained to detect objects and classify them. The process is given in detail in Figure 2.

Table 2. Features and methods used in processing color images to identify apples in real scenes (Azizi et al., 2024).

Feature	Techniques				References
Color features	Color space transformation	Color histogram	Color moments	Color level co-occurrence matrix	Jidong et al. (2016); Jana et al.(2017)
Shape features	Contour extraction	Region properties	Hu moments	Hough transform	Cai, and Xu (2006); Liu et al.(2019)
Segmentation	Thresholding	Region growing	Watershed algorithm	Active contours	Xu and Lv (2018); Tabb et al. (2006)
Textural features	Gray level co-occurrence matrix	Wavelets	Local binary pattern	Gabor filters	Zhang et al. (2020); Ropelewska (2021)

In recent years, the use of neural networks, especially DL, in image classification has become widespread. The availability of powerful computing devices such as graphics processing units (GPUs) has further increased the success of these methods. After 2018, deep learning has been applied to various agricultural tasks, with the number of studies focusing on fruit detection increasing significantly compared to previous years. As a result, it is seen that deep learning has been used in most of the studies carried out on apple detection in the last years.

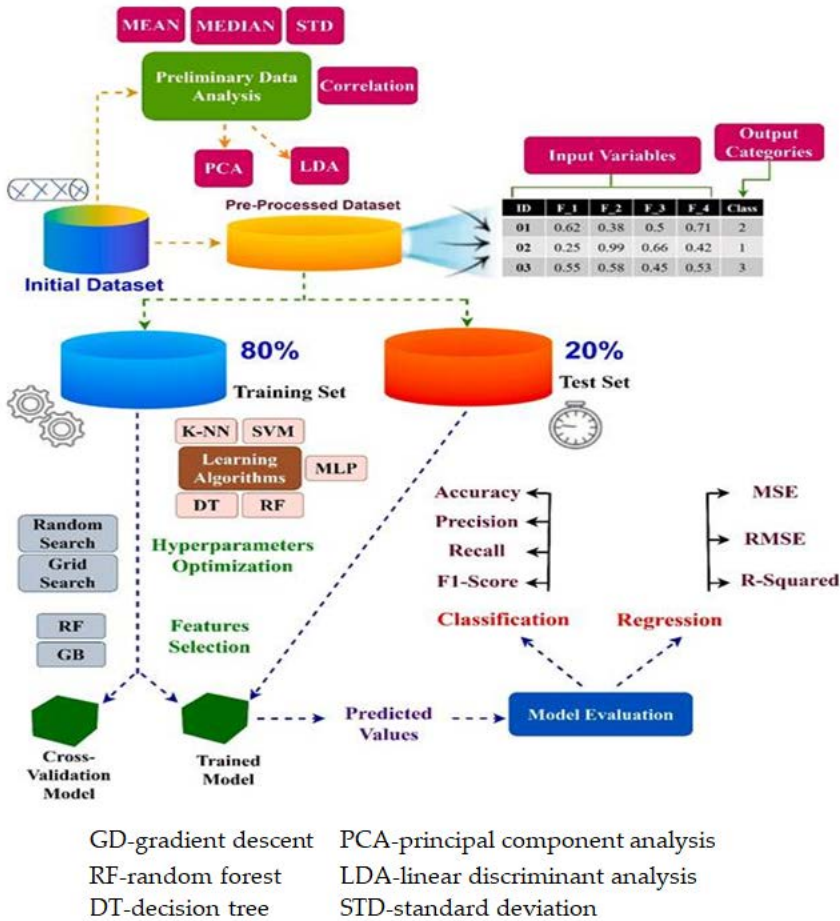


Figure 2. Procedure of supervised classical learning in ML domain. (Azizi et al., 2024).

According to Azizi et al. (2020), the DL approach emerged to enable the computer to process signals such as images, videos, etc., and to enable feature extraction and classification without human intervention. The authors stated that this is the fundamental distinction between DL and ML. They noted that a number of studies have consistently shown that the most important place where deep learning has been successful is deals with images.

b) Finding Fruits on Apple Trees and Determining Their Locations

Advanced ML algorithms, in particular DL techniques, have been proposed to cope with complex orchard environments and to address the limitations of classical methods, such as the inability to optimally distinguish

between unripe and ripe fruit. Using these methods it can be identified subtle visual cues related to fruit ripeness while adapting to different background conditions and lighting. Furthermore, using transfer learning with data augmentation increases model robustness and improves overall performance by training on diverse datasets simulating various orchard scenarios. Studies show the potential of these innovative approaches to improve apple detection in challenging environments, significantly increasing reliability and detection accuracy compared to traditional methods. (Azizi et al., 2024).

The two-stage apple detectors, SPPNet and RCNN, were among the first deep learning based object detection models developed based on incremental training. The ROIs proposed using Region Proposed Networks (RPNs) represent trainable tasks, unlike traditional search methods such as selective search and window shifting. This feature is the most important aspect of RCNNs as it contributes to computational efficiency. Studies have shown that RCNNs improve mAP by 30% compared to classical object detection algorithms, and future two-stage object detection such as Fast-R-CNN, Mask RCNN, and Faster R-CNN forms the basis for models. (Azizi et al., 2024).

Kaymak et al (2019) used IP techniques to detect and count red apples on trees in orchards. To achieve this purpose, software was developed in a computer environment. The developed software finds the apples on the tree using IP techniques using the apple tree images transferred from the digital environment. The center points of the detected apple objects were marked and the apple count was performed. The application can take images from photographs, instant images or live videos. They detected the apples on the tree with 78.47% success (Kaymak et al., 2019).

YOLO, one of the most commonly used DL libraries, is the first single-stage and actively used image processing model for object detection. The working principle of YOLO is to divide the given image into grids and search for the existence of objects in each grid. In YOLOv1, the aspect ratio and size of objects are taken into account. In YOLO, the sum of squares of the errors is used as the loss function, unlike two-stage object detectors that calculate separate losses for bounding box regression (BBR) and classification. The evolution of the YOLO models since its inception is illustrated in the Figure 3 (Azizi et al., 2024).

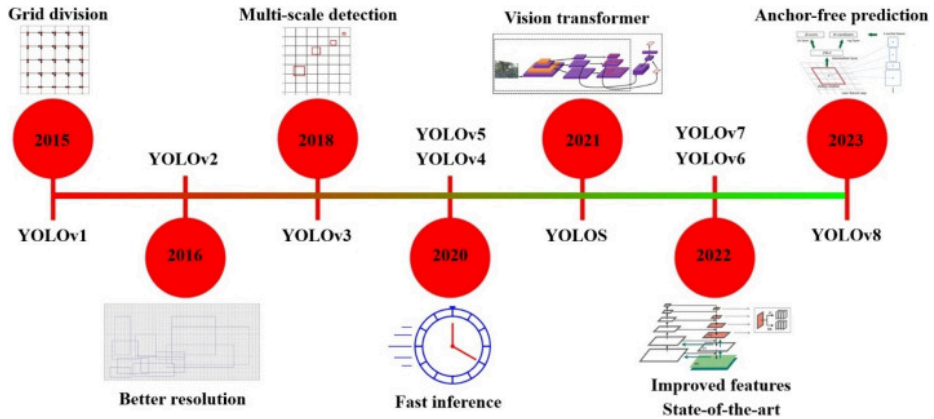


Figure 3. The evolution trend of the YOLO model (Azizi et al.,2024)

In their study, Li et al. (2024) developed a method for apple detection and yield estimation using the YOLOv5 deep learning model. They stated that they proposed a deep learning-based solution because traditional methods cannot cope with challenges such as lighting, shadows, and complex environmental conditions. They used images containing various lighting conditions, angles, and maturity levels for the application. In the first stage, apple images were manually labeled with the labeling tool. In the second stage, the data was divided into training and test sets (Figure 4). The YOLOv5s model was used for training. The performance of the model was optimized by adjusting parameters such as batch size and learning rate. The generalization performance of the model was evaluated using the test set and detection was performed on new images. The number of apples was calculated using the detected boundary areas. They stated that the model had difficulty in detecting small objects. They suggested adding multi-scale feature fusion mechanisms to detect a wide variety of apple types. They stated that this method will contribute to smart agriculture applications and provide an effective tool for apple detection and yield estimation (Li et al., 2024).

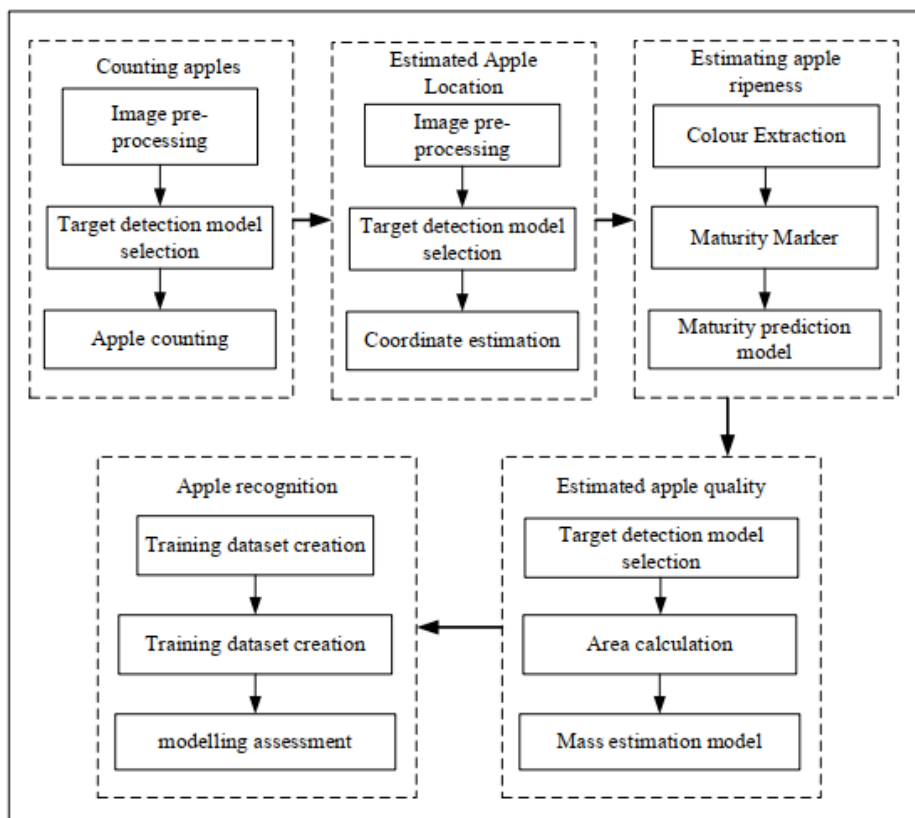


Figure 4. Overall flow chart of the study (Li et al., 2024)

c) Artificial Intelligence Productivity and Data-Based Decision Support Systems in Agriculture

Mizushima and Lu (2013) stated in their study that the first step in image analysis is segmentation. Segmentation separates images into meaningful regions and that directly affects the results of subsequent image analysis results. They developed an automatic adjustable method for the segmentation of colored images using Otsu's thresholding method and linear SVM for apple separation and grading. To assess the accuracy of the proposed method, tests were performed with 300 apples with different colour features (orange, dark red, striped). The segmentation error for fixed SVM ranged between 3% and 25%, while adjustable SVM achieved accurate and consistent results for each training set, and the segmentation error was found to be less than 2%. The proposed method provides a robust and effective segmentation tool for separating and grading apples in a multi-

channel colour space. They wrote that it can be easily adapted to other imaging-based agricultural applications (Mizushima and Lu, 2013).

In their study, Yu et al. (2023) classified 13 different apple varieties using 7,439 images using various deep learning networks such as AlexNet, ResNet18, ResNet50, ResNet101, and VGG19. In the study conducted with two different datasets, the VGG-19 model in particular gave the best result by reaching 100% classification accuracy. The training period also increased as the depth of the models increased. The results showed that CNN-based models have high accuracy rates in apple classification and that these methods can be applied in the agricultural sector (Figure 5) (Yu et al., 2023).

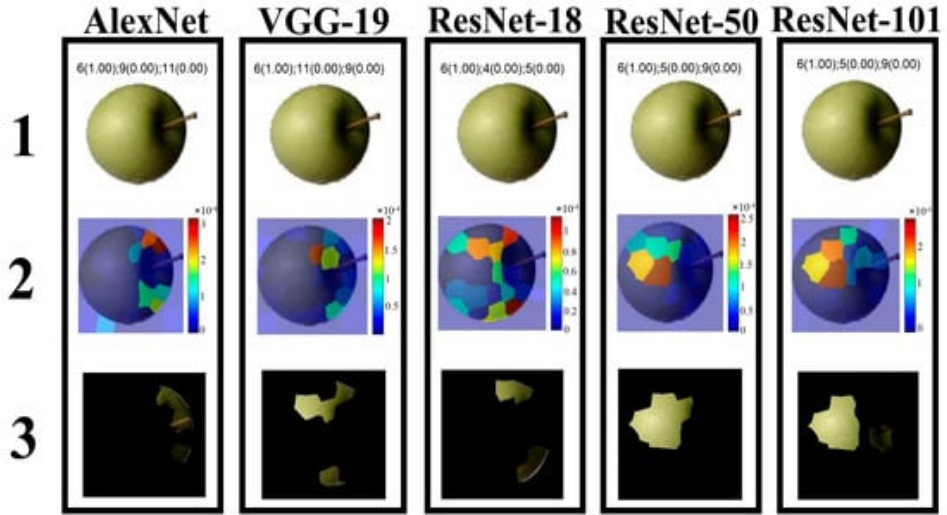


Figure 5. Performance comparison of CNN-based models (Yu et al., 2023).

Chen et al. (2022) used the Multi-Attention Fusion CNN (MAFNet) model to identify 30 different species from apple leaf images. In the study where leaves from different growth periods were used, the accuracy of the model was recorded as 98.14%. In particular, the species "Red General", "SinanoGold" and "Jonagold" were classified with 100% accuracy (Table 3). MAFNet is seen as a practical option for rapid detection of apple species by providing a low-cost and high-throughput solution (Chen et al., 2022).

Table 3. Accuracy for each Variety (Chen et. al., 2022).

Apple Varieties	TP	FP	FN	TN	Precision	Recall	F1-score
Asta	235	5	3	6957	0.979	0.987	0.983
Chengji No.1	237	3	12	6948	0.988	0.952	0.969
Fuji 2001	238	2	17	6943	0.992	0.933	0.962
Gala	239	1	3	6957	0.996	0.988	0.992
Gala Mitchgla	234	6	7	6953	0.975	0.971	0.973
GanHong	232	8	1	6959	0.967	0.996	0.981
Golden Delicious	239	1	3	6957	0.996	0.988	0.992
Honey Crisp	231	9	0	6960	0.963	1.000	0.981
Honglu	229	11	4	6956	0.954	0.983	0.968
Huashuo	227	13	0	6960	0.946	1.000	0.972
Idared	236	4	4	6956	0.983	0.983	0.983
Indo	239	1	5	6955	0.996	0.980	0.988
Jingning No.1	235	5	0	6960	0.979	1.000	0.990
Jonagold	240	0	0	6960	1.000	1.000	1.000
Kuihua	232	8	1	6959	0.967	0.996	0.981
KCo8	227	13	6	6954	0.946	0.974	0.960
Liuyuexian	238	2	4	6956	0.992	0.984	0.988
MATO	239	1	0	6960	0.996	1.000	0.998
Orin	235	5	8	6952	0.979	0.967	0.973
Pinova	238	2	5	6955	0.992	0.979	0.986
Red General	240	0	8	6952	1.000	0.968	0.984
Ruby	239	1	1	6959	0.996	0.996	0.996
Ruixue	239	1	5	6955	0.996	0.980	0.988
Ruiyang	238	2	2	6958	0.992	0.992	0.992
Rustless Goldspur	237	3	0	6960	0.988	1.000	0.994
Shoufu 1	226	14	3	6957	0.942	0.987	0.964
SinanoGold	240	0	0	6960	1.000	1.000	1.000
Taiga	237	3	7	6953	0.988	0.971	0.979
Yanfu 0	232	8	7	6953	0.967	0.971	0.969
Yanfu 3	238	2	18	6942	0.992	0.930	0.960
macro-P = 0.9814	macro-R = 0.9818			macro-F1 = 0.9814			

Taner et al. (2024) performed a classification study on 5808 images taken with a 20 megapixel resolution camera in constant light and distance on 10

apple varieties. 70%, 15%, and 15% of the data was used for training, validation, and, testing respectively. In transfer learning, they used 7 previously trained CNN models VGG16, VGG19, Xception, , InceptionV3, MobileNet, DenseNet201, and ResNet150V2. The last layers of the models were designed according to the target classes. 1920 features extracted from the DenseNet201 model were trained with traditional machine learning models SVM, MLP, RFC, KNN. They stated that DenseNet201 was the most successful model with 10-fold cross-validation. DenseNet201 classified apple varieties with 97.48% accuracy. They achieved 98.28% accuracy with SVM, 98.05% with MLP (with raw data), and 99.77% with MLP (with PCA). They stated that the accuracy of the MLP model increased to 99.77% after PCA (Taner et al., 2024).

Cheng et al. (2017) used artificial neural networks to estimate early harvest in ‘Gala’ and ‘Pinova’ apple varieties using tree trunk and fruit features in an orchard belonging to the University of Bonn, Germany. The trees were pruned in the form of a “slender spindle” and planted at 1.5 x 3.5 meters intervals and images were taken with a 3 Mpixel camera. A total of 180 images were collected in two different periods (after June fall and during ripening period). The images were converted from RGB to binary images to determine the number and area of apples and apple clusters and leaf area were determined with separate algorithms. Total apple number (FN), total apple area (FA), apple cluster area (FCA), and leaf area (LA) were determined as canopy features. Two different back propagation neural network (BPNN) models were developed: Model 1 for small green fruits after June fall and Model 2 for large red fruits during ripening period. The model used fruit number FN, fruit area FA, fruit bunch area FCA, and leaf area (LA) as inputs. Estimated apple yield was determined as output. Model performance was evaluated by metrics such as R^2 , MAPE, RMSE and MFE. Model 1; (After June fall): R^2 : 0.81, RMSE: 2.34 kg/tree, MAPE: 10.7% were found. Model 2; (Ripening period): R^2 : 0.83, RMSE: 2.3 kg/tree, MAPE: 8.9% were obtained (Cheng et al., 2017).

Li et al. (2021) studied the identification and classification of apple image quality. In this study, a new model based on CNN was proposed, aiming at accurate and rapid apple quality grading. ‘Yantai Red Fuji’ apples were purchased from RT-MART supermarket in Jinan City, Shandong Province. In order to improve the robustness and accuracy of the model, the angle, time, and light intensity of the image acquisition process were varied. Totally, 3600

original images (3120×4160 resolution) were obtained with the mobile camera (Redmi Note 4X, 13 megapixels, ISO speed = 151, Exposure time = $1/50$ s, F-Stop = $f/2$, Focal length = 4 mm), which were then classified into three categories: first-class, middle-class and poor-class. The image acquisition system is given in Figure 6. Compared to the Google InceptionV3 model and conventional IP classification methods, the proposed model achieved satisfactory performance. The training process was performed on Intel i7-10700 processor and 16 GB RAM computer using TensorFlow and TensorBoard was used for visualization. At the same time, an independent test dataset (300 apples, 100 per class) was also created to test the performance of the proposed model in an online detection system. In the test stage, four images of each apple were taken from different angles by the camera and then these images were predicted and scored by the trained model. Several results are shown in Figure 7. The quality category with the highest total score (first-class apple, middle-class apple and bad apple) was accepted as the predicted result. The proposed model showed attractive performance for separate test dataset. The performance of the proposed model was evaluated with the help of a confusion matrix in Figure 8. As seen from the confusion matrix, 96 apples were correctly identified as first-class apples. 4 first-class apples were predicted as middle apples. 93 medium apples were predicted as a medium class. 5 and 2 medium apples were predicted as first class, and bad apples class, respectively. 97 bad apples were correctly classified while 3 bad apples were predicted as medium apples. The total classification accuracy of the proposed model for the test set was found to be 95.33%. On the same dataset, the SVM classifier detected the apple quality with a total accuracy of 77.67% for the test data set (Li et al., 2021).

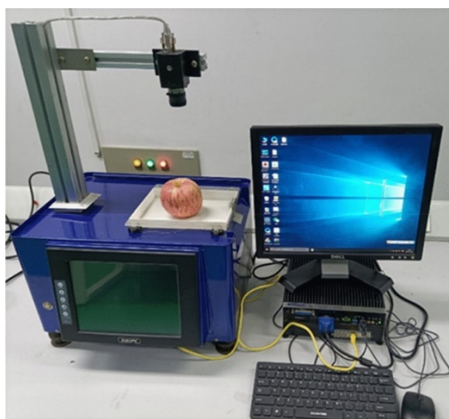


Figure 6. The online detection system for quality determination of apples (Li et al., 2021).



Figure 7. Several of the prediction results for independent test datasets (Li et al, 2021).

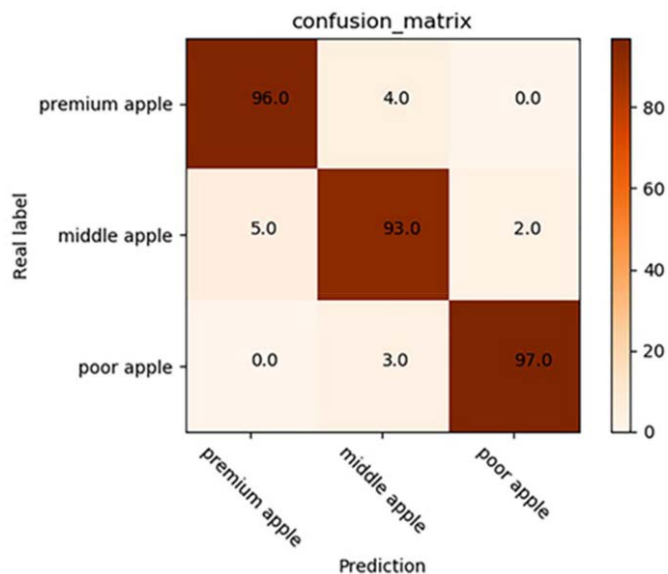


Figure 8. Confusion matrix for the proposed model for the separate test dataset (Li et al., 2021).

d) Anomaly Detection and Disease Diagnosis in Apple Farming with Machine Learning and Deep Learning

Artificial intelligence is widely used in the early detection of diseases and pests in apple trees. Image processing and deep learning methods are often applied.

Fan et al. (2020) studied 'Fuji' apples with normal surfaces and several types of common defects (physical damage, insect damage, rot, and wounds). They purchased the apples from a local supermarket in Beijing. They took images of a total of 300 apples, 150 normal and 150 defective fruits, in the system they developed in the laboratory. They established a four-lane fruit sorting system and used it to classify apple fruits according to their external quality. They created a conveyor consisting of a black fruit container to transport apple fruits and rotate each fruit freely. Thus, the entire surface of each fruit was imaged by a FLIR brand RGB camera (BFLY-PGE-05S2C-CS). These cameras were connected to a c-mount lens (M0814-MP2) with a focal length of 6 mm. They designed an illumination system with two 0.5 W white light strip LEDs. The two linear lights are mounted above the fruit level. The cameras adjusted at an angle of approximately 45° to illuminate the camera field of view. An industrial computer was used to control the system (Intel E7400 CPU, 2.8 GHz, 16 GB SDRAM). The test setup is given in Figure 9 (Fan et al., 2020).

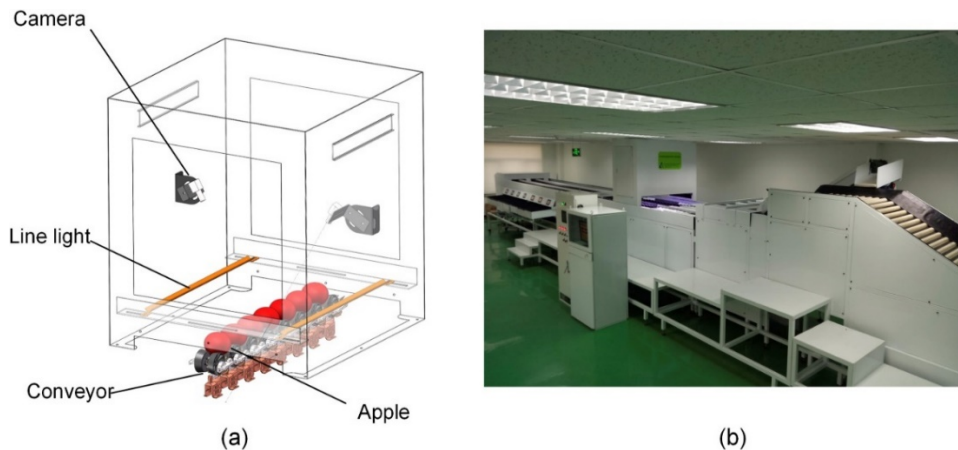


Figure 9. (a) Schematic of the light chamber, (b) photograph of the four-lane fruit sorting machine (Fan et al., 2020).

After removing the background by thresholding the red components using the Otsu method, the minimum bounding rectangle was calculated for

each image to obtain apple images. Then, all images were resized to 80 pixels×80 pixels×3 channels using the Resize function in OpenCV. Representative images of defective apples with different types of defects and normal apples are shown in Figure 10. Compared to the intact area, the defective segments and calyx/stem tips had lower light intensity. The edge of the fruit in the image had lower intensity compared to the central part. To detect defective apples in different orientations and increase the diversity of the dataset, the images were rotated by 90°, 180°, and 270°, and then the hue and brightness were adjusted by ± 0.1 and 0.05, respectively. The final dataset reached a total of 79200 images, 39600 for both defective and normal apples. Representational images in the final dataset are shown in Figure 11. To evaluate the proposed method's performance in the detection of defective apples, 80% and 20% of the images were used for training and validation of the CNN. Thus 63360 images were in training, while 15840 images were in validation set. The CNN-based deep learning architecture was combined with a computer vision module consisting of a commercial camera and LED line lights developed in the laboratory and used to detect defective apples on a four-line fruit sorting machine. The images of defective and normal apples were taken from samples moving at a speed of 5 apples per second. A CNN-based classification model was trained and achieved 96.5%, 100% and 92.9% accuracy, recall and specificity on the test set, respectively. The CNN-based model was loaded into the dedicated software of the fruit sorting system to validate the online performance using 200 apples and achieved 92% accuracy with a processing time of less than 72 ms per apple. The total results showed that the combination of the CNN-based classification algorithm with a computer vision system has a great potential to be applied in the commercial apple packaging line (Fan et al., 2020).

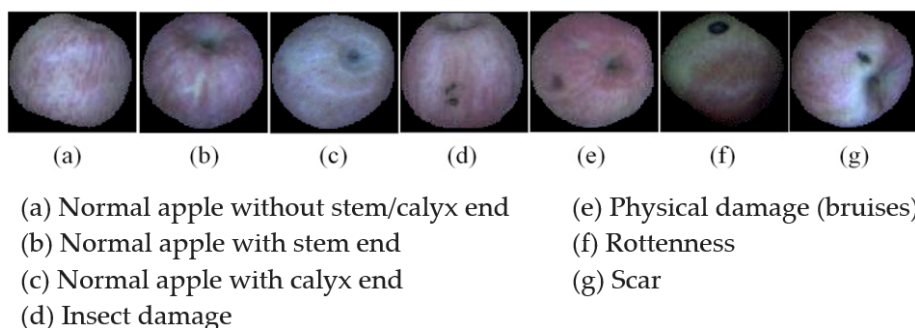
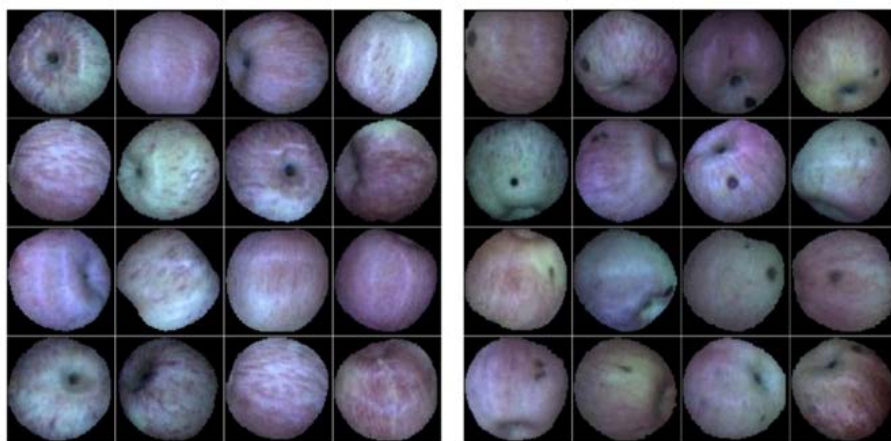


Figure 10. Representational defective and normal apples (Fan et al., 2020).



a) Normal apple

b) Defective apple

Figure 11. Representational images of apples in the final data set (Fan et al., 2020).

In their study, Li et al. (2023) aimed to accurately detect diseases on apple leaves among the complex backgrounds of natural environments and proposed an improved disease detection method based on the YOLOv5s model. They selected (a) images with varying light intensity according to the time of day, (b) images taken using different shooting angles, (c) images with different disease intensities, and (d) images from different disease stages from the datasets collected from PlantDoc, Plant Pathology Challenge 2020, and Plant Pathology Challenge 2021 to ensure the diversity and richness of the dataset. Finally, they selected a total of 2099 apple leaf disease images. In the images, 2099 images containing common apple leaf diseases such as rust, leaf spot disease, scab were, and powdery mildew studied on 10,727 lesion samples (Table 4). The dataset was named Apple Leaf Disease Data (ALDD) and was used for training and testing the model. They used mosaic data expansion and online data augmentation techniques to increase the diversity of images and improve the robustness of the model. The YOLOv5s model has the ability of multi-scale feature fusion such as bidirectional feature pyramid network Bidirectional Feature Pyramid (BiFPN), transformer and Convolutional Block Attention Module (CBAM), and transformer and attention mechanisms were added to reduce unnecessary background information. The model was optimized with 640x640 resolution images for 150 epochs with a learning rate of 0.01. Labellmg software was used to label the images with categories such as width, height, center coordinates, and

disease type of each disease point. SGD was used as the optimization method. It was found that the highest BTC-YOLOv5s model (Figure 12) provided 1.6% improvement over the YOLOv5s model with an average accuracy of 84.3% mAP@0.5. They showed that the BTC-YOLOv5s model achieved a mAP@0.5 of 84.3% on the ALDD test set with a model size of 15.8 M and a detection rate of 8.7 FPS on an eight-core CPU device. Compared with models such as Faster R-CNN and SSD, the BTC-YOLOv5s model was shown to be lighter, faster, and more accurate. The proposed model proved its robustness by maintaining an accuracy rate of over 80% even in difficult conditions such as low light, bright light, and blurred images. The BTC-YOLOv5s model contributes to agricultural intelligence by providing a lightweight, fast, and accurate result for the detection of apple leaf diseases (Table 4) (Li et al., 2023).

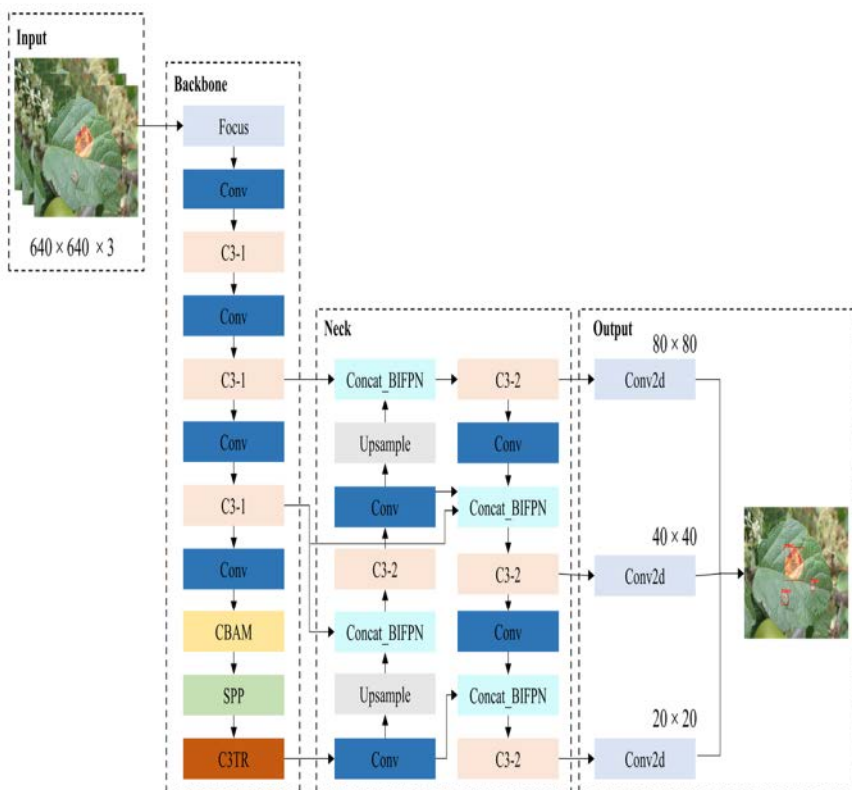


Figure 12. BTC-YOLOv5s model structure diagram (Li et al., 2023).

Table 4. Label distribution of ALDD (Li et al., 2023).

Disease	Number of Images	Number of Labeled Instances
Powdery mildew	499	748
Frogeye leaf spot	600	3091
Rust	502	2166
Scab	498	4722
Total number	2099	10727

Apple leaf diseases seriously affect the sustainable production of apple fruit. Early monitoring of apple leaf infections and timely disease control measures are the key to ensure normal growth and high economic production of apples.

Another study is Gong and Zhang (2023), which aimed to detect apple leaf diseases with high accuracy by making improvements on the Faster R-CNN algorithm. More successful extraction of disease features was achieved by using Res2Net and Feature Pyramid Network (FPN) and 63.1% average sensitivity was achieved. The authors stated that computer vision-based disease detection methods will overcome the shortcomings of traditional disease detection methods, which are time-consuming and have high error rates. They proposed an improved, faster region-based CNN method to solve the limitations ranging from complex background environments to dense and small apple leaf disease features (Figure 13). The improved feature pyramid network architecture and Res2Net were demonstrated as a feature extraction network to extract reliable and multidimensional features, and then RoIAlign was used to replace RoIPool to generate accurate candidate regions for addressing object location. Using the generated dataset apple leaf disease (AALDD), the following main conclusions were reached;

a) The AR and A P₅₀ values of the Faster R-CNN model developed with Res2Net-50-FPN are 68.5% and 62.9%, respectively, which are the highest values among other different backbones such as Reg-Net-FPN, ResNet-50-FPN, ResNeSt-50-FPN, ResNet-101-FPN, and ResNeXt-101-FPN

b) The AP₅₀ of Faster R-CNN with RoIAlign is 0.6%, 0.7% and 0.4% higher than Faster R-CNN with RoIPool for scab, powdery, mosaic, and mildew detection respectively. The AR and AP₅₀ of Faster R-CNN with RoIAlign also have an improvement of 2.7% and 2.9% compared to Faster R-CNN with RoIPool.

c) Eight different detection methods were used to compare the recognition results of specific apple leaf diseases. The AP₅₀ of the improved Faster R-CNN in detecting powdery mildew, rust, frog-eye leaf spot, mosaic, and scab is 98.9%, 88.6%, 82.4%, 94.1% and 95.3%, respectively. Moreover, the AP₅₀ of mosaic and powdery mildew has the best performance.

d) The improved Faster R-CNN using soft NMS can achieve 71.4% AR and 63.1% AP, and outperforms Faster R-CNN using NMS. It also has an advantage over the original Faster R-CNN in detecting high-density disease objects.

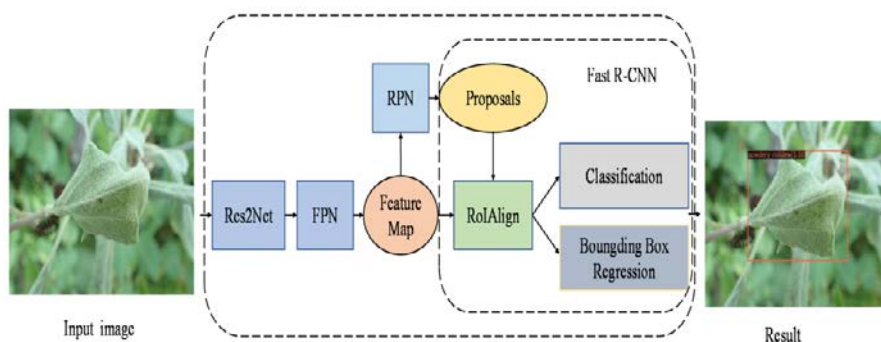


Figure 13. The flowchart of the detection model using Faster R-CNN. (Gong and Zhang, 2023)

Vishnoi et al. (2023) discussed the development of a DL-based CNN model for the detection of apple leaf diseases. The study aimed to detect diseases such as cedar rust, black rot, and apple scab with high accuracy using images from the PlantVillage dataset. They used 3,171 RGB apple leaf images taken from the PlantVillage project as the dataset. The images have a resolution of 256x256 pixels and are divided into 4 classes: a) Healthy leaves, b) Black rot, c) Apple scab, d) Juniper rust. The diversity of the training set was increased by applying data augmentation techniques (shift, rotation, zoom, scaling). The model called Conv-3 DCNN consists of 3 convolutional layers, 2 fully connected layers and an output layer. ReLU activation function is used in convolution layers and Softmax function is used in output layer. Dropout layers are added to prevent overfitting. In training and testing process, dataset is divided and used as 70% training, 20% validation and 10% test ratio. Training is performed using NVIDIA P100 GPU on Google Colab and trained with Adam optimization algorithm for 1000 epochs. Hyperparameter setting is optimized by random search method. Performance of the model is evaluated with metrics such as, F1-score,

accuracy, recall, precision, and AUC-ROC curves. The model showed similar or better performance with lower storage and computational power requirements compared to pre-trained CNN models such as VGG19, ResNet50, and MobileNet. The developed model classified apple leaf diseases with 98% accuracy. Black rot disease was detected with higher accuracy than other diseases. This model is suitable for working on mobile devices thanks to its low-dimensional and energy-efficient structure. They stated that the developed system can be made available as a mobile application and help farmers detect diseases on site (Vishnoi et al., 2023).

In their study, Sulaiman et al. (2023) developed a transfer learning-based model to provide early diagnosis and management of leaf diseases of apple trees. The proposed model aims to contribute to sustainable agricultural practices. They used 23,187 high-resolution RGB images of 11 different apple leaf disease classes from the Plant Pathology Dataset 2020 as a dataset. Disease classes include disease types such as Complex, healthy, frog eye leaf spot, scab, powdery mildew, and rust. Images were taken under different environmental conditions, from various angles and lighting levels. Canon Rebel T5i DSLR (18 MP APS-C sensor) camera and lens were used. Images were reduced to 224x224 pixels and data augmentation (vertical/horizontal flip, rotation) was applied. 80% of the dataset was reserved for training and 20% for testing. EfficientNetB3, InceptionResNetV2, ResNet50, AlexNet, VGG16 algorithms were used for training. The proposed models are shown in Figure 14. The models were optimized by fine-tuning with global average pooling, smoothing, dropout and fully connected layers. In the test results, performance comparisons were made based on accuracy, F1-score, recall and precision. The EfficientNetB3 model, which provided the best performance, was tested with Adam, SGD and Adagrad optimization algorithms. The results are given in Figure 15 and Figure 16. Accordingly, the EfficientNetB3 model achieved 89% accuracy, 86% precision, 88% recall, and 86% F1 Score. EfficientNetB3 was found to have a higher performance than other models with its success. The Adam model left other optimization methods behind with the highest accuracy values of 89% and F1 Score of 86%. SGD and Adagrad showed lower performance.

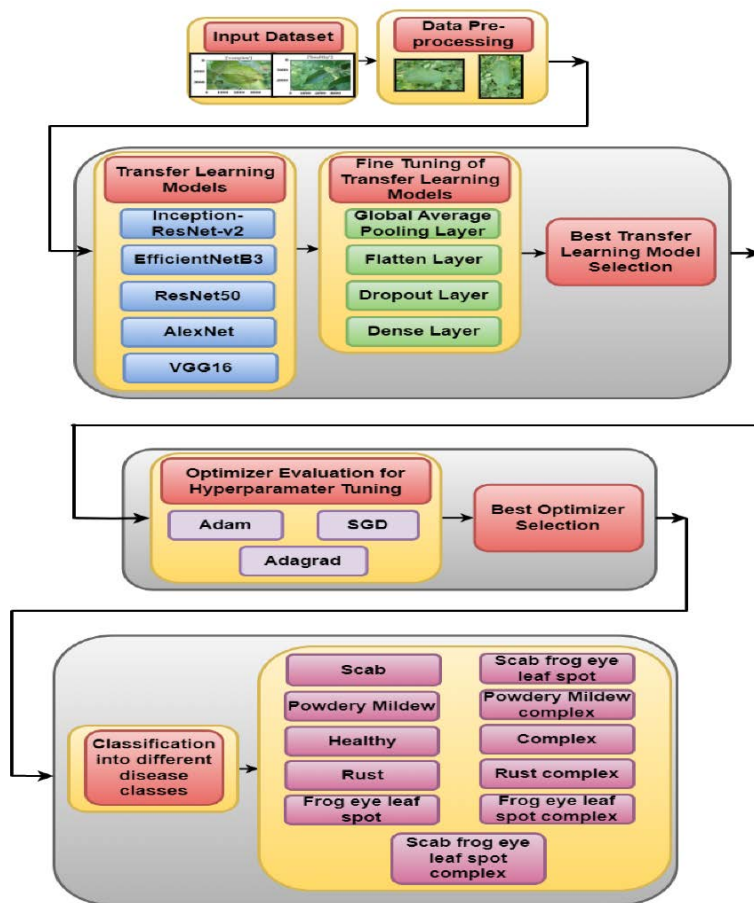


Figure 14. Proposed methodology (Sulaiman et al., 2023).

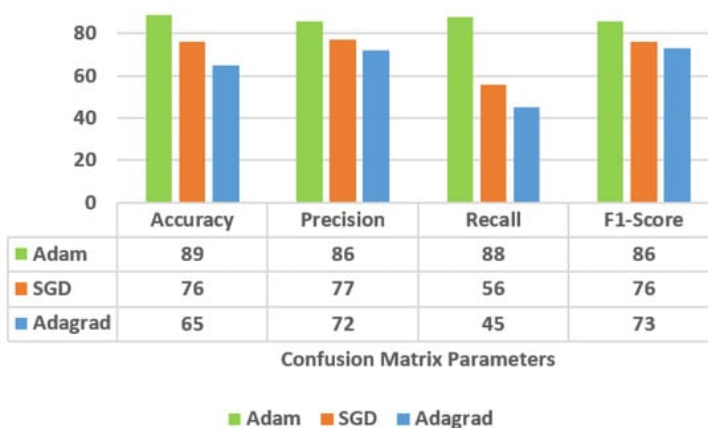


Figure 15. Comparison of transfer learning models with confusion matrix parameters (Sulaiman et al., 2023).

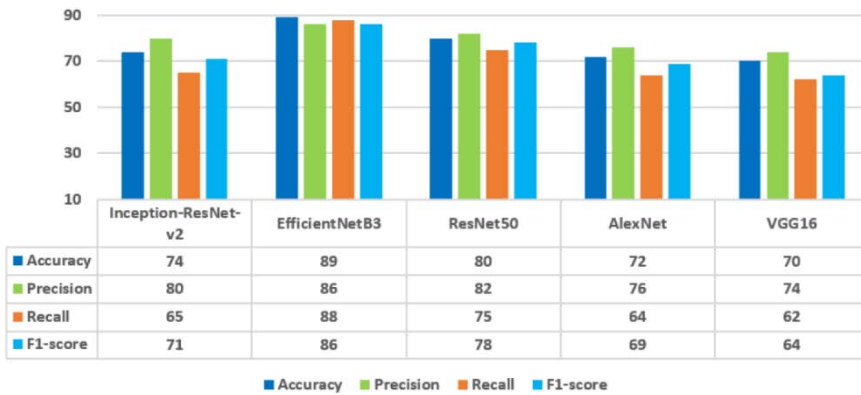


Figure 16. Comparison of the three optimizers' confusion matrices (Sulaiman et al., 2023).

e) Apple studies with Robotic and Autonomous Systems based on Unmanned Aerial Vehicles in Agriculture

In orchard environments, detecting and locating apples using image analysis and AI techniques are important to enable fruit harvesting by robotic vehicles or drones. Classical methods to detect and localize apples on trees are being studied together with more advanced approaches using DL methods which have appeared in the last years. The challenges encountered in apple detection and localization are changing lighting conditions and clustering of adjacent apples, detection of apples in the back row or in the front row, light changes, environmental factors affecting the performance of the algorithms. Research is being conducted on the use of 3D vision for a comprehensive analysis of dynamic and complex orchard environments and precise determination of fruit locations using depth information and point cloud data.

The use of agricultural drones has become widespread in recent years. They obtain data by flying over crop fields to collect data about products or to perform various tasks. Drone-based imaging and artificial intelligence-based DL algorithms have been used to increase harvest efficiency in apple orchards. Compared to traditional methods, drones and automatic models reduce the need for manpower and save time. Detection of apples in apple orchards has become a field of expertise. With the YOLOv7 model, recognition algorithms are used in detection. However, among the important problems in the accurate detection of apples, overlapping, overlapping due to leaves, branches or other objects are encountered. Therefore, in order to

overcome this problem, studies are being carried out to correct the error margin of the DL approach of the apple detection model (Azizi et al., 2024).

In their research, Kumar and Kumar (2023) developed a method to detect apples and estimate their depth using drone technology and the YOLOv7 model. Data were collected using a drone and reflex cameras in two different orchards located in Italy. Images and videos were taken at intervals of 30-60 cm from the plant. No additional light or artificial lighting was used during the flight. The drone includes a DJI Mavic mini 3 and Stereo labs ZED 2iw Polarizing Filter, a high-resolution drone video with 5 km range HD Video transmission, GPS, a three-axis gimbal, a camera capable of taking 2688×1520 resolution images, and a recording setup. The dataset was created by labeling the location and depth information of the apples in the images. The dataset was divided into training (60%), testing (30%) and validation (10%) sets. Data augmentation techniques such as brightness, blur and noise augmentation were applied. The workflow is given in Figure 17 (Kumar and Kumar, 2023).

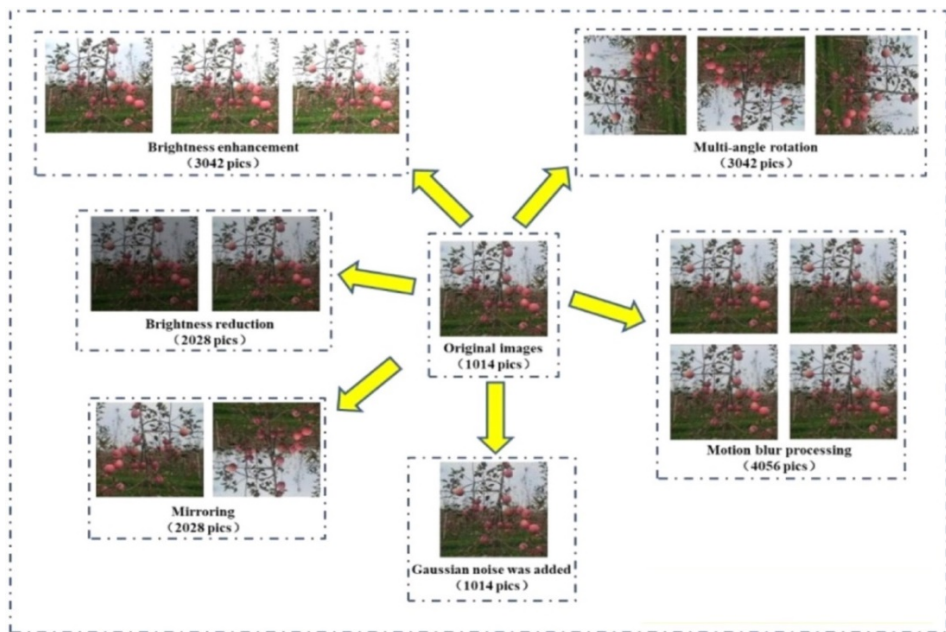


Figure 17. Data augmentation process (Kumar and Kumar, 2023)

The YOLOv7 architecture is used for fast and accurate object detection. The results of the proposed method to detect apples in the obtained image are shown in Table 5. It shows the apple detection performance of live extraction in apple field using modified YOLOv7. Figure 18(a) shows the

The model was developed in Python language. They tested the method they used for apple detection using PyTorch library on a system with Intel i7 CPU, NVIDIA GeForce RTX 3090 graphics card with 24 GB RAM and Ubuntu 16.04 operating system. The performance of the proposed method was compared with existing systems such as AlexNet, Faster R-CNN, ResNet, ResNet+FasterRCNN, AlexNet+Faster R-CNN, YOLOv3, YOLOv5, YOLOv7 and improved YOLOv7. The performance comparison of the models is shown in Table 5. It was seen that the most successful model was improved YOLOv7. YOLOv7 Precision was calculated as 91%, Recall as 96% and F1-Score as 92% (Kumar and Kumar, 2023).

Table 5. Performance comparison between original image and illuminated variation (Kumar and Kumar, 2023)

Method	Original Images			Illumination Variations		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
ResNet	0.73	0.77	0.75	0.73	0.70	0.71
ResNet+Faster R-CNN	0.88	0.65	0.75	0.73	0.77	0.74
AlexNet	0.67	0.73	0.70	0.62	0.66	0.64
Faster R-CNN	0.84	0.80	0.82	0.69	0.72	0.71
AlexNet+Faster R-CNN	0.89	0.85	0.87	0.69	0.75	0.72
YOLOv3	0.83	0.87	0.85	0.71	0.79	0.74
YOLOv5	0.84	0.89	0.87	0.82	0.87	0.84
YOLOv7	0.86	0.89	0.90	0.83	0.88	0.85
Improved YOLOv7	0.91	0.96	0.92	0.86	0.93	0.87

Yıldırım and Ulu (2023) used micro flying vehicles to estimate apple yield in their study. These vehicles are equipped with cameras and deep learning algorithms and follow a certain route in the orchards and perform apple counting. The experiments were carried out in a 350-decare apple orchard in Yeşilhisar, Kayseri, Turkey. The orchard contains 90 thousand trees, 5% of which are granny smith, 5% pink lady, 10% golden, and 80% red (scarlet spur, red chief, oregon spur). The flying robotic system is equipped

with a Pixhawk Cube 2 control unit, KDE-Direct motors and a GoPro Hero 9 camera. The system collected images with a resolution of 5120x2160 pixels and as a result of analyzing 40 trees on a 50-meter corridor, 4000 labeled apple images were created, each with an average of 40 apples. To create a dataset, images were labeled with LabelImg software. For training images with CNN, the data was divided into 80% training and 20% testing. SSD-Mobilenet and Faster R-CNN models were used as algorithms. Python and Dronekit library were used for trajectory tracking planning and flight control (Figure 19). As a result, Faster R-CNN model was determined as the highest performing with a 93% accuracy rate. SSD-Mobilenet was faster with 46% accuracy but lower accuracy rate. Faster R-CNN model provided 10% more accuracy and 6 times more time saving compared to traditional methods thanks to correct apple counting. Faster R-CNN was shown as an effective method for high accuracy. However, optimization requirement regarding energy and processing time, model training with larger data sets, reducing false detections and increasing algorithm accuracy, and studies on increasing position accuracy and energy efficiency with Simultaneous Localization and Mapping (SLAM) were suggested (Yıldırım and Ulu, 2023).

UAV are widely used in tree crown detection and segmentation, detection of diseases and pests, evaluation of fruit production and tree development monitoring, and yield estimation. UAVs are more flexible and cost-effective than satellites and ground vehicles. They can be more effective in data collection, especially in areas with dense tree cover. UAV-based analysis has accelerated manual labeling processes by over 80%. Deep learning models have shown similar or better performance to human observation. Real-time processing algorithms such as YOLO have become ideal tools for situations where rapid intervention is required, such as the detection of pests. The combination of UAVs and ANNs in orchard monitoring has revolutionized agriculture in terms of productivity and sustainability

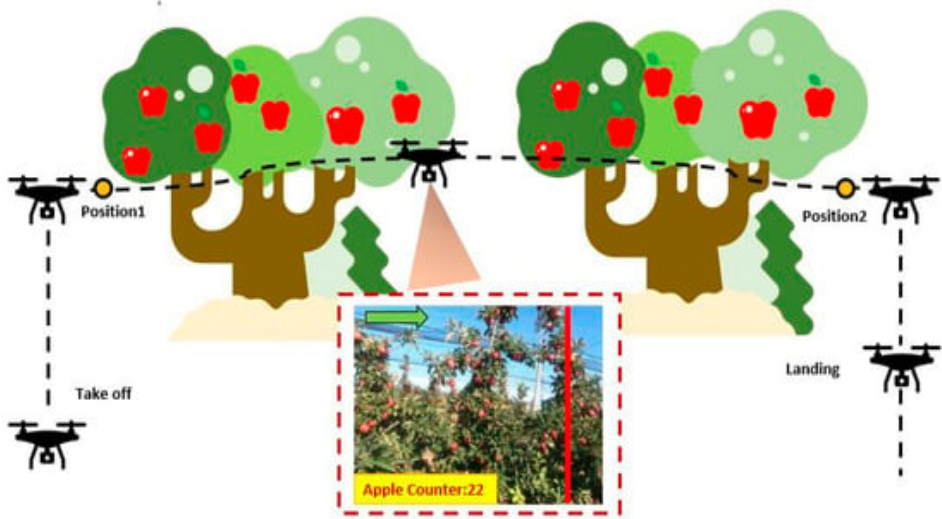
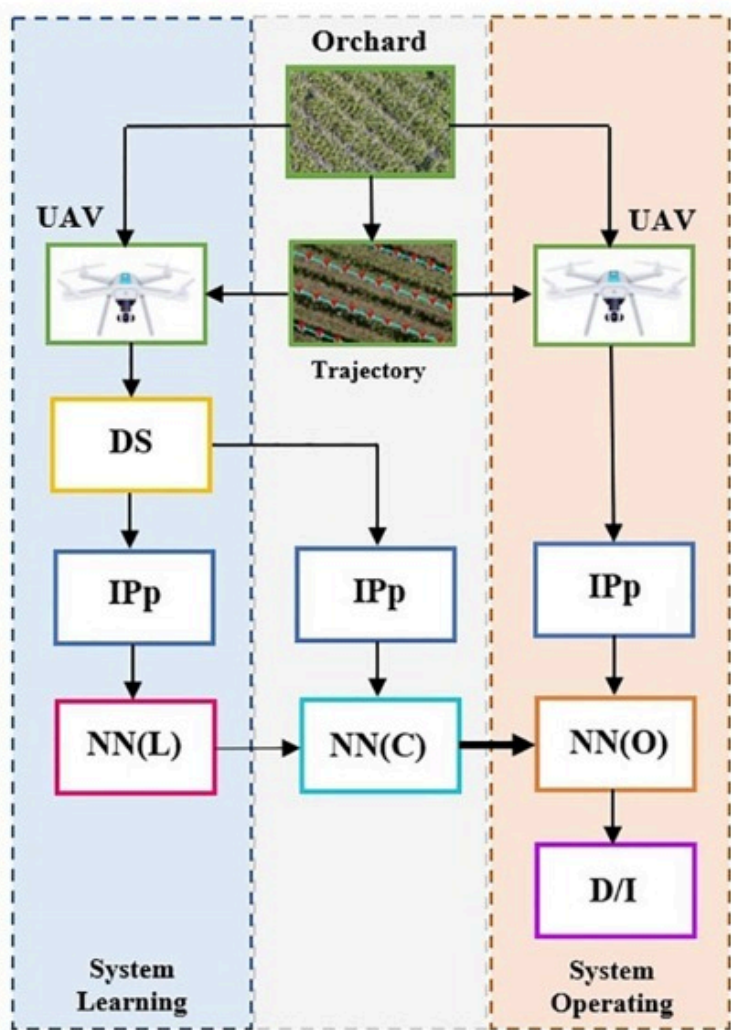


Figure 19. Trajectory tracking planning of FRS in the apple orchard (Yildirim and Ulu, 2023)

Popescu et al. (2023) designed an orchard monitoring method using UAVs and artificial neural networks in their studies. They stated that UAVs are the primary imaging tools used in orchards and are generally used with RGB cameras and multispectral cameras. They were usually used to analyze the status of fruit trees from images obtained at distances between 10-100 meters. Trajectory planning was organized according to the distances between trees and within the rows, and a distance of 3-4 meters was used in apple orchards. YOLO, Faster R-CNN, U-Net, Mask R-CNN, and ResNet from deep neural network models were used in applications such as fruit detection, disease diagnosis, identification of pests, and water stress analysis (Figure 20). Data sets were expanded with data augmentation techniques (rotation, zoom). Images were divided into 70% for training, 20% for validation, and 10% for testing. While YOLO provides fast and high-accuracy object detection, Mask R-CNN was found to be successful in the detailed segmentation of fruits and diseases with masks. Faster R-CNN provided fruit and disease detection with up to 93% accuracy, and they showed that it provided effective results even in difficult conditions such as leaf cover or light. UAV-based analysis accelerated manual labeling processes by 80%. They stated that deep learning models perform close to or better than human observation, and real-time processing algorithms such as YOLO are ideal tools for situations where rapid intervention is required, such as the detection of pests. They suggested that the integration of UAVs with IoT facilitates real-

time decision-making processes and that precise positioning solutions such as RTK modules should be used to prevent GPS signal loss (Popescu et al., 2023).



UAV – unmanned aerial vehicle (drone), DS – data set

IPp – image preprocessing module

NN(L) – neural network learning (parameters and weights)

NN(C) – final NN configuration (after validation)

NN(O) – neural network implemented for operating phase

Figure 20. Structure of the orchard monitoring system composed of UAVs and neural networks. (Popescu et al., 2023).

Jemaa et al. (2023) discussed the development of a system that uses UAVs and computer vision techniques to detect trees in apple orchards and assess their health status. Images were obtained from two different apple orchards (46.44633N, 62.08151W) in Prince Edward Island, Canada, using a DJI Matrice 100 drone with a MicaSense RedEdge3 multispectral camera. The camera uses five spectral bands: red, red edge, blue, green, and near-infrared. The images were orthorectified and merged using Pix4D software. The images were then segmented into 512x512 pixel patches and trees were manually marked. First, a tree detection model was used using a hard negative mining strategy using RGB UAV images (Figure 21 and Figure 22). Then, they sought to solve the health classification problem by utilizing the vegetation indices derived from the multispectral images. Object detection models such as YOLO and DeepForest were used as models. In order to reduce false detections, the sensitivity of the model was increased by adding false positive examples to the training data. NDVI, GNDVI, DVI 12 different vegetation indices were calculated to evaluate the health status of the trees. Methods such as Decision trees, RF, and SVM were tried from ML Models and the random forest algorithm was determined with an accuracy rate of 97.52%. The comparative results of the models are given in Table 6.

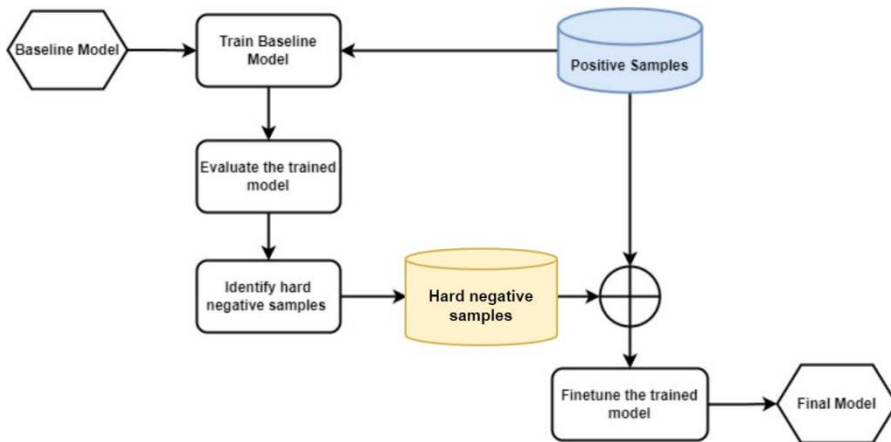


Figure 21. Tree detection stage with hard negative mining strategy (Jemaa et al.,2023).

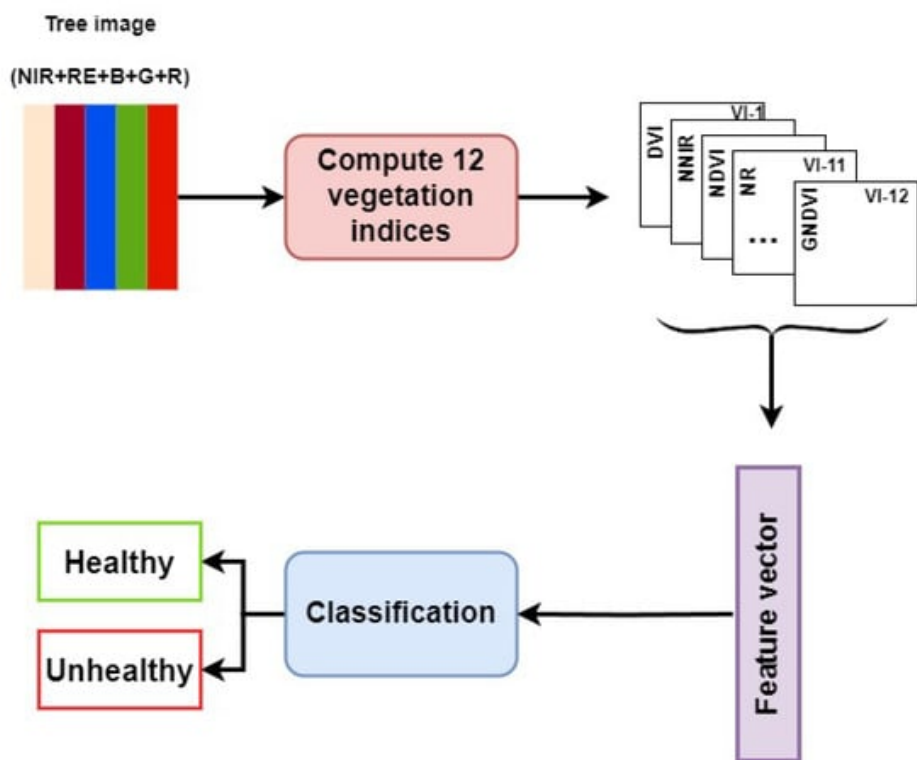


Figure 22. Tree health assessment using an ML classifier based on a set of selected vegetation indices (Jemaa et al., 2023).

Table 6. Cross-validation results (accuracy, precision, recall, and F1 score) of different ML classifiers in classifying tree health status using vegetation indices (Jemaa et al., 2023).

	Health Status	Pc (%)	Rc (%)	F1-Score (%)	Accuracy (%)
Random Forest Classifier (RF)	Healthy	98.8	98.8	98.8	97.52
	Unhealthy	95.5	95.5	95.5	
Light Gradient Boosting Machine (LightGBM)	Healthy	99	98.8	98.9	97.47
	Unhealthy	95.6	96.1	95.8	
K-nearest neighbors (KNN)	Healthy	98.6	98.1	98.4	97.07
	Unhealthy	92.9	95	93.9	
Support Vector Machine (SVM)	Healthy	99.4	95.8	97.6	96.31
	Unhealthy	86.2	97.8	91.6	
Decision Tree Classifier (DT)	Healthy	98.4	97.9	98.1	95.91
	Unhealthy	92.3	93.9	93.1	

Kuznetsova et al. (2021) compared the YOLOv3 and YOLOv5 algorithms used in apple harvesting robots in their study and evaluated the apple detection performance. They aimed to increase the efficiency by testing the speed and accuracy potential of YOLO algorithms in object detection, especially in agricultural environments. The images were taken in apple orchards in the Oryol Region of Russia, under different weather conditions and various lighting levels. The dataset contains a total of 878 images and the images include 5142 ripe apples (red and green varieties). Nikon D3500 camera and 18–55 mm lenses were used. Shooting distances varied between 0.2 m and 2.0 m. The accuracy of the algorithms was measured by manually labeling the apples. YOLOv3 was implemented as Standard and improved with preprocessing (adaptive histogram alignment, region division, lighting adjustment) and post-processing (size filtering, false positive reduction). YOLOv5 was tested without any pre- or post-processing. Table 7 shows F1 Score, Precision, Recall, False Positive Rate, False Negative Rate. YOLOv5 has been shown to provide higher accuracy and sensitivity compared to YOLOv3 without any preprocessing or post-processing. Extensive preprocessing and post-processing procedures were needed for YOLOv3 to be more effective. They stated that YOLOv5 provides a more efficient solution for apple harvesting robots with its F1 score and low false negative rate. These results indicate that agricultural robot technology will become rapidly applicable with the development of deep learning algorithms (Table 7).

Table 7. Comparison of models (Kuznetsova et al. 2021)

Model	No. of images	Precision	Recall	F1-Score	FNR	FPR
LedNet	150	–	84.10%	84.90%	5.90%	–
DaSNet-v2	560	88.00%	86.80%	87.30%	12.00%	13.20%
Faster-R-CNN	150	–	81.40%	81.40%	8.60%	–
YOLOv3	560	87.00%	85.20%	86.00%	13.00%	14.80%
YOLOv3	150	–	80.10%	80.30%	9.90%	–
YOLOv3-Dense	480	–	–	81.70%	–	–
YOLOv3 without pre and post processing	878	90.00%	9.10%		90.90%	10.00%
YOLOv3 with pre and post processing	878	92.20%	90.80%	91.50%	9.20%	7.80%
YOLOv5	878	96.50%	97.20%	96.90%	3.00%	3.50%

Xiong et al. (2022) stated in their study that the application of dwarf and dense planting cultivation technology in standard apple orchards and the intelligent and mechanized operation of orchard production have become suitable. They wrote that the spindle-shaped standard fruit tree form, characterized by fast fruiting, high land utilization, and high yield, is widely used in China to improve the efficiency of orchard production management and to facilitate mechanized operations. They tested the robot they developed in the orchard with a row spacing of 3.5 m, a plant spacing of 1 m and a tree height of 3-3.5 m. They wrote that a vertical fruit wall was formed when the crowns of adjacent fruit trees touched and crossed each other. The crowns of 3-year-old Fuji apple trees in northern China were divided into sampling blocks with width, length, and height of 20 cm×50 cm×50 cm in different layers and orientations, and the crown was 1 m or less above the ground, and there were 1-2 m crowns (Figure 23). Each layer was divided into inner compartment (<20 cm away from the trunk) and outer compartment (>20 cm away from the trunk) with the trunk as the central axis. The number of fruits in each sampling block and at the crown level were counted separately. The fruit density was lower at 5 fruits/m², while the density of the lower and middle layers was higher at 12 fruits/m² and 13 fruits/m². The fruit density analysis showed that 95% of the fruits in tall spindle-shaped apple trees were distributed within the range of 1–2.5 m. The double manipulator prototype was mainly composed of two sets of longitudinally aligned picking mechanical arms and their respective independent drive components. Three degrees of freedom were designed for each picking arm, horizontal, vertical and telescopic. The mounting base of the outer frame is set as the *O* origin, the horizontal and the vertical movement are parallel to the *X* and *Z* axis direction, respectively. The pneumatic telescopic part is driven by a cylinder, which is used to quickly move the picking gripper back and forth in the non-picking area between the robot and the crown. They have increased the positioning efficiency of the robot to the picking tip holder. The fast response time of the telescopic arms is provided by the pneumatic system, while electric servo motors are used for precise speed control. The parts and tasks of the developed robot are given in Figure 24. NSGAII is a genetic algorithm method that uses fast non-dominated ranking and elite mechanism to solve multiobjective optimization problems. The implementation steps are given in Figure 25. The ideal structure parameters are optimized using genetic algorithms (NSGAII) and CRITIC-TOPSIS methods. The CRITIC-TOPSIS joint method is used to evaluate and screen the multiobjective optimum

solution. The final optimization result indicated that the length of the upper collection arm was 1119.3 mm, the horizontal elevation angle was 39.4° , the length of the lower collection arm was 898.7 mm, the horizontal elevation angle was 26° , and the outer frame mounting base was 755.3 mm from the center of the tree trunk. The optimum design supported the target collection area with 100% coverage, and the unnecessary area rate was reduced to 16.62%.

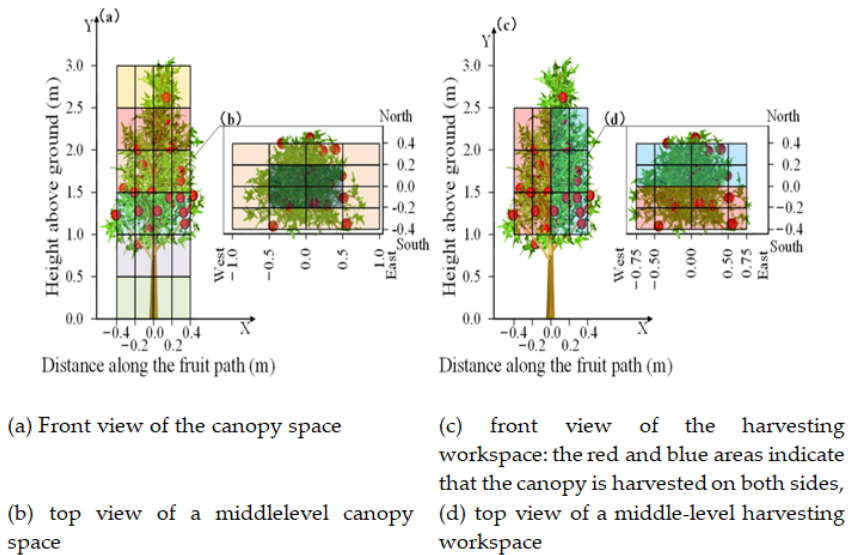


Figure 23. Fruit distribution statistics. (Xiong et al., 2023).

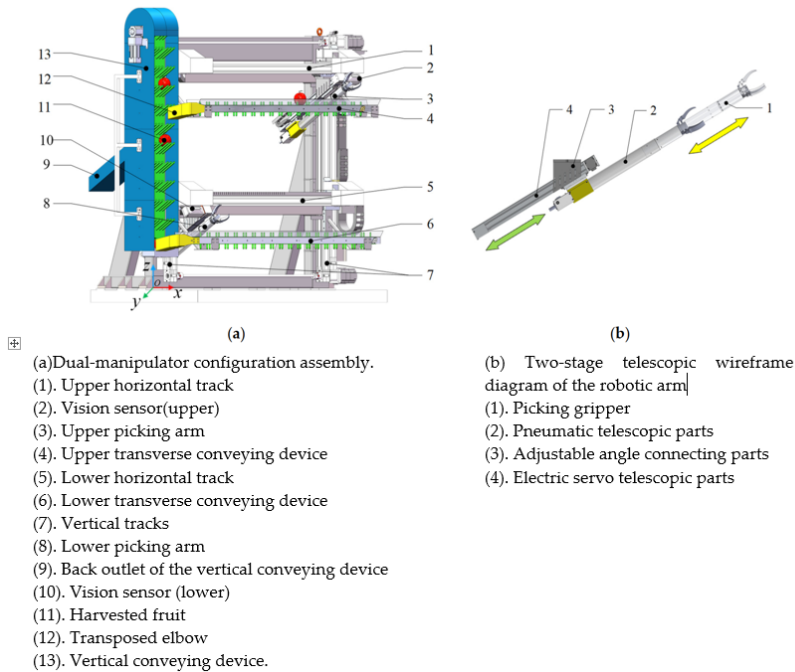


Figure 24. The parts and tasks of the robot (Xiong et al., 2023).

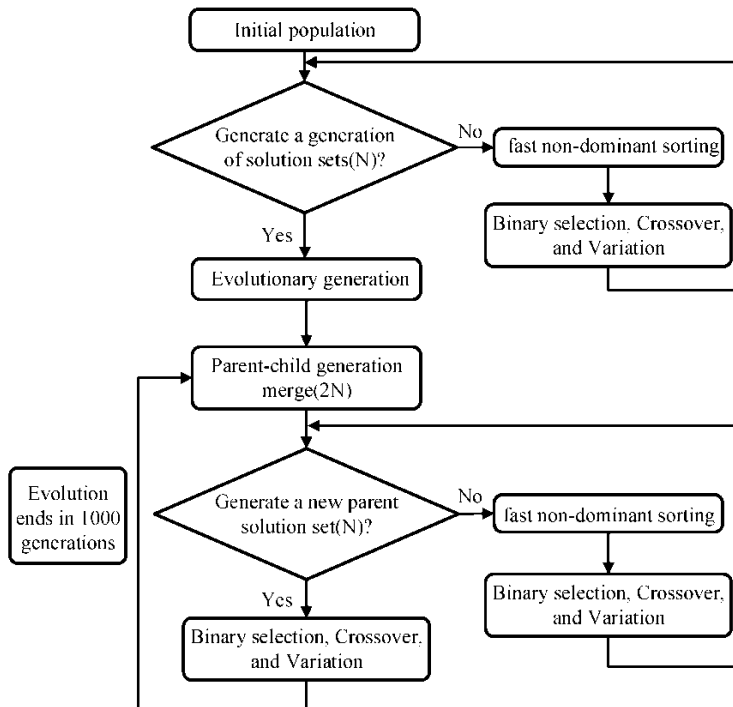


Figure 25. NSGA-II algorithm flowchart (Xiong et al., 2023).

f) Monitoring Apple Production with Virtual Reality and 3D Imaging Methods

The unstructured nature of the orchard environment presents significant challenges for the autonomous navigation of orchard robots. Teleoperation combined with VR is emerging as a promising solution to overcome the limitations of autonomous navigation capabilities built into general-purpose robots. However, creating accurate and meaningful VR maps for orchard environments remains a challenge.

Wang et al. (2024) proposed a novel VR map generation framework for orchard robot teleoperation visualization. The developed orchard management robot is used as the platform for the teleoperated robot. The installation of the robot and sensors is shown in Figure 26. The orchard management robot is designed as a crawler mobile robot. The GNSS system uses a CTI P3-DU Beidou high-precision positioning lateral receiver. Two Beidou receiving antennas are magnetically attached to the top of the robot. The directional antenna is located on the robot's head and the positioning antenna is on its back; the GNSS main unit is installed in a limited space on the robot. A Robense 16-line lidar (RS-LIDAR-16) is installed on top of the robot. The center point of the lidar is 1.2 m from the ground and 0.37 m horizontally from the GNSS directional antenna. the EZVIZ Cloud C3W network camera is mounted below the lidar sensor. Advantech's MIC770Q embedded industrial computer controls the system.



Figure 26. Research Robot Platform for VR Teleoperation (Wang et.al., 2024)

The VR system consists of two main components: joystick-based human-computer interaction (HCI) and virtual displays. The virtual display includes functions such as map loading, loading and relocation of scale robot models.

First, a preoptimized raster map is loaded. The repositioning program and Beidou satellite continuously monitor the robot's movements and provide real-time location information on the map. The virtual display is implemented using the Three.js JavaScript front-end 3D framework and the Windows VR plug-in SteamVR. SteamVR provides a graphical user interface (GUI) for the HTC VIVE headset and the Three.js framework is directly integrated into the map display developed in this study (Figure 27).

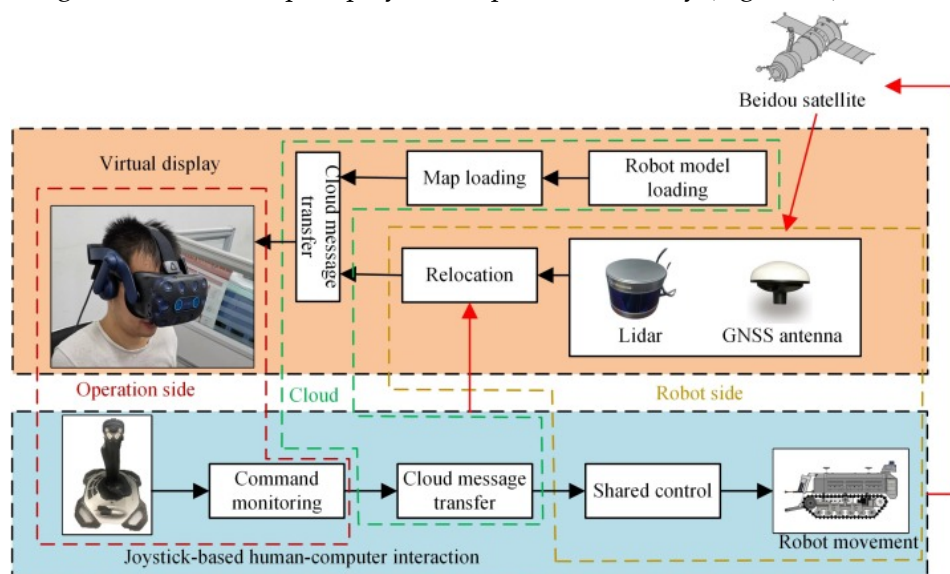


Figure 27. Constructed VR System for Teleoperation (Wang et.al., 2024).

The study area is an apple orchard (33.451°N , 118.301°E) in Yanghe Town, China and the surroundings of the university campus (32.079°N , 118.417°E). They used a sliding window based algorithm that combines GNSS and laser matching data. It provides seamless switching to laser matching mode when there is no GNSS signal. They performed global optimization between GNSS and laser matching to reduce positioning errors. They used fast segmentation based on point cloud segmentation and densification, a sparse point cloud, the radar model of the robot and the assembly features. They proposed a refined segmentation approach for the densified ground point cloud using the RANSAC algorithm. Map Optimization, environmental obstacles were highlighted using Octree based point cloud rasterization. This method enables operators to quickly and effectively identify obstacles in a VR environment. Map Generation with VR is enriched with semantic information such as map, ground and tree trunks.

It offers dynamic visualization to facilitate operators' understanding of the robot's environment (Figure 28).

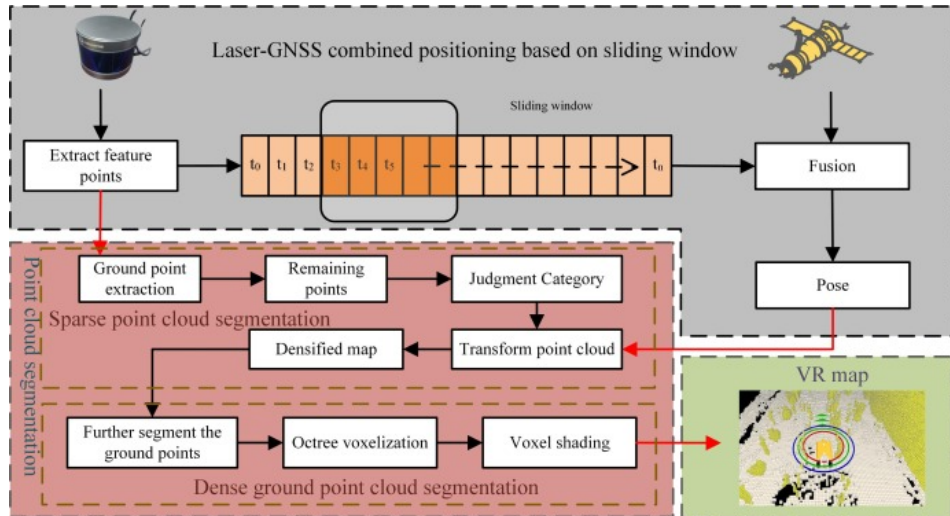


Figure 28. Overall Framework of VR Map Construction (Wang et.al., 2024)

The proposed algorithm for positioning and mapping provided more precise positioning even in cases where GNSS was missing. Mapping accuracy produced better results compared to the LOAM algorithm (maximum error: 0.44 m, relative error: 2.30%). Semantic Information and Visualization, accurate segmentation of obstacles such as tree trunks and ground was performed. Roads and fruit trees were clearly defined on the VR map. The average processing time as Algorithm Running Time is 81.64 ms. It meets the real-time VR mapping requirements by working in harmony with the laser scanner frequency (5–10 Hz). This study contributed to the development of VR-based mapping and teleoperation systems so that agricultural robots can work effectively in complex garden environments, and a Sliding Window Based GNSS-LiDAR Combined Positioning Algorithm was proposed (Figure 29).

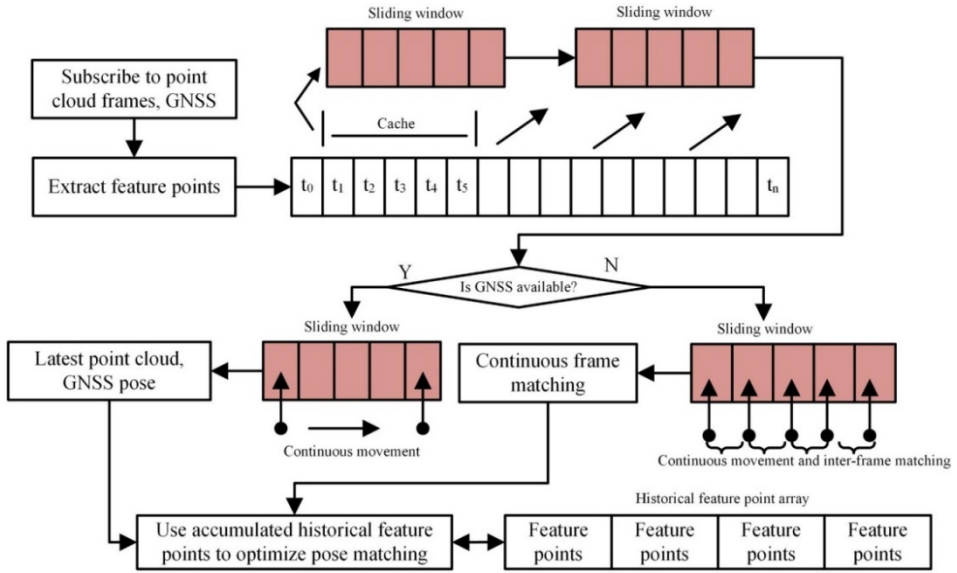
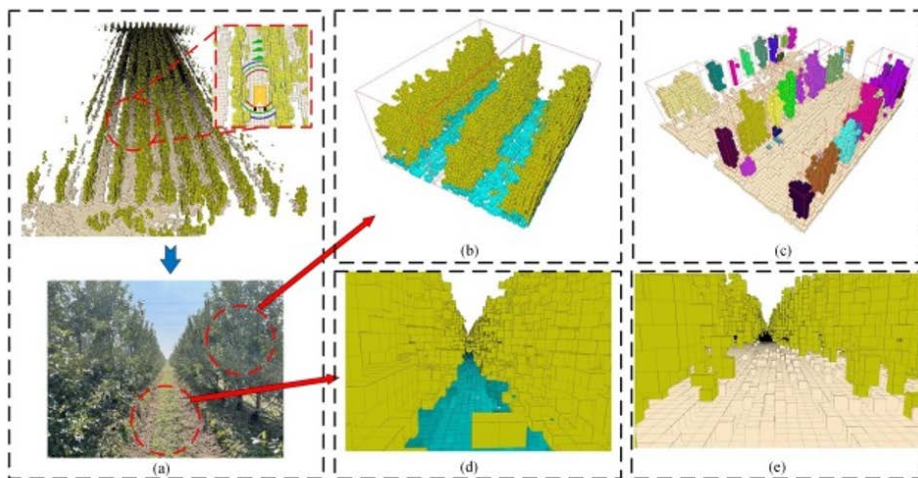


Figure 29. Sliding Window-Based Data Fusion (Wang et.al., 2024).

They aimed to determine the position of the robot accurately by combining laser matching and GNSS data in cases where the GNSS signal is weak. When the GNSS signal is available, they optimized the laser matching results. When GNSS is missing, they tried to provide seamless positioning by processing the laser data with the sliding window mechanism. The algorithm is planned to use the complementary features of GNSS and laser sensors together. The RANSAC algorithm is planned to segment the ground and obstacles in the dense point cloud. They defined the points under a certain error threshold as "compatible points" and provided more accurate segmentation using these points. They used Octree Based Rasterization to visualize the environmental obstacles more clearly in complex garden environments. They distinguished different elements in the garden environment such as tree trunks and ground with the Semantic Point Cloud Segmentation Algorithm. The algorithm effectively classified tree trunks, branches and leaves and provided segmentation (Figure 30). They achieved more stable mapping by combining GNSS and LiDAR data with Multi-Frame Laser-Mapping Optimization.



(a) Selected Local Maps and Orchard Row-Level Scenes
 (b) The Local Map with DBSCAN General Segmentation
 (c) The Local Map Generated by the Proposed Algorithm with DBSCAN Segmentation
 (d) In-Row Views without Sparse Segmentation
 (e) In-Row Views of the Proposed Algorithm

Figure 30. Semantic Comparison of Orchard Maps (Wang et.al., 2024)

Result

Apple fruit is the most well-known and widely produced fruit in the world. The effects of technological development and its applicability in every field are also seen in apple farming. Image processing algorithms, deep learning techniques, and the combined use of these techniques are seen in many areas from apple production to harvest and sale. With image processing techniques, critical information such as the health status of apple trees, and leaf and fruit characteristics can be analyzed quickly and accurately. Deep learning algorithms in particular reach high accuracy rates in disease detection and classification. It also enables earlier and more effective interventions for disease management. This also contributes to the reduction of environmental impacts by optimizing the use of chemical pesticides.

Deep learning algorithms provide high accuracy rates in classifying apple diseases and detecting infection sites. Model performance is improved, especially using data augmentation techniques and large-volume labeled datasets. Spectral imaging and hyperspectral analyses also go beyond traditional RGB imaging, allowing early detection of changes in chlorophyll levels and plant metabolism.

The use of UAVs equipped with camera systems allows the scanning of large agricultural areas quickly and enables detailed analyses to be carried out at the garden level. These systems accelerate data collection processes such as the location of apples in apple orchards, counting their numbers, and monitoring their development stages. In this way, high-resolution data collection is provided in large areas in apple orchards. Drone systems equipped with multispectral and thermal cameras are used to detect both plant health and water stress and nutrient deficiencies. Integration with geographic information systems (GIS) increases the accuracy of topography and location-based analyses, facilitating the creation of customized management plans at the field level. The data obtained with these technologies allows for water, fertilizer, drug use, disease, and record-breaking estimations. In line with the data, production and process planning has become possible for use in disease, record-breaking estimations, and yield analyses.

Machine learning algorithms provide powerful tools for yield prediction in apple production. Algorithms such as SVM, Naive Bayes, and RF develop predictive models based on various parameters such as fruit size, flowering density, and meteorological data. Data collected during the flowering and fruiting processes of apple trees supports forecasting models and enables producers to make more accurate planning.

Robotic technologies have provided automation in labor-intensive processes such as apple harvesting and increased both the speed and efficiency of these processes. The precision of robotic systems has revealed the potential to reduce labor costs while minimizing product losses. The integration of these technologies into apple cultivation has the potential to transform not only the production process but also the supply chain and market analysis. Supported by big data analytics, IoT devices and cloud computing systems, these technologies will strengthen the decision support systems of apple producers and create a more sustainable agricultural ecosystem. In addition, the development of affordable versions of the technologies for small-scale producers is important in terms of increasing inclusiveness in the sector.

As a result, agricultural applications supported by artificial intelligence technology offer revolutionary opportunities in terms of quality, efficiency and sustainability in apple production. It is seen that technological studies on apples and apple trees will increase rapidly, and the success of DL and ML

algorithms will increase. It is thought that autonomous vehicles will enter many areas from spraying to harvesting and will be widely used in gardens. However, the adoption and effective implementation of these technologies requires not only technical but also educational, policy and infrastructure investments. In the future, thanks to cooperation and innovative approaches in these areas, the digital transformation of the agricultural sector will accelerate even more and significant gains will be achieved in every area from planting to reaching the consumer.

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Maturity Classification of Dragon Fruits Using Deep Learning Methods

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Introduction

One of the most promising approaches for detecting fruit maturity is achieved via the use of deep learning models. These models have demonstrated outstanding effectiveness in image classification problems (Gencturk et al., 2023; Tutuncu et al., 2022), making them a suitable choice for analyzing the maturity of dragon fruit based on its appearance. Pitaya, or dragon fruit, is a widely consumed fruit that comes in different varieties and colors (Khatun et al., 2024). The tropical fruit, with its stunning appearance and delicious flavor, has gained popularity among consumers due to its unique appearance and nutritional benefits. To meet the increasing demand for dragon fruit, it is essential to develop efficient methods for detecting the maturity of the fruit (Kamilaris & Prenafeta-Boldú, 2018).

By obtaining a dragon fruit image dataset and training deep learning models on this data, we can develop a reliable system for automatically assessing the maturity of dragon fruit. This could have significant implications for the agricultural industry, enabling farmers and distributors to better manage their inventory and ensure quality control (Kamilaris & Prenafeta-Boldú, 2018; Khatun et al., 2024).

The intention of this research is to figure out how to obtain a dragon fruit image dataset from the Mendeley Data website and demonstrate deep learning models' efficiency in categorizing the fruit's maturity. Our objective is to encourage the growth of automated systems by revolutionizing how we assess and manage fruit maturity in agriculture. Pre-trained deep learning models provide a practical and efficient solution for real-time maturity

detection, empowering agricultural professionals to make informed decisions about optimal harvesting and post-harvest handling (Ayuçlu et al., 2023; Kursun, Bastas, et al., 2023; Sabanci et al., 2015). This approach not only provides a practical and efficient solution for farmers but also minimizes crop losses and enhances productivity. Accurate classification enables informed decisions regarding harvesting and post-harvest treatments (Kursun, Yasin, et al., 2023), ensuring consumers receive high-quality dragon fruits with optimal taste and nutritional value (Kamilaris & Prenafeta-Boldú, 2018; Yu et al., 2019; Zhang et al., 2019).

The effectiveness of deep learning in fruit classification demonstrated by Gill and Khehra, they proposed a novel approach using CNN, RNN, and LSTM, achieving superior accuracy compared to existing techniques (Gill & Khehra, 2022). Similarly, Fahad et al., created an arrangement for categorizing fruits and vegetables as per freshness, using VGG-16 and YOLO models. The dataset used in the study is a collection of 11 distinct fruits and vegetables represented by 60,000 images, each categorized into three freshness levels. The average test accuracy for VGG-16 is 82.2% (Fahad et al., 2022). Mimma et al., focused on fruit detection and classification, achieving high accuracy with YOLOv7, ResNet50, and VGG16 models. The "Dataset" used in the study includes the FIDS-30 dataset, this consists of 30 fruit classifications in the public field and 8 fruit categories that are mostly found in Bangladesh in a special private dataset. 761 images including apples, bananas, guavas, limes, oranges, grapes, coconuts, and tomatoes could be found in the customized dataset. Using the ResNet50 approach, they attained 99% accuracy, and using the VGG16 model, 98% accuracy (Mimma et al., 2022). Kathepuri also used CNN, VGG16, and ResNet50 for fruit recognition and classification, with CNN performing well on pre-processed data and ResNet50 on augmented data. ResNet50 obtained test accuracy of 0.9522, CNN with 0.9256, and VGG16 with lowest accuracy of 0.8602 (Kathepuri, 2020).

A series of studies have explored through deep learning techniques for the classification of dragon fruit. Patil et al., designed methods for sorting and grading making use of CNN, ANN, and SVM algorithms, focusing on shape, size, weight, color, and diseases (Patil et al., 2021). Minh Trieu and Thinh both used machine learning and image processing combined, with the latter achieving a high accuracy of 98.5% and a six-fold increase in sorting capacity

compared to manual methods (Minh Trieu & Thinh, 2021; Trieu & Thinh, 2022).

Patil et al., focused on developing grading and sorting techniques for dragon fruits using machine learning algorithms such as Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Support Vector Machine (SVM). The goal is to classify dragon fruits according to criteria such as size, weight, color, form, and diseases to maintain ideal for manufacturing and promoting purposes (Patil et al., 2021). A study was conducted by Minh Trieu and Thinh, to classify the quality of dragon fruits using a Convolutional Neural Network (CNN) to support export efforts in Vietnam. The dataset consisted of images of dragon fruits with diverse external characteristics. The study obtained high accuracy in categorizing fruits, with a Support Vector Machine (SVM) model reaching 96.38% accuracy across three dragon fruit groups. Furthermore, a self-training approach boosted the SVM model's accuracy from 85.9% to 92.9%. The proposed CNN model achieved 97.38% accuracy, surpassing other leading techniques (Minh Trieu & Thinh, 2021).

The determination of maturity in pulp dragon fruit, red and white was explored by Lata et al., which found harvesting comes around 31 and 36 days following blooming (DAF) resulted in optimal maturity and quality (Lata et al., 2022). Lata et al., investigated the expansion and improvement patterns of red and white pulp dragon fruit to determine the optimal harvest time for quality fruit production. The research collected data at seven intervals (7, 14, 21, 26, 31, 36, and 41 days after flowering) to assess maturity using both destructive (total soluble solids, titratable acidity) and techniques that aren't destructive (specific gravity, fruit weight, heat units, peel color). The dataset included measurements of physico-chemical and sensory attributes at each interval. The study concluded that harvesting dragon fruits between 31-36 days after flowering resulted in ideal maturity and quality (Lata et al., 2022). Junior et al., identified peel and scale colors as reliable indicators of fruit quality, recommending harvesting at stages S2 or S3 (Junior et al., 2021). Jamaludin et al., observed significant changes in color, soluble solids concentration, and betacyanin content during fruit development (Jamaludin et al., 2011). Wanitchang et al., developed a non-destructive maturity prediction model based on specific weight, sphericity, color value, and light reflectance spectrum (Wanitchang et al., 2010). These studies collectively

provide valuable insights into the determination of maturity in red and white pulp dragon fruit.

These studies collectively showcase the potential of deep learning in automating fruit classification (Koklu et al., 2023; Yasin et al.), with a focus on dragon fruit and various external features. Through diverse models and techniques, they underscore the efficacy of deep learning in accurately categorizing fruits, offering promising outcomes (Isik et al., 2023; Koklu et al., 2021). A summary of chosen studies is shown in Table 1.

Table 1. Summary information about the studies found in the literature.

Ranking	Number Of Data	Method	Accuracy	References
1	Not explicitly mentioned	SVM	0.963	(Gill & Khehra, 2022)
		FFNN	0.965	
		ANFIS	0.973	
		RNN-CNN	0.975	
2	60,059 images 11 different fruits and vegetables	VGG-16	82%	(Fahad et al., 2022)
		YOLO-v5	84%	
		YOLOv7	96.1%	
3	761 images	ResNet50	98%	(Mimma et al., 2022)
		VGG16	99%	
4	90,483 images 131 different types of fruits	Base CNN	0.9691	(Kathepuri, 2020)
		VGG16	0.9639	
		ResNet50	0.9692	
5	Not explicitly mentioned	CNN ANN SVM	Not mentioned	(Patil et al., 2021)
6	Dragon dataset 3000	SVM	96.38	(Minh Trieu & Thinh, 2021)

In addition to the aforementioned studies, several others have contributed to the classification of fruits and vegetables (Kursun & Koklu, 2023), with a particular focus on dragon fruit (Saranya et al., 2020; Vijayakumar & Vinothkanna, 2020). Diverse datasets have been employed in these investigations, each offering unique insights. Notably, the dataset utilized in the present study stands apart from those employed in prior research, save for its originators. While the volume of available literature is

extensive, we have provided these examples to elucidate classification studies, aiming to enhance comprehension of the underlying concepts.

Materials and Methods

In this section, the methodological framework of the study is presented in detail. In order to understand the workflow of the study and to express the methodological process with visuals, a flowchart was created for this purpose and illustrated in Figure 1. The first step of the study process is the data collection phase. The selected dragon fruit dataset has been determined through detailed analysis and selection process. Subsequently, image preprocessing steps were applied to optimize the dataset and make it applicable for the study. Then, the data was divided into commonly preferred proportions in the literature, with 80% for training and 20% for testing (Yasin et al., 2023).

Choosing models for deep learning constituted the focus of the study. With the assistance of experts, ShuffleNet, EfficientNet-b0, and Xception models were selected as the most suitable models for dragon fruit ripeness analysis. After the specified procedures were successfully completed, the dataset was transferred to the study environment. The training of the models was conducted on the MATLAB R2022b platform and completed according to the parameters determined in the study process. The best model was identified in the performance evaluation step. Performance evaluations were an important step to test the applicability of the models. All these processes have formed the methodological framework of the study, providing a basis to measure the success of dragon fruit ripeness and quality analysis (Kursun et al.; Özaltın et al., 2022; Yasin & Koklu, 2023).

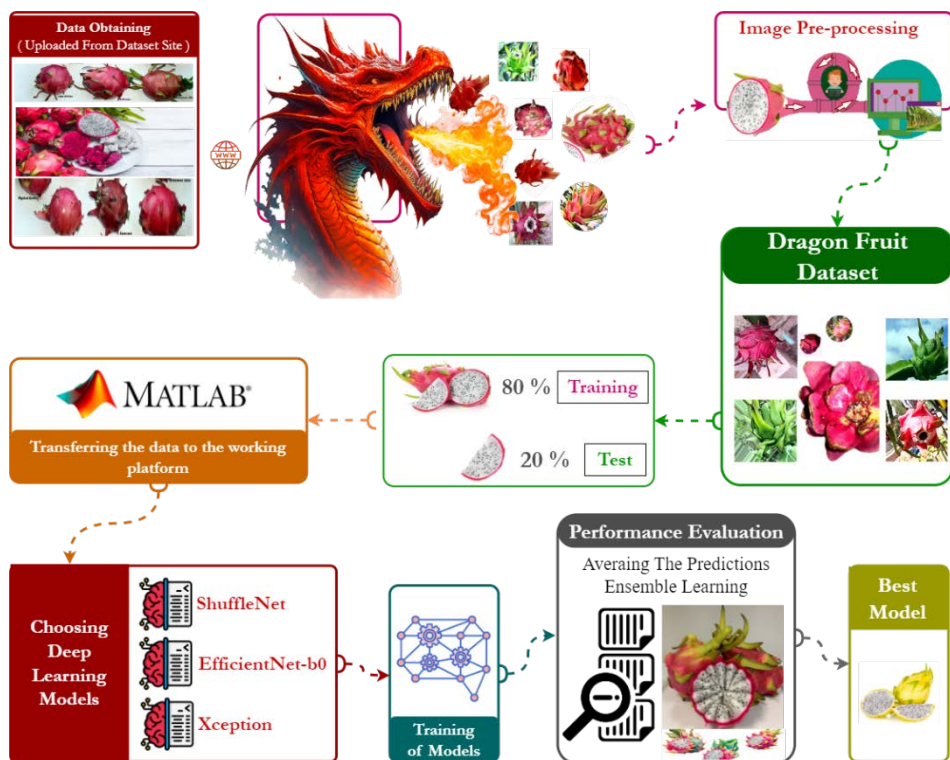


Figure 1. Block diagram illustrating the workflow of the study

Dataset and Image Acquisition

The dataset used in the study consists of a total of 10,000 images of dragon fruit. The images in the dataset were obtained from the Mendeley Data website (Khatun et al., 2024). Upon in-depth review, it was noticed that the same data was repeated, and therefore the dataset was reorganized. With the support of experts, the existing 2-class dataset used in previous studies was revised to include examples of being enrolled in 3 distinct classes for this research. The process was carried out to ensure that the dataset is more representative and diverse. Steps were taken to balance the dataset, and a homogeneous distribution was achieved among the classes. The dataset contains labels for three different classes: Immature Dragon Fruit, Mature Dragon Fruit, and Defective Dragon Fruit (Khatun et al., 2024). For every class, the quantity of images is 3000, 4000, and 3000, respectively. Dragon fruits were photographed in the field and then cropped to create new images for the dataset to be used. Data balance was ensured during the creation process of the dataset, and detailed examination and editing steps were

applied. Image data is in ".jpg" format and resized to 800 x 800 pixels. Various image preprocessing techniques were applied to the data to create a unique structure. Among the preprocessing steps applied to the image data are size standardization, color normalization, and cropping. Details regarding the dataset that were used in the research provided in Figure 2.

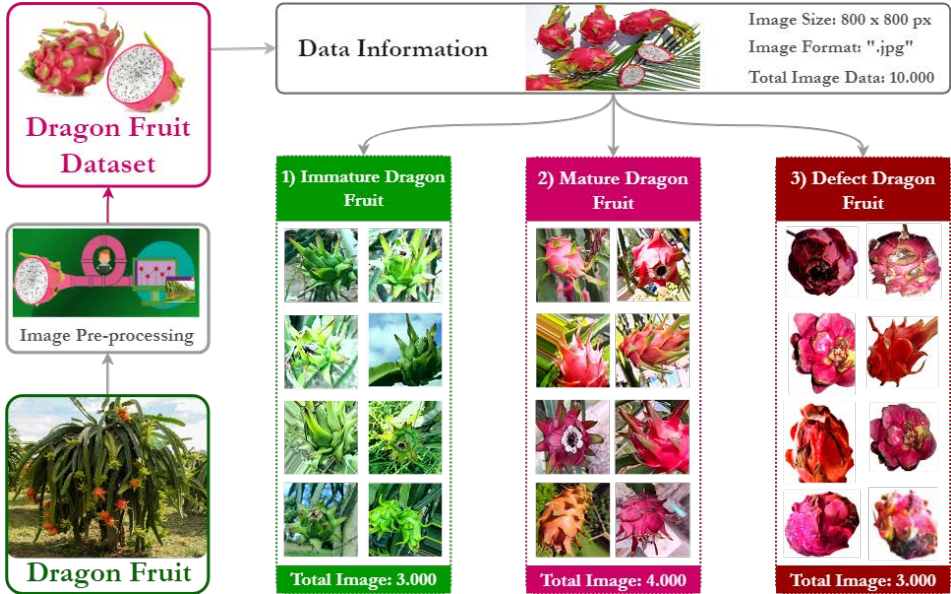


Figure 2. Details regarding the images within the dataset

As shown in Figure 2, the data preprocessing stage is evident in the creation process of the dataset. Data preprocessing steps are crucial for successfully identifying the maturity and quality of dragon fruits to achieve higher model performance. With the increase in the number of classes in the dataset, models can provide a more detailed analysis by discerning subtle differences in maturity levels and quality attributes of dragon fruits. This approach aims to facilitate more effective control and management of the industrial use and commercial value of dragon fruits. As a result of all the processes, the dataset has been automatically partitioned into commonly used 80% training and 20% test data splits.

Deep Learning Models

They are instances of learning models in computer science and artificial intelligence that involve artificial neural networks with the ability to learn

from intricate datasets. These models are known for their capacity to take in knowledge from large amounts of data and perform tasks such as recognizing complex patterns, classification, regression, and other tasks. The models used in the study are ShuffleNet, EfficientNet-b0, and Xception, respectively.

ShuffleNet is a convolutional neural network (CNN) architecture that is particularly effective in applications sensitive to computational resources. EfficientNet-b0 is a CNN model optimized for scalability and performance. On the other hand, Xception is another CNN model that offers high performance and general learning abilities in deep learning applications. These three models have been used for the analysis of maturity of dragon fruits. They were selected to perform tasks such as fruit classification, determining maturity levels, and quality analysis by learning complex patterns in the dataset. Detailed explanations and structures of the relevant models are provided sequentially.

ShuffleNet

The neural network architecture ShuffleNet was developed to efficiently and accurately classify images. This model utilizes a combination of depth-wise separable convolutions and channel shuffling operations (Ma et al., 2018). The primary goal of ShuffleNet is to reduce the computational complexity and memory requirements of traditional CNNs, while still achieving high accuracy. The fundamental concept behind ShuffleNet is to divide the convolutional filters into groups and then shuffle the feature maps across these groups (Zhang et al., 2018). This shuffling operation promotes information exchange between different filter groups and encourages the network to learn more diverse and representative features (Iandola et al., 2016). To achieve this, ShuffleNet employs a combination of pointwise and depth-wise separable convolutions. Point-wise convolutions are used to adjust the number of channels in each group, while depth-wise separable convolutions capture spatial dependencies within each group (Iandola et al., 2016). Lastly, the channel shuffling operation is applied to blend information from different groups. The total layers are 172 layers in ShuffleNet model.

EfficientNet-b0

The convolutional neural network architecture known as EfficientNet-b0, is a cutting-edge model that attains impressive precision with a reduced

number of parameters in contrast to alternative models. The functioning of this model relies on the meticulous adjustment of network dimensions, namely depth, width, and resolution, For the sake of accomplishing a harmonious balance (Tan & Le, 2019). This process of adjusting dimensions, referred to as compound scaling, permits EfficientNet-b0 to exhibit exceptional performance in a multitude of image classification tasks.

EfficientNet-b0, a convolutional neural network architecture, was introduced by Google researchers in 2019. Its purpose is to achieve high accuracy on image classification tasks while using fewer computational resources and model size. The model incorporates various optimizations to enhance its efficiency (Tan & Le, 2021). One of these optimizations is compound scaling, where the network's resolution, depth, and width are uniformly adjusted. This adaptation enables EfficientNet-b0 to accommodate different resource constraints and achieve superior efficiency compared to previous models. The methodology of EfficientNet-b0 involves training the network on a large dataset, such as ImageNet, to learn the recognition of diverse visual patterns. During training, the model fine-tunes its parameters to reduce the difference between the predictions and the actual data labels. It accomplishes this through a combination of convolutional layers, pooling layers, and fully connected layers. These layers take the input images' characteristics and extract them, reduce spatial dimensions through pooling, and make final predictions as per the features that acquired (Tan et al., 2019). Total layers presented are 290. EfficientNet-b0 displayed remarkable efficacy in image categorization tasks, surpassing previous models with fewer parameters and less computation power.

Xception

Xception is an architectural framework for deep learning that is founded on the concept of depth wise separable convolutions with 170 layers. Depth wise separable convolutions are a technique employed in convolutional neural networks with the objective of diminishing the computational complexity of conventional convolutions by dividing them into two distinct operations: depth wise convolutions and pointwise convolutions (Chollet, 2016). The depth wise convolution undertakes a distinct convolution operation on each input channel, while the pointwise convolution combines the output of the depth wise convolution utilizing 1x1 convolutions. This decomposition enables a substantial reduction in the number of parameters and computations required, thus rendering the network more

computationally efficient (Duan et al., 2020). The Xception model capitalizes on this depth wise separable convolution technique to establish a network architecture that is concurrently efficient and proficient in handling visual data.

The Xception model adheres to a *modus operandi* that encompasses several stages (Szegedy et al., 2016). Initially, the input image traverses a sequence of convolutional layers, where each layer employs a collection of filters to extract distinct features from the image. These features are subsequently subjected to the depth wise separable convolutions, which further refine and extract more intricate information from the features (Chollet, 2016). Subsequently, the output of the depth wise separable convolutions is subjected to pooling using techniques such as max pooling or average pooling, which decrease the spatial dimensions of the feature maps while preserving the most crucial information. Finally, the pooled feature maps are flattened and passed through fully connected layers, which act as classifiers to generate predictions founded on the extracted features (Chollet, 2016).

Averaging Predictions

This method involves averaging the probabilities predicted by each model for each class and then choosing the class with the highest average probability. In our study, we have utilized Averaging Predictions as an ensemble learning technique to enhance the robustness and accuracy of our classification models. Averaging Predictions involves combining the outputs of multiple models to produce a final prediction, aiming to reduce variance and improve overall performance. In this approach, each model makes its own predictions, and these predictions are then averaged to obtain a consensus result. By leveraging the strengths of different models, such as ShuffleNet, EfficientNet-b0, and Xception. Averaging Predictions helps to mitigate individual model biases and errors. This method effectively smooths out fluctuations and discrepancies in predictions, leading to a more reliable classification outcome. The aggregated result from Averaging Predictions in our study contributes to achieving high classification accuracy and enhancing the overall effectiveness of the dragon fruit maturity classification system.

Experimental Results

The deep learning models' experimental outcomes that have been used for the level of maturity study of dragon fruits are presented in this section. The results obtained after the successful completion of the training processes of dragon fruit classification models are presented to evaluate the performance of these models in real-world applications. Performance evaluations of each deep learning model have been conducted based on criteria such as Accuracy, Precision, Recall, and F-Score, which are success metrics of the models. Additionally, averaging the probabilities predicted by each model for each class and then choosing the class with the highest average probability mentioned. The results obtained through visual graphics and tables demonstrate how effectively the models can classify dragon fruits and perform quality analysis. Additionally, the computer's technical characteristics as used in model training are also included in this section. The detailed information about the high processing capacity of the computer has accelerated the model training processes and contributed to obtaining more effective results is presented in Table 2.

Table 2. Computer specification details used for training deep learning models

Configuration Item	Value
Display Card (GPU)	NVIDIA GeForce RTX 3080 Ti
Processor (CPU)	12th Gen Intel(R) Core (TM) i7-12700K 3.61 GHz
RAM	64 GB
Hard Disk	1 TB SSD + 8 TB HDD
Operating System	Windows 11 Pro Education

The 12th Generation Intel(R) Core (TM) i7-12700K processor, NVIDIA GeForce RTX 3080 Ti graphics card, 64 GB RAM, and a combination of 1 TB SSD and 8 TB HDD with ample storage capacity have enabled deep learning models to quickly learn their complex structures. Additionally, the NVIDIA GeForce RTX 3080 Ti graphics card has facilitated the rapid implementation of deep learning algorithms through its parallel processing capabilities and accelerated GPU computations.

Three different deep learning models used in the study were trained with the training settings provided in Table 3. These common training settings

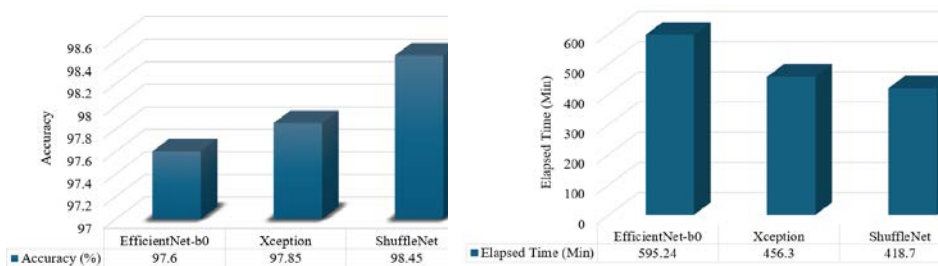
were carefully selected to optimize the models and enhance their generalization abilities.

Table 3. Required parameters used in the training models

Parameters	Values
Output Class:	3
Initial Learn Rate:	0.0001
Solver:	sgdm
Max Epochs:	3
Validation Frequency:	5
Mini Batch Size	11

The stochastic gradient descent with momentum (SGDM) optimization algorithm, widely used in literature, has been preferred to optimize the weights of the models. The Initial-Learn-Rate value is set to 0.0001 for all models. This value determines the initial learning rate of the models during the training process. The Validation-Frequency parameter ensures that the validation dataset used to evaluate the model's performance is updated every 5 iterations during training. The Max-Epochs value is set to 3, controlling how many epochs the model's training process will last. The Mini-Batch-Size value is chosen as 11, determining the number of data samples used in each iteration. The use of small mini batches reduces memory usage and accelerates the training process.

These common training settings have enabled comparisons between models and effectively managed the overall training process. The training process has ended for each model by completing a maximum of 3 epochs set. During this period, each epoch contained 727 iterations, totaling 2181 iterations. This total value was the maximum number of iterations set during the training process. In contrast to these common values, the training times of each model vary. Figure 3 presents the total training times and overall classification accuracies chart of the models.



Total Training Time (1764,01 min)

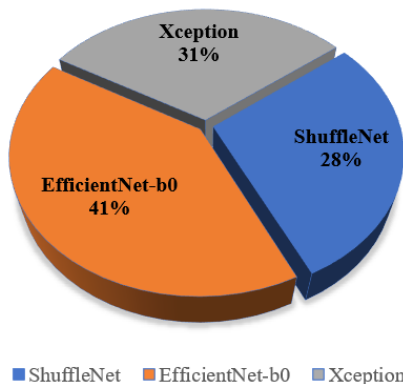


Figure 3. Total training durations and classification accuracy graphs

Models trained with equivalent datasets and on the same computer. The completion times of ShuffleNet measured as (418.7), EfficientNet-b0 was (595.24), and Xception was (456.3) minutes, respectively. Parameters such as model architecture, learning algorithms, and the number of layers directly influence these durations. Despite differences in training periods, the models exhibit very similar training accuracy. Detailed information on each model's training graph, confusion matrix, and performance evaluation metrics are provided.

ShuffleNet Model

According to the confusion matrix, the classification accuracy of the ShuffleNet model was 98.45%. This indicates that the model performs well overall. The visual representation was shown in Figures 4 and 5.

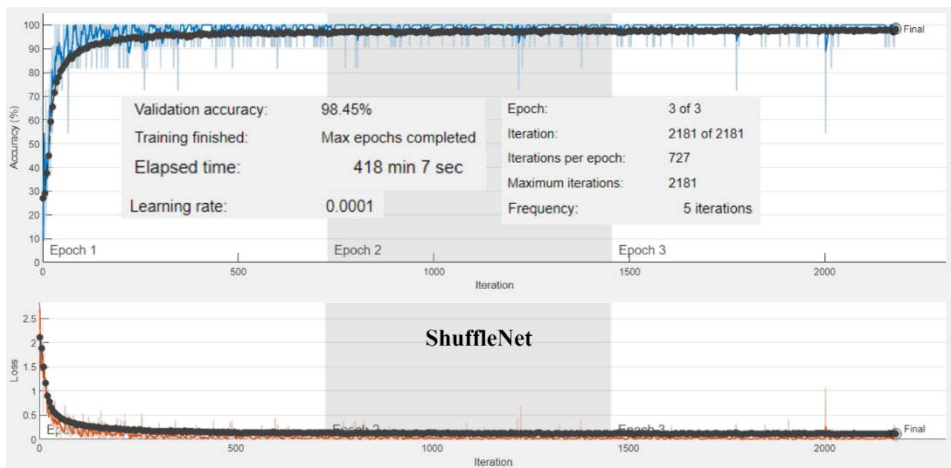


Figure 4. Accuracy and Loss curve illustration for ShuffleNet

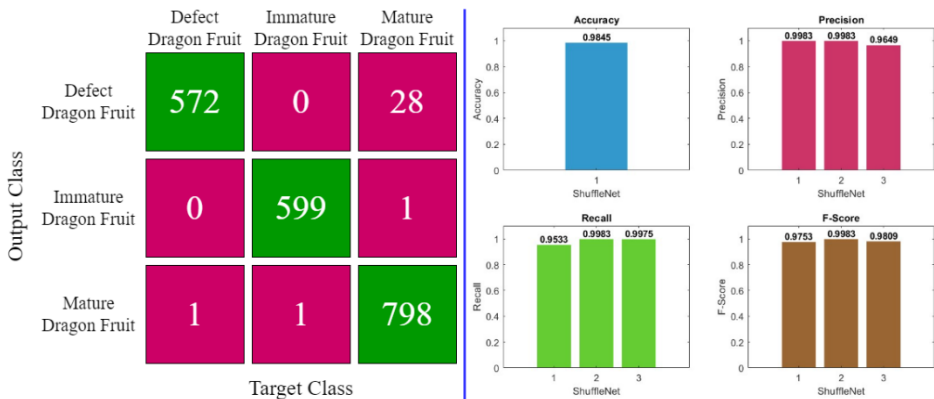


Figure 5. ShuffleNet performance measurement visualization

EfficientNet-b0

Following analysis for the EfficientNet-b0 model, the model trained with epochs of 3, iteration of 2181 and iteration per each epoch of 727, the time for training measured as 595 min and 24 sec. With a learning rate of 0.0001 a Validation-accuracy of 97.60% was obtained and presented in Figure 6.

The confusion matrix for the dragon dataset (Khatun et al., 2024) using EfficientNet-b0 model presented that actually mature dragon class predicted as defected dragon class misclassified the most.

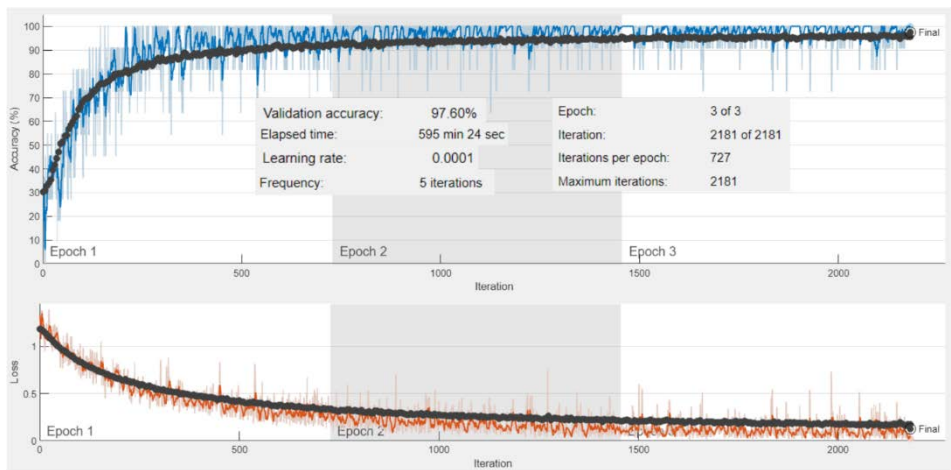


Figure 6. Accuracy and Loss curve illustration for EfficientNet-b0

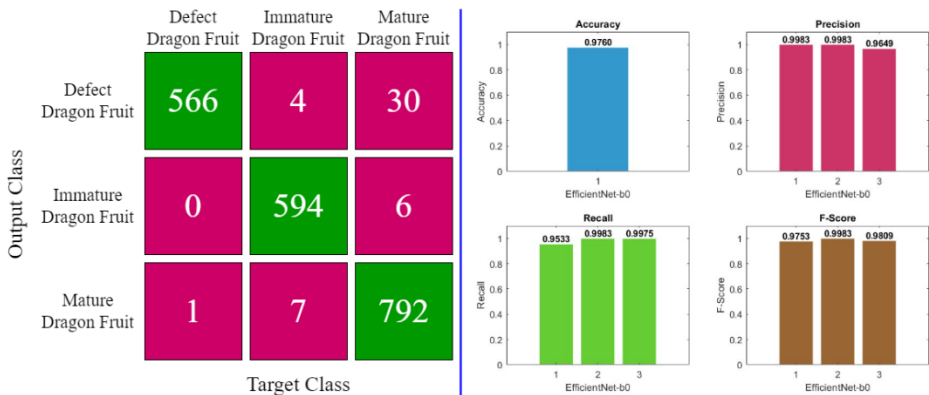


Figure 7. EfficientNet-b0 performance measurement visualization

Xception

Following the analysis conducted on the Xception model, which underwent a training process consisting of 3 epochs and a total of 2181 iterations, with an average of 727 iterations per epoch, the duration of the training was measured to be 456 minutes and 3 seconds. The training period was shorter than EfficientNet-B0. By utilizing a learning rate of 0.0001, the Xception model was able to achieve a validation accuracy of 97.85%, as illustrated in Figure 8. The performance metrics are presented in Figure 9.

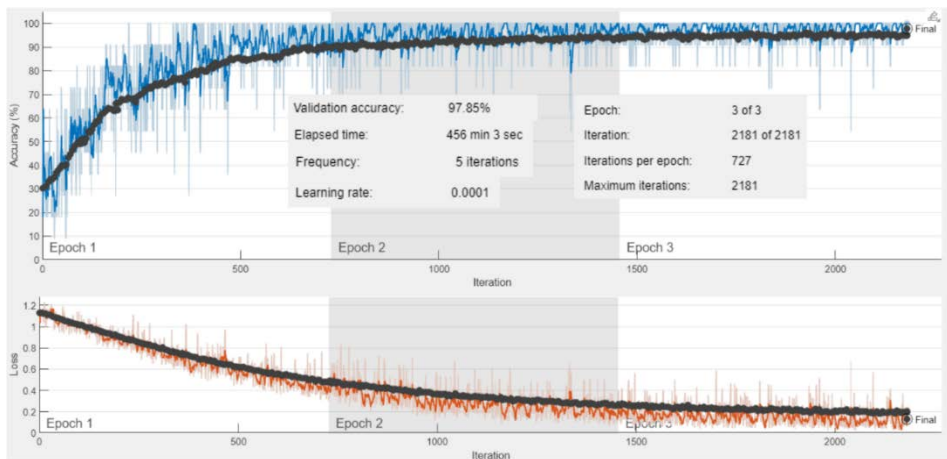


Figure 8. Accuracy and Loss curve illustration for Xception

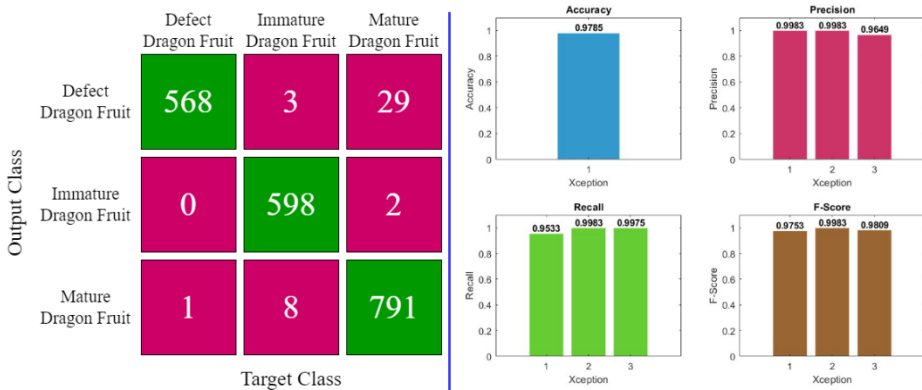


Figure 9. Xception performance measurement visualization

Averaging Predictions and Ensemble Learning

The results of this study indicate that each of the deep learning models (Xception, ShuffleNet, and EfficientNet-b0), demonstrated high accuracy in classifying the maturity of dragon fruits. Specifically, Xception achieved an accuracy of 97.85%, ShuffleNet achieved 98.45%, and EfficientNet-b0 achieved 97.60%. To further improve classification performance, we employed the Averaging Predictions method as an ensemble learning approach. This method involves averaging the predictions of the individual models to produce a more robust and reliable final prediction.

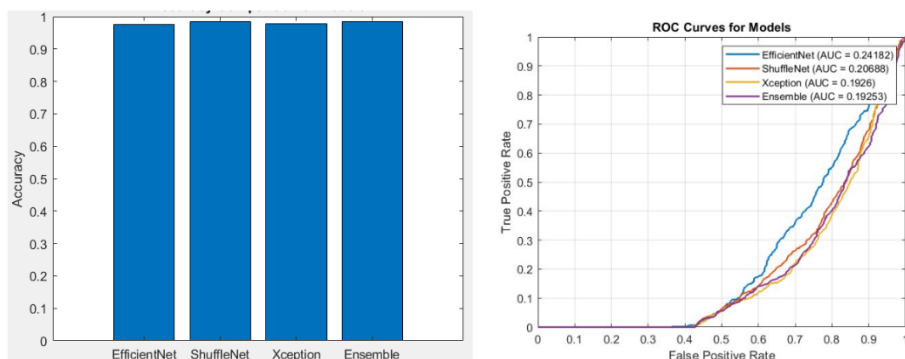


Figure 710. Averaging predictions an ensemble learning ROC Curve



Figure 11. Averaging predictions an ensemble learning confusion matrix

As illustrated in Figure 10 and 11, sample scores from each model illustrate their performance, with EfficientNet-b0 showing consistent but slightly varied scores, ShuffleNet exhibiting near-perfect scores, and Xception maintaining high accuracy with minimal errors. When we averaged these predictions, the resulting scores demonstrated improved stability and

accuracy, with sample averaged scores consistently reflecting high confidence in the correct classifications. The ensemble model, leveraging these average predictions, achieved an overall accuracy of 98.45%. This ensemble approach effectively enhanced the reliability of our dragon fruit maturity classification system, confirming that combining multiple model predictions can lead to superior performance compared to individual models alone.

Conclusion and Discussion

Discussion:

The efficacy of employing deep learning models for the analysis of dragon fruit maturity is demonstrated by the experimental results. The models' capabilities in real-world applications have been thoroughly assessed by evaluating key performance metrics such as Accuracy, Precision, Recall, and F-Score. The utilization of high-performance computing resources, notably the NVIDIA GeForce RTX 3080 Ti graphics card and 12th Generation Intel Core i7-12700K processor, significantly expedited the training processes, resulting in more efficient outcomes. The training settings, standardized across all models, facilitated direct comparisons, and optimized the models for enhanced generalization abilities. Despite variations in training durations, likely influenced by factors such as model architectures and optimization algorithms, the models exhibited comparable training accuracies. The ShuffleNet model demonstrated an accuracy of 98.6% and excelled in identifying Immature and Mature Dragon Fruit classes, although it faced challenges in classifying Defect Dragon Fruit. Similarly, both the EfficientNet-b0 and Xception models achieved high validation accuracies of 98.30%. These models also excelled in identifying Immature Dragon Fruit with perfect accuracy and showcased promising performance in classifying Defected and Mature Dragon Fruit classes. The slight misclassifications observed between Defected and Mature Dragon Fruit classes indicate areas for potential refinement, underscoring the importance of continuous improvement in model training and evaluation.

Conclusion:

In conclusion, the efficacy of deep learning models in the maturity analysis of dragon fruits is emphasized by the experimental results. The

models exhibited commendable performance, with high validation accuracy across all tested architectures, by leveraging advanced computing resources and standardized training settings. Although each model accurately identified certain fruit classes, such as Immature Dragon Fruit, there are still opportunities for improvement, particularly in refining the classification of Defect Dragon Fruit.

Through the successful implementation and evaluation of deep learning models for dragon fruit maturity detection, this study aims to demonstrate the practicality and effectiveness of automated systems in the agricultural industry. By empowering stakeholders with reliable and efficient maturity assessment tools, we aspire to contribute to the optimization of fruit harvesting and post-harvest practices, ultimately enhancing the quality and marketability of dragon fruit products.

Moving forward, further research can be focused on fine-tuning model parameters and expanding the dataset to address these areas of improvement. By iteratively refining model architectures and training methodologies, it is possible to achieve even higher accuracy and robustness in dragon fruit maturity analysis. This achievement paves the way for practical applications in agricultural quality assessment and supply chain management.

Availability of Data and Material

Contacting the corresponding authors Tania Khatun (Khatun et al., 2024), or accessing the study's dataset through the Mendeley Data website here;

<https://data.mendeley.com/datasets/2jpzbx8tm6/1>

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Multiple External Disease Classification in Potato Images

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Introduction

Today, one of the most basic needs of humanity is food. The basis of the food industry is agriculture. If humanity continues to exist, the food industry will always be important. Today, due to reasons such as incorrect planting, incorrect irrigation, and incorrect fertilization, the desired yield cannot be obtained from agricultural products. In addition, global warming has a negative impact on the agricultural sector. Changing climate conditions affect agricultural products and require farmers to take precautions.

Potato is one of the most important agricultural products. In addition, potatoes are one of the most consumed foods in Turkey and the world. Potato was first introduced to Turkey in 1870 and has become the most consumed product today and has begun to be used in many sectors. For example, it has become an indispensable product of the fast-food sector and restaurants. Increasing demand requires automation in potato factory facilities. However, classification and quality control processes are carried out manually in potato factory facilities. In addition, the potato industry struggles with many problems such as inconsistent sorting, grading, human errors, increased labor costs, and production waste. To overcome such problems, factories have begun to show interest in machine learning systems.

According to Omid et al. (2010), the use of image processing and machine learning technology in agriculture and food has recently gained importance. Image analysis and machine learning systems are used to increase the market value of products and to comply with quality control and standards. Image processing technology can be successfully realized thanks to the ability to objectively determine the visual characteristics of food items such as color intensity, color distribution, visual defects, size and shape. Computer vision algorithms are frequently used to detect and classify diseases of vegetables and fruits and to classify them according to their size and weight (Pérez et al., 2017).

Potatoes and potato diseases

Potatoes are the most consumed food product in the world after wheat, rice and corn. Potatoes are important for humans as food thanks to the protein, carbohydrates, minerals and vitamins they contain. Changing needs have accelerated agricultural research. Especially today, changing climate and weather conditions have led people to do more research on agriculture (Çetiner, 2016).

Many products today were brought to Europe by Columbus and his friends after the discovery of the New World in 1492. However, potatoes were not among these products. This is because potatoes grew in the cool temperate climate of the Andes Mountains of South America and were not discovered by the Spanish until 1532. Potatoes did not appear in literature until 1552. It is not known exactly when potatoes came to Europe (Hawkes and Ortega, 1993).

Potatoes are used almost everywhere in the world due to their low price, high nutritional value, high yield per unit area, easy digestibility, wide usage area and ability to grow in all climate conditions. At the same time, potatoes, alcohol and starch are also important raw materials of the industry (Kargı, 2016).

With a history of approximately 150 years in Turkey, potatoes have become one of the most widespread agricultural products of the country. There is no definite information on how and where potatoes were brought to Turkey. According to Russian scientists, potatoes were first planted in the Sakarya River valley, near the Bosphorus and in Akova in the Adapazarı region in the 1850s. According to another source, they came to northern Turkey from Russia and the Caucasus in 1870 and were grown on the high plateaus in Eastern Anatolia and the Black Sea region.

Potato production can fluctuate due to factors like reductions in cultivated land, price volatility, and climate variations. In 2022, Turkey produced 5.2 million tons of potatoes, marking an increase of about 2% compared to the previous year. Niğde leads in production with 679.7 thousand tons (13.1%), followed by Afyonkarahisar with 607.5 thousand tons (11.7%), and Konya in third place with 518.7 thousand tons (10%) (Yegül, 2023).

Types of potato diseases

Potato plants are exposed to many diseases and pests during their growth and development. Tuber yield varies significantly depending on the degree of this effect. When diseases and pests are dealt with in a timely and technically appropriate manner, the possible damage will be significantly reduced, and the yield will not be negatively affected. Otherwise, potato diseases cause great losses. There are various types of diseases in the roots and stems of potatoes. Some of these bacteria originate from the soil structure and are effective in some. Table 1 shows 20 common diseases and their effects on potatoes.

This study describes Black Scurf, Common Scab and Powdery Scab diseases. These three diseases are very dangerous due to their various effects and will provide great benefits if detected. For example, since Common Scab disease is a contagious disease, no crop should be planted within three years and the seeds should not be separated from the collected soil.

Table 1: Summary of important aspects of 20 potato diseases and defects (Miller, 2006)

Disease	Location on Tuber	Spread within storage
CommonScab	External, general	No
PowderyScab	External, general	Yes
Rhizoctonia	External, general, must wash	No
SilverScurf	External, general, must wash	Yes
Bacterial soft rot	External, general; Internal, general	Yes
Blackleg	External, stem end; cut internal, stem end, and longitudinal	No
Early Blight	External, general; Internal, make shallow cuts through lesions	Yes
Freezing and Chilling	External; cut internal, stem end and cross section	No
Fusarium rot	External, general; Internal, cut through lesions	No
Late Blight	External, general; Internal, cut through lesions	Yes
Leak	External, general; Internal, cut around wounds and stem end	No
Mechanical Injury	External, general; Internal, cut through damage area	No
Pink rot	External, stem end eyes,lenticels; cut internal, turns pink	Yes
Ring rot	External, skin cracks; cut internal, near stem end	No
Root knot	External, general; internal, cut tangential	No
Black heart	Cut internal, longitudinal	No
Black spot	Cut internal, stem end half or on shoulder	No
Fusarium wilt	Cut internal, through stem end, only in xylem	No
Leafroll	Cut internal, cross section	No
Verticillium wilt	Cut internal, extends through vascular ring	No

Black Scurf

Rhizoctonia solani (Black Scurf) is a fungal disease that affects potatoes, leading to issues like root cankers, brown spots on tubers, and abnormal tuber growth. The characteristic black or brown patches can come from either the soil or infected seeds (Figure 1). Infected roots, stems, and stolons develop reddish-brown necrotic areas known as cankers, which stunt plant growth. Leaves may also curl at the top, showing symptoms like blacklegs. At the base of the stem and on stolons, brown, slightly depressed lesions with clear borders appear. Over time, a white ring may form around the stems at ground level. This can cause stem pruning, resulting in uneven emergence and crop gaps (AHDB Potatoes, 2024).



Figure 1: BlackScurf diseased potato images (Vinay, 2024)

Common Scab

Common Scab disease in potatoes is caused by three types of viruses: *S. scabies*, *S. acidtaba*, and *S. turgidiscabies*. Although these viruses are only seen in most potato fields and do not affect yield, they cause significant loss of tuber quality. The virus can be found on beets, radishes, rutabagas, turnips, and parsnips, but these plants are rarely of economic importance. Symptoms are limited to tubers with a glaze and dark brown, circular or irregular lesions with a rough texture (Figure 2). The type of lesion depends on the potato variety, tuber maturity at infection, soil organic matter content, type of pathogen, and environment (University of Massachusetts Amherst, 2013).



Figure 2: CommonScab diseased potato images (University of Massachusetts Amherst, 2022).

Powdery Scab

Spongospora subterranea is a soilborne pathogen responsible for Powdery Scab, a major issue for potato production in certain regions. This pathogen is highly resilient to environmental stresses and can infect seed potatoes as well as spread through contaminated soil. In the past ten years, substantial knowledge has been gained about the pathogen's biology and the disease's epidemiology. However, no single control method has proven fully effective. Managing powdery scab can be more successful if the disease risk associated with the pathogen in seeds or soil is accurately assessed (Merz and Falloon, 2009).



Figure 3: Powdery scab diseased potato images (Fera Science Ltd., 2024)

Literature Review

Image-based analysis provides advantages in both reducing human error and performing fast and secure analysis of high numbers of products. Many studies have been conducted on the detection of diseases through images in agriculture. These studies have been divided into 3 categories and examined.

Identification and Classification of Diseases in Fruits

Date	Study	Author(s)	Plant species	Method	Abstract
2009	Image pattern classification for the identification of disease-causing agents in plants	Camargo, A., and Smith, J.S.,	Cotton	Support Vector Machines (SVM)	In the study, digital images showing diseased areas of cotton plants were analyzed. The features of the images were extracted and classified using Support Vector Machines (SVM).
2011	Identification and Classification of Normal and Affected Agriculture/horticulture Produce Based on Combined Color and Texture Feature Extraction	Anami, B.S., Pujari, J.D., and Yakkundimath, R.,	Fruits (apple, pomegranate, banana, grape), Vegetables (tomato, potato), Cereals (wheat, rice) and commercial crops (sugar cane, hot pepper, soybean, bean)	Artificial Neural Networks (ANN)	In this study, the method of recognizing and classifying normal and diseased agricultural and horticultural products by combining color and texture features was discussed.
2014	Adapted Approach for Fruit Disease Identification using Images	Dubey and Jalal	Apple	SVM	The K-Means clustering algorithm was employed to identify infected regions on the fruit. Key features like texture and color were then extracted from these segmented areas. Feature extraction was carried out using the Local Binary Pattern (LBP) algorithm. The proposed approach achieved a classification accuracy of up to 93%.

2016	Identification and Classification of Fruit Diseases	Ranjit, K.N., Chethan, H.K., and Naveena, C.,	Apples, bananas, citrus fruits, grapes	k-Nearest Neighbor Algorithm	To validate the proposed approach, 243 images were collected for 34 disease classes from 10 different fruits such as apple, banana, citrus, grape. Each fruit type consists of different fruit diseases. Segmentation process was applied using K-Means and C-Means algorithms to detect spots and textures caused by fruit diseases.
2017	Fruit Disease Detection and Classification	Sulakshana, A.G., Kalyani, S.D., Monali, K.W., and Priyanka, R.D.,	Apple	SVM	In this study, the K-Means clustering technique was applied to detect and classify apple diseases, while SVM was utilized for image segmentation and classification.

Identification and Classification of Diseases on Leaves

Date	Study	Author(s)	Plant species	Method	Abstract
2008	Grape leaf disease detection from color imagery using hybrid intelligent system	Meunkaewjinda, A., Kumsawat, P., Attakitmongcol, K., and Srikaew, A.,	Grape	SVM	A backpropagation neural network with a feature map is utilized to identify grape leaf colors. Disease segmentation of grape leaves is carried out using feature maps, and classification is performed with support vector machines and genetic algorithms. Lastly, the segmented image is filtered using a Gabor wavelet to enhance the analysis of color features related to leaf disease.
2011	Fast and Accurate Detection and Classification of Plant Diseases	Al-Hiary, H., Bani-Ahmad, S., Reyat, M., Braik. M., and ALRahamneh, Z.,	Tomato	SVM	In this study, Gabor wavelet transform was used for feature extraction to detect diseases on tomato leaves, and classification was conducted using SVM with various kernel functions.
2013	Detection of unhealthy region of plant leaves and	Arivazhagan, S., Shebiah, R.N., Ananthi, S., and Varthini, S.V.,	Banana, Bean, Guava, Jackfruit, Lemon,	SVM	In this study, leaf images were processed to identify diseased areas and then these areas were classified. In the study, plant leaf diseases were classified with 94% accuracy based on texture analysis.

	classification of plant leaf diseases using texture features		Mango, Potato, Tomato, Sapota		
2013	Diagnosis and Classification of Grape Leaf Diseases using Neural Networks	Sannakki, S.S., Rajpurohit, V.S., Nargund, V.B., and Kulkarni, P.,	Grape	ANN	In this study, image processing and artificial intelligence techniques were applied to diagnose diseases in grape plant leaf images. Disease segmentation on grape leaves was achieved using the K-means clustering method. For classification, the Feedforward Backpropagation Neural Network produced the best results.
2015	Tomato leaves diseases detection approach based on support vector machines	Mokhtar, U., Ali, M.A.S., Hassenian, A.E., and Hefny, H.,	Tomato	SVM	The features of diseased areas on the leaf were extracted using Gabor wavelet transform. SVM was used for classification. Since the diseased spots and tissues are similar, SVM kernel model was adopted to distinguish them. Cauchy, Invmult and Laplacian Kernel were used, and the performances were compared.
2015	In Situ Leaf Classification Using Histograms of Oriented Gradients	Olsen,A., Han, S., Calvert, B., Ridd,P., and Kenny, O.,	Situ Leaf	SVM	The HOG algorithm was utilized to extract texture features, and leaf images were classified using logistic regression (LR), linear support vector machines (LSVM), Gaussian support vector machines (GSVM), and artificial neural networks (ANN). The highest accuracy, 94.72%, was achieved with Gaussian support vector machines.
2016	SVM and ANN Based Classification of Plant Diseases Using Feature Reduction Technique	Pujari, J.D., Yakkundimath, R., and Byadgi. A.S.,	Plant leaves	SVM, ANN	In this study, two different classifiers, SVM and ANN, were used to detect plant diseases. It was determined that SVM made better classification compared to ANN.

2020	ToLeD: Tomato leaf disease detection using convolution neural network.	Agarwal, M., Singh,A., Arjaria, S., Sinha, A., & Gupta, S.	Tomato	Convolutional Neural Network (CNN)	A deep learning-based approach is proposed in this study for disease detection. CNN is used for disease detection and classification. The classification accuracy of the proposed model was found to be 91.2% for 9 disease classes and 1 healthy class.
2022	Disease Detection in Tomato Leaf Images by Deep Feature Combination Approach in Classification Problem	Ertem, S., and Özbay, E.,	Tomato	SVM, CNN	In this study, a dataset consisting of 18,160 tomato leaf images, including 9 diseased classes and 1 healthy class, was used. A total of 3,000 features were extracted from the tomato leaf images using CNN-based DenseNet 201, ResNet 101, and ShuffleNet models. Dimensionality reduction was applied using Principal Component Analysis (PCA) to reduce the feature set. The SVM algorithm was employed to classify diseases on tomato leaves. According to the classification analysis performed in this study, a 99.2% accuracy rate was achieved with the best performing Cubic SVM classifier and the One vs All Multi-Class method.

Identification and Classification of Diseases in Potatoes

Date	Study	Author(s)	Plant species	Method	Abstract
2011	Common Scab Detection on Potatoes Using an Infrared Hyperspectral Imaging System	Nieto, A.D., Formella, A., Carrion, P., Fernandez, E.V., and Delgado. M.F.,	Potato	SVM and Random Forest (RF)	In this study, hyperspectral imaging method was used to detect common scab disease, which is commonly seen in potatoes. The system detects diseased areas on the surface of potatoes and measures how much of the surface is affected by the disease. In the experiments conducted using SVM and RF classifiers, the highest success rate of 97.1% was obtained with the SVM model. The system's use of 6 wavelengths selected from hyperspectral images provided accuracy and accelerated the processing time.
2012	Scab Diseases Detection of Potato using Image Processing	Samanta.D., Chaudhury, P.P., and Ghosh.A.,	Potato	K-Means clustering algorithm	In this article, image processing techniques were used to detect common scab disease in potatoes. In the study, images taken under field conditions were analyzed by various processes and diseased areas were separated by segmentation method. The disease stage was determined by using histogram analysis and the disease was graded with the consultations received from agricultural experts.

2012	A real-time mathematical computer method for potato inspection using machine vision	Razmjooy.N, Mousavi, B.S., and Soleymani.F.	Potato	SVM	In this article, a system that detects surface defects of potatoes using image processing has been developed. Images were processed in RGB color space, and defects were separated using the Otsu thresholding method. High accuracy was achieved using classifiers such as SVM, K-nearest neighbor (Knn) and multilayer perceptrons (MLP). As a result of the classification, approximately 95% accuracy was obtained for defect detection and 96.86% accuracy was obtained for size ranking.
2017	Detection of Potato Diseases Using Image Segmentation and Multiclass Support Vector Machine	Islam, M., Dinh, A., Wahid. K., and Bhowmik, P.,	Potato	SVM	In this study, leaf images were processed to identify and classify diseased areas. In the study, plant leaf diseases were classified with 94% accuracy based on texture analysis.
2018	Developing a machine vision system to detect weeds from potato plant	Sabzi S, Abbaspour Gilandeh Y & Javadikia H	Potato	Hybrid artificial neural network-ant colony algorithm (ANN-ACO)	In this study, a machine vision system was developed to detect weeds in potato fields. Three weed species— <i>Chenopodium album</i> , <i>Polygonum aviculare</i> L., and <i>Secale cereale</i> L.—were considered along with potato plants, and a hybrid artificial neural network-ant colony algorithm (ANN-ACO) was used for classification. The hybrid ANN-ACO classifier achieved 99.6% accuracy on the test data, surpassing other methods such as the RBF artificial neural network and Discriminant analysis.
2022	Plant disease detection using GLCM feature extractor and voting classification approach	Mathew A, Antony A, Mahadeshwar Y, Khan T & Kulkarni A	Potato	Combination of SVM, KNN and decision trees	In this study, GLCM (Gray Level Co-occurrence Matrix) feature extraction method and voting classification approach were used for plant disease detection. Classification was done using the classification method (combination of SVM, KNN and decision trees) and showed good performance up to 92%.
2023	Potato Plant Leaf Disease Detection Using Deep Learning Method	Sofuoğlu, C.İ., and Birant, D.,	Potato	CNN	This study proposed a novel deep learning model for accurately classifying plant leaf diseases in the agriculture and food sectors. It identified plant diseases on potato leaves from images by designing a new CNN architecture. Experimental results on a real-world dataset demonstrated that the proposed model (98.28%) achieved a significant improvement in accuracy, with an average increase of 8.6% compared to the state-of-the-art models in the literature (89.67%). 40 mini

Image and Pattern Classification

Digital image processing can be applied across various industrial sectors. Through image processing techniques, digital image data can be enhanced, enabling object recognition. Image processing involves a series of operations that begin with capturing the image and continue through the application of various techniques. With advancements in technology, the use of high-speed computers in image processing has expanded its application beyond traditional areas (Samtaş and Gülesin, 2011).

Patterns are distinct features within an image. Pattern recognition is essentially the classification of data based on acquired knowledge or statistical information derived from patterns and their representations. In a typical pattern recognition application, raw data is processed and transformed into a format suitable for artificial intelligence systems. The patterns extracted from the image should remain unaffected by transformations such as rotation, shifting, and scaling.

Classification involves creating a model using a training dataset. This model is then tested with other data, and an appropriate class label is assigned. Learning, as part of the classification process, entails training a system with specific examples and adjusting the system to ensure it can correctly classify new, unseen data. The quality of the learning phase is dependent on the performance of the provided data, making this step crucial. The effectiveness of learning depends on the algorithms used during this phase.

Datasets are typically divided into two sets: one for training the system and the other for testing the trained system. The training set consists of a collection of images used to teach the system. The algorithms employed during training define how input images are mapped to output images. Generally, 80% of the dataset is used for training, and 20% is used for testing (Sakil Ansari, 2019).

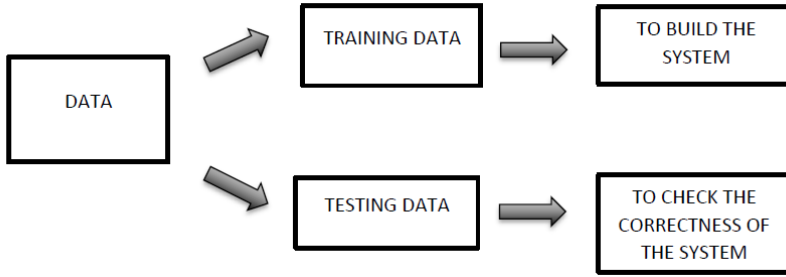


Figure 4: Pattern Recognition steps (sakilAnsari,2024)

$$D(A, B) = \sqrt{\sum_i (A(i) - B(i))^2} \quad (4.1)$$

Feature Extraction

Feature extraction is a low-level image processing technique that involves extracting various characteristics from an image, such as color, shape, size, and texture. Feature extraction algorithms are used to identify these characteristics, which are essential for object recognition and classification. Some of the key feature extraction algorithms include Accelerated Robust Features (SURF), Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP) (Naik and Patel, 2017). The image classification process using feature descriptor algorithms typically involves the following stages: feature detection, feature description, and feature matching.

Feature Detection

The features extracted from the image are distinctive points that can be easily identified, such as edges or spots. Feature detection involves determining whether a point can be selected as a specific feature. This step is crucial for successful image classification, as feature detectors must be repeatable, meaning they should reliably identify the same points of interest under varying viewing conditions.

Feature Description

Once the features are detected, the region surrounding each feature is isolated and defined. The neighboring areas around each feature should be similarly defined. Subsequently, feature descriptors are calculated for each region. A feature vector is an n-dimensional vector that represents a feature based on specific metrics related to the image's attributes.

Feature Matching

Feature vectors, which represent objects, allow for the comparison of two images in terms of their similarities or differences. This comparison is made by comparing the feature vectors of the two images. There are two primary methods for comparing images: by measuring the distance between two feature vectors or by assessing their similarity. For example, two features can be compared by calculating the distance between their descriptors: the shorter the distance, the greater the similarity. A commonly used distance measure is Euclidean distance (Alwanin, 2014).

Speeded Up Robust Features (SURF)

SURF (Speeded-Up Robust Features) algorithm is a feature extraction algorithm used in image processing and computer vision. It was developed by Herbert Bay and his colleagues (Bay et al., 2008) in 2006 as a more efficient alternative to the SIFT (Scale-Invariant Feature Transform) algorithm developed by David Lowe (2004). SURF is used in tasks such as object recognition, image matching and panorama creation by determining key points in images and extracting features around these points.

Key Features:

- **Scale and Rotation Invariance:** SURF can recognize features in images with different scales and rotations, making it scale and rotation invariant.
- **Speed:** It is faster compared to SIFT. This speed increase is achieved by using integral images and simplified filters.
- **Hessian Matrix Based:** Hessian matrix is used to determine key points, which increases the accuracy of the algorithm.

Some of the studies using SURF algorithm in food and agriculture are as follows. Pooja and Madival (2016) used a SURF-based feature bag for the identification of food products. Pyramid compatible kernel approaches were used for classification and 86% classification rate was obtained. In the tissue analysis study conducted by Dailey et al. 2014, SVM was used as the classifier. As a result of the tests, 85% success was achieved for pineapple and 100% success for bitter melon. Another study using the SURF algorithm was done by Yogesh and Dubey in 2016. Defects in the fruit were identified in their proposed study. When the studies in this field are examined, SURF algorithm proved to be successful in disease detection.

Histogram of Oriented Gradients (HOG)

Histogram of Oriented Gradients (HOG) (Dalal et al., 2005) are feature descriptors commonly used in object processing (Zulkifli, 2009). HOG analyzes the occurrence of gradient orientations in local sections of an image, like edge orientation histograms. It also scales variable feature transformation descriptors and shape contexts. However, it is computed on a dense grid of evenly spaced cells and uses overlapping local contrast normalization to enhance accuracy. The HOG algorithm suggests that local object appearance and shape in an image can be described by the distribution of intensity gradients or edge orientations.

To apply these descriptors, the image is divided into small, interconnected regions called cells. For each cell, a histogram of edge orientations is generated based on the pixels within that cell. The combination of these histograms forms the descriptor. To improve accuracy, an intensity measure is calculated for a larger region of the image to normalize the local histograms. This value normalizes all cells in the block, which are referred to as blocks. This normalization process is effective in handling illumination changes or shadows. Since the HOG descriptor works on regional cells, it is not significantly affected by geometric and photometric transformations, except for object orientation.

The HOG concept is particularly useful for leaf classification due to the visibility of veins in certain regions (Fig. 5). These veins provide valuable information about the specific class of the leaf (Tsolakidis et al., 2014).

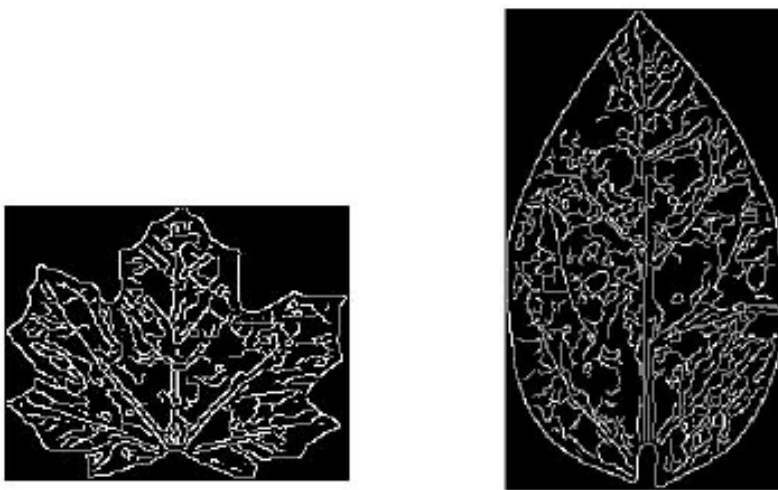


Figure 5: Veins of leaf (Tsolakidis et al., 2014)

In agriculture, HOG algorithm is used in many areas for object preparation and recognition. In 2014, the proposed method (Tsolakidis et al., 2014) classified plant leaves by combining HOG algorithm with Zernike Moments. SVM algorithm was used for classification and Flavia and Sweden leaves were selected as datasets.

In another study (Southgate, 2016), the HOG algorithm was used for food segmentation. Similarly, in a different study (Olsen et al., 2015), HOG was applied to extract features from in situ leaves. HOG features are derived by computing orientation histograms of the local region's edge density. To begin, edge gradients and orientations are calculated for each pixel within the local region, with Sobel filters used to obtain these gradients and orientations.

These local regions are then divided into smaller areas known as "cells," with each cell measuring 4x4 pixels. Histograms of 8 orientation edge gradients are computed for each of these cells. As a result, the total number of HOG features becomes 128, which is calculated as $8 \times (4 \times 4)$, forming a HOG feature vector (Figure 6).

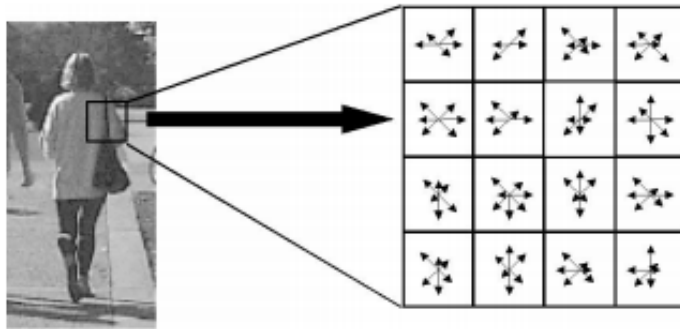


Figure 6: Extraction process of HOG feature (Kobayashi et al., 2007)

To prevent abrupt changes in the descriptor, small adjustments should be made to the position of the windows, and less emphasis should be placed on the distant gradients in the center of the descriptor. A Gaussian weight function, with a value of σ equal to half the width of the descriptor window, is used to weight the size of each pixel. The features extracted using the HOG algorithm are resilient to local geometric and photometric transformations due to their histogram representation. The use of local spatial bins enhances tolerance to rotation and translation (Kobayashi et al., 2007).

Local Binary Pattern (LBP)

The LBP (Local Binary Pattern) approach is a nonparametric method that creates a local structure by comparing neighboring pixels in an image. This method, which produces very strong results in texture analysis, is widely used in areas such as face analysis, image and video recognition, environmental modeling, image tracking, motion analysis, and biomedical and satellite images, as proposed by Ojala et al. The LBP algorithm is highly effective in texture recognition. It works by assigning binary values based on the comparison of pixel values in the center of 3x3 windows with their neighboring pixels, where the central pixel value serves as the threshold. The resulting binary number sequence is called the LBP code, which enables the identification of different types of features in the image, such as edges, corners, light or dark areas, and line regions. However, 3x3 operators may not be sufficient for capturing dominant features, and therefore, the size of the operator should be chosen according to the specific problem or assigned adaptively. Instead of using fixed 3x3 windows, LBP definitions are made in a circular manner. Two parameters must be defined in this process: the number of symmetric circular neighboring sample points (P) and the radius measurement (R).

LBP operator L , is created from the neighboring P pixel set and 2^P different output values are defined. In addition, if the binary LBP code obtained because of LBP has two or less transitions, it is called uniform LBP. For example, 00000000, 00111000, 11100001 are uniform LBP codes. LBP histogram also contains information about the distribution of local micro patterns (edges, bright areas, etc.) in the image. Thus, the characteristic of the image can be defined statistically (Kızrak, 2014).

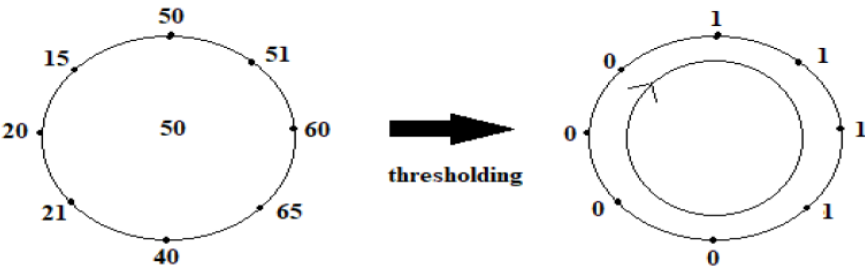


Figure 7: LBP Algorithm (Kızrak, 2014)

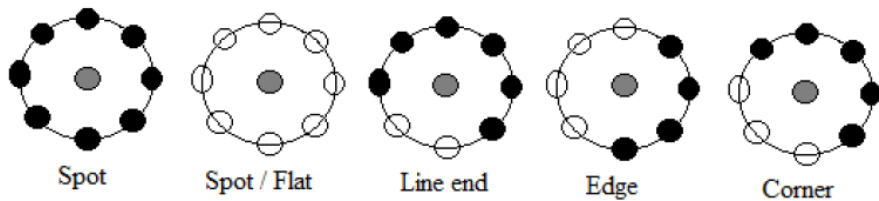


Figure 8: Meaning of LBP patterns in the image (Shan et al., 2009)

LBP histogram calculates micro patterns on the entire image without location information. The image shape information is evenly distributed into small regions such as $R_{0,1}, \dots, R_m$ produced by LBP histogram. The features of the global shape and local texture of the image are extracted from this histogram. There is a good balance between the feature vector length and recognition performance (Kızrak, 2014).

Object Classification: Bag of Visual Words Algorithm

The bag of words model is a widely used method for object classification. The core idea of the algorithm is to match each key point extracted from the image with visual words. Each image is then represented by a histogram of these visual words. To generate visual words, a clustering algorithm (such as k-means) is applied. The concept of a "visual bag of words" is based on the same principle as a "bag of words" in text processing. In the bag of words model, text is represented vectorially for use with machine learning algorithms, without considering the order or position of words. Instead, words are treated as a collection of key points within the text. Similarly, documents that contain many of the same words are considered relevant to each other, regardless of the order in which those words appear. This approach is also applied to object categorization (Zhang et al., 2015).



Figure 9: Local Patches Identified from an image (Shah, 2012)

Keypoints are vectors in a higher dimensional space, usually represented by local patches (Figure 9, Figure 10). To handle these keypoints efficiently, each extracted keypoint is classified into a bag of visual words. Then, each image is represented by a histogram of visual words (Figure 11).

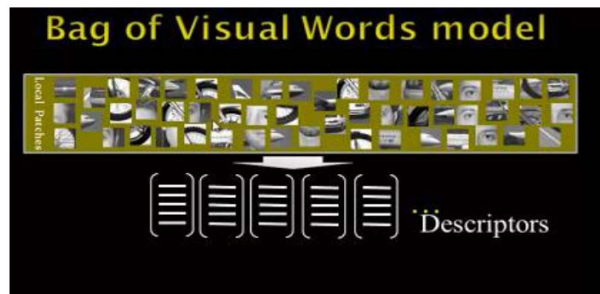


Figure 10: Key points (Shah, 2012)

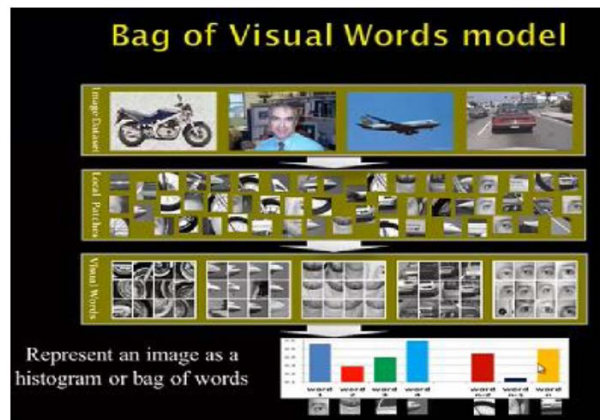


Figure 11: Portray an image as a histogram or bag of words (Shah, 2012)

This is commonly known as a bag-of-words representation, which essentially transforms the object classification problem into a text classification problem. A clustering procedure, such as K-means, is typically used to group keypoints from all the training images into multiple clusters. The center of each cluster represents a distinct visual word (Figure 12).

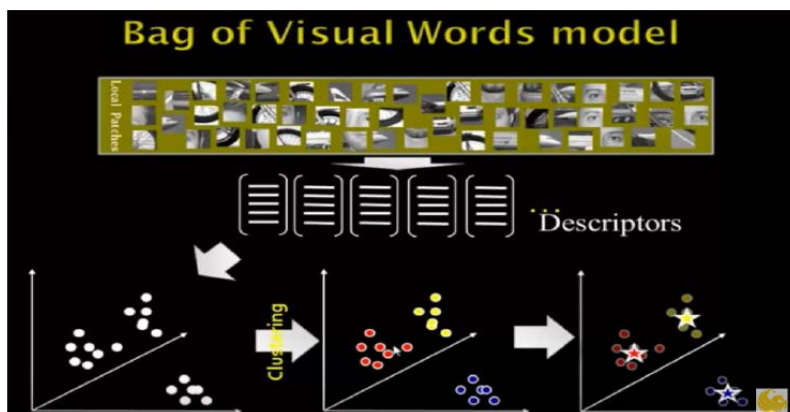


Figure 12: Bag of Words Clustering Procedure (Shah, 2012)

Classification Algorithms

Basic classification algorithms are shown in Figure 13; Random Forest algorithm, ID3 (Decision Tree) Algorithm, K-Nearest Neighbor Algorithm, Naive Bayes Algorithm, SVM, ANN

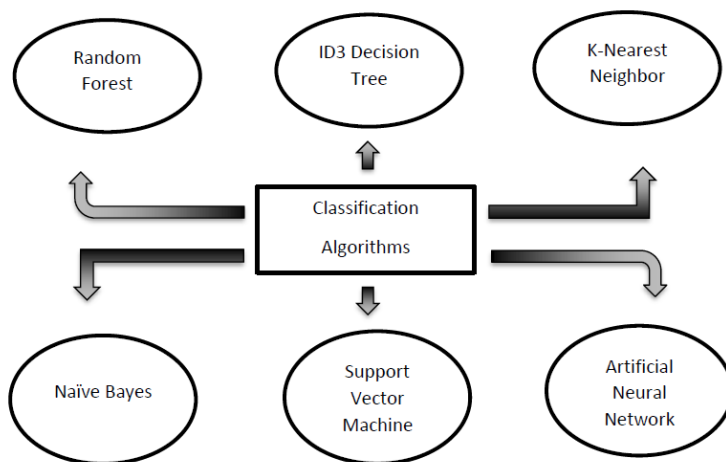


Figure 13: Classification Algorithm

Table 2: Advantages and Disadvantages of Classification Algorithm (Nikam, 2015)

ALGORITHM	FEATURES	LIMITATIONS
C4.5 Algorithm	• Build Models can be easily interpreted. • Easy to implement • Can use both discrete and continuous values • Deals with noise.	• Small variation in data can lead to different decision trees. • Does not work very well on a small training data set. • Overfitting
ID3 Algorithm	• It produces the more accuracy result than the C4.5 algorithm. • Detection rate is increase and space consumption is reduced.	• Requires a lot of searching time. • Sometimes it may generate very long rules which are very hard to prune. • Requires large amount of memory to store tree.
K- Nearest Neighbor Algorithm	• Classes need not be linearly separable. Algorithm • Zero cost of the learning process. • Sometimes it is Robust about noisy training data. • Well suited for multimodal classes.	• Time to find the nearest Neighbors in a large training data set can be excessive. • It is Sensitive to noisy or irrelevant attributes. • Performance of algorithm depends on the number of dimensions used.
Naive Bayes Algorithm	• Simple to implement. Algorithm • Great Computational efficiency and classification rate • It predicts accurate results for most of the classification and prediction problems.	• The precision of algorithm decreases if the amount of data is less. • For obtaining good results it requires a very large number of records.
Support Vector Machine Algorithm	• High accuracy. machine Algorithm • Work well even if data is not linearly separable in the base feature space.	• Speed and size requirements both in training and testing is more. • High complexity and extensive memory requirements for classification in many cases.
Artificial Neural Network Algorithm	• It is easy to use, with few parameters to adjust. • A neural network learns, and reprogramming is not needed. • Easy to implement. • Applicable to a wide range of problems in real life.	• Requires high processing time if neural network is large. • Difficult to know how many neurons and layers are necessary. • Learning can be slow.

Support Vector Machines

Support Vector Machine (SVM) is a nonparametric classification method grounded in statistical learning theory. Originally developed for binary classification (Foody and Mathur, 2004), SVM determines the optimal boundary between classes in the feature space using the most suitable algorithm. Initially designed for the classification of linear, two-class data, it was later extended to handle multi-class and non-linear data. The core principle of SVM is to identify the hyperplane that best separates the two classes (Vapnik, 1995).

Advantages (Ülgen, 2017):

- SVM is effective in high-dimensional spaces.
- It performs well when the number of samples is smaller than the dimension of the feature space.
- The decision function only uses a limited number of training points, which helps reduce memory usage.
- It is versatile, as various kernel functions can be applied for the decision function.

Linear Support Vector Machines

SVM can be used for classification when the samples from two classes are linearly separable. In this case, the goal is to separate the two classes using a decision function derived from the training data. The line that divides the dataset into two is called the decision line. While an infinite number of decision lines can be drawn, it is crucial to identify the optimal decision line (Figure 14) (Ülgen, 2017).

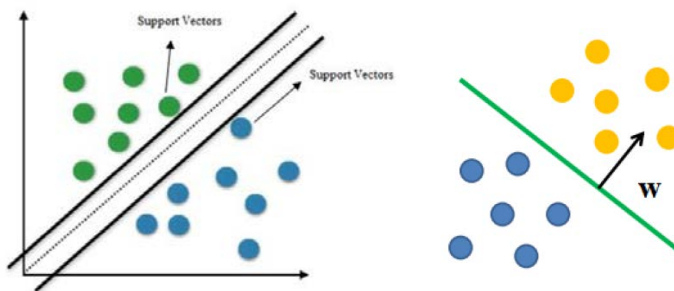


Figure 14: Support Vectors and Linear SVM Two Linear Separable Classes w is weight vector (Ülgen, 2017).

If we denote each feature point in feature space as $X_i, Y_i \in \{1, -1\}$ the output representing the class to which the samples belong, and $p \in P$, high dimensional input vector; (X_i, Y_i) when a set of n volumes of pairs of S is given, it will best distinguish the samples from different classes,

$$w \cdot x + b \quad (4.2)$$

It is the machine learning algorithm belonging to the class of supervised learning algorithms which helps to find linear hyperplane (Soman et al., 2011). Here, w , the normal of the hyperplane is also defined as the weight vector and b is constant.

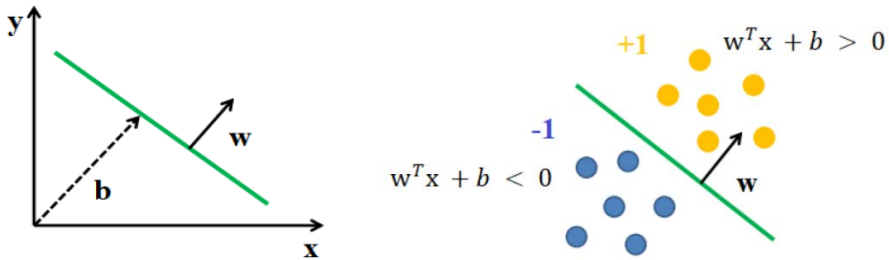


Figure 15: b constant value and w weight vector and Class Labels (Ülgen, 2017)

The plane passing through the middle of the boundary planes and equidistant from both planes is defined as hyper plane. In Figure 15, $(-1, +1)$ shows the class labels, w is the weight vector (normal of the hyperplane) and b is the constant value (Osuna et al., 1997).

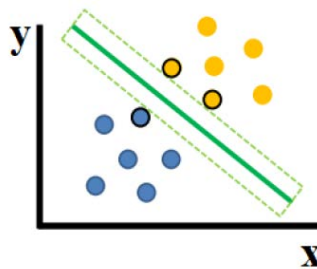


Figure 15: Boundary Planes (Ülgen, 2017)

The planes on which the support vectors (Figure 16) are located and indicated by dashed lines are called boundary planes. If the training data set

can be separated linearly, the DVM tries to find the separation hyperplane with the largest boundary. To find this separation hyperplane, all the samples in the data set must provide the following inequalities (Soman et al., 2011).

$$f(x_i) = (w, x_i) + b \geq +1, y_i = +1 \quad (4.3)$$

$$f(x_i) = (w, x_i) + b \leq -1, y_i = -1 \quad (4.4)$$

Inequalities in (4.3) and (4.4) can be combined into a single inequality, as given in below equation.

$$y_i ((w, x_i) + b) - 1 \geq 0 \quad (4.5)$$

w is the norm of the normal plane w called the weight vector. Therefore, the distance to the hyperplane of the samples closest to the hyperplane must be equal to the norm of the weight vector that it has (Gunn, 1998; Schölkopf and Smola, 2002). Based on this theorem, the hyperplane that best separates the training examples is the plane that minimizes the following equation.

$$A(w) = \frac{1}{2} \|w\|^2 \quad (4.6)$$

Solving the optimization in the equation below gives an optimal separation hyperplane is obtained to maximize the distance between the support vectors of the classes (Gunn, 1998; Cortes and Vapnik, 1995).

$$\min \frac{1}{2} \|w\|^2 \quad \text{and} \quad y_i ((w, x_i) + b) - 1 \geq 0 \quad (4.7)$$

Nonlinear Support Vector Machines

In practical applications, it is often not possible to linearly separate a dataset with a hyperplane. Nonlinear SVMs are used when the dataset cannot be separated by a linear function, either fully or with a specific margin of error. In such cases, class separation is achieved by estimating a separation curve. However, estimating this curve can be challenging in practice. The geometric representation of the nonlinear separation of the dataset is shown in Figure 16 (Ayhan and Erdoğan, 2014). In this scenario, the p -dimensional input vector x must be transformed into the P -dimensional feature vector Φ (Cortes and Vapnik, 1995).

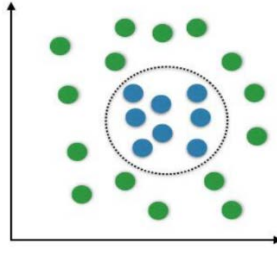


Figure 16: Two Class Problem of Linear Separation Case (Ülgen, 2017)

For this conversion, the optimal separation plane must be defined in the property space. To achieve this, a nonlinear mapping approach is used. Nonlinear mapping is an approach used to realize the linear separation of the original input space x into a higher dimensional F property space, a Hilbert space. Hilbert space is expressed as full inner product spaces with positive scalar products and elements of functions. The geometric explanation of the nonlinear mapping approach for a two-dimensional non-linearly separated data set is given in Figure 17. With the nonlinear mapping approach, the two-dimensional data set was moved to the three-dimensional property space to provide linear separation of the data set (Ayhan and Erdoğan, 2014).

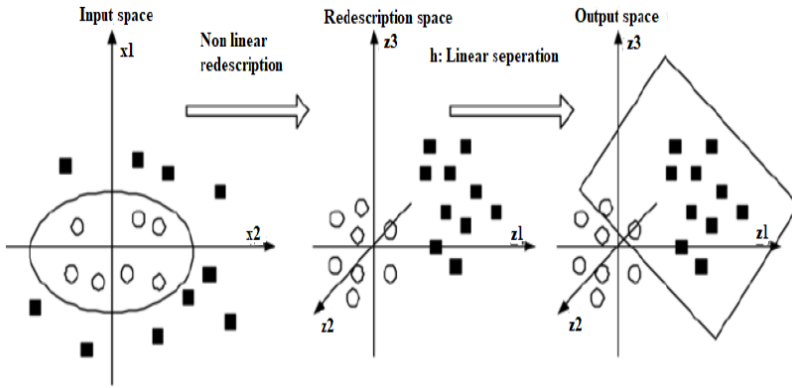


Figure 17: Example of Nonlinear Mapping Approach (Ayhan and Erdoğan, 2014)

In Figure 17, the property space of the functions, the two-dimensional input vector (X_1, X_2) and the three-dimensional property space (Z_1, Z_2, Z_3) , is shown by the following equation.

$$A: R^2 \rightarrow R^3 \quad (x_1, x_2) \rightarrow (z_1, z_2, z_3) = (x_1^2, \sqrt{2} x_1 x_2, x_2^2) \quad (4.8)$$

Inner products of input vectors mapped in property space are obtained as in below equation (Soman et al., 2011).

$$= (x_2^2 x_2'^2 + 2 x_1 x_1' x_2 x_2' + x_2^2 x_2'^2)^2 \quad (4.9)$$

Thus, the mapping process is carried out by elevating the data set from two-dimensional space to three-dimensional space (Soman et al., 2011). As a result, the classifier decision function for the nonlinear SVM, depending on the separation hyperplane defined in the property space, is expressed by the following equation (Ülgen, 2017).

$$f(x) = \text{sign}((w', x_1) + b') = \text{sign}(\sum_{i=1}^a y_i a_i < Q(x_1), Q(x_1) >) \quad (4.10)$$

This mapping is called kernel. In statistical learning methods such as SVM, which kernel is used for which problem is an important problem. Appropriate kernel functions can lead to a significant increase in the generalization capability of the developed learning system (Barla et al., 2003).

The kernel function is an inner product in feature space, and is usually denoted as:

$$K(x, y) = < Q(x), Q(y) > \quad (4.11)$$

In 4.11, K represents the kernel function, and Q denotes a non-linear mapping function. By using a kernel function, the algorithm can be transformed into a higher-dimensional space without explicitly mapping the input points into that space. The kernel trick can be easily applied due to the original SVM formulation, which relies on dot products. As a result, the classifier's hyperplane in the high-dimensional feature space may appear non-linear in the original input space (Souza, 2014).

$$\sum_{i=1}^n w_i (z_i, x) + b \longrightarrow \sum_{i=1}^n w_i (Q(z_i), Q(x)) + b \longrightarrow \sum_{i=1}^n w_i k(z_i, x) + b \quad (4.12)$$

Inner product

inner product applied to a

Kernel function

(possibly non-linear) mapping Q.

Some of the most used kernel methods: (Ülgen, 2017)

- Polynomial Kernel
- Radial Basis Kernel
- Histogram Intersection Kernel
- Chi-Square Kernel

A Kernel function converts training data. Thus, a nonlinear decision surface is transformed into a higher dimensional linear equation. If property data can be converted to a higher dimension, it is easier to separate classes with a linear function. The way to do this is to use the kernels functions (Crowley, 2016) (Figure 18).

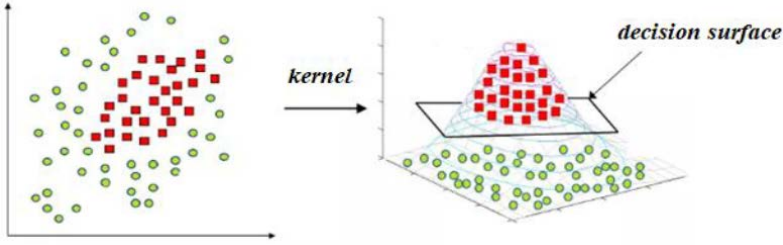


Figure 18: Separating classes using SVM kernel function (Ayan,2019)

Polynomial Kernel

The polynomial kernel is appropriate for problems where all training data is normalized. The corresponding kernel function is expressed by the following formula:

$$K(x, y) = (a x^t y + c)^d \quad (4.13)$$

Among the adjustable parameters, alpha is the slope, c is the term constant, and d is the degree of polynomial (Güldoğan et al., 2017).

Radial Basis Kernel

It is observed that the radial basis kernel function is commonly used in applications in literature because it tends to produce better results. However, it is not certain whether the radial basis kernel function is suitable for solving problems in every field. The performance of kernel functions can vary depending on the dataset and the specific problem. The Gaussian kernel is an example of a radial basis function kernel. The corresponding kernel function is expressed by the following formula:

$$K(x, y) = \exp\left(-\frac{\|x - y\|^2}{2\alpha^2}\right) \quad (4.14)$$

As an alternative,

$$K(x, y) = \exp(-y \|x - y\|^2) \quad (4.15)$$

is expressed by the formula.

In the case of overestimation, the exponential expression becomes approximately linear and high-dimensional projection begins to lose its non-linear structure. However, if the estimate is lower than the actual value, the function will not smooth and the decision limit will be extremely sensitive to noise values in the training data (Ayhan and Erdoğan, 2014).

Histogram Intersection Kernel

The histogram intersection algorithm uses color information to identify objects. This method was proposed by Swain and Ballard in their article "Color Indexing." It is particularly effective when color is a strong indicator of the object's identity.

The histogram intersection does not require precise separation of the object from its background and is robust to occlusions caused by foreground objects. A histogram is a graphical representation of the distribution of values in a digital image. This distribution represents the color appearance, and in the Human Visual System (HVS) model, it reflects the saturation of a color. Histograms are invariant to translation and change gradually under different viewing angles, scales, and in the presence of occlusions. Given the histogram **I** of the input image (camera frame) and the histogram **M** of the model (object frame), each containing **n** bins, the intersection is defined as:

$$\sum_{j=1}^n \min(I_j, M_j) \quad (4.19)$$

The result of the intersection is the number of pixels in the model that have corresponding pixels of the same colors in the input image. To normalize the result between 0 and 1, divide it by the total number of pixels in the model histogram:

$$\frac{\sum_{j=1}^n \min(I_j, M_j)}{\sum_{j=1}^n M_j} \quad (4.20)$$

When an unknown object image is given as input is compute the histogram intersection for all the stored models, the maximum value is the best match (Patacchiola, 2016)

In color images, the Histogram Intersection Kernel measures similarity between two color histograms. It is an algorithm unaffected by scale changes. It can be used successfully in non-segmented images as well (Barla et al., 2003). That intersection is larger when the two distributions are similar (Figure 19).

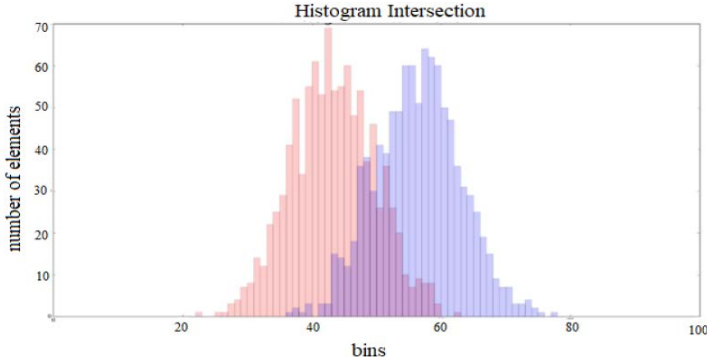


Figure 19: Histogram Intersection Kernel (Barla et al., 2003)

Chi- Square Kernel

It is a kernel model commonly used in computer display applications. The Chi-Square Kernel (Maji et al., 2012) measures the distance between probability distributions. The Chi-Square Kernel is based on a comparison of the obtained values of the frequency of a class because it is divided by the expected frequency of the class. The chi-square Kernel is a commonly used algorithm for histogram-based image comparison, such as the Histogram kernel. Linear SVMs are preferred for efficiency reasons. However, non-linear kernels are used because they produce more accurate results in computer vision. Histogram Intersection Kernel and Chi-Square kernel kernels are commonly used to compare low-level histograms such as color and texture calculated on the image and to train the SVM classifier.

$$K(x_i, x_j) = \exp\left(-\gamma \sum_k \frac{(x_{ik} - x_{jk})^2}{x_{ik} + x_{jk}}\right) \quad (4.21)$$

Multi Class SVM Classification

SVM is mainly used to separate data from two classes. In cases where there is more than one class, Multi class SVM is used. When there are multiple classes, there are two types of approaches to distinguish between classes.

- Reduction of the problem into binary groups (One-to-one approach)

- Modeling the problem from a single group to all groups (One-to-all approach)

One-to-One Approach

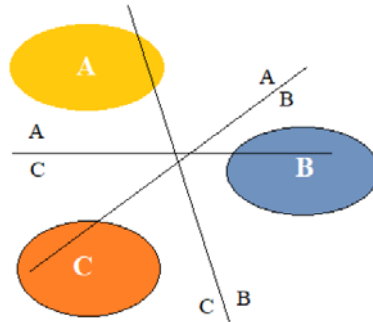


Figure 20: One- to- One Approach (Kizil,2019)

In the above figure, a separate SVM was trained for both classes. During the classification of a new sample, each pair is questioned. That is, the AB, BC and AC pairs are questioned and whichever of these questions gets the most answers is put in this class.

Consider, for example, the results for the following queries:

AB-> A

BC-> B

AC-> A

In two of the above three queries, result A was reached, so the new sample was considered closer to the A class.

One-to-Many Approach

According to the one-to-many approach used in multi-class classification, the problem turns into a “winner takes all”. In this approach, a binary SVM classifier is trained for each class and checks if the sample belongs to that class or not. To classify a test sample, this sample should belong to only one class. Below is the SVM extracted between three classes using this method.

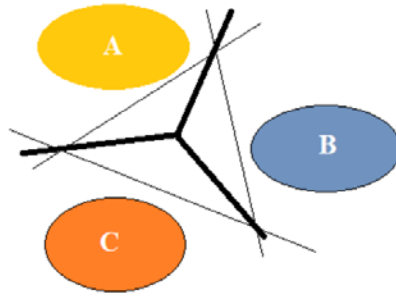


Figure 21: One-to-All Approach (Kızıl,2019)

As can be seen in the figure above, the first three equations were found (fine lines in the figure). Then, by combining these line equations, a general SVM is used to differentiate the three classes (bold lines in the figure). For a sample to be marked as class A, SVM classifier for A vs others should select A, and SVM classifiers for B and C should select others.

Disease Classification Using Support Vector Machines

The steps to be followed for classification of potato diseases using SVM are as follows. (Kızıl,2019)

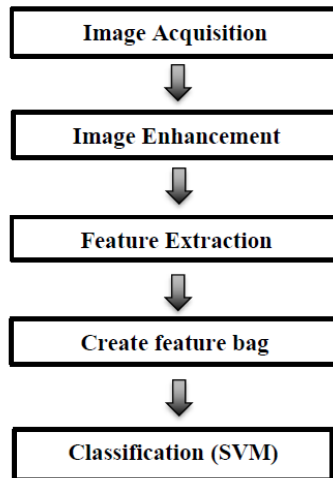


Figure 22: Steps in the classification of potato diseases (Kızıl,2019)

In this study, three diseases which are frequently observed in potatoes namely Common Scab (*Streptomyces scabiei*), Black Scurf (*Rhizoctonia solani*) and Powdery Scab (*Spongospora subterranea*) were examined. The stains and tissues formed in these 3 diseases exhibit differences. To detect

these stains and textures, feature extraction algorithms were applied, and classification was performed by using multiple class SVM. Figure 5.2 shows images of common diseases in potatoes.

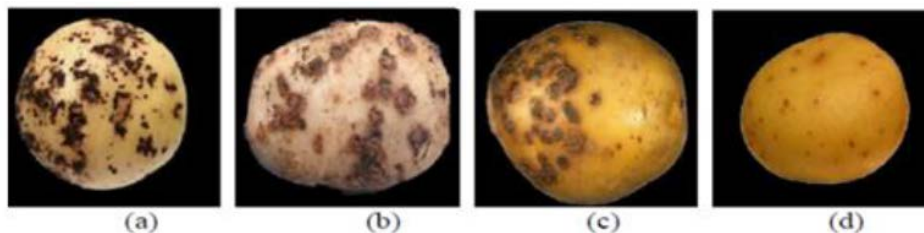


Figure 23: (a) Black scurf (b) Common Scab (c) Powdery Scab (d) Healthy potato (Kızıl,2019)

Image Acquisition

The images to be used in the study were obtained from previous studies that have worked with potatoes, from the website of the Turkish Ministry of Agriculture (Gıda Tarım ve Hayvancılık Bakanlığı, 2016) and the Internet. In this study, there are 4 classes including 3 diseased and 1 healthy. 100 images were obtained for each class. There are 400 images for a total of 4 classes. Since 400 images will not be enough for classification, data augmentation has been performed. For this purpose, each image is rotated at 60-degree angles to produce 6 different copies of an image. Thus, the total number of images was 2400. This augmentation by rotation also provides robustness to orientation changes. Figure 24 shows 60 degrees rotated examples of images of BlackScurf disease.

Image Enhancement

After obtaining the images related to potatoes, image enhancement operations were performed. Since potato images were obtained from different sources, they all had to be converted to the same format. First, background noise was removed using OTSU algorithm (Açıl, 2017) and the images of the potatoes were distinguished. Then the images were resized to the same size.

OTSU thresholding algorithm was used to subtract the potato image from the background. The threshold process is to make a black and white image according to a certain threshold value. In Otsu Threshold operation, this threshold value is determined automatically. As shown in Figure 25, a

mask for the potato image is formed. The image was separated from the background by passing the potato through the mask.

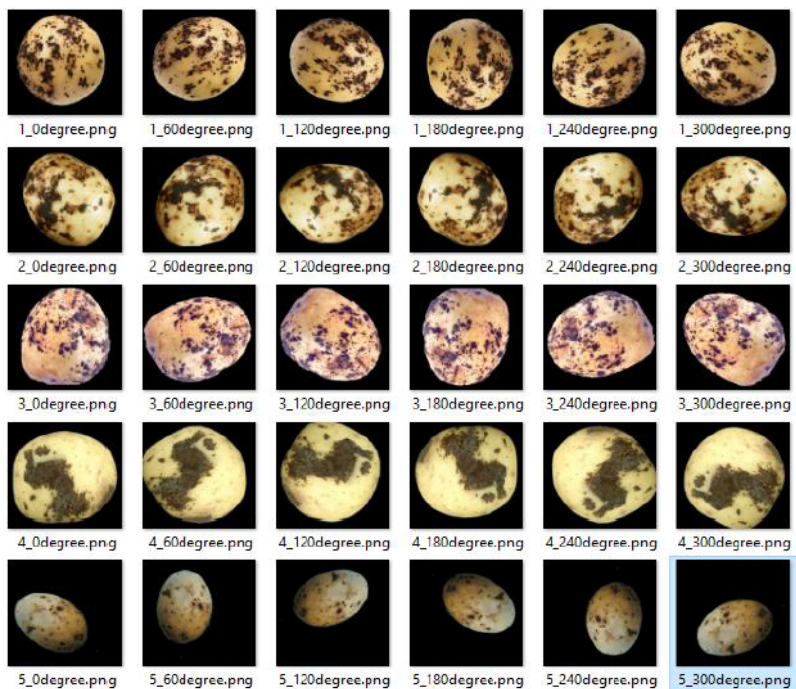


Figure 24: 60 degrees rotated samples of potato images of BlackScurf disease (Kizil,2019)

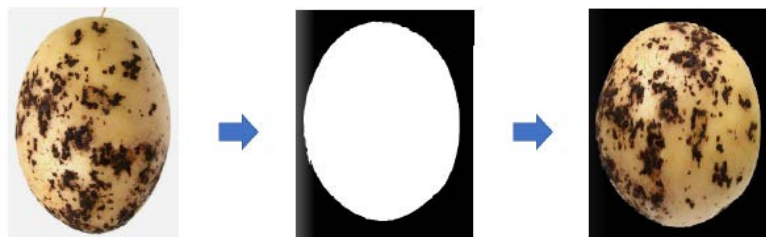


Figure 25: Masked image of Blackscurf disease (Kizil,2019)

Since the pictures available on the internet are of different sizes, they are all brought to the same dimensions. For this purpose, it was sized in the dimensions of 400×400 , 600×600 , 800×800 . The system was tested in all three dimensions. The best results are obtained on 600×600 images.

Feature Extraction

Feature extraction is to identify unique patterns that may be present in an image. Feature extraction algorithms are used to detect descriptors in an image. The most used algorithms are SURF (Speed up Robust Features) and HOG (Histogram of Oriented Gradients). SURF and HOG algorithms have been applied to images. After the classification process, the success of the system trained with the features extracted with the HOG algorithm was higher than the SURF algorithm. After the features were extracted, the SVM algorithm was used for the classification process.

Creating a feature bag using bag-of-words algorithm

The process of creating a bag of features is to group similar features after creating meaningful features on the image. Below are the images of BlackScurf (Figure 26) diseases represented using the Bag of Words algorithm.

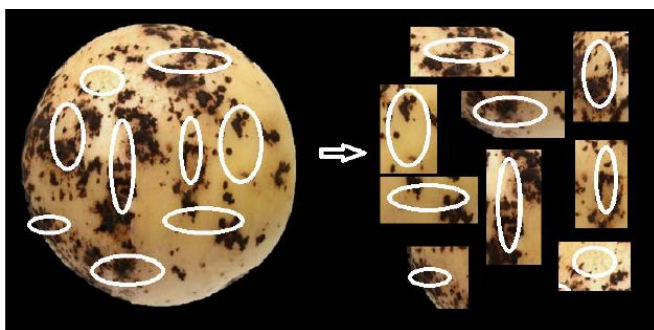


Figure 26: Black scurf disease image and Collection of Visual Words (Kızıl,2019)

Multi-class Support Vector machine training and classification

In the literature research, it was seen that SVM algorithm gives the best results in the classification of vegetable and fruit diseases. Since there is more than one disease class, more than one approach model was used for multi-Class SVM classifier. In the classifier training, SVM was trained by creating a histogram according to the frequency of the features in the feature bag for all images.

Chi-Square and Histogram Intersection Kernel were used as SVM kernel methods. The reason for using these two kernels is that they are widely used to compare low-level histograms such as color and texture calculated from images.

Result

In this study, an approach is proposed to identify and classify potato external diseases using multi-class SVM. In the proposed method, three common diseases, namely BlackScurf, CommonScab and PowderyScab diseases, were examined. The system was trained according to the spot and texture characteristics caused by these diseases. In the study, a success rate of 96% was obtained because of various experiments. The algorithms used to achieve this result have a great effect. The compatibility of the HOG algorithm and Histogram Intersection Kernel methods increased the system performance. Since both approaches are histogram-based, successful results were obtained. The developed method can be used in a possible automation system that allows automatic classification of potatoes before production and consumption.

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Optimized Classification of Cotton Leaf Diseases Using Machine Learning and Feature Selection Techniques

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Introduction

Cotton (*Gossypium*) is an annual plant grown in various regions of the world. The most valuable part of this plant is its structure, known as the "cotton cocoon". Cotton cocoons have a wide range of applications, including textiles, edible oil production, paper production, animal feed and medical products. For this reason, cotton is a very important raw material for a large number of industries (Egbuta et al., 2017).

Cotton is a valuable commercial product that plays a fundamental role in the production of natural fibers. Cotton production contributes significantly to textile production and supports the growth of the textile industry. However, plant protection is a very important issue for sustainable cotton production. Plant diseases represent a major challenge in agriculture as they cause significant crop losses. These diseases constitute one of the biggest threats to agriculture, which causes a decrease in productivity, resulting in a decrease in the total amount of production (Rai & Pahuja, 2023) (Kursun, Gur, et al., 2024).

The detection of plant diseases by traditional methods typically begins with observational analyses performed by experts visiting the areas. But these methods take a lot of time and work, and they often need to be watched all the time. In addition, traditional diagnostic methods do not always provide an accurate assessment of plant diseases. Plant diseases cause both qualitative and quantitative losses for the plant. Recently, researchers have been increasingly focusing on methods in which automated methods are used to detect plant diseases in the agricultural sector (Ramazan Kursun et al., 2023) (Ahmed, 2021).

In their study, Prajapati et al. aimed to detect and classify diseases such as *Alternaria* leaf spot, *Cercospora* leaf spot, bacterial blight and red spot on cotton leaves in India. In the study, image processing and machine learning techniques have been used to address the challenge of distinguishing these diseases through a specialist's visual examination. In their study, they preprocessed and segmented leaf images captured from cotton fields using digital cameras using background removal and Otsu thresholding methods. After extracting color, shape and texture features, they used these features as inputs for classifier algorithms to detect diseases. They reported that this approach enabled accurate and efficient diagnosis of cotton leaf diseases (Prajapati et al., 2016).

Memon et al. aimed to accurately identify cotton leaf diseases using a meta deep learning based model in their study. They collected a dataset consisting of 2385 healthy and diseased leaf images and used data augmentation method for training. They evaluated models including custom CNN, VGG 16, ResNet 50 and the proposed meta deep learning model. They reported that the proposed model achieved superior performance with 98.53% accuracy, showing high reliability and generalization for effective disease detection in cotton agriculture (Memon et al., 2022).

Another study has provided a comprehensive review of the existing methods used for the detection and classification of cotton leaf diseases. Cotton production has been significantly impacted by leaf diseases such as bacterial blight, foliar diseases, and *Alternaria*. The necessity of developing automated, cost-effective, reliable, and rapid diagnostic systems to enhance cotton production has been emphasized in the study. The strengths and weaknesses of the methods employed in various stages, including image processing, segmentation, feature extraction, and classification, have been examined. The study concludes by highlighting the need for the development of fully automated computer-aided systems in the future and offering recommendations for future research directions (Manavalan, 2022).

Another study aimed to reduce agricultural crop losses by employing artificial intelligence-based approaches for the detection of cotton leaf diseases. The study applied transfer learning methods using CNN models such as ResNet50, VGG19, InceptionV3, and ResNet152V2 to identify cotton leaf diseases. In tests conducted on a standardized dataset of cotton leaf images, the ResNet152V2 model achieved the best performance with an accuracy of 98.36%. The model demonstrated superior effectiveness

compared to other methods, with 60,380,648 parameters. These results indicate that the ResNet152V2 model is a highly accurate and practical method for detecting plant diseases (Sivakumar et al., 2021).

This study has aimed to enhance agricultural sustainability through the development of a flexible approach for detecting and predicting diseases in cotton crops. Feature extraction for classifying cotton leaves through lightweight CNN models and LBP has been encompassed in the study. Disease diagnosis has been carried out utilizing Coral Reef Optimization alongside ResNet50-VGG16 hybrid classifiers, drawing inspiration from tomato diseases. Additionally, disease prediction has been conducted by integrating weather data with Quantitative Regression Forests and LSTM algorithms. This strategy has been designed to enhance productivity through the establishment of a cohesive framework for the proactive management of cotton diseases (Vasanthi et al., 2024).

In order to identify and categorize diseases that appear in cotton leaves, computer vision and deep learning approaches have been applied by Borugadda et al. A cotton leaf dataset consisting of 2,275 images has been used for the purpose of feature extraction. Out of these images, 1,952 have been designated for training purposes, while the remaining 324 have been reserved for validation. Five convolutional layers have been utilized by the model to extract features from the images. Additionally, machine learning algorithms such as AdaBoost, Decision Tree, Gradient Boosting, K-Nearest Neighbors (KNN), Logistic Regression (LR), Random Forest (RF), and Support Vector Machine (SVM) have been utilized to classify the images. Furthermore, three fully connected layers have also been employed. According to the findings of the research, AlexNet's three fully connected layers have achieved the best results, with an F1 score of 94.92% and an estimated training time of roughly 51 minutes (Borugadda et al., 2021).

Devi et al. have aimed to explore deep learning techniques for the detection and identification of illnesses in cotton leaves. An extensive dataset of tagged healthy and diseased cotton leaves has been used in the research. The statistics have illustrated the various phases of the illness and the corresponding environmental factors. Data collection, preprocessing, and model training have been conducted using contemporary deep learning architectures throughout the application phase. The trained model has been shown to have the capability to properly differentiate between sick and healthy material (Devi et al., 2024).

Ganguly et al. have created a hybrid model that classifies six distinct illnesses, including fungal, bacterial, and viral pathogens, with an accuracy of 96%. The suggested model has integrated the interpretability of DenseNet121 with the stability of ResNet50, enabling accurate diagnosis of cotton leaf diseases and offering comprehensive analysis. The findings have indicated that the model provides a thorough and dependable solution for disease control in the cotton industry, with the objective of enhancing crop health, production, and sustainability (Ganguly et al., 2024).

This study proposes a bilinear coordinate attention module-based model aimed at accurately detecting cotton leaf diseases in the natural environment. The model reduces information loss and increases the focus on disease regions by adding spatial coordinate information and feature fusion to feature maps. While attention to unnecessary information such as healthy areas is reduced, disease areas are identified and enlarged more precisely. As a result of the experiments, the proposed model has been reported to have a superior performance in the detection of cotton leaf diseases with an accuracy rate of 96.61% (Shao et al., 2023).

Kaur et al. in their study, they aimed to present an innovative approach by using a fine-tuned VGG16 deep learning model for the diagnosis and classification of cotton leaf diseases. Four main diseases, such as Cotton Bacterial Blight, Verticillium Wilt, Fusarium Wilt and Cotton Leaf Curl Disease, were studied with a data set based on leaf images. The model, optimized with data augmentation and model adjustment techniques, successfully classified diseases with an accuracy rate of 93.8%. The results, they reported, show that deep learning models are effective tools for early disease detection and management in agriculture (Kaur et al., 2024).

Kukadiya et al. have proposed a unified deep convolutional neural network (DCNN) model based on the VGG16 and InceptionV3 pre-trained models for the early diagnosis and prevention of leaf diseases in cotton plants. The model has been trained and tested on a cotton leaf dataset, and it has been reported that higher accuracy rates have been achieved compared to the basic models. In order to optimize the performance of the model, extensive experiments on hyperparameters such as learning rate, epoch number, and optimizer have been carried out. By using the recommended hyperparameter settings (learning rate 0.0001, 20 epochs, and SGD optimizer), 98% accuracy rates in training and 95% accuracy rates in testing have been reached (Kukadiya et al., 2024).

There are many more sources related to cotton leaf disease in the literature. In Table 1, the methods used in the studies related to these resources, the number of data sets and the success rates of the studies are given.

Table 1 Summary information about other studies in the literature

Techniques	Dataset	Accuracy	References
Back Propagation Neural Network (BPNN)	Cotton leaves images	92.7%	Bashish et al. (2010)
Median filter, K-Means, Multi-SVM	Cotton leaves images	96.3%	Jenifa et al. (2019)
Cross Information gain Deep forward Neural Network (CIGDFNN) with Particle Swarm Central (PSO)	Cotton diseases images	95%	Revathi and Hemalatha (2014)
SVM with Genetic algorithm (SVM-GA)	Cotton leaf diseases	99.3%	Sivasangari et al. (2014)
VGG16 and RESNET50	3000 cotton leaf images	92.5% and 96.2%	Banu and Mani (2020)
CNN	2293 cotton leaves images	97.98%	Rai (2022)
SVM	130 cotton leaves images	98.46%	Bhimte and Thool (2018)
Random Forest (RF)	900 Cotton diseases images	83.26%	Sarangdhar and Pawar (2017)
ResNet34	1600 Cotton diseases images	98.1%	Alves et al. (2020)
GoogleNet and Resnet50	60,659 images	86.6% and 89.2%	Caldeira et al. (2021)

Materials and Methods

In this study, a comprehensive methodology was used to ensure the accurate detection and classification of cotton leaf diseases. The SqueezeNet deep learning model was used for feature extraction, feature selection methods including tree-based feature selection and Gray Wolf Optimization (GWO) algorithm were applied to improve the extracted features. Machine learning algorithms such as Artificial Neural Networks (ANN), Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Logistic Regression were used for classification. Basic criteria such as Accuracy, Accuracy, Recall and F1 Score were used to evaluate the models' performance and a robust analysis of model effectiveness was provided. A

flow chart was created as shown in Figure 1 to visually represent the workflow and methodological process of the study.

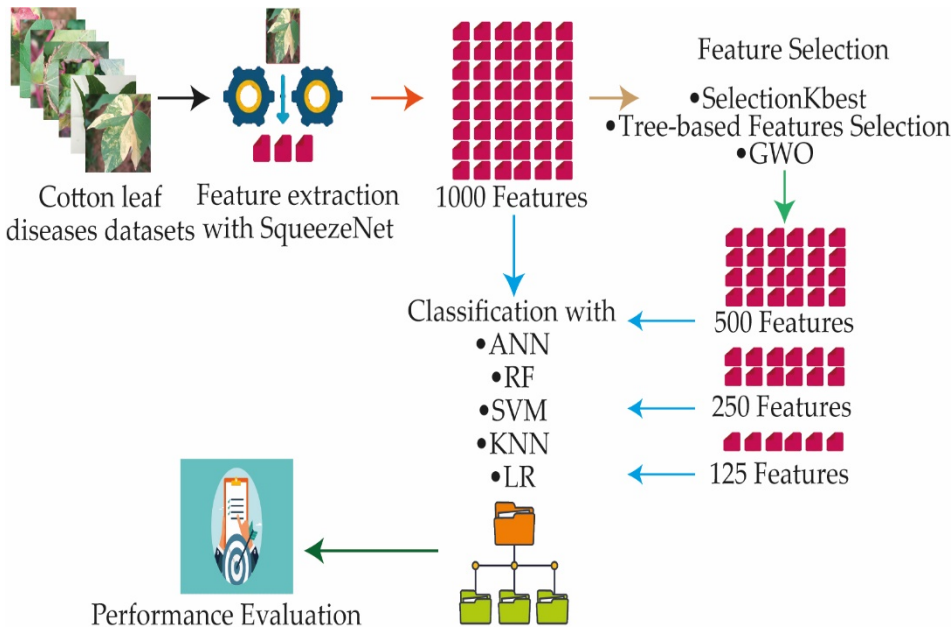
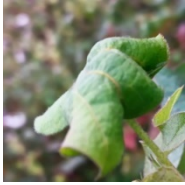
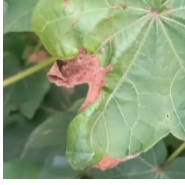
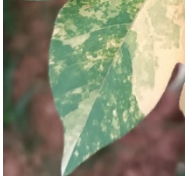
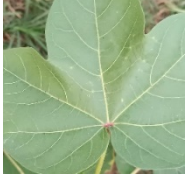


Figure 1 Block diagram illustrating the workflow of the study

Dataset

The data of the study includes diseases that occur consistently among cotton crops from the area of the national cotton research institute in a country (Manavalan, 2022). The photos are 3000 x 4000 pixels, 2239 x 2239 pixels and 1597 x 1597 pixels in size and were taken using a mobile phone with the help of field experts to make sure that they accurately represent the cottonseed oil disease class. Table 2 shows the images and classes belonging to this data set.

Table 1 Summary of Cotton Leaf Diseases and Visual Dataset

Class Name	Number of Images	Image Examples
Bacterial Blight	250	
Curl Virus	431	
Herbicide Growth Damage	280	
Leaf Hopper Jassids	225	
Leaf Redding	578	
Leaf Variegation	116	
Healthy Leaf	257	
Total	2137	

Deep Learning Models

Deep learning is an artificial intelligence method that is a sub-branch of machine learning. It aims to extract meaningful features, especially from complex and large data sets. It processes data in layers using artificial neural networks similar to the way the human brain works. In this process, each layer is able to create more complex relationships by learning features at different levels within the data. Traditional methods provide lower efficiency and accuracy in many areas such as image processing, voice recognition, natural language processing, deep learning and bioinformatics. Especially in agriculture, deep learning techniques in the early diagnosis and classification of plant diseases both save time and help farmers make decisions by analyzing large data sets. As a result, deep learning is seen as an important tool in both scientific and practical applications (Tunc et al., 2022).

SqueezeNet Models

SqueezeNet stands out among deep learning architectures as a convolutional neural network (CNN) that aims to provide a lightweight and fast neural network model by significantly Decrement the number of parameters. The model consists of units called "fire modules" as the basic building block. Each fire module contains a squeeze layer to compress the data (uses 1x1 convolution) and then an expand layer to expand the data (1x1 and 3x3 convolutions). Thanks to this structure, SqueezeNet aims to maintain high accuracy rates while significantly reducing the parameter size in standard models. The model consists of 8 fire modules and 1 convolution layer in total. This layer structure extracts 1000 features in a way that can make a class distinction. In addition, it has 50 times fewer parameters compared to AlexNet, and the model size is only under 0.5 MB. With these features, SqueezeNet is effectively used in systems with limited hardware resources (Koklu et al., 2023; Yasin et al., 2023).

Feature Selection

Feature selection identifies the features most strongly associated with the target variable within a dataset. This method of data preprocessing seeks to remove redundant or minimally impactful features. This approach plays an essential role in enhancing model performance, minimizing computational costs, and mitigating overfitting, particularly in high-dimensional datasets. Feature selection methods are typically classified into three categories: filter

methods, embedded methods, and helical methods. Filter methods evaluate properties according to statistical criteria, whereas embedded methods, such as decision trees or random forests, determine the significance of properties during the model training process. Helical methods aim to identify the optimal subset by testing various combinations of properties to achieve the best outcomes (Guyon & Elisseeff, 2003) (Kursun et al., 2022).

This method is applicable across various domains, including bioinformatics, financial analysis, natural language processing, and image processing. This process seeks to enhance both model accuracy and interpretability (Koklu et al., 2012; Taşpınar et al., 2021).

SelectKbest

SelectKBest is one of the feature selection methods for data processing and machine learning. This approach aims to select the most appropriate k number of properties by analyzing the relationship of the properties that make up the dataset with the target variable. Various statistical tests, such as ANOVA F and chi-square test, can be used to determine the relevant characteristics. Feature selection plays a very important role in improving model performance, reducing computational costs, and preventing over-learning in large-sized datasets (Pedregosa et al., 2011) (Jamei et al., 2024).

SelectKBest is widely used as a method for classification and regression problems. This method helps to develop faster and more efficient models by filtering unnecessary or low-contributing features in a high-dimensional dataset. In Table 3, the pseudo code for the SelectKBest method is provided, where the step-by-step process for selecting the most relevant features from a dataset is shown.

Table 2 Pseudo Code for the SelectKBest Method

Steps	Process
1	Load the dataset (X, y)
2	Determine the number of K (the number of features to choose the best)
3	Select an appropriate score function (for example, F-score, chi-square)
4	Define the SelectKBest function by the score function and k
5	Apply feature selection (convert X with fit_transform)
6	View selected features and scores
7	Use the new feature set in the model

Tree-based Feature Selection

Tree-based feature selection is a method that aims to select important features by taking advantage of the capabilities of tree-based models, such as decision trees or random forests. In this method, the contribution of each feature to the model performance is typically evaluated on the basis of "feature importance scores." The ranking and selection of the features are conducted in accordance with these scores, and the most effective features are selected (Breiman, 2001; Freeman et al., 2013).

This method aims to both improve the performance of the model and reduce the computational cost by working effectively, especially on high-dimensional datasets. Tree-based feature selection is widely used in many fields such as bioinformatics, financial analysis, image processing, and natural language processing. Since models such as random forest have the ability to explore both linear and nonlinear relationships, this method provides a flexible solution for different types of data (Aouedi et al., 2021). Table 4 presents the pseudo code for the Tree-based feature selection method, outlining the step-by-step process for selecting the most relevant features from a dataset.

Table 3 Pseudo Code for the Tree-based Feature Selection Method

Steps	Process
1	Load the dataset (X, y)
2	Define a tree-based model (for example, RandomForestClassifier)
3	Adapt the model to the dataset (with the fit method)
4	Get feature importance scores (feature_importances)
5	Sort properties by importance scores
6	Select properties according to a certain threshold value or k best properties
7	Use the new feature set in the model

Gray Wolf Optimizer (GWO)

We use GWO, a powerful and effective tool, to solve nonlinear and complex optimization problems. It has a wide range of applications, such as parameter optimization, feature selection, route planning, and energy management. The flexibility and intuitive structure of the algorithm offer effective results in high-dimensional data sets and multi-purpose optimization problems (Hu et al., 2020). Table 5 presents the pseudo code for

the GWO method, outlining the step-by-step process for selecting the most relevant features from a dataset.

Table 4 Pseudo Code for the GWO Method

Steps	Process
1	Determine the initial parameters (wolf population, number of iterations)
2	Start the population randomly (create solutions)
3	Calculate the compliance value of each solution
4	Identify the alpha, beta and delta wolves (the three best solutions)
5	Cycle (up to the number of iterations): a- Update solutions according to alpha, beta and delta wolves b- Calculate new positions and turn around the prey c- Update the eligibility values
6	Rotate the position of the alpha wolf at the end of the loop (the best solution)

Machine Learning Algorithms

Machine learning algorithms are techniques that do not require data programming and allow computers to learn from data. These algorithms make predictions or make decisions based on future data by extracting relationships and patterns from a data set. Machine learning algorithms are divided into three main categories. Reinforcement learning allows a model to learn the best movement strategy by interacting with its environment; unsupervised learning performs tasks such as classification or regression by working with labeled data; and it is used for tasks such as classification or size reduction.

Machine learning algorithms are used in a wide variety of industries such as medicine, finance, agriculture, automation, natural language processing and image processing. For example, it is used in the diagnosis of diseases in health services, credit risk analysis in finance, detection of crop diseases in agriculture, robot control in automation systems for solving various problems. ANN, LR, DT, SVM, RF, KNN and deep learning models are among the algorithms that are widely used today. Machine learning algorithms increase the efficiency in large data sets and at the same time significantly facilitate accurate forecasting and decision-making processes (R. Kursun et al., 2023).

Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) in machine learning emulate the functioning of neurons in the human brain. Artificial neural networks (ANNs) can simulate intricate data interactions and generate significant patterns. The structure typically comprises an input layer, one or more hidden layers, and an output layer. Data processing primarily relies on mathematical weights that link the neurons within each layer. The output is generated by passing the processed input data from one layer to the subsequent layer. The efficacy of artificial neural networks in addressing complex problems is contingent upon their capacity to simulate nonlinear interactions (Koklu, Kursun, et al., 2021).

This technology is utilized in various applications, including image processing, voice recognition, financial forecasting, health diagnostics, and biological data analysis. Examples of effective implementation of these applications include disease diagnosis in medicine, crop health analysis in agriculture, and the application of quality control methods in industry. The network can be employed in a backpropagation technique to optimize weights and minimize errors. Artificial neural networks demonstrate high accuracy rates in large data sets, serving as a crucial method in contemporary artificial intelligence applications (Yildiz et al., 2024).

Random Forest (RF)

Random Forest is a machine learning method that combines multiple decision trees to create a powerful and flexible model. RF is an ensemble method used in both classification and regression problems and is based on the "bagging" (bootstrap aggregation) technique. The model generates multiple decision trees by extracting random samples from the training dataset and derives the final outcome by aggregating the predictions of each tree. In classification tasks, the outcome is determined by the majority vote, whereas in regression tasks, the mean value is utilized. This methodology mitigates the danger of overfitting the model and enhances its overall efficacy (Taspinar et al., 2021).

Random Forest is used in many areas due to its high accuracy rates and ability to learn both linear and nonlinear relationships. It is also used as an effective tool in dimension reduction and feature selection processes thanks to its ability to determine feature importance scores. RF stands out with its efficient operation in large data sets, resistance to noisy data and easy interpretability (M. Isik et al., 2024).

Support Vector Machine (SVM)

Support Vector Machine (SVM) is one of the powerful machine learning methods used in classification and regression problems. SVM aims to provide the maximum margin when creating a decision sequence (hyperplane) in order to optimally Decouple between data. The model works with support vectors representing the positions of data points and is converted into much higher dimensional spaces using kernel functions in problems that are not correct. These functions are effectively provided by bile in cases where the correct sequencers are not enough (Taspinar et al., 2022).

SVM is especially popular in small and medium-sized data sets with its high accuracy rates and resistance to down-learning. In particular, performance advantage is offered in inaccurate and high-dimensional data. Responsibility for noisy data as a disadvantage, this question can be overcome with correct parameterization and data preprocessing (Koklu et al., 2022; Yasin et al., 2024).

K-Nearest Neighbors (KNN)

A basic but effective machine learning approach for classification and regression is K-Nearest Neighbors (KNN). KNN uses the labels of the nearest k neighbors to classify or value a data point. A data point is assigned to the majority class of its neighbors via "majority voting" or by averaging the neighbors' values in regression. KNN handles nonlinear and complicated distributed data well (Koklu & Sabancı, 2016).

KNN is utilized in medical diagnosis, suggestion, handwriting, and picture categorization. Large data sets have considerable processing cost, but data reduction and indexing can overcome this (Koklu & Sabancı, 2015).

Logistic Regression (LR)

Logistic regression is a technique that is utilized in situations where the dependent variable is categorical. It is typically designed to address problems that involve binary categorization. This model provides an estimate of the likelihood that a particular event will take place and expresses the result as a value that falls somewhere between 0 and 1. It works like a linear model, but thanks to the sigmoid function, it is able to make nonlinear predictions. This feature makes it possible to clearly define the Decisional boundary between the two classes. The model is used to analyze the relationship between the

independent variables and the target variable and to make probability Decency estimation (Koklu, Sarigil, et al., 2021).

Logistic regression is applied in many fields such as disease risk analysis in health, customer behavior prediction in marketing, credit risk analysis and sentiment analysis. It is widely preferred due to its simple structure, fast operation and easy interpretability. However, since it is based on linear decision boundaries, different methods may need to be used in complex and nonlinear problem (Cinar et al., 2023).

Performance Metrics

Performance metrics are used to evaluate the accuracy, reliability, and overall effectiveness of machine learning models. These metrics are essential for assessing the accuracy of the model's predictions and identifying its errors, especially in classification problem (H. Isik et al., 2024; Kursun, Yasin, et al., 2024; Taşpınar et al., 2020).

- Accuracy represents the proportion of correct forecasts relative to the total number of forecasts and serves as a metric for assessing overall performance. Nonetheless, it may yield misleading outcomes in unbalanced data sets.
- Precision quantifies the proportion of positively predicted values that are true positives, which is essential for minimizing false positives.
- Recall, also known as sensitivity, indicates the number of true positives accurately identified. It is especially significant in contexts where false negatives are of concern.
- F1 Score, provides a balanced performance assessment through the harmonic average of precision and recall, making it a more effective indicator, especially in unstable data sets.

Experimental Results

In this section, we present the experiments and results performed to evaluate the performance of the proposed models. Performance metrics such as accuracy, precision, recall, and F1 score are used to evaluate the features obtained from the SqueezeNet deep learning model. These metrics are also used to measure the classification accuracy efficiency of the machine learning algorithms for each feature reduction result. Metrics such as accuracy and recall were examined more extensively to prevent misleading results from occurring in imbalanced datasets. These findings provide an important basis

for understanding how well the proposed techniques perform for classification problems.

Each model used in this study was trained on a system with 64 GB RAM, an Intel i7-12700K CPU running at 3.61 GHz, and an NVIDIA RTX 3080 Ti GPU. Jupyter Notebook 7.2.1 and Python 3.8.5 were used for training.

Evaluation of SelectKbest for Feature Reduction

The properties obtained through SqueezeNet were categorized using AN, RF, SVM, KNN and LR algorithms. The classification process was carried out using 1000 characteristics obtained at the beginning. Later, the number of features was reduced to 500, 250 and 125, respectively, and the classification operations were carried out again. The results of classification performance obtained by feature reduction processes are shown in Table 6. In order to improve the understanding of table data, the graph obtained from these data is presented in Figure 2,3,4,5.

Table 5 Comparison of Model Performance Across Different Feature Sizes

Number of features	Model	Accuracy	Precision	Recall	F1_Score	Duration
1000	ANN	0.990654	0.990990	0.990654	0.990780	1.191953
	RF	0.967290	0.966261	0.967290	0.961200	6.373510
	SVM	0.989097	0.988904	0.989097	0.988686	0.148025
	KNN	0.992212	0.992340	0.992212	0.992265	0.135163
	LR	0.990654	0.990480	0.990654	0.990520	0.071197
500	ANN	0.989097	0.989713	0.989097	0.989313	0.507587
	RF	0.968847	0.969839	0.968847	0.962609	4.642087
	SVM	0.992212	0.992092	0.992212	0.992042	0.084781
	KNN	0.990654	0.990654	0.990654	0.990654	0.058635
	LR	0.992212	0.992092	0.992212	0.992042	0.044574
250	ANN	0.992212	0.992125	0.992212	0.992157	0.597368
	RF	0.968847	0.969839	0.968847	0.962609	2.854248
	SVM	0.989097	0.988904	0.989097	0.988686	0.026000
	KNN	0.989097	0.989267	0.989097	0.989171	0.049990
	LR	0.987539	0.987539	0.987539	0.987539	0.030471
125	ANN	0.990654	0.990654	0.990654	0.990654	0.452507
	RF	0.968847	0.967946	0.968847	0.963467	2.296400
	SVM	0.985981	0.985575	0.985981	0.985675	0.025505
	KNN	0.992212	0.992340	0.992212	0.992265	0.044260
	LR	0.984424	0.983872	0.984424	0.983962	0.024838

The comparative analysis across the metrics (accuracy, precision, recall, and F1-score) for various models and feature sizes reveals several insights:

Accuracy:

- Models like KNN and ANN consistently achieve high accuracy, even as the number of features is reduced.
- RandomForest and Logistic Regression show a slight decline in accuracy as the feature set size decreases.

Precision:

- Precision remains robust for KNN and ANN across all feature sizes, while RandomForest and Logistic Regression exhibit more variability.
- SVM maintains competitive precision but shows sensitivity to feature reduction at smaller feature sizes.

Recall:

- Recall is generally high across models but shows a stronger decline in Logistic Regression and RandomForest with reduced features.
- KNN consistently retains high recall, reflecting its ability to minimize false negatives effectively.

F1-Score:

- F1-score trends align closely with recall and precision patterns, highlighting KNN and ANN as the most balanced models in terms of both precision and recall.
- Logistic Regression shows a notable drop in F1-score with reduced features, indicating less balanced performance.

This analysis underscores the strengths of KNN and ANN in maintaining robust performance across all metrics, even with reduced feature sets. In contrast, RandomForest and Logistic Regression are more feature-dependent.

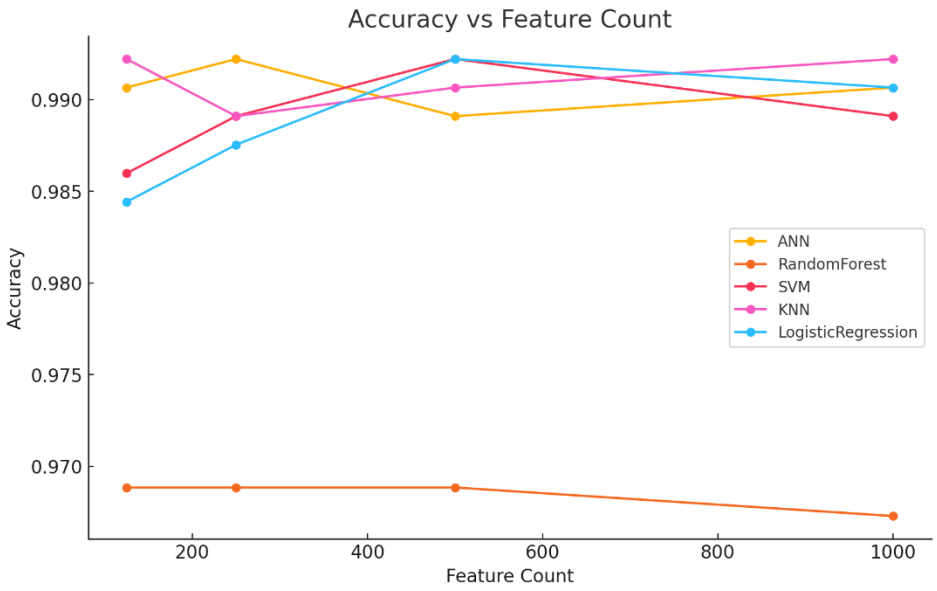


Figure 2 Accuracy Performance Across Classifiers with SelectKbest

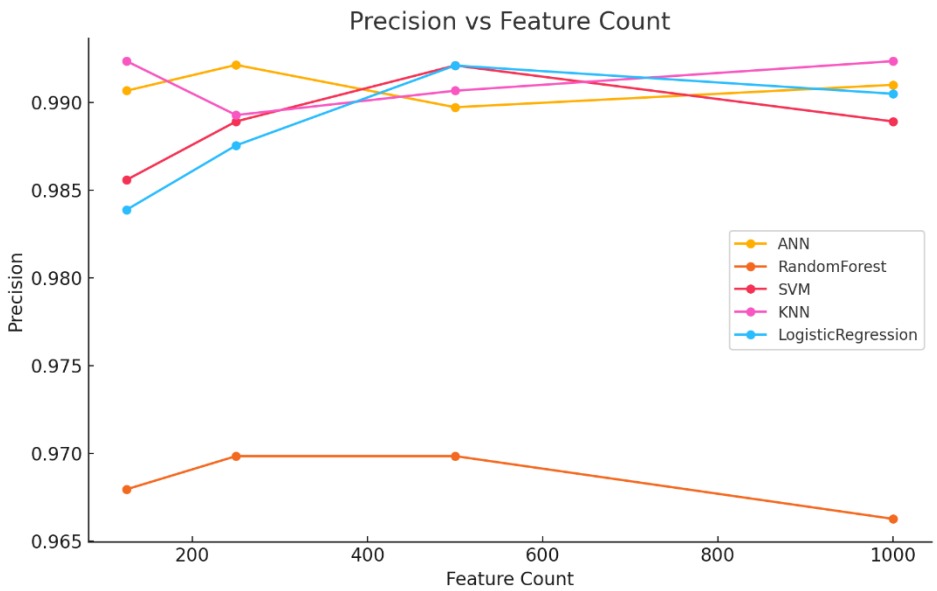


Figure 3 Precision Performance Across Classifiers with SelectKbest

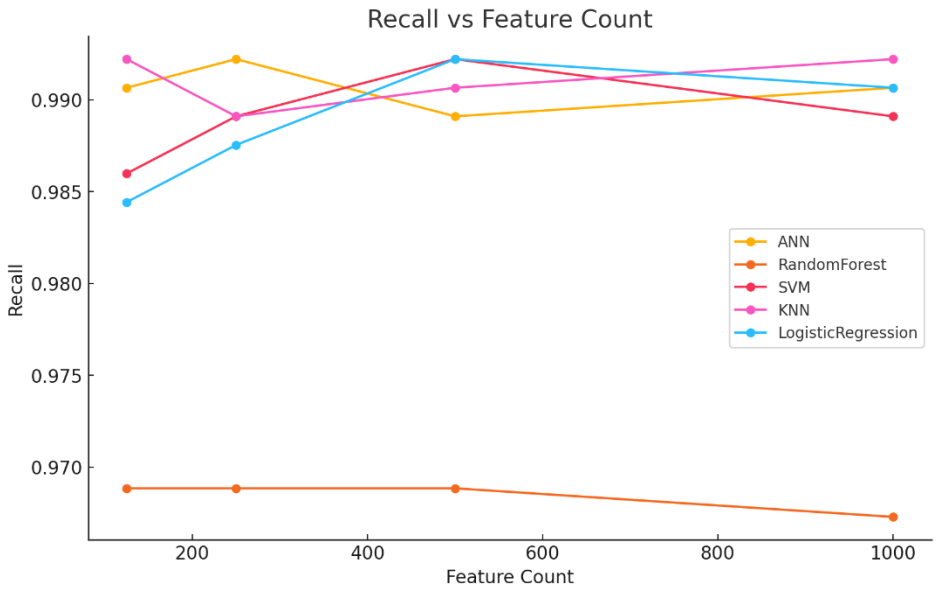


Figure 4 Recall Performance Across Classifiers with SelectKbest

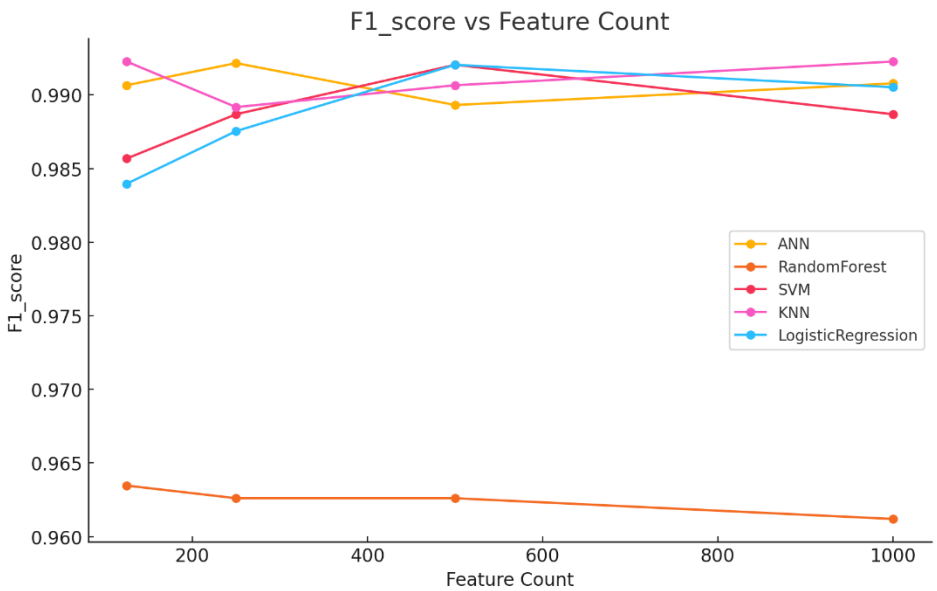


Figure 5 F1-score Performance Across Classifiers with SelectKbest

The provided table and graph illustrate the correlation between the amount of features and the accuracy of different models. Upon examination of the graphs, each curve illustrates the variation in model accuracy as the size of the feature set diminishes. Significant observations encompass:

- The general trend indicates that most models sustain good accuracy across various feature sizes, however a few exhibit minor declines with a reduction in features.
- The Optimal Models: KNN and ANN regularly demonstrate good accuracy despite a reduced number of features, indicating their robustness against feature reduction.
- Feature Sensitivity: Models like randomForest may exhibit greater performance variability when features are diminished, suggesting a heightened dependence on a wider array of features.

Evaluation of Tree-Based Feature Selection for Feature Reduction

Using tree-based feature selection methods, the extracted features were classified with ANN, RF, SVM, KNN, and LR algorithms. The classification process initially utilized the full set of 1000 features. Subsequently, the feature set was progressively reduced to 500, 250, and 125 features, and the classification process was repeated at each stage. The results obtained highlight the effects of tree-based feature reduction on classification performance, offering a detailed examination of how reducing the feature set influences the efficiency and accuracy of various classifiers. The results of classification performance obtained by feature reduction processes are shown in Table 7. In order to improve the understanding of table data, the graph obtained from these data is presented in Figure 6,7,8,9.

Table 7 Comparison of Model Performance Across Different Feature Sizes with Tree-based Feature Selection

Number of features	Model	Accuracy	Precision	Recall	F1_Score	Duration
1000	ANN	0.990654	0.99099	0.990654	0.99078	1.228181
	RF	0.96729	0.966261	0.96729	0.9612	6.351347
	SVM	0.989097	0.988904	0.989097	0.988686	0.143039
	KNN	0.992212	0.99234	0.992212	0.992265	0.177740
	LR	0.990654	0.99048	0.990654	0.99052	0.061763
500	ANN	0.992212	0.992709	0.992212	0.992367	0.559566
	RF	0.968847	0.969839	0.968847	0.962609	4.734189
	SVM	0.990654	0.990497	0.990654	0.990377	0.090513
	KNN	0.990654	0.99048	0.990654	0.99052	0.054401
	LR	0.985981	0.985805	0.985981	0.985882	0.042996
250	ANN	0.989097	0.988965	0.989097	0.98902	0.551048
	RF	0.968847	0.967946	0.968847	0.963467	2.966102
	SVM	0.989097	0.988833	0.989097	0.988858	0.027515
	KNN	0.989097	0.988965	0.989097	0.98902	0.049898
	LR	0.987539	0.987539	0.987539	0.987539	0.034097
125	ANN	0.998442	0.998445	0.998442	0.998431	0.426141
	RF	0.97352	0.97424	0.97352	0.96929	2.310871
	SVM	0.992212	0.992092	0.992212	0.992042	0.027580
	KNN	0.987539	0.987539	0.987539	0.987539	0.079418
	LR	0.987539	0.987272	0.987539	0.98736	0.033566

The relationship between feature selection and model performance demonstrates distinct patterns across the evaluated machine learning models. As the number of features decreases (from 1000 to 125), ANN and KNN models show consistent or even improved performance, with ANN's accuracy slightly increasing from 0.990 to 0.998. Conversely, models such as Random Forest experience fluctuations, with noticeable drops in metrics like f1_score, despite minor gains in accuracy. This indicates that ANN and KNN are less dependent on the total feature set, while Random Forest appears more sensitive to feature reduction.

When comparing the models' performance with respect to feature selection, ANN proves to be highly adaptable, maintaining superior performance across all metrics regardless of the feature count. KNN exhibits

similar stability, making these models suitable candidates for scenarios with limited features. SVM shows relatively stable performance with only minor changes in classification accuracy as the number of features decreases. This shows that it is dependent on the number of features. However, Random Forest shows sensitivity to the number of features and as a result, consistent classification accuracy is achieved. However, significant decreases in f1_score are observed when the number of features is reduced. Logistic Regression, although generally stable, showed the most significant performance decreases in scenarios with fewer features (125) and cannot be said to be very successful in reducing features. In terms of overall model comparison, ANN and KNN showed superior performance in terms of accuracy, precision, recall and f1_score. These models consistently adapt to changing feature counts with minimal loss of efficiency. On the other hand, Random Forest and Logistic Regression did not show stable performance with decreasing number of features. SVM showed itself as a mid-range classifier that provides consistent and stable performance across different number of features.

Feature selection significantly affects the performance of machine learning models; ANN and KNN show remarkable robustness in feature reduction. These models stand out as ideal candidates for scenarios where feature optimization is required. Random Forest and Logistic Regression, although effective with larger feature sets, exhibit more sensitivity to feature reduction, indicating the need for careful feature engineering when using these algorithms. Meanwhile, SVM offers stable and reliable performance at all feature numbers, making it a balanced choice for various scenarios. Overall, ANN and KNN stand out as the most reliable models under feature selection constraints, especially in tasks requiring high accuracy and robustness to reduced input sizes.

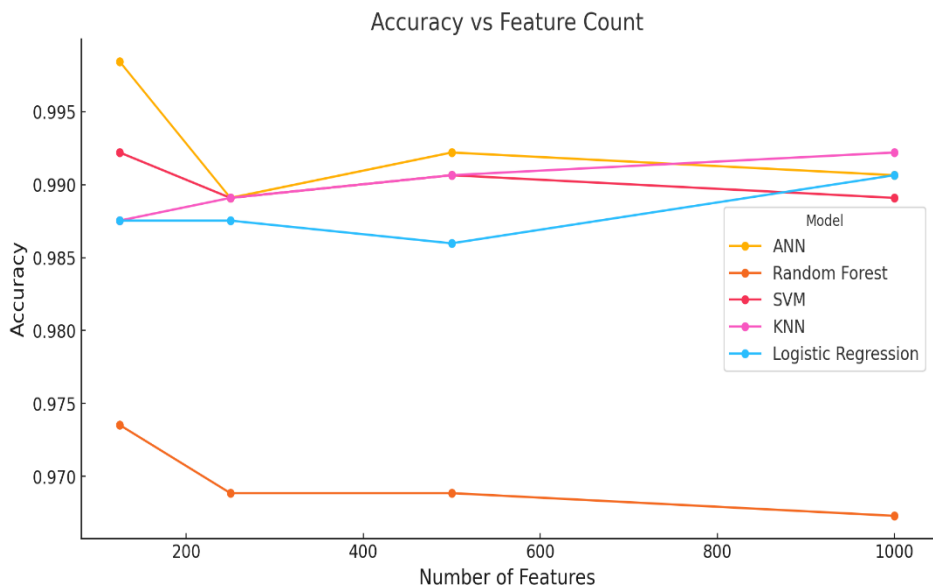


Figure 6 Accuracy Performance Across Classifiers with Tree-Based Feature Selection

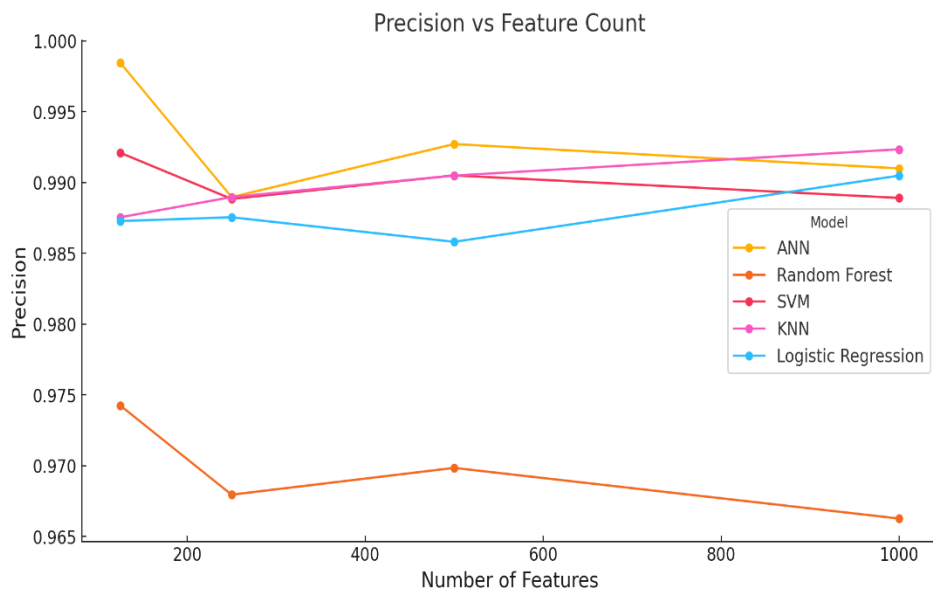


Figure 7 Precision Performance Across Classifiers with Tree-Based Feature Selection

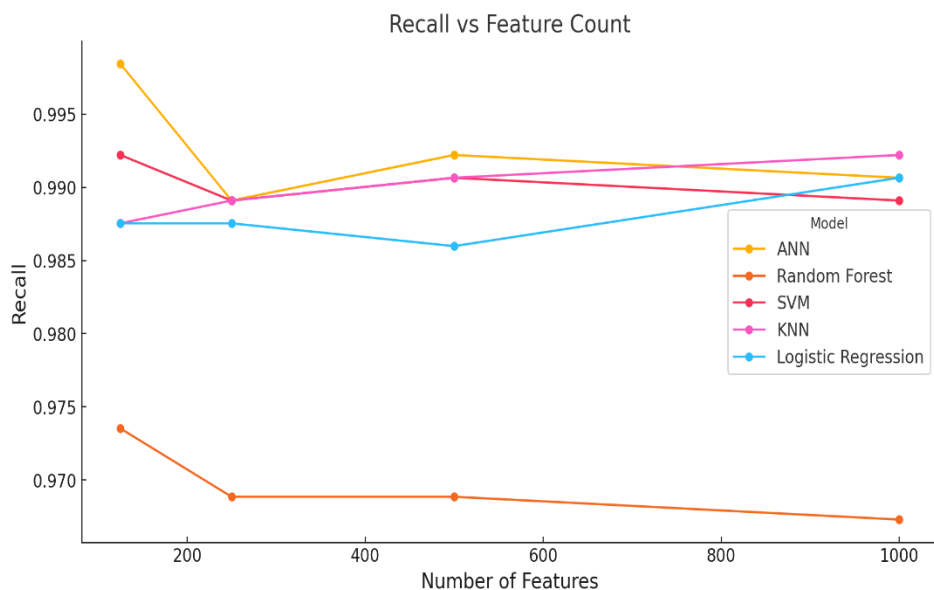


Figure 8 Recall Performance Across Classifiers with Tree-Based Feature Selection

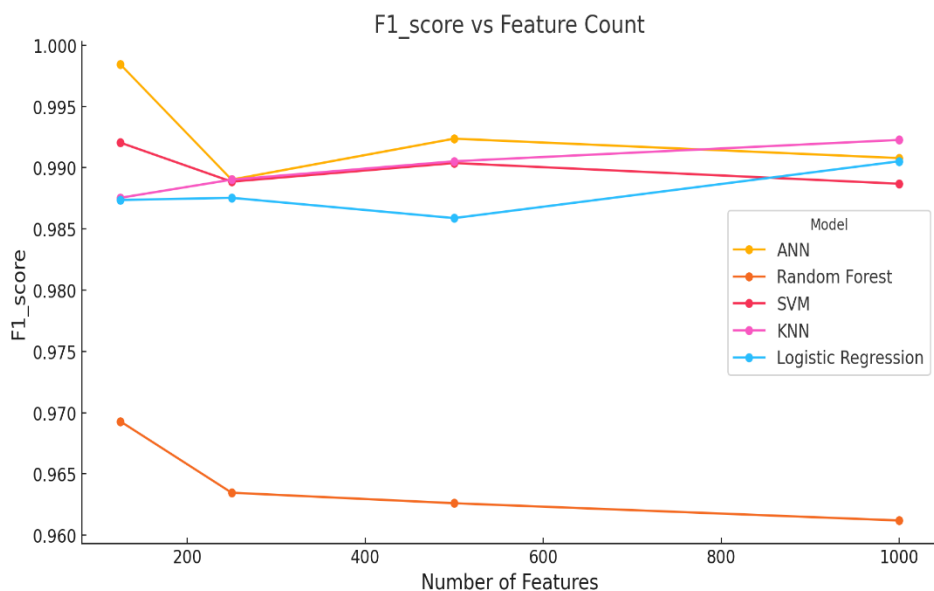


Figure 9 F1-score Performance Across Classifiers with Tree-Based Feature Selection

The graphs illustrate the relationship between feature count and classification performance across different models. ANN and KNN

consistently demonstrate robust performance regardless of feature reduction, maintaining high accuracy and f1_score values. In contrast, Random Forest and Logistic Regression exhibit greater sensitivity to feature reduction, with noticeable fluctuations in f1_score. SVM shows stable behavior across all feature sets, making it a balanced option. Overall, the results highlight the varying resilience of classifiers to dimensionality reduction, with ANN and KNN standing out as the most reliable under constrained feature sets.

Evaluation of GWO for Feature Reduction

The Grey Wolf Optimizer (GWO) was employed for feature selection, and the resulting features were classified using ANN, RF, SVM, KNN, and LR algorithms. The classification process initially utilized the complete set of 1000 features. Subsequently, the feature set was gradually reduced to 500, 250, and 125 features, and classification was performed at each stage. The findings highlight the impact of GWO-driven feature reduction on classification performance, offering an in-depth evaluation of how reducing the feature set affects the accuracy and efficiency of various classifiers. The results of classification performance obtained by feature reduction processes are shown in Table 8. In order to improve the understanding of table data, the graph obtained from these data is presented in Figure 10,11,12,13.

Table 8 Comparison of Model Performance Across Different Feature Sizes with GWO

Number of features	Model	Accuracy	Precision	Recall	F1_Score	Duration
1000	ANN	0.990654	0.99099	0.990654	0.99078	1.111227
	RF	0.96729	0.966261	0.96729	0.9612	6.310448
	SVM	0.989097	0.988904	0.989097	0.988686	0.125519
	KNN	0.992212	0.99234	0.992212	0.992265	0.154159
	LR	0.990654	0.99048	0.990654	0.99052	0.085847
500	ANN	0.990654	0.99048	0.990654	0.99052	0.447018
	RF	0.964174	0.96548	0.964174	0.955352	4.001328
	SVM	0.989097	0.988904	0.989097	0.988686	0.050000
	KNN	0.990654	0.99048	0.990654	0.99052	0.056521
	LR	0.990654	0.990497	0.990654	0.990377	0.032361
250	ANN	0.992212	0.99234	0.992212	0.992265	0.527361
	RF	0.965732	0.966929	0.965732	0.957842	2.687086

125	SVM	0.987539	0.987312	0.987539	0.986967	0.031938
	KNN	0.995327	0.995285	0.995327	0.995294	0.041794
	LR	0.984424	0.983872	0.984424	0.983962	0.027976
	ANN	0.985981	0.985575	0.985981	0.985675	0.422658
	RF	0.965732	0.966929	0.965732	0.957842	1.629490
	SVM	0.984424	0.983878	0.984424	0.983708	0.028003
	KNN	0.979751	0.978791	0.979751	0.978989	0.042198
	LR	0.981308	0.980559	0.981308	0.980755	0.022000

The table highlights the performance of various classifiers across different feature counts. ANN and KNN consistently achieve high accuracy, precision, recall, and F1 scores, demonstrating robustness to feature reduction. SVM also maintains stable performance, with minimal fluctuations across metrics. In contrast, Random Forest and Logistic Regression exhibit greater sensitivity to reduced feature sets, showing noticeable declines in F1 scores. Overall, ANN and KNN emerge as the most reliable models under varying feature dimensions.

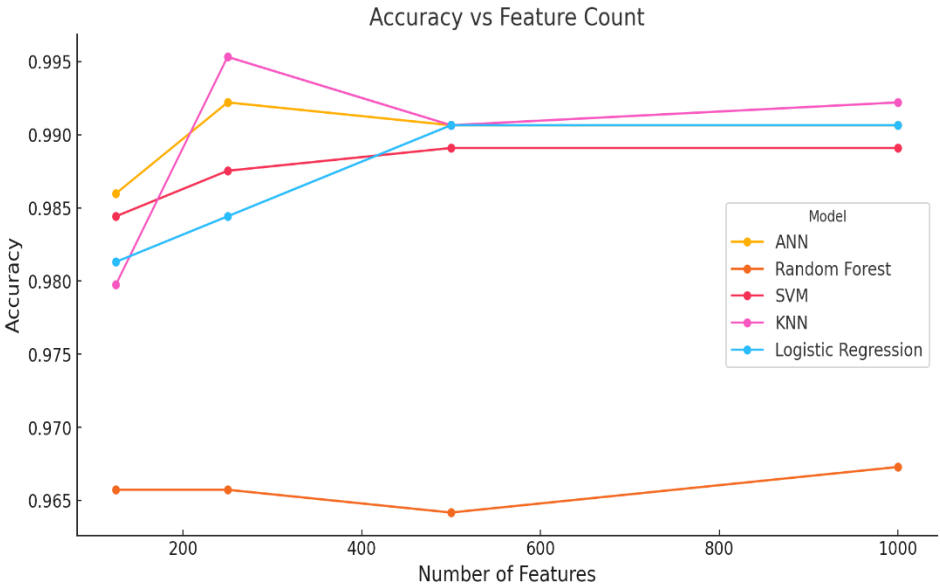


Figure 10 Accuracy Performance Across Classifiers with GW0

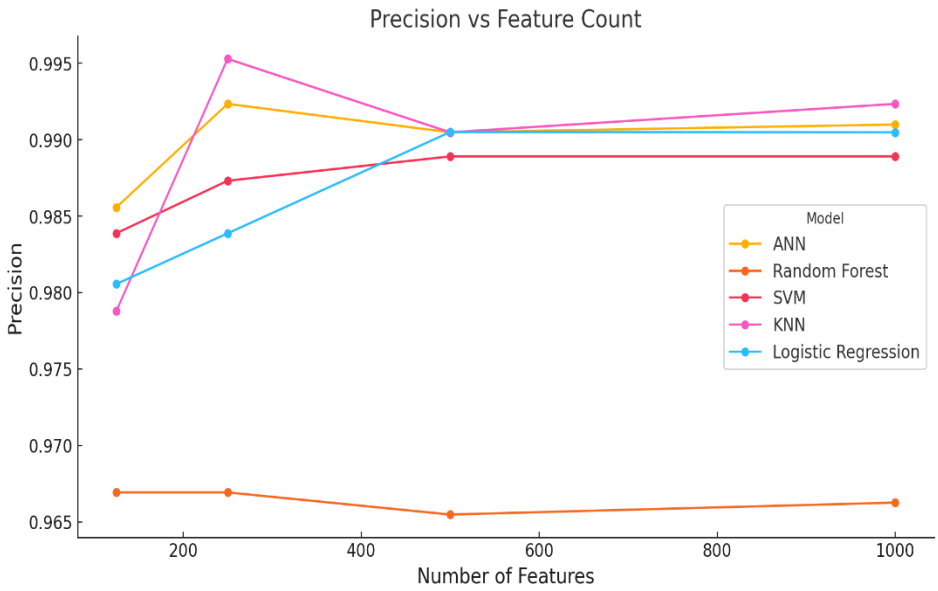


Figure 11 Precision Performance Across Classifiers with GWO

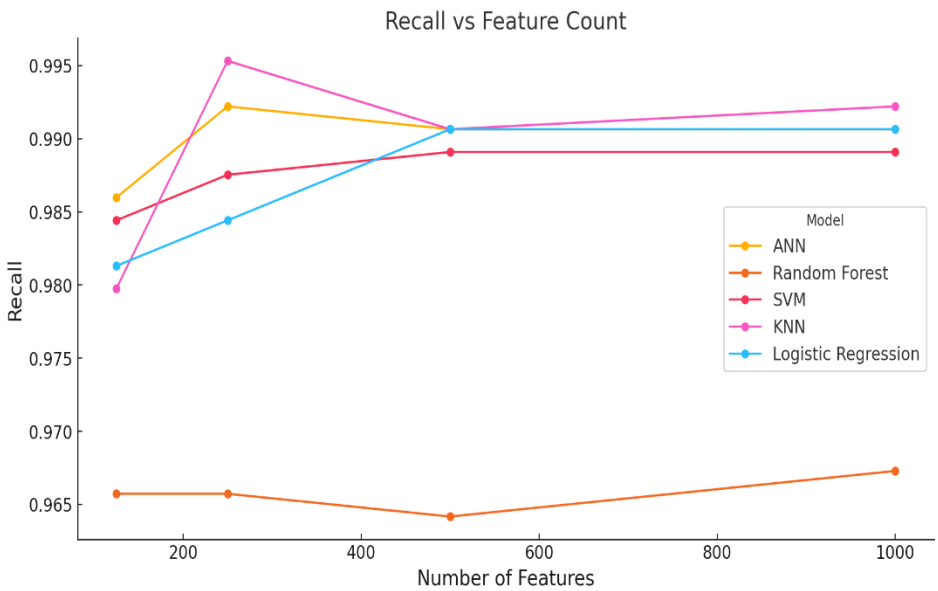


Figure 12 Recall Performance Across Classifiers with GWO

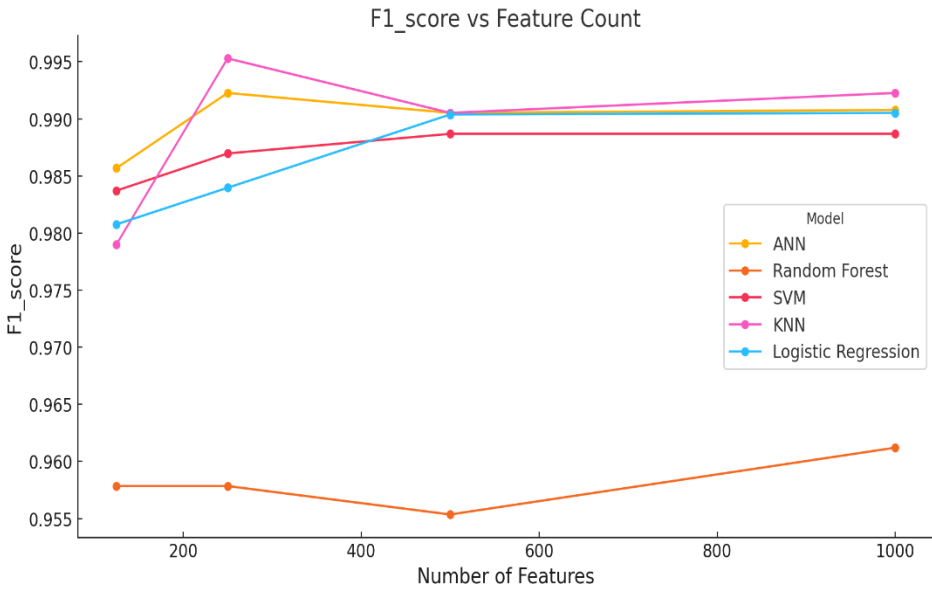


Figure 13 F1-score Performance Across Classifiers with GW0

The graphs provided highlight the performance trends of various classifiers of different feature counts. ANN and KNN have consistently demonstrated high accuracy, sensitivity, recall and F1 scores and have demonstrated stable performance in feature reduction. In contrast, the Random Forest shows a slight decrease in accuracy and F1 score as the feature set decreases, indicating its sensitivity to a decrease in the number of data. Logistic Regression shows similar behaviors, especially in precision and F1 score, where performance decreases with fewer features. The SVM has provided relatively stable performance on all metrics with minor changes. In general, ANN and KNN are emerging as the most reliable models, consistently outperforming other classifiers, regardless of the number of features. This situation shows the importance of their durability and adaptability in classification tasks involving reduced feature sets.

- **SelectKBest** consistently provided strong classification performance, especially for ANN and KNN models, regardless of the number of features. However, the computational time for Random Forest was significantly higher than for other models, highlighting the inefficiency for this classifier.

- **Tree-Based Feature Selection** achieved an outstanding classification accuracy of 99.84% especially for the ANN model on the dataset with the lowest feature count of 125 as the number of features decreased. Random

Forest showed improved precision compared to selectkbest while KNN maintained its robust classification accuracy performance. However, this classifier also required significant computational time. Logistic Regression showed a stable performance across metrics.

- GWO has efficiently optimized the feature set by balancing performance and computational time. ANN and KNN have shown superior accuracy and Formula 1 scores, especially with fewer features. In particular, GWO has shortened the computational time for Random Forest and SVM compared to selectkbest, making it a more computationally efficient choice for feature selection.

Conclusion and Recommendations

This study primarily focuses on the classification of cotton leaf diseases using machine learning algorithms. For feature extraction, the Squeeze Net deep learning model was used, which produces 1000 features per image. Although the distribution between classes is unbalanced, the dataset consists of 2137 images in seven classes. The extracted features were first classified using ANN, RF, SVM, KNN and LR machine learning algorithms. Then, the obtained 1000 features were reduced to 500, 250 and 125 features using three different feature selection methods: SelectKBest, Tree-Based Feature Selection and Gray Wolf Optimization (GWO). The classification processes were then repeated for each reduced feature dataset.

The resulting tables show the performance metrics (accuracy, precision, recall, and F1 score) and execution times for each feature selection method combined with machine learning algorithms. As a result of these observations:

- **Feature Selection Impact:**

- Reducing feature dimensionality improved the efficiency of classification accuracy in most cases without significantly compromising computational performance. This highlights the importance of effective feature selection methods in optimizing model performance and processing times.

- **Performance Comparison:**

- Among the feature selection methods, Tree-Based Feature Selection achieved the highest classification accuracy and precision measurements, demonstrating its robustness, especially with smaller feature sets.

- Performance and computational efficiency were balanced, making it suitable for real-time or resource-constrained applications.
- SelectKBest demonstrated its practicality for speed-first scenarios, providing consistent results with minimal computational requirements.

Algorithm Efficiency:

- KNN and ANN consistently outperformed other algorithms across a variety of feature selection methods and feature sizes, maintaining high accuracy and reliability.
- RF and LR showed minimal sensitivity to feature size reduction, highlighting their reliance on datasets with larger numbers of features for optimal performance.

Recommendations:

- In future studies, class imbalances in the dataset should be addressed to ensure fair and unbiased evaluation of machine learning algorithms and datasets with more balanced class distribution should be created.
- Integration of other advanced feature selection techniques and different hybrid models can be investigated for better classification accuracy and efficiency.
- It is thought that the application of the proposed model and methods in the study to other crop diseases or agricultural datasets can verify their versatility and scalability.
- As a result of the data obtained from the results, utilizing lightweight and efficient methods such as GWO together with robust classifiers such as KNN can provide practical solutions for real-world applications in precision agriculture.

This study underlines the importance of feature selection in improving classification performance and computational efficiency, providing valuable information to advance machine learning applications in agricultural disease management.

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Deep Learning and Machine Learning Approaches for Coffee Leaf Disease Diagnosis

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Introduction

Coffee, one of the most traded crops in tropical regions, is produced by approximately 25 million smallholder farming families worldwide. This production accounts for 80 per cent of the global total. Analyses to 2021 show that Brazil is the world leader in coffee exports, followed by Indonesia and India (Aufar et al., 2023). Coffee is an agricultural product generally produced in low-income countries. It provides an important economic income for these countries. It contributes significantly to export revenues worldwide.

Coffee is one of the most widely consumed beverages worldwide and has a growing market share. However, climate change and sudden changes in environmental conditions lead to the emergence of various diseases in coffee plants, negatively affecting the quality and quantity of production. This situation not only reduces the income of coffee producers but also poses significant economic challenges for the industry. In the agricultural sector, the process of detecting diseases largely relies on human labor, requiring expert individuals to identify diseases in coffee plants, which slows down the process. Moreover, manual inspections are prone to errors, reducing reliability and efficiency. Therefore, there is an increasing need for automated and innovative methods that can detect diseases in coffee plants more quickly, accurately, and reliably. In recent years, automated solutions that combine artificial intelligence techniques with smartphone applications have begun to be used in automated crop protection methods (Esgario et al., 2020).

Related Works

Yaman et al. (2022) utilized deep learning methods for disease detection in agriculture. The DarkNet53 and ResNet101 models achieved the best results. With the proposed method, an accuracy rate of 99.58% was achieved (Yaman & Tuncer, 2022).

Sevli et al. (2022) aimed to improve efficiency in apple farming, reduce losses from diseases, and enhance quality for sustainable agriculture and economy. Using convolutional neural networks (CNN), they classified a dataset of 1,821 samples. The model achieved 98.76% accuracy, and data augmentation was found to improve success (Sevli, 2022).

Ozdemir et al. (2023) aimed to evaluate the effectiveness of deep learning methods in the early detection of rice leaf diseases. They used the Paddy Doctor dataset, which includes 4,160 images of 13 different rice diseases. The Xception model achieved the highest accuracy at 93.37%. The study shows that the models used have great potential for disease diagnosis (Ozdemir, 2023).

Esen et al. (2022) aimed to study diseases on plant leaves using deep learning methods. Various CNN models, including AlexNet, DenseNet, VGG16, ResNet18, and EfficientNet, were used in the study. The VGG16 model achieved the highest accuracy at 94.88%. The dataset was taken from the Mendeley Plant Diseases Dataset, and 39 different plant leaves were analyzed (Esen & Onan, 2022).

Gunes and Topcu (2024) examined the performance of deep learning algorithms in diagnosing plant diseases. Using the ResNet model, they aimed to diagnose diseases and classify symptoms from images of plant leaves. The model achieved an accuracy of 91%, showing its effectiveness in detecting plant diseases (Gunes & Topcu, 2024).

Parraga-Alava et al. (2019) used the RoCoLe dataset, collected via smartphones, to classify plant leaves. Using the InceptionV3 and SqueezeNet models, they achieved accuracy rates of 82.8% and 81.1%, respectively. This study highlights the importance of AI and deep learning methods for detecting plant diseases (Parraga-Alava et al., 2019b).

Tassis et al. (2021) proposed a new CNN architecture to overcome background complexity in field images of coffee plants. Using Mask R-CNN, they achieved 73.90% accuracy in sample segmentation and 71.90% AP in object detection. For semantic segmentation with UNet and PSPNet, they

achieved MIoU results of 94.25% and 93.54%, respectively. While UNet gave slightly better results, PSPNet's ability to mark lesion edges more clearly helped better analyze the transition between lesions and healthy leaves (Tassis et al., 2021).

Simonyan and Zisserman (2014) studied the impact of convolutional network depth on large-scale image recognition tasks. They found that networks with 16-19 layers and 3×3 small filters significantly improved accuracy. They showed that their model took first and second place in the ImageNet Challenge 2014. They emphasized that deep networks performed well on other datasets as well, demonstrating strong generalization and the ability to compete with complex recognition methods. These findings confirm the importance of depth in visual representations and performance improvement (Simonyan & Zisserman, 2014).

Faisal et al. (2023) proposed a hybrid feature fusion approach for early and accurate detection of coffee leaf diseases. In their study, they used MobileNetV3, Swin Transformer, and Variational Autoencoder (VAE) to extract image features, which were then combined using early and late fusion networks. MobileNetV3 was effective in extracting local features, while Swin Transformer captured more distant interactions. The proposed approach achieved an accuracy of 84.29% on the RoCoLe dataset, outperforming individual models. This demonstrates that the hybrid fusion approach is effective for detecting coffee leaf diseases under real-world conditions (Faisal et al., 2023).

Javierto et al. (2021) applied deep learning algorithms to reduce yield losses in Robusta coffee, which makes up a large part of coffee production in the Philippines. In their research, they used YOLOv3 and MobileNetv2 to identify biotic agents on coffee leaves. The model was optimized to perform effectively even with low GPU power. Tests showed that the model achieved 90% accuracy in disease detection, which was made possible by adequate lighting and a homogeneous background (Javierto et al., 2021) .

Dias and Saito (2021) developed a system for segmenting coffee plant images using the JSEG algorithm. They obtained results at four different segmentation scales with window sizes ranging from 9x9 to 65x65. At smaller scales (scale 1), the segments were smaller and colors more homogeneous, while at larger scales, the segments were larger and colors more heterogeneous. For disease detection, scales 1 and 2, where lesions appeared in reddish tones, were found to be more suitable. They suggested that in the

future, neural networks should be trained using normalized histogram values from JSEG segmentation as input, with segments containing disease spots from scales 1 or 2 selected as training samples (de Souza Dias & Saito, 2021).

Lelis et al. (2023) proposed a method using convolutional neural network (CNN) architectures to detect coffee leaf rust disease in the Philippines. They used twenty-five different CNN models, with the best performing models being ResNet101V2, InceptionV3, ResNet50V2, Xception, and DenseNet169. These models achieved training accuracy rates of 92.62%, 96.90%, 93.45%, 98.45%, and 96.79%, respectively. The best test accuracy was achieved by ResNet101V2 with 95.56% (Lelis et al., 2023).

Yasin and Maki (2022) used image processing methods to classify coffee plant diseases. To detect the disease status of leaves, they applied the Color Moments approach in the RGB and YCrCb color spaces to extract color information, and used different angles of the Gray Level Co-occurrence Matrix (GLCM) method to extract texture information. The K-nearest neighbors (KNN) algorithm was used for classification, and the model achieved an accuracy rate of 81.3% (Yasin & Al Maki, 2022).

Chavarro et al. (2023) studied the impact of hyperparameters in classification solutions using transfer learning for coffee leaf rust disease recognition. Their evaluations, based on over 800 trained models, found that the backbone type hyperparameter could affect accuracy by up to 70%, while the optimizer type could make a difference of up to 20%. Learning rate also proved to be an important parameter, varying up to 10% depending on the optimizer and transfer learning network. The study proposed a practical approach with 256-neuron fully connected (FC) layers and shallower models, suggesting that model architectures should be treated as hyperparameters (Chavarro et al., 2023).

Yebasse et al. (2021) used deep learning architectures to classify coffee diseases and analyzed model focus areas with visualization methods (Grad-CAM, Grad-CAM++, Score-CAM). They achieved 98% accuracy on the Robusta coffee leaf dataset, while the traditional approach reached 77% (Yebasse et al., 2021).

Waldamichael et al. (2022) used HSV color space segmentation and transfer learning with a MobileNetV2 architecture to detect coffee leaf diseases. Their proposed HSV segmentation algorithm achieved higher

accuracy than k-means and YCgCr methods, with a 72.13% MIoU and 82.54% F1 score (Waldamichael et al., 2022).

When we look at the literature in general, the success of CNN models in the field of fast and accurate diagnosis of leaf diseases is seen. The compatibility and success of deep learning models such as DarkNet53, ResNet101, Xception and VGG16 in this field have been emphasised.

The main motivation of this study is to speed up the process and increase agricultural productivity by using deep learning and machine learning algorithms for early detection of coffee diseases. The fact that environmental factors cause diseases in plants negatively affects the amount of production and the income of producers, while existing manual methods are time-consuming, error-prone and impractical increases the need for more effective and reliable methods. In this context, deep learning models such as InceptionV3, SqueezeNet and VGG-19 were used in this study to extract features from the photographs in the RoCoLe dataset. The extracted features are classified by various machine learning algorithms such as Logistic Regression, Neural Network, Gradient Boosting, KNN, Naive Bayes, Random Forest, SVM, Tree and AdaBoost. This comprehensive approach aims to determine the most effective methods by comparing the performance of different algorithms in the diagnosis of coffee leaf diseases and aims to contribute to sustainable agricultural practices by increasing productivity in agricultural production.

Materials and Methods

This section presents the methods and steps followed in the implementation of the study in detail. First, the structure and characteristics of the dataset used in the study are introduced. Then, feature extraction methods using deep learning models such as InceptionV3, SqueezeNet, and VGG-19 are discussed. In the study, classification tasks were performed using machine learning algorithms including Logistic Regression, Neural Network, Gradient Boosting, KNN, Naive Bayes, Random Forest, SVM, Tree, and AdaBoost. The performance of these algorithms was comprehensively evaluated using various performance metrics and cross-validation techniques to enhance the reliability of the results. The process flow is shown in Figure 1 as a flowchart.

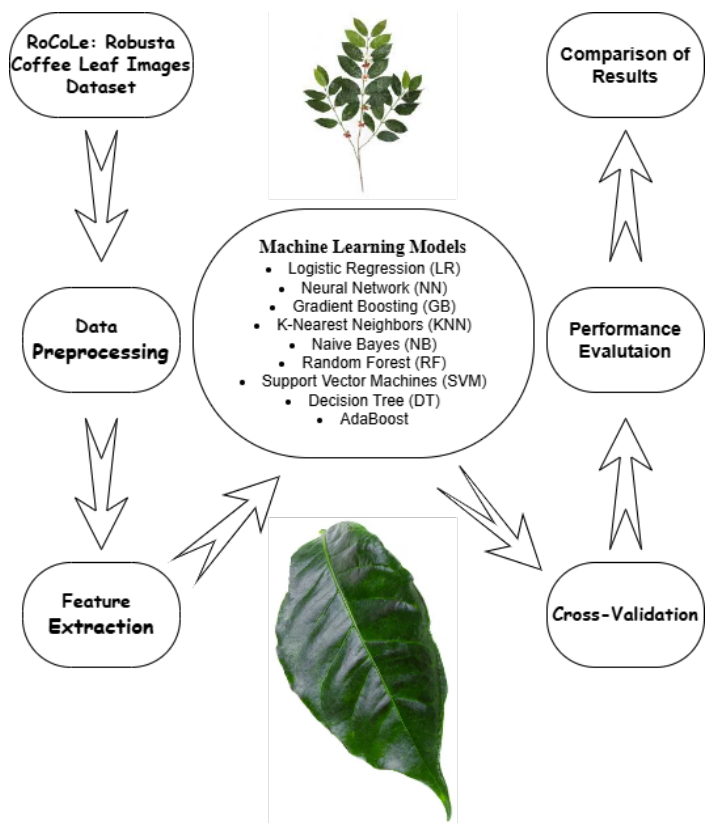


Figure 3. Flowchart.

RoCoLe: a Robusta Coffee Leaf Images Dataset

In this study, the dataset "RoCoLe: A robusta coffee leaf images dataset for evaluation of machine learning-based methods in plant diseases recognition" was used. This dataset, created by Jorge Parraga-Alava, Kevin Cusme, Angélica Loor, and Esneider Santander, consists of images captured in real field conditions using a smartphone camera at the same coffee farm. In the dataset, leaves showing disease symptoms such as red mites and spots are classified as "unhealthy," while leaves without any disease symptoms are classified as "healthy." For each of the 390 coffee plants in the farm, a total of 4 images were included. The dataset contains a total of 1560 images, with 791 images in the "healthy" class and 769 images in the "unhealthy" class (Parraga-Alava et al., 2019a, 2019b). Figure 2 shows the number of photos in the RoCoLe dataset, categorized by class.



Figure 4. RoCoLe: a Robusta Coffee Leaf Images Dataset.

Preprocessing

A) InceptionV3

InceptionV3 is a deep learning architecture, particularly used in large-scale image classification problems (Szegedy et al., 2016). This model was developed by Google and optimized on the ImageNet dataset, featuring a deep network structure composed of multiple layers. It aims to optimize computational costs without increasing depth (Yasin et al., 2023). The core component of the model is the Inception blocks, which allow for the analysis of images at different spatial scales. These blocks perform multiple convolution operations using filters of varying sizes (Dong et al., 2020). InceptionV3 has been enhanced with techniques such as factorized convolutions and label smoothing to make it faster and more efficient. As a result, it achieves higher accuracy rates (Guan et al., 2019).

B) SqueezeNet

SqueezeNet is a convolutional neural network (CNN) architecture developed to make deep learning-based image classification models effective on devices with limited hardware resources, such as mobile and embedded systems (Kursun et al., 2022). Proposed by Iandola and colleagues in 2016, this model aims to achieve high accuracy with significantly fewer parameters (Iandola, 2016). The main feature of SqueezeNet is that it reduces the parameter size of the model by replacing large-sized filters with small-sized filters and reducing the weights (Sayed et al., 2021).

C) VGG-19

A convolutional neural network (CNN) architecture consisting of 19 layers is popular among deep learning-based image classification models. Developed in 2014 by Simonyan and Zisserman, this model aims to provide higher accuracy in image classification by increasing depth (Simonyan & Zisserman, 2014). In the basic structure of VGG-19, a deeper mesh is obtained

by using small convolution filters of size 3x3. ReLU activation function is applied after each convolution process. Thanks to its strong performance, VGG-19 is preferred in many applications such as object recognition, face recognition and similar applications (Mateen et al., 2018; Yildiz et al., 2024).

Machine Learning Algorithms

Machine learning algorithms are statistically and mathematically based methods that make decisions by learning from data and recognising patterns (Alpaydin, 2020). These algorithms are generally divided into two main categories, supervised and unsupervised learning. Supervised learning algorithms are trained with labelled data and are used to classify or predict future data (e.g. logistic regression, support vector machines, decision trees). Unsupervised learning aims to discover patterns in unlabelled data (e.g. k-means such as clustering algorithms). Machine learning algorithms have strong applications in many fields such as medicine, finance, marketing and are effective in solving complex problems with big data (Mahesh, 2020).

A) Logistic Regression-LR

Logistic regression is a statistical model that enables the classification of data into numerical or categorical categories. The model is particularly preferred when the dependent variable is categorical, as it analyzes the probability distribution of the dependent variable to make class predictions (Boateng & Abaye, 2019). Logistic regression uses a linear function similar to linear regression, but this function is restricted to a logistic (sigmoid) function. In this way, the results are estimated as a probability between 0 and 1 (Kursun et al., 2023b; Schober & Vetter, 2021).

B) Neural Network-ANN

Artificial neural networks are multilayer learning models modelled on the biological nervous system. These models transfer information from the input layer to hidden layers and then to the output layer to process data and recognise patterns (Zhu & Bain, 2017). Each link has a specific weight value and these weights are updated throughout the learning process. It represents complex relationships that the model learns from the data. Neural networks are successful in many areas such as image recognition, language processing and classification (Tassis et al., 2021; Yildiz et al., 2024).

C) Gradient Boosting-GB

Gradient Boosting is a machine learning technique that builds a strong model by successively training weak predictors (Natekin & Knoll, 2013). At each step, the model improves its forecasting performance by focusing on reducing previous forecast errors. In this process, each new model learns from the errors of the previous model and is optimised to correct them. Gradient Boosting is an effective method for learning complex data relationships by successively combining simple models such as decision trees (Bentéjac et al., 2021).

D) K-Nearest Neighbors-KNN

K-Nearest Neighbour is a simple and intuitive machine learning algorithm used in classification and regression problems (Zhang et al., 2017). The class of a data point is determined by its k nearest neighbours in space. The KNN algorithm selects the nearest neighbours to classify new incoming data by measuring the distance with respect to the training dataset. The k value representing the number of neighbours is determined. The model assigns the test data point to the appropriate class according to the classes of these k nearest neighbours. KNN is particularly effective in classifying the proximity relationships of labelled instances (Uddin et al., 2022).

E) Naive Bayes-NB

It is a probabilistic machine learning algorithm based on Bayes' theorem and assumes that features are independent of each other. This algorithm evaluates each feature independently. Calculates the contribution of each of them to the class separately (Yang, 2018). Its ability to work flexibly with large datasets makes it a widely used method in practice. For classification purposes, Naive Bayes attempts to assign a given piece of data to the most appropriate class. To perform this operation, the algorithm expresses the combined probability of the features as the product of the prior probabilities and the conditional probabilities, thus solving the classification problem in a probabilistic approach (Calders & Verwer, 2010; Kenan et al., 2023).

F) Random Forest-RF

Random Forest is a machine learning method created by combining multiple decision trees. This method trains each decision tree using a randomly selected subset of data and random features. This increases the generalisability of the model and reduces the risk of overfitting (Schonlau & Zou, 2020). Random Forest is effective in both classification and regression

problems. It gives good results especially on large data sets. Furthermore, the model's transparency in the decision-making process and importance ranking features help users to analyse data (Biau & Scornet, 2016; Koklu et al., 2023).

G) Support Vector Machine-SVM

Support Vector Machines is a powerful machine learning algorithm used in classification and regression analyses. SVM tries to find a hyperplane that best separates the data. In the case of binary classification, this hyperplane is positioned to provide the widest margin between the two classes (Chandra & Bedi, 2021). SVM can transform the data into a higher dimensional space by using kernel functions to be effective in non-linear data sets. This feature makes SVM successful in complex classification problems and gives high accuracy rates in many applications (Abdullah & Abdulazeez, 2021; Yasin et al., 2024).

H) Decision Trees-DT

Decision trees are a simple and intuitive method for classifying or regressing data. This method creates a tree structure by branching the data according to certain features. Each node makes a decision based on a feature, while leaf nodes represent the final classifications (Charbuty & Abdulazeez, 2021). Decision trees can work with both categorical and continuous variables. They are easy to understand thanks to their visualisation of complex relationships. Pruning methods are applied to prevent overfitting (Cengel et al., 2024; Somvanshi et al., 2016) .

I) AdaBoost

AdaBoost (Adaptive Boosting) is a learning method used to build a strong classifier by combining weak learners (Shahraki et al., 2020). This method trains each weak learner sequentially, focusing on correcting the errors of the previous learners. In each cycle, more weight is given to misclassified instances, which allows the model to better learn difficult classes. AdaBoost has delivered high accuracy rates in many applications due to its flexibility and ability to work with a variety of weak learners. Furthermore, by combining the results, it increased generalizability by reducing the risk of overfitting (Wang & Sun, 2021).

Performance Evaluations

Cross Validation

In this study, k-fold cross validation method is used to evaluate the performance of classification algorithms. K-fold cross validation divides the data set into k equal parts and uses one part at a time as test data and the remaining k-1 parts as training data. This process was repeated k times, each part was used as a test set, and finally the accuracy measures of the k separate models were averaged to calculate the overall performance value. This method provided an effective strategy to assess the generalization ability of the model and reduce the risk of overfitting (Kohavi, 1995).

The 10-fold cross-validation used in the study aims to evaluate the model's performance in a more balanced and reliable way by randomly splitting the dataset into 10 parts. This method reduces the risk of overfitting by testing the model on different data segments and ensures a more accurate reflection of classification performance (Blum et al., 1999).

Confusion matrix

In this study, the classification performance of two types of coffee leaf images, "healthy" and "unhealthy", is analysed using confusion matrix. Confusion matrix method evaluates correct and incorrect classification and is important for efficiency (Powers, 2020; Yasin et al., 2023). In Table 1, the classes of the confusion matrix are shown.

True Positive (TP): Correct classification of leaves as "healthy" when their true class is "healthy".

True Negative (TN): Leaves whose true class is "unhealthy" are correctly classified as "unhealthy".

False Positive (FP): Leaves that are actually of the "unhealthy" class but are incorrectly classified as "healthy" (Type I error).

False Negative (FN): Leaves that are actually of the "healthy" class but are incorrectly classified as "unhealthy" (Type II error).

Table 4. Confusion matrix for two classifications.

		Predicted	
		healthy	unhealthy
Actual	healthy	TP	FP
	unhealthy	FN	TN

Performance metrics

They are metrics used to evaluate the performance of a model. These metrics are an indication of the extent to which the system fulfils successfully (Kursun et al., 2023a).

Accuracy: Measures the correct classification rate of the model. It is shown as Equation 1. The ratio of all correct predictions (TP + TN) to the total number of samples (Kursun & Koklu, 2023; Tang et al., 2018).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Recall: It measured the ability of the model to find correct examples in the "unhealthy" class. It is shown as Equation 2. Also used as True Positive ratio (Kursun et al., 2024; Tang et al., 2018).

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

Precision: Measured the proportion of samples that the model categorised as "unhealthy" that were actually correct (Taspinar et al., 2021). It is shown as Equation 3.

$$\text{Precision} = \frac{TP}{TF+FP} \quad (3)$$

F1 Score: Harmonic mean of Recall and Precision, used to measure performance on imbalanced data sets (Kursun et al., 2023; Vapnik, 2013). It is shown as Equation 4.

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \quad (4)$$

Experimental Results

InceptionV3, SqueezeNet and VGG-19 deep learning models were used for feature extraction from the photographs in RoCoLe: A Robusta Coffee Leaf Images Dataset. After each feature extraction model, classification was performed using Logistic Regression (LR), Neural Network (ANN), Gradient Boosting (GB), K-Nearest Neighbors (KNN), Naive Bayes (NB), Random Forest (RF), Support Vector Machine (SVM), Tree (DT) and AdaBoost algorithms. After each feature extraction model, the performance of the algorithms was evaluated with confusion matrices. The results obtained with InceptionV3 are presented in Table 2, the results obtained with SqueezeNet are presented in Table 3, and the results obtained with VGG-19 are presented in Table 4.

Table 2. Confusion matrix of machine learning algorithms after feature extraction with InceptionV3.

InceptionV3									
LogisticRegression					Neural Network				
Actual	Predicted			Σ	Actual	Predicted			Σ
	healthy	unhealthy				healthy	unhealthy		
	healthy	668	123	791		healthy	668	123	791
	unhealthy	145	624	769		unhealthy	152	617	769
	Σ	813	747	1560		Σ	820	740	1560
Gradient Boosting					KNN				
Actual	Predicted			Σ	Actual	Predicted			Σ
	healthy	unhealthy				healthy	unhealthy		
	healthy	658	133	791		healthy	665	126	791
	unhealthy	157	612	769		unhealthy	279	490	769
	Σ	815	745	1560		Σ	944	616	1560
Naive Bayes					Random Forest				
Actual	Predicted			Σ	Actual	Predicted			Σ
	healthy	unhealthy				healthy	unhealthy		
	healthy	594	197	791		healthy	620	171	791
	unhealthy	211	558	769		unhealthy	251	518	769
	Σ	805	755	1560		Σ	871	689	1560
SVM					Tree				
Actual	Predicted			Σ	Actual	Predicted			Σ
	healthy	unhealthy				healthy	unhealthy		
	healthy	568	223	791		healthy	546	245	791
	unhealthy	238	531	769		unhealthy	255	514	769
	Σ	806	754	1560		Σ	801	759	1560
AdaBoost									
Actual	Predicted			Σ	Actual	Predicted			Σ
	healthy	unhealthy				healthy	unhealthy		
	healthy	553	238	791		healthy	553	238	791
	unhealthy	281	488	769		unhealthy	281	488	769
	Σ	834	726	1560					

Table 3. Confusion matrix of machine learning algorithms after feature extraction with SqueezeNet.

SqueezeNet

Neural Network

Predicted

healthy

unhealthy

Σ

Actual

healthy

unhealthy

649

142

791

153

616

769

Σ

802

758

1560

Gradient Boosting

Predicted

healthy

unhealthy

Σ

Actual

healthy

unhealthy

646

145

791

174

595

769

Σ

820

740

1560

Logistic Regression

Predicted

healthy

unhealthy

Σ

Actual

healthy

unhealthy

611

180

791

178

591

769

Σ

789

771

1560

Random Forest

Predicted

healthy

unhealthy

Σ

Actual

healthy

unhealthy

622

169

791

218

551

769

Σ

840

720

1560

KNN

Predicted

healthy

unhealthy

Σ

Actual

healthy

unhealthy

653

138

791

276

493

769

Σ

929

631

1560

Native Bayes

Predicted

healthy

unhealthy

Σ

Actual

healthy

unhealthy

603

188

791

229

540

769

Σ

832

728

1560

AdaBoost

Predicted

healthy

unhealthy

Σ

Actual

healthy

unhealthy

577

214

791

246

523

769

Σ

823

737

1560

Tree

Predicted

healthy

unhealthy

Σ

Actual

healthy

unhealthy

543

248

791

241

528

769

Σ

784

776

1560

SVM

Predicted

healthy

unhealthy

Σ

Actual

healthy

unhealthy

569

222

791

277

492

769

Σ

846

714

1560

Table 4. Confusion matrix of machine learning algorithms after feature extraction with VGG-19.

VGG-19

Neural Network

Predicted

		healthy	unhealthy	Σ
Actual	healthy	649	142	791
	unhealthy	153	616	769
	Σ	802	758	1560

Gradient Boosting

Predicted

		healthy	unhealthy	Σ
Actual	healthy	646	145	791
	unhealthy	174	595	769
	Σ	820	740	1560

Logistic Regression

Predicted

		healthy	unhealthy	Σ
Actual	healthy	611	180	791
	unhealthy	178	591	769
	Σ	789	771	1560

Random Forest

Predicted

		healthy	unhealthy	Σ
Actual	healthy	647	144	791
	unhealthy	217	552	769
	Σ	864	696	1560

KNN

Predicted

		healthy	unhealthy	Σ
Actual	healthy	653	138	791
	unhealthy	276	493	769
	Σ	929	631	1560

Naive Bayes

Predicted

		healthy	unhealthy	Σ
Actual	healthy	603	188	791
	unhealthy	229	540	769
	Σ	832	728	1560

AdaBoost

Predicted

		healthy	unhealthy	Σ
Actual	healthy	577	214	791
	unhealthy	246	523	769
	Σ	823	737	1560

Tree

Predicted

		healthy	unhealthy	Σ
Actual	healthy	543	248	791
	unhealthy	241	528	769
	Σ	784	776	1560

SVM

Predicted

		healthy	unhealthy	Σ
Actual	healthy	569	222	791
	unhealthy	277	492	769
	Σ	846	714	1560

When Table 2 is analysed, it is seen that the models with the highest correct classification rates are Logistic Regression and Neural Network. The high correct classifications in the "Healthy" and "Unhealthy" classes indicate that these algorithms are powerful in terms of disease diagnosis. On the other

hand, it was observed that algorithms such as AdaBoost, which showed low correct classification rates, were less effective with InceptionV3 features.

Table 3 shows that Neural Network and Gradient Boosting algorithms obtained the highest correct classification rates with SqueezeNet feature extraction. These algorithms attracted attention by minimising the error rate between "Healthy" and "Unhealthy" classes. On the other hand, SVM and Tree algorithms were observed to have lower performance.

In Table 4, Neural Network and Gradient Boosting algorithms achieved high correct classification rates with the VGG-19 feature extraction method. On the other hand, the performance of AdaBoost and SVM algorithms remained low compared to other algorithms.

After analysing the confusion matrices, the results are discussed in detail to evaluate the performance metrics and the performance metrics of the features extracted with the InceptionV3 model in machine learning algorithms are presented in Table 5, the metrics of the features extracted with the SqueezeNet model are presented in Table 6 and the results obtained with VGG-19 feature extraction are presented in Table 7.

Table 5. Performance metrics of machine learning algorithms after feature extraction with InceptionV3 model.

InceptionV3				
Model	Accuracy	F1 Score	Precision	Recall
Logistic Regression	0.828	0.828	0.828	0.828
Neural Network	0.824	0.824	0.824	0.824
Gradient Boosting	0.814	0.814	0.814	0.814
KNN	0.740	0.737	0.749	0.740
Naive Bayes	0.738	0.738	0.738	0.738
Random Forest	0.729	0.729	0.732	0.729
SVM	0.704	0.704	0.704	0.704
Tree	0.679	0.679	0.679	0.679
AdaBoost	0.667	0.667	0.668	0.667

Table 5 shows that the Logistic Regression algorithm performs the best with an accuracy of 0.828. Neural Network algorithm shows a success close to Logistic Regression with an accuracy of 0.824. This shows that Logistic Regression and Neural Network algorithms are effective in classification with InceptionV3 feature extraction. On the other hand, AdaBoost (0.667 accuracy) and Tree (0.679 accuracy) algorithms have the lowest performance with InceptionV3 features.

Table 6. Performance metrics of machine learning algorithms after feature extraction with SqueezeNet model.

SqueezeNet				
Model	Accuracy	F1 Score	Precision	Recall
Neural Network	0.811	0.811	0.811	0.811
Gradient Boosting	0.796	0.795	0.796	0.796
Logistic Regression	0.771	0.771	0.771	0.771
Random Forest	0.752	0.752	0.753	0.752
KNN	0.735	0.732	0.742	0.735
Naive Bayes	0.733	0.732	0.733	0.733
AdaBoost	0.705	0.705	0.705	0.705
Tree	0.687	0.687	0.687	0.687
SVM	0.680	0.680	0.681	0.680

When Table 6 is analysed, it is seen that the Neural Network algorithm performs the best with SqueezeNet feature extraction with an accuracy of 0.811. Gradient Boosting algorithm ranks second with an accuracy of 0.796, while Logistic Regression ranks third with an accuracy of 0.771. SVM, AdaBoost and Tree algorithms are found to have a lower performance with 0.680, 0.705 and 0.687 accuracy rates, respectively. Unlike InceptionV3, it is seen that the most successful algorithm is Neural Network and this algorithm provides the highest compatibility with SqueezeNet feature extraction.

Table 7. Performance metrics of machine learning algorithms after feature extraction with VGG-19 model.

VGG-19				
Model	Accuracy	F1 Score	Precision	Recall
Neural Network	0.811	0.811	0.811	0.811
Gradient Boosting	0.796	0.795	0.796	0.796
Logistic Regression	0.771	0.771	0.771	0.771
Random Forest	0.769	0.768	0.771	0.769
KNN	0.735	0.732	0.742	0.735
Naive Bayes	0.733	0.732	0.733	0.733
AdaBoost	0.705	0.705	0.705	0.705
Tree	0.687	0.687	0.687	0.687
SVM	0.680	0.680	0.681	0.680

According to Table 7, the Neural Network algorithm showed the best performance after VGG-19 feature extraction with an accuracy rate of 0.811. The Gradient Boosting algorithm ranked second with an accuracy of 0.796, while Logistic Regression ranked third with an accuracy of 0.771. On the other hand, the performance of AdaBoost (0.705 accuracy) and Tree (0.687 accuracy) algorithms were observed to be low compared to other algorithms. It is noteworthy that the low performance of AdaBoost and Tree algorithms is similarly at the bottom of the results obtained with SqueezeNet and InceptionV3 feature extraction. It is also observed that the most successful algorithm with VGG-19 is Neural Network, which is also consistent with the results obtained with SqueezeNet feature extraction.

Considering the three feature extraction models, it is noteworthy that the Neural Network algorithm has consistently high performance with each model. InceptionV3 and VGG-19 models also provided high accuracy rates

with Logistic Regression and Gradient Boosting algorithms. InceptionV3, in particular, achieved an accuracy of 0.828 with Logistic Regression, providing a strong result in terms of classification. These results indicate that InceptionV3 and Logistic Regression are more suitable methods for the diagnosis of coffee leaf diseases. In addition, AdaBoost and Tree algorithms performed poorly with all feature extraction models, indicating that they are not a suitable alternative for classification.

Discussion

This study classifies diseased and healthy coffee leaves using machine learning algorithms on the RoCoLe dataset. Various performance levels were evaluated after classification and comparison with different machine learning methods using deep learning models such as InceptionV3, SqueezeNet and VGG-19. As a result, it was observed that ANN and LR algorithms reached the highest value and achieved superior success in comparison with other algorithms.

Especially the performance of InceptionV3, LR and ANN is remarkable. In the literature, it is a known fact that InceptionV3 has convolutional designs with proven efficiency. LR showed a superior performance with an accuracy rate of 82.8% and the model was found to be able to handle complex visual data.

Although SqueezeNet, which works with less computation, was developed especially for limited resources, it could not surpass InceptionV3 in terms of overall accuracy. The prominence of ANN and Gradient Boosting algorithms thanks to SqueezeNet features is consistent with the findings of the study regarding the ability of SqueezeNet to maintain its performance.

VGG-19, which is a deeper architecture, provided a high accuracy rate thanks to convolution filters and achieved successful results with Artificial Neural Network (ANN) and Gradient Boosting algorithms. The results show the success of VGG-19 in tasks requiring advanced feature abstraction. In addition, the low performance of AdaBoost and Tree algorithms showed that they are limited in complex and high-dimensional situations.

Compared to existing studies on plant disease, the use of deep learning models in combination with advanced machine learning methods has shown that the classification performance is highly efficient. These findings suggest that feature extraction methods are critical in disease detection tasks and that

results can be optimised by selecting the appropriate classifier. The literature shows that artificial intelligence is becoming increasingly important in precision agriculture to monitor crops and reduce the dependence on human expertise.

As a result of this study, optimising feature extraction methods and using them with deep learning ensemble methods can lead to future research to achieve higher classification performance. In real-world applications, pre-processing techniques such as data augmentation can improve the adaptability of the model to changing environmental conditions.

Conclusions and Recommendations

In this study, the effect of the features extracted by InceptionV3, SqueezeNet and VGG-19 deep learning models on the performance of various machine learning algorithms on the classification of coffee leaf images in the RoCoLe dataset as healthy and unhealthy is investigated. The study has shown that especially LR and ANN algorithms give better results than other algorithms with high accuracy values.

The algorithms with the highest accuracy rates on the features extracted with InceptionV3 were Logistic Regression (Accuracy = 0.828) and Neural Network (Accuracy = 0.824). Similarly, Neural Network showed the highest performance in features extracted with SqueezeNet and VGG-19 (Accuracy = 0.811). Algorithms such as AdaBoost and Tree were less effective in disease classification as they had lower accuracy rates in all three feature extraction models.

In line with these results, it is suggested that using InceptionV3 or VGG-19 models for feature extraction in coffee leaf disease diagnosis and classification with algorithms such as Logistic Regression or Neural Network can improve classification accuracy. In addition, the feature extraction process can be improved by fine-tuning the deep learning models to further improve the classification accuracy.

Recommendations:

1. Since Logistic Regression and Neural Network were successful in the classification of coffee leaf diseases, they can be tried for similar purposes in other datasets.
2. Additional data preprocessing steps, e.g. data augmentation or data balancing methods, may be applied to improve the accuracy of the study.

3. Testing different versions of deep learning models, especially by fine-tuning the parameters that may affect the success of feature extraction, may positively affect the classification performance.

4. In other agricultural applications where classification accuracy is important, the use of similar feature extraction and classification methods can be recommended.

This study has demonstrated the effectiveness of deep learning based feature extraction and machine learning classification methods in the discrimination of healthy and unhealthy coffee leaves, and shows that especially algorithms such as Logistic Regression and Neural Network provide robust solutions with high classification accuracy.

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Robotic Applications in Agriculture

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Agriculture and Agricultural Production

Agriculture and agricultural production is a critical sector that provides a livelihood for millions of people worldwide and is one of the fundamental building blocks of the global economy. Global challenges such as food security, population growth, climate change and sustainable use of natural resources require new approaches for the future of agriculture. In this context, robotic applications in agriculture are becoming increasingly important. Traditional agricultural methods have been carried out with human labor and manual equipment for many years. However, in the last decade, with the rapid development of technology, the agricultural sector has also undergone a significant transformation. In addition to increasing efficiency in agriculture, robotic technologies offer the potential to reduce costs and reduce environmental impacts .

Robotic applications in agriculture enable the automation of production processes, allowing both time saving and minimizing human errors. For example, robotic systems can autonomously perform many agricultural activities such as harvesting, irrigation, fertilization and spraying. With this approach, called precision agriculture, the amount of water, fertilizer and medicine needed by each plant in the field can be determined, thus ensuring more efficient use of resources. This application not only reduces production costs, but also minimizes damage to the environment. The ability of robotic systems to perform soil analysis, diagnose plant diseases early and provide effective solutions in pest control makes the agricultural sector more sustainable by increasing the quality and quantity of production (Wu & Li, 2022).

Harvesting robots have an important place among the robotic systems used in agriculture. Harvesting with traditional methods is largely labor-

based and is a time-consuming and tiring process. Especially the collection of sensitive products such as fruits and vegetables requires attention and care. Robots can determine the most appropriate harvest time by analyzing the maturity level, size and color of plants with the support of sensors and artificial intelligence. In this way, the products are collected at the right time, both quality is preserved and labor costs are reduced. In addition, the harvest process is accelerated and seasonal production limitations are overcome thanks to robots that can work at night.

In addition, drones used in agriculture are also an important part of robotic technologies. Drones facilitate field management by providing large-scale monitoring of agricultural areas. Detailed information about plant health, irrigation requirements and soil conditions can be collected with superior imaging technologies. This information provides important feedback to farmers to increase their productivity and provides optimization in agricultural production. Drones are also used in operations such as fertilization and spraying, allowing precise intervention in designated areas on the field.

One of the biggest advantages of robotic technologies in agriculture is their potential to solve labor problems. The agricultural sector, especially in developed countries, has difficulties in finding labor, which negatively affects production processes. Robotic systems can help overcome this problem by reducing dependence on human labor. At the same time, these technologies can significantly increase agricultural productivity, as they make production processes faster and more consistent (Lytridis et al., 2021).

As a result, the increasing prevalence of robotic applications in agriculture and agricultural production is creating a radical transformation in the sector. Advantages such as increasing efficiency, reducing costs, reducing environmental impacts and ensuring sustainability encourage the use of robotic technologies in agriculture. In the future, with the further development and widespread use of these technologies, the agricultural sector will become more efficient, sustainable and competitive.

There are a number of studies in the literature on agriculture and agricultural production. The most recent of these are given in Table 1.

Table 1. Studies on agriculture and agricultural production

Authors	Study	Year
Ozdemir (Ozdemir, 2024)	Reconsidering agricultural credits and agricultural production nexus from a global perspective	2024
Cihandio et al. (Chandio et al., 2024)	Exploring the energy-climate-agriculture (ECA) nexus: a roadmap toward agricultural sustainability in Asian countries	2024
Yu and Wang (Yu & Wang, 2024)	Ecological agriculture farming models and associated technologies: Current status and prospects	2024
Usigbe et al. (Usigbe et al., 2024)	Enhancing resilience in agricultural production systems with AI-based technologies	2024

Historical Development of Robotic Applications in Agriculture

Agriculture, as one of the oldest and most fundamental activities in human history, has played an important role in shaping the social, economic and cultural structures of societies. With the transition of people to a settled life, agriculture replaced hunting and gathering and paved the way for the emergence of the first great civilizations. The Neolithic Revolution, which began around 10,000 BC, made it possible for people to produce their own food through agricultural production with the birth of agriculture. During this period, human communities first cultivated plants such as wheat, barley and lentils and began to domesticate animals. These developments enabled the formation of a social division of labor and trade for the first time, and also triggered population growth. In ancient times, agricultural activities were largely dependent on natural conditions. With the development of irrigation systems, agricultural production became more regular and efficient. Especially the civilizations around the Nile, Euphrates, Tigris and Indus rivers had large agricultural areas thanks to advanced irrigation techniques. Civilizations such as Ancient Egypt, Mesopotamia, China and India established large cities and established trade networks thanks to the increase in agricultural production. During the same period, agriculture became not only an economic activity but also a central element of religious and social life. Festivals, rituals and ceremonies organized for agricultural gods show the profound impact of agriculture on societies. In the Middle Ages, agriculture was still one of the most important economic activities in European societies. Land ownership, which formed the basis of the feudal system, caused agriculture to become a factor determining the social

structure. During the Middle Ages, significant developments were made in agricultural techniques in Europe, and innovations such as the three-field planting system, heavy plows and water mills increased agricultural productivity. During this period, the vast majority of people living in rural areas in particular made their living from farming, and agriculture continued to be the main source of life for society. At the same time, trade in agricultural products contributed to the growth of cities and the expansion of the economic structure (Lytridis et al., 2021).

With the Industrial Revolution, radical changes took place in agriculture. Starting in the 18th century, production processes became more mechanized with the use of steam power in agriculture. The development of the first tractors and agricultural machines reduced the dependence on human and animal power and significantly increased agricultural productivity. During this period, the use of chemical fertilizers and pesticides in agricultural areas also became widespread. The Industrial Revolution led to the migration of the rural population to cities and to the gradual transformation of agriculture into a more commercial activity. These developments laid the foundations of modern agriculture and contributed to the increase in agricultural production on a global scale. In the 21st century, agriculture became even more modern with the advancement of science and technology. Innovations in fields such as genetic engineering, biotechnology, seed breeding and agricultural robotics transformed agricultural production processes. In this process called the Green Revolution, it was aimed to increase agricultural production capacity, especially in developing countries, and important steps were taken in the fight against hunger. While modern agricultural practices increased productivity, they also brought about concerns about environmental sustainability. The impact of agricultural activities on climate change has become an important agenda item in today's agricultural policies. Today, the agricultural sector is rapidly advancing towards a more efficient and sustainable structure with digital agriculture, precision agriculture and robotic technologies. From past to present, agriculture has continued to exist as a fundamental activity that shapes the economic and social structure of societies (Lioutas, Charatsari, & De Rosa, 2021).

The first agricultural robots emerged towards the end of the 20th century thanks to developing technology and automation systems. Designed to reduce labor costs and increase efficiency in agricultural production, these robots were developed primarily for use in activities such as harvesting,

planting and spraying. The first robotic systems emerged by making mechanical machines generally used on large farms autonomous. In particular, the automatic driving systems of tractors can be considered the forerunners of agricultural robots. These systems were integrated with GPS technology and could move autonomously on determined routes in the fields.

In the 1990s, developments in sensor and imaging technologies made agricultural robots more sensitive and capable. The first harvesting robots were used to collect products such as fruits and vegetables. These robots could harvest at the appropriate time thanks to sensors and image processing software that could analyze the maturity levels of plants. However, robots in this period had limited mobility and low processing power, which made it difficult to use them widely in large-scale agricultural production. The first agricultural robots took an important step in the transformation process of modern agriculture and formed the basis of the advanced robotic systems used today. With developing technologies, these robots have become more sophisticated and effective today (Da Silveira, Lermen, & Amaral, 2021). Various studies have been conducted in the literature throughout history on the development of robotic applications in agriculture. Some of these studies are given in Table 2.

Table 2. Some studies on the development of robotic applications in agriculture.

Authors	Study	Year
Gupta and Gupta (Gupta & Gupta, 2024)	Robotics and Artificial Intelligence (AI) in Agriculture with Major Emphasis on Food Crops	2024
Upadhyay et al. (Upadhyay et al., 2024)	Advances in ground robotic technologies for site-specific weed management in precision agriculture: A review	2024
Raja (Raja, 2024)	Software Architecture for Agricultural Robots: Systems, Requirements, Challenges, Case Studies, and Future Perspectives	2024
Jin and Han (Jin & Han, 2024)	Robotic arms in precision agriculture: A comprehensive review of the technologies, applications, challenges, and future prospects	2024

Advantages of Robotic Applications in Agriculture

Robotic applications in agriculture are among the technological developments that have revolutionized the modern agricultural sector and

provide numerous advantages to the sector. Robotic technologies, which stand out with their benefits such as increasing efficiency, reducing costs and reducing environmental impacts in agriculture, optimize production processes, reduce the workload of farmers and create a more sustainable agricultural model.

One of the biggest advantages of using robotic systems in agriculture is increased productivity. Agricultural robots can work much faster and more accurately compared to human power, and offer more consistent results by minimizing the error rate in constantly repetitive tasks. For example, harvesting robots collect products according to the determined maturity level, preventing both time loss and preserving product quality. This provides producers with higher efficiency and quality. At the same time, agricultural robots have the capacity to work uninterruptedly, thus preventing seasonal labor shortages and enabling 24-hour production.

Another important advantage is reducing costs. Robotic systems significantly reduce labor costs in the long term. While a large number of workers are needed in traditional agriculture, especially in large-scale farms, robotic systems largely eliminate this need. For example, operations such as irrigation, fertilization and spraying can be done more efficiently and accurately by autonomous robots. Robots can apply fertilizer or water only to the required areas of the field, preventing resource waste and minimizing costs. In addition, risks such as health problems and accidents that arise due to human labor are greatly reduced with robotic systems (Cheng, Fu, Su, & Ren, 2023).

The use of robotic technologies in agriculture also has significant environmental advantages. Agricultural robots work with minimal damage to the environment thanks to sensors and artificial intelligence systems. With precision agriculture applications, robots can perform soil analysis to determine how much water, fertilizer or medicine plants need and prevent waste by using only the necessary amount of resources. This ensures more efficient use of natural resources and reduces the negative effects of agricultural activities on the environment. For example, pests can be detected in large areas of fields using autonomous drones, and only the areas where the pest is located are sprayed, preventing unnecessary chemical use. This both contributes to environmental protection and increases product quality.

In addition, robotic systems facilitate data collection and analysis processes in agriculture. Robots can continuously monitor the health, growth

rates and soil conditions of plants in the field and provide the data they collect to farmers instantly. Thanks to this data, farmers can manage their production processes more effectively and make decisions based on data. For example, sensors that constantly monitor soil moisture provide farmers with information about when and how much water should be given, thus optimizing the irrigation process and saving water and growing healthier plants.

As a result, robotic applications in agriculture offer numerous advantages such as increased efficiency, reduced costs, environmental sustainability and data-driven agricultural processes. The further spread of these applications with developing technology triggers a significant transformation in the agricultural sector and opens the door to a more sustainable future. These advantages offered by robotic systems carry great potential for the future of agriculture (Oliveira, Moreira, & Silva, 2021).

Increased productivity in agriculture is a critical factor in terms of both economic and environmental sustainability. The rapid increase in population constantly increases the demand for food, while natural resources remain limited. In order to overcome these challenges, innovative solutions are required to increase efficiency in agricultural production. At this point, the use of robotic technologies in agriculture offers great potential for increasing productivity. With the widespread use of robotic systems in agriculture, it has become possible to produce more using fewer resources, which has significantly increased productivity.

One of the biggest factors in the increase in productivity in agriculture is the automation of work processes by robots. While many processes in traditional agricultural methods rely on human power, these processes can now be done faster, more consistently and uninterruptedly thanks to robotic systems. For example, processes such as planting and harvesting can take hours or days with human power, while agricultural robots can complete these tasks in a much shorter time. Autonomous harvesters can analyze the maturity levels of plants and ensure that harvesting is done at the most appropriate time, thus minimizing product losses and accelerating the production process. Similarly, robotic planters optimize growth conditions and increase productivity by planting seeds at the most ideal depth and spacing. Another important dimension of the increase in productivity provided by robots in agriculture is the optimization of resource use. Agricultural robots prevent waste by precisely managing processes such as

irrigation, fertilization and spraying. Precision agricultural applications, thanks to sensors and satellite imaging systems, can determine the amount of water and nutrients each plant in the field needs and only intervene in the necessary areas. In this way, agricultural inputs such as water, fertilizer and medicine are not wasted, both costs are reduced and negative impacts on the environment are reduced. For example, thanks to sensors that measure the humidity level on a field, only the dry areas are irrigated, saving water and preventing plants from being exposed to water stress. This method plays a critical role in increasing agricultural productivity, especially in regions where water is scarce (B. Zhang, Xie, Zhou, Wang, & Zhang, 2020).

In addition, agricultural robots increase efficiency in data collection and analysis processes. Robotic systems provide farmers with real-time data by constantly monitoring the growth process of plants, soil structure and weather conditions. This data offers farmers the opportunity to manage their production processes in a more conscious and optimized way. For example, sensors that monitor plant health provide farmers with early warnings when disease symptoms appear in plants, shortening the intervention time and preventing yield losses. In addition, thanks to this data, farmers can instantly learn how much water or fertilizer each plant needs and use resources in the most efficient way.

Increased productivity also reduces dependence on labor. Agricultural robots speed up production processes by minimizing the need for manpower in repetitive and difficult tasks. Especially in periods or regions where there is a labor shortage in the agricultural sector, robotic systems contribute greatly to solving this problem. With their ability to work uninterruptedly 24 hours a day, robots eliminate seasonal or time limitations, making the production process continuous and taking agricultural productivity to higher levels. As a result, productivity increases in agriculture are provided by factors such as automation, resource use optimization, data analytics and labor efficiency offered by robotic technologies. These technologies not only produce more products, but also contribute to sustainable agricultural practices by using resources more effectively. These innovative approaches that increase productivity will shape the future of agriculture and play a key role in ensuring food security worldwide (Kulkarni, Dhanush, Chetan, Gowda, & Shrivastava, 2020). Some of the studies on the contributions of robotic applications in agriculture are shown in Table 3.

Table 3. Studies on the advantages of robotic applications in agriculture

Authors	Study	Year
Bale et al. (Bale, Varsha, Naidu, Vinay, & Tiwari, 2024)	Autonomous Aerial Robots Application for Crop Survey and Mapping	2024
Papadopoulos et al. (Papadopoulos et al., 2024)	Economic and Environmental Benefits of Digital Agricultural Technologies in Crop Production: A review	2024
Shvets et al. (Shvets, Morkovkin, Basova, Yashchenko, & Petrusevich, 2024)	Robotics in agriculture: Advanced technologies in livestock farming and crop cultivation	2024
Hu et al. (Hu et al., 2025)	Transforming Agriculture with Advanced Robotic Decision Systems via Deep Recurrent Learning	2024

Robotic Technologies Used in Agriculture

Robotic technologies used in agriculture are among the innovations that make significant contributions to the transformation of modern agriculture. Developed to increase efficiency in agricultural production, optimize labor, and support environmental sustainability, these technologies are spread over a wide range and are used in many different tasks. Agricultural robots are involved in almost every stage of agriculture, from harvesting to planting, from irrigation to fertilization, speeding up processes and providing a more precise production opportunity.

One of the most common robotic technologies is harvesting robots. These robots are used especially in the collection of products such as fruits and vegetables. Harvesting with traditional methods is both time-consuming and labor-intensive. However, harvesting robots can detect the maturity level of plants thanks to sensors and image processing systems and collect only the products to be harvested. In this way, product loss is minimized and the harvesting process is much faster. Preventing human-made errors, especially in sensitive products, also increases the quality of the products.

Another important robotic technology is autonomous tractors and planting machines. Equipped with GPS and artificial intelligence technologies, these machines move autonomously in the field and perform planting and other agricultural operations. Autonomous tractors can operate on specified routes without human intervention and place seeds in the soil in the most efficient way. Thanks to these machines, seeds are planted at the ideal depth and frequency determined, optimizing the growth conditions of

the plants. In addition, planting machines can determine the most appropriate planting time by taking into account the soil structure and weather conditions. Thus, productivity and product quality are increased while labor costs are also reduced. Spraying and fertilizing robots used in agriculture are also among the important innovations. Since traditional spraying and fertilizing methods are largely based on human power, pesticides or fertilizers are usually applied to the entire agricultural area. However, robots can detect the needs of the plants through sensors and apply pesticides or fertilizers only to the necessary areas. This both reduces chemical use and prevents plants from being damaged by unnecessary chemicals. At the same time, costs are reduced and negative effects on the environment are minimized. Drone technology is frequently used in this field in particular. Drones provide speed and efficiency by spraying from the air in large areas of the field (Upadhyay et al., 2024).

Irrigation robots are also widely used in agriculture. Smart irrigation systems measure the water needs of plants through sensors and save water by irrigating only the areas where it is needed. This technology is of critical importance for sustainable agricultural practices, especially in regions where water resources are limited. Thanks to soil moisture sensors and environmental data collection capabilities, robots use water most efficiently and prevent plants from experiencing water stress.

In addition, agricultural robots are also used in soil analysis and data collection processes. Equipped with sensors and imaging systems, these robots can continuously monitor the structure of the soil in the field, the growth rate of plants, their health status and environmental conditions. This collected data offers farmers the opportunity to optimize their production processes. In this way, it is determined how much fertilizer or water each plant needs and resources are used more effectively.

As a result, robotic technologies used in agriculture offer great advantages in terms of increasing efficiency, reducing costs and minimizing environmental impacts. Technologies such as harvesting robots, autonomous tractors, irrigation and spraying robots are revolutionizing agricultural production and shaping the sustainable agricultural practices of the future. The spread of these technologies makes agricultural production smarter, more efficient and more environmentally friendly, and offers important solutions in terms of food security and resource management (Rahmadian & Widyartono, 2020).

Drone technology in agriculture stands out as an important innovation that revolutionizes modern agricultural practices. Drones have a wide range of uses as versatile tools that provide speed, efficiency and precision in agricultural activities. In particular, their roles in processes such as field management, plant health monitoring, spraying, fertilizing and irrigation contribute greatly to optimizing agricultural production. Drones offer significant advantages to farmers with the efficiency and resource savings they provide in agriculture.

One of the most important functions of drones is field management. Since drones are equipped with high-resolution cameras and sensors, they can collect detailed images over large areas. These images can be used to analyze the growth status, health status, and environmental conditions of plants. For example, thanks to the data collected by drones, signs of disease or the presence of pests in plants can be detected at an early stage. This allows farmers to intervene in a timely manner, preventing yield losses. In addition, this data can be collected to create a field map, so farmers can determine which areas require more maintenance. The use of drones in spraying and fertilizing processes also increases the effectiveness of agricultural applications. In traditional methods, drug and fertilizer applications are usually made to the entire field area. However, drones can determine the needs of the plants and apply drug or fertilizer only to the necessary areas. This precise application both prevents the waste of agricultural inputs and minimizes environmental impacts. Drones reach a wider area of the fields with the spraying operations they perform from high altitudes, providing an effective and fast solution. In addition, the air flow provided over the field allows better distribution of pesticides and effectively targets pests on the plants .

Another advantage of drones is their contribution to irrigation planning. Drones integrated with smart irrigation systems can accurately determine the need for irrigation by monitoring soil moisture levels. Drones detect moisture differences in the field and offer the opportunity to irrigate only the dry areas. In addition to saving water, this prevents plants from experiencing water stress and supports their healthier growth. Such applications are of critical importance for sustainable agriculture, especially in regions where water resources are limited.

The advantages provided by drone technology in agriculture are not limited to efficiency and cost savings. Their capabilities in data collection and

analytics allow farmers to make more informed decisions. Drones regularly collect aerial photographs and data to monitor plant health and provide farmers with analyses. This data helps farmers determine which plants in their fields need more attention and which areas need to be developed. Especially in large farms, this information provided by drones offers a great opportunity to optimize production processes.

As a result, drone technology in agriculture has great potential in terms of increasing productivity, using resources more effectively and minimizing environmental impacts. The advantages they provide at every stage of agricultural production contribute to making agricultural practices smarter and more sustainable. Drones, as an important tool shaping the future of modern agriculture, provide a revolutionary transformation in the agricultural sector by offering farmers more efficient, faster and environmentally friendly production methods. This technology plays a critical role in ensuring food security and increasing agricultural sustainability (Botta et al., 2022). Some studies on robotic technologies used in agriculture are given in Table 4.

Table 4. Studies on robotic technologies used in agriculture

Authors	Study	Year
Warbhe et al. (Warbhe, Verma, & Rewatkar, 2024)	A Review on the Use of AI and Robotics in Agricultural Practices	2024
Zhang (Q. Zhang, 2024)	Opinion: Agricultural Robotics, issues worthy to study	2024
Yun et al. (Yun, Sheng, & Zhang)	Advanced Sensing and Robotics Technologies in Smart Agriculture	2024
Rehman et al. (Rehman et al., 2024)	Smart agriculture technology: An integrated framework of renewable energy resources, IoT-based energy management, and precision robotics	2024

Development of Robotic Applications in Agriculture

The future of robotic applications in agriculture is shaped by the combination of technological developments and agricultural needs. The rapid increase in the population, the continuous increase in food demand and the limited natural resources increase the need for innovative solutions in agricultural production. In this context, the integration of robotic technologies into agriculture constitutes the cornerstone of sustainable and

efficient agricultural applications. In the coming years, agricultural robots are expected to become more widespread and take on more complex tasks.

In the future, autonomous robots and drones will become more prevalent in the field of agriculture. Autonomous tractors and harvesters will reduce the dependency on labor by working independently in the fields thanks to GPS and artificial intelligence-supported systems. These robots will be used effectively in many stages from planting to harvesting and will save farmers time. In particular, the operation of autonomous machines will enable more accurate and efficient agricultural applications and reduce production costs. However, the widespread use of such technologies may also cause changes in the labor market. Farmers will need more technical knowledge and training in the management of robotic systems.

In addition, precision agriculture applications will be further strengthened by robot technologies in the future. Sensors and satellite imaging systems allow continuous monitoring of fields, while robots will use this data to precisely perform operations such as irrigation, fertilization and spraying according to the needs of the plants. This will not only prevent waste of resources, but also minimize environmental impacts. For example, robots that monitor plant health will detect disease symptoms early and warn farmers, thus preventing yield losses with early intervention. Artificial intelligence and machine learning play an important role in the development of agricultural robots. In the future, the impact of these technologies on the analysis and management of agricultural data will increase. Robots will analyze the data they collect, provide suggestions to farmers and make agricultural decision-making processes more efficient. For example, it will be possible to optimize production by developing irrigation and fertilization strategies specific to plant species. In addition, artificial intelligence-supported systems will make production planning smarter by taking into account external factors such as climate change (Botta et al., 2022).

In the future of robotic applications in agriculture, sustainability and environmental protection will also have an important place. The protection of natural resources will become one of the biggest priorities of agriculture in the future. Robots will play an important role in reducing environmental impacts in agricultural production. For example, precision irrigation systems that save water and spraying robots that minimize chemical use will support environmentally friendly agricultural practices.

As a result, the future of robotic applications in agriculture will be shaped by technological advances and sustainability goals. The spread of autonomous systems, the development of precision agricultural applications and the integration of artificial intelligence will make agricultural production more efficient, sustainable and environmentally friendly. This transformation is of critical importance both in terms of ensuring food safety and protecting natural resources. The future of robotic technologies in the agricultural sector will increase the quality of life of farmers and play an important role in meeting the food demand worldwide (Chunjiang, Beibei, Jin, & Qingchun, 2023). Some studies on the development of robotic technologies used in agriculture are given in Table 5.

Table 5. Studies on the development of robotic technologies used in agriculture

Authors	Study	Year
Padhiary et al. (Padhiary, Kumar, & Sethi, 2024)	Navigating the Future of Agriculture: A Comprehensive Review of Automatic All-Terrain Vehicles in Precision Farming	2024
Balyan et al. (Balyan et al., 2024)	Seeding a Sustainable Future: Navigating the Digital Horizon of Smart Agriculture	2024
Barua et al. (Barua, Bhowmik, Banerjee, & Banerjee, 2024)	The Emerging Advancement of Robotics in the Modern Agriculture Field	2024
Mac et al. (Mac, Nguyen, Dang, Nguyen, & Nguyen, 2024)	Intelligent agricultural robotic detection system for greenhouse tomato leaf diseases using soft computing techniques and deep learning	2024

Artificial Intelligence and Machine Learning in Agriculture

Artificial intelligence (AI) and machine learning (ML) are revolutionizing the agricultural sector. These technologies have a number of advantages, such as increasing agricultural productivity, using resources more efficiently, and supporting environmental sustainability. While artificial intelligence is a field that enables computer systems to gain human-like thinking and learning abilities, machine learning is a branch of AI that allows computers to improve their performance by learning from data. These two fields are emerging as powerful tools for data analysis, decision-making processes, and automation applications in agriculture.

One of the most obvious examples of AI and machine learning applications in agriculture is precision agriculture applications. These

applications analyze soil and plant data, allowing farmers to determine the most appropriate irrigation, fertilization, and spraying schedules. For example, data on soil moisture, weather, plant health, and productivity are analyzed using machine learning algorithms. The results obtained from this data help farmers make more informed and efficient decisions, thus optimizing resource use and reducing costs (Shaikh, Rasool, & Lone, 2022).

Image processing techniques are another important advantage of AI and machine learning in agriculture. Drones and satellite imaging systems collect high-resolution images of fields, while AI algorithms can analyze these images to assess plant health. Diseases, pests, or water stress are detected at an early stage with image processing techniques. Thus, farmers can intervene in a timely manner and prevent yield loss. In addition to reducing harvest losses in agriculture, this also contributes to increasing product quality. Artificial intelligence and machine learning also play an important role in agricultural forecasting and planning processes. Climate change is a significant factor affecting agricultural production, and this can lead to uncertainties in farmers' production planning. AI-supported systems can analyze past data to predict future weather conditions and help develop production strategies in line with this information. For example, machine learning models that combine climate data with soil properties can be used to determine under which conditions a crop will grow best. In this way, farmers can optimize their production by determining the most appropriate planting time and strategies.

Autonomous systems are another example of the integration of AI and ML. When equipped with AI algorithms, autonomous tractors, irrigation systems, and harvesters can operate independently without human intervention. These systems can move autonomously within the field, monitor plant health, and perform agricultural operations using GPS and sensor data. This reduces farmers' workload while making agricultural processes faster and more efficient.

As a result, AI and machine learning stand out as powerful tools that increase productivity, reduce costs, and support environmental sustainability in agriculture. The integration of these technologies makes agricultural practices smarter, allowing farmers to make more informed decisions. The use of AI and ML in agriculture will shape not only today but also future agricultural production and play a critical role in ensuring food security. This transformation has the potential to provide sustainable

solutions to meet the world's food needs while improving the quality of life of farmers (Ben Ayed & Hanana, 2021). Some studies on AI and machine learning in agriculture are given in Table 6.

Table 6. Studies on AI and machine learning in agriculture

Authors	Study	Year
Espinel et al. (Espinel, Herrera-Franco, Rivadeneira García, & Escandón-Panchana, 2024)	Artificial Intelligence in Agricultural Mapping: A Review	2024
Hamed et al. (Hamed et al., 2024)	Artificial Intelligence in Agriculture: Enhancing Productivity and Sustainability	2024
Hernandez et al. (Hernandez, Pasha, Yusuf, Nurfaizi, & Julianingsih, 2024)	The role of artificial intelligence in sustainable agriculture and waste management: Towards a green future	2024
Kashyap et al. (Kashyap et al., 2024)	Revolutionizing Agriculture: A Comprehensive Review of Artificial Intelligence Techniques in Farming	2024

Benefits and Challenges of Robotic Applications in the Agricultural Sector

Robotic applications in the agricultural sector have great potential to increase the efficiency of agricultural production, reduce costs and achieve sustainability goals. Autonomous tractors, robotic harvesters, drones and other robotic technologies allow farmers to work more effectively by optimizing agricultural processes. One of the biggest benefits of these applications is that they reduce the need for labor. Especially in rural areas, farmers who have a labor shortage can perform agricultural operations more quickly and effectively with robotic systems. In addition, the precise applications provided by robots allow for more efficient use of resources; this includes situations such as optimizing the use of water and fertilizer. For example, thanks to robotic systems, irrigation operations can be automatically adjusted according to the needs of the plants, which saves water. In addition, robots help detect diseases and pests in the fields. Thanks to advanced sensors and image processing technologies, the health status of the plants can be regularly monitored and potential problems can be detected at an early stage. This helps farmers prevent yield loss by intervening in a timely manner. However, the adoption of robotic applications in agriculture also brings some challenges. First of all, the initial costs can be quite high. The

cost of purchasing, installing and maintaining autonomous systems can be a serious obstacle, especially for small-scale farmers. In addition, the lack of training and knowledge required for technology adoption is also a significant challenge. Farmers need to be knowledgeable about technology in order to use robotic systems effectively. This may prevent some farmers from adopting these new technologies. A second challenge is technological dependency. The dependence of agricultural production on robotic technologies can create uncertainty about how farmers will proceed in cases such as natural disasters, technical failures or software errors. For example, if an autonomous tractor breaks down, farmers run the risk of having their work processes stopped or disrupted. In addition, the environmental impacts of robots should be considered. For example, excessive mechanization can cause changes in soil structure, which can affect productivity in the long term (Cheng et al., 2023).

Finally, the social impacts of adopting robotic applications on agricultural communities should also be considered. Some farmers may be concerned about the impact of robotics on the workforce, which may create social unrest. The widespread use of robotics in agriculture may lead to changes in the agricultural workforce, which may affect the economic structure in rural areas. However, the productivity gains and sustainable practices provided by robotics may contribute significantly to the development of the agricultural sector in the long term.

In conclusion, the benefits and challenges of robotic applications in the agricultural sector constitute an important balance for the future of farmers and the agricultural sector. While robotics have the potential to provide efficiency, cost savings and environmental sustainability in agricultural production, challenges such as high costs, training requirements and social impacts should also be considered. The successful integration of robotic applications in agriculture will be possible by maximizing these benefits and minimizing the challenges.

The environmental impacts of robotic applications in agriculture play a critical role in achieving sustainable agriculture. While robotics have the potential to reduce environmental impact by optimizing agricultural production processes, they may also bring some negative impacts. First of all, robotic applications offer significant advantages in optimizing water and fertilizer use. Autonomous irrigation systems and precision fertilization technologies minimize resource waste by adjusting water and fertilizer

supplements according to the needs of the plants. This contributes to the conservation of water resources and helps maintain the nutrient balance of the soil. In this way, sustainability in agricultural production can be achieved while negative impacts on the environment can be reduced. In addition, robots allow the use of chemicals such as pesticides and herbicides to be reduced. Advanced sensor and imaging technologies can continuously monitor plant health and detect diseases and pests at an early stage. In this way, chemicals used in agriculture are applied only when necessary. This application both reduces the amount of chemicals harmful to the environment and is important for protecting biodiversity. For example, the habitats of insects, which are natural enemies of pests, are protected, which helps the ecosystem to remain balanced (Ghobadpour, Monsalve, Cardenas, & Mousazadeh, 2022).

However, robotic applications also have some negative environmental effects in agriculture. Excessive mechanization can negatively affect the physical structure of the soil. The continuous use of heavy machinery can lead to soil compaction, which reduces the ability of water to penetrate the soil and increases the risk of erosion. In addition, intensive machinery use can cause a decrease in soil organic matter, which threatens soil health in the long term.

Energy consumption is another important factor contributing to environmental effects. The use of robotic systems can increase energy needs. Especially fossil fuel-powered machines can have negative effects on climate change by increasing greenhouse gas emissions. However, electrically powered robots should also be carefully planned in terms of energy consumption. The integration of renewable energy sources is an important step to overcome this problem; however, this transition process needs to be accelerated.

In addition, the waste management problem that arises with the use of robotic technologies should also be taken into account. Robots used in agriculture may lose their functionality or become obsolete after a certain period of time. This situation can lead to an increase in electronic waste and this waste can harm the environment. Effective management of robot recycling processes is critical to reducing environmental impacts (Pramod, 2022).

As a result, the environmental impacts of robotic applications in agriculture are an important component of achieving sustainable agriculture. While optimization of water and fertilizer use provides positive effects such

as reducing chemical substances and protecting biodiversity, negative effects such as excessive mechanization, energy consumption and waste management should also be taken into account. Achieving this balance is necessary for the development and implementation of environmentally friendly agricultural practices. Sustainable use of robotic technologies in the agricultural sector will both reduce environmental impacts and increase the efficiency of food production (Chunjiang et al., 2023). Some studies on the benefits and challenges of robotic applications in the agricultural sector are given in Table 7.

Table 7. Studies on the benefits and challenges of robotic applications in the agricultural sector

Authors	Study	Year
Bagargani and Deemyad (Bazargani & Deemyad, 2024)	Automation's impact on agriculture: opportunities, challenges, and economic effects	2024
Saha et al. (Saha, Ghimire, Manik, Tiwari, & Imran, 2024)	Exploring Benefits, Overcoming Challenges, and Shaping Future Trends of Artificial Intelligence Application in Agricultural Industry	2024
Sahoo et al.(Sahoo, Kushwaha, Pradhan, & Kumar)	Advancements and Challenges in Agri-Robots in India	2024
Hamed et al. (Hamed et al., 2024)	Artificial Intelligence in Agriculture: Enhancing Productivity and Sustainability	2024
Das (Das, 2024)	Transforming Agriculture: Harnessing Robotics and Drones for Sustainable Farming Solution	2024

Economic Impacts of Robotic Applications in Agriculture

The economic effects of robotic applications in agriculture are of great importance in terms of modernizing agricultural production and increasing productivity. The integration of robotic technologies into agriculture has the potential to reduce costs and increase total productivity while ensuring the efficient use of labor. First of all, robotic applications reduce labor costs and ease the economic burden of farmers. In traditional agricultural methods, labor employment constitutes a significant cost item. Autonomous tractors, robotic harvesters and other automation systems reduce dependence on manpower, allowing agricultural processes to be carried out more quickly and efficiently. This increases the productivity of farmers, especially in regions with labor shortages, and increases their total income. Another economic advantage provided by robotic systems is increased productivity. Autonomous systems continuously monitor and analyze plant health with

precision agricultural applications. In this way, farmers can better determine the needs of plants and optimize irrigation, fertilization and pesticide applications. For example, robotic irrigation systems that can make automatic adjustments according to the water and nutrient needs of plants reduce water consumption and increase efficiency. Thus, it offers the opportunity to obtain more products with less resources. In addition, early detection of diseases and pests minimizes harvest losses and increases farmers' economic gains. Robotic applications in agriculture also help balance seasonal labor demands by increasing the speed of agricultural production processes. For example, the use of robotic technologies to meet the increased labor demand during harvest periods both speeds up the production process and reduces farmers' labor costs. This provides a significant advantage, especially for farmers who are dependent on seasonal labor. The integration of robots ensures that agricultural production takes place in a continuous cycle, which makes farmers' annual incomes more predictable (Lowenberg-DeBoer, Huang, Grigoriadis, & Blackmore, 2020).

However, the adoption of robotic technologies requires high initial investments. The cost of autonomous systems may be a barrier for small and medium-sized farmers. However, the cost savings and increased efficiency they provide in the long term can offset these initial investment costs. In addition, the development of robotic technologies in agriculture contributes to the creation of new job opportunities. Companies specializing in areas such as robot design, production and maintenance can contribute to economic growth by creating employment opportunities.

The economic impacts of robotic applications in agriculture are not limited to individual farmers; they also affect the general structure of the agricultural economy. The spread of robotic technologies has a significant impact on the sustainability and competitiveness of agricultural production. This contributes to the increase in the market value of agricultural products, ensuring food security and increasing the capacity of the agricultural sector to compete in international markets (Gil, Casagrande, Cortés, & Verschae, 2023).

As a result, the economic impacts of robotic applications in agriculture offer many advantages such as increased productivity, reduced costs and the creation of new job opportunities, while also facing challenges such as the high initial investments required. When these challenges are overcome, robotic technologies can transform agricultural production, improve the economic situation of farmers and contribute to the sustainability of the

agricultural sector. The adoption of robotic applications in agriculture stands out as a strategy that will provide long-term benefits for both individual farmers and the agricultural economy. One of the most important economic advantages of robotic applications in agriculture is cost reduction. In traditional agricultural methods, labor, time and resource use are important cost elements. However, robotic systems allow farmers to run a more economical production process by greatly reducing these cost items. In particular, the reduction of dependence on human labor provides great savings for agricultural enterprises. For example, autonomous tractors and robotic harvesters can complete operations that require hours of manual labor in a much shorter time. This reduces labor costs and increases efficiency in agriculture.

In addition, robotic applications allow for more efficient use of resources. In particular, precise application of agricultural inputs such as water and fertilizer minimizes waste. Robotic systems continuously monitor and analyze the needs of plants and provide only the required amount of water and fertilizer. This offers significant benefits both environmentally and economically. Efficient use of resources helps farmers increase their profit margin by reducing input costs (Uwaoma et al., 2023).

In addition, maintenance and repair costs of robots are generally low compared to initial investment costs. Robotic agricultural machines require less maintenance in the long term and have high production capacity. As a result, operating costs are reduced and the production process continues continuously and uninterruptedly. All these factors clearly reveal the cost-reducing effects of robotic technologies in agriculture and offer economic advantages to farmers in the long term. Some studies on the economic effects of robotic applications in agriculture are given in Table 8.

Table 8. Studies on the economic effects of robotic applications in agriculture

Authors	Study	Year
Mana et al. (Mana et al., 2024)	Sustainable AI-Based Production Agriculture: Exploring AI Applications and Implications in Agricultural Practices	2024
Sharma et al. (A. Sharma et al., 2024)	Exploring the Role of Robotic Automation in Climate Vulnerability Mitigation: Towards Sustainable Horticulture	2024
Armanini et al. (Armanini et al., 2024)	Soft robotics for farm to fork: applications in agriculture & farming	2024

Social Impacts of Robotic Applications in Agriculture

The social impacts of robotic applications in agriculture lead to a wide range of changes and transformations from rural areas to urban centers. The integration of robotic technologies into the agricultural sector has profound effects on the workforce, education, rural economies and social structures. One of the most obvious social impacts of these applications is the changes they create on the agricultural labor market. Many people working in traditional agricultural jobs may worry about losing their jobs when robots come into play. Especially in rural communities that rely on agricultural workers, this situation can lead to economic and social imbalances along with a decrease in income sources. However, this transformation can also create new job opportunities and areas that require skills. New lines of work specializing in technical tasks such as maintenance, programming and development of robots may emerge, which can increase the quality of the rural workforce (Ryan, 2023).

The widespread use of robotic technologies in agriculture also requires a significant change in education and skill development. Adapting to new processes focused on automation and digital technology instead of traditional agricultural methods requires agricultural workers to learn new skills. Therefore, the transition to robotic applications in agriculture requires the modernization of education and training programs. It is an important part of social transformation for individuals working in the agricultural sector to develop new skills such as managing robots, analyzing data, and using technology effectively. In this context, investing in technology education and digital literacy in rural areas is a critical step for social cohesion. Another social impact of robotic applications is their impact on rural economies. Robotic technologies can contribute to the revitalization of rural economies by increasing agricultural production. Higher productivity and lower production costs can increase the competitiveness of farmers and stimulate economic activities in rural areas. However, investing in robotic technologies can be costly for small-scale farmers. High start-up costs can deepen inequalities between large agricultural enterprises and small farmers. While large farms become more productive and profitable by investing in robotic technologies, small farmers may have difficulty accessing these technologies and lose their competitiveness. This can lead to increased socioeconomic inequalities in rural areas and the risk of small farmers losing their livelihoods (Lowenberg-DeBoer et al., 2020).

Robotic applications in agriculture also affect the social structure of rural communities. Rural communities generally have traditional social structures based on solidarity and cooperation. The integration of robots into agricultural production can lead to the emergence of individual production and a technology-based working style. This can weaken social relations based on agricultural cooperation. However, the widespread use of robotic technologies also offers the potential to adopt technology and develop new cooperation models in rural communities. Approaches such as technology sharing and access to robotic systems through cooperatives can preserve the culture of cooperation among rural communities and ensure that the advantages of modern agriculture are widely utilized.

In conclusion, the social impacts of robotic applications in agriculture are complex and multifaceted. Issues such as changes in the workforce structure, need for education, transformation of rural economies and reshaping of social structures are critical elements to be considered in the process of adopting these technologies. While robotic technologies increase productivity and profitability in the agricultural sector, fair and inclusive policies need to be developed to maintain social balance and prevent inequalities. In this way, robotic applications can contribute to both economic and social sustainability in agriculture (Balafoutis, Evert, & Fountas, 2020).

The spread of robotic applications in agriculture has significant impacts on employment changes. Traditional agricultural methods have relied on a large workforce for many years. However, the integration of robotic machines and automation into agriculture is radically changing the employment structure by reducing the need for human resources in agricultural production processes. This technological transformation creates uncertainties, especially for agricultural workers. While robots used in agricultural production allow tasks such as planting, irrigation, harvesting and spraying to be done more quickly and efficiently, the fact that these tasks are traditionally performed by humans brings with it the risk of many workers becoming unemployed.

However, in addition to the employment losses caused by the introduction of robots in agriculture, new job opportunities are also created. New occupational groups specializing in technical areas such as the design, development, programming and maintenance of robotic systems are emerging. The demand for qualified labor is increasing, especially in areas such as engineering, software and data analysis. Therefore, the use of robotic

technologies in agricultural production necessitates a change in the quality of the workforce in the agricultural sector. While traditional agricultural workers are being replaced by individuals competent in technology, the need for education and skill development programs for employees in the agricultural sector to keep up with this transformation is also increasing. Especially in rural areas, the spread of robotic agricultural applications can encourage the young population to turn to technological skills. Thus, although employment changes in agriculture may have negative consequences such as loss of labor in the short term, they have the potential to create new job opportunities in the agricultural sector in the long term, which can contribute to rural development (Barrett & Rose, 2022).

Ethical and Legal Aspects of Robotic Applications in Agriculture

While the widespread use of robotic applications in agriculture offers the potential to increase productivity and efficiency, the ethical and legal dimensions brought about by these developments also lead to important discussions. The integration of robotic technologies into agricultural processes brings up various ethical and legal issues, especially issues such as labor, data security, environmental protection and responsibility. With the widespread use of robotic systems in agriculture, the social, economic and environmental impacts of these applications should also be closely examined.

First of all, the ethical issues that arise in terms of labor are important. The use of robots in agricultural work can trigger the problem of unemployment by reducing the need for manual labor. Agricultural workers, especially those living in rural areas, may lose their jobs with the widespread use of these technologies. This situation may pose a major threat to low-income groups working in agricultural production and may deepen social inequalities. In this context, in the process of integrating robotic technologies into the agricultural sector, it is necessary to develop training and re-employment programs for unemployed workers. From an ethical perspective, it is important that technological developments are implemented without victimizing people and supported by policies that take social welfare into account.

The use of robotic technologies also raises issues of data security and privacy. Robots used in agriculture can collect and analyze large amounts of data. This data includes sensitive information such as soil conditions, plant health, and irrigation needs. The correct processing and protection of this

data is vital to the economic interests of farmers. Misuse of data or commercial advantage in the wrong hands can create economic and legal pressure on farmers. Therefore, comprehensive legal regulations should be made regarding the security and privacy of agricultural data.

Another important legal issue is the liability of robotic technologies. Robots used in agriculture are designed to make certain decisions on their own as autonomous systems. In this case, who will be responsible if an agricultural robot makes a mistake or causes a problem in agricultural production may create legal uncertainty. For example, who will be responsible for the damage that will occur if a harvesting robot malfunctions or if an irrigation robot malfunctions and uses excessive water stands out as a legal issue. In such cases, legal regulations should be made on how the responsibility will be shared between the manufacturer, the farmer or the software developer who programs the robot. As the use of robots equipped with artificial intelligence increases in agriculture, it will be inevitable to solve these liability issues. Environmental impacts are also part of the ethical and legal dimensions of robotic agricultural applications. Just as robots must operate in a sustainable and environmentally friendly manner in agricultural lands, they must also comply with regulations regarding the protection of natural resources. Water and energy consumption of robotic technologies should be compatible with sustainable agricultural practices without harming the environment. In this context, it is of great importance to update environmental laws and introduce new regulations to match the use of robotic agricultural machines.

As a result, the ethical and legal dimensions of robotic applications in agriculture should be carefully considered, taking into account the effects of technology on society and the environment. The establishment of ethical principles and legal frameworks in critical areas such as employment, data security, responsibility and environmental sustainability will contribute to the effective and fair use of robotic technologies in agricultural processes. In this process, along with the modernization of agricultural production, ensuring social balance and justice also poses a great responsibility.

With the widespread use of robotic applications in agriculture, data privacy has become an important issue. Robots collect critical data such as soil condition, plant health, and irrigation requirements in agricultural processes, and this data helps farmers increase production efficiency. However, the unauthorized use of this information by malicious individuals

or companies can cause serious economic and legal problems for farmers. The unauthorized use of data for commercial purposes can lead to large agricultural companies gaining a competitive advantage over small farmers, which can deepen injustices in agricultural production.

When the data collection capabilities of robotic technologies in agriculture are integrated into big data and artificial intelligence systems, they create a great opportunity for agricultural enterprises. However, the security and privacy of this data stand out as both an ethical and legal responsibility. Sharing or selling agricultural data, which belongs to farmers' private property, without their consent leads to a violation of their privacy rights. At this point, strong data protection laws and regulations are needed in the agricultural sector to protect farmers' rights regarding data ownership.

In addition, it is also of great importance that the data collected by robots is processed and stored correctly. Data breaches or incorrect data usage can cause farmers to make wrong decisions in agricultural production processes. This can lead to financial losses and production errors, as well as negatively affect agricultural sustainability. Therefore, establishing clear policies regarding data privacy and security in agricultural robotic systems ensures both the protection of individual farmers' rights and the assurance of agricultural productivity (Sparrow & Howard, 2021). Some studies on the ethical and legal aspects of robotic applications in agriculture are given in Table 9.

Table 9. Studies on the ethical and legal aspects of robotic applications in agriculture

Authors	Study	Year
Uddin et al. (Uddin, Chowdhury, & Kabir, 2024)	Ethical and Legal Aspects of Robotic Applications in Agriculture	2024
Van Der Burg et al. (van der Burg, Giesbers, Bogaardt, Ouweltjes, & Lokhorst, 2024)	Ethical aspects of AI robots for agri-food; a relational approach based on four case studies	2024
Ali et al. (Ali, Mijwil, Buruga, Abotaleb, & Adamopoulos, 2024)	A Survey on Artificial Intelligence in Cybersecurity for Smart Agriculture: State-of-the-Art, Cyber Threats, Artificial Intelligence Applications, and Ethical Concerns	2024
Sharma et al. (Sharma, Kaushik, & Kushwaha, 2024)	Prospects and Potential Impacts of Cloud Robotics in Ameliorate Agricultural Farm Produce: A Case of India	2024

The Future of Robotic Applications in the Agricultural Industry

The future of robotic applications in the agricultural industry is taking shape with the transformation of agriculture with automation, digitalization and artificial intelligence. This transformation redefines not only production processes but also the economic, social and environmental aspects of agriculture. The future of robotic technologies in agriculture offers a roadmap to create a more sustainable, flexible and customizable agricultural model beyond increasing efficiency.

One of the biggest benefits of robotic applications in agriculture is increased efficiency. In the future, robots will be widely used in almost every stage of agricultural processes, from seed planting to harvesting, from irrigation to spraying. These robots will have the capacity to work faster, more precisely and more accurately, replacing manual tasks performed by humans. For example, autonomous tractors, unmanned aerial vehicles (drones) and harvesting robots will be able to work on large agricultural lands without the need for human intervention. This will ensure that agricultural production continues uninterrupted even in situations where the workforce is reduced or insufficient.

One of the most important results of the use of robots in agricultural production is that it saves time and cost. Operations that may take days in traditional agricultural methods can be completed in hours thanks to robots. In addition, automated agricultural machines can reduce error rates by performing certain tasks in a programmed manner and ensure more efficient use of agricultural inputs. In the future, robots will become the basic elements of agricultural systems that can be customized according to soil and climate conditions. Thus, farmers will be able to optimize their production processes by choosing the most appropriate agricultural application for a specific region. One of the biggest challenges facing agricultural production in the future will be environmental sustainability. Factors such as population growth, climate change, and limited natural resources necessitate agricultural production to take on a more sustainable structure. In this context, robots can facilitate the implementation of environmentally friendly agricultural techniques. Robotic systems, which save water and energy, protect the structure of the soil, and minimize the use of chemical pesticides, can reduce the ecological footprint of agriculture (B. Zhang et al., 2020).

Another environmental advantage of robotic applications in agriculture is that they enable the use of smart irrigation systems and precision farming

techniques. Robots can continuously monitor the moisture status of the soil and the water needs of the plants through sensors and prevent waste by using only as much water as necessary. This will be an important step in making agricultural production sustainable in regions experiencing water scarcity. Similarly, robots can help reduce environmental pollution by optimizing the use of pesticides and fertilizers. In the future, more integrated technologies are expected to be developed to minimize the environmental impact of agricultural robots and protect natural resources.

The future of robotic applications in agriculture will not only be limited to the automation of physical labor, but will also include the widespread use of advanced algorithms such as artificial intelligence (AI) and machine learning in agricultural processes. Future agricultural robots will be able to make more strategic and predictive decisions in agricultural processes by working integrated with big data analytics and artificial intelligence technologies. These robots will be able to analyze the data they collect from the fields and provide instant feedback to farmers on many issues such as plant health, harvest timing, and irrigation needs.

AI-supported robots can analyze soil and plant data to determine which areas need what type of fertilizer or medicine. In this way, targeted interventions can be made in agricultural production and unnecessary chemical use is prevented. In addition, AI-based robots allow farmers to take proactive measures by detecting plant diseases and pests early. This minimizes agricultural product loss and contributes to the cultivation of healthier and higher quality products. In the future, the integration of artificial intelligence and robotic technologies will increase efficiency and sustainability in agricultural production and will be the driving force of digital transformation in the agricultural sector. The future of robotic applications in agriculture will have profound effects on the agricultural workforce. With the widespread use of robots and automated systems, a decrease in the number of workers working in traditional agricultural work is expected. In particular, the replacement of manual work by robots can change the workforce dynamics in rural areas. This situation can bring about problems such as unemployment and social imbalances. However, it will also create new job opportunities in areas such as the maintenance, programming and development of agricultural robots. In the future, workers in the agricultural sector will need to have higher technological skills (Khan et al., 2021).

The social impacts of robotic applications in agriculture will not be limited to the workforce. With the integration of technology into agricultural processes, rural life and social structure will also transform. The spread of agricultural technologies in rural areas can increase the interest of the young population in agricultural production and contribute to the development of technology-focused agriculture. At the same time, agricultural cooperatives and community-based agricultural initiatives will be able to develop new models focused on cooperation and sharing by utilizing robotic technologies.

The future of robotic technologies in agriculture will also bring with it important ethical and legal questions. Since agricultural robots collect and analyze large amounts of data, they will require sensitivity regarding data privacy and security. The use of farmers' soil data, product information and data related to production processes for commercial purposes can create an ethically controversial area. Therefore, stricter regulations and transparency policies will be needed in the future regarding agricultural data management.

In addition, the ability of robots to make autonomous decisions in agricultural production processes will also bring legal issues such as liability and error management to the agenda. For example, it is unclear who will be responsible if an agricultural robot makes wrong decisions and causes damage. At this point, clarifying legal responsibilities among manufacturers, farmers, and technology providers will play a critical role in the digital transformation of agriculture. The widespread use of robotic technologies in agriculture can provide solutions to food security problems on a global scale. Increasing populations and decreasing agricultural lands necessitate more efficient and sustainable production methods in the future. Agricultural robots can optimize agricultural processes, allowing more crops to be grown and fewer resources to be used. This can help reduce the risk of food shortages worldwide by increasing efficiency in agricultural production.

The widespread use of robotic applications in the agricultural industry will cause radical changes in agricultural production processes in the future. While these technologies offer significant opportunities in areas such as increased productivity, sustainability and food safety, they will also bring challenges such as workforce changes, ethical issues and economic imbalances. The integration of robotic technologies in agriculture will play a critical role in the future of agricultural production and will lead the digitalization of the global agricultural sector. However, the fair, ethical and sustainable application of technology in this process is of great importance

for the future of agriculture (Liu, Ma, Shu, Hancke, & Abu-Mahfouz, 2020). Some studies on the future of robotic applications in the agricultural industry are given in Table 10.

Table 10. Studies on the future of robotic applications in the agricultural industry

Authors	Study	Year
Raj et al. (Raj et al., 2024)	A Brief Overview of Technologies in Automated Agriculture: Shaping the Farms of Tomorrow	2024
Licardo et al. (Licardo, Domjan, & Orehovački, 2024)	Intelligent robotics—A systematic review of emerging technologies and trends	2024
Barua et al. (Barua et al., 2024)	The Emerging Advancement of Robotics in the Modern Agriculture Field	2024

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Fuzzy Logic-Based Autonomous Greenhouse System for Ideal Air Control

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Introduction

Agricultural activities are of great importance in the global economy for the use of food and raw material resources, as individuals need food to survive (Sanyaolu & Sadowski, 2024). For this reason, it is of great importance to protect agricultural land and maximize yields.

Traditional agricultural methods often lead to excessive irrigation, fertilizer and pesticide use, causing soil erosion, water pollution, reduced biodiversity and climate change problems (de Ponti, Rijk, & van Ittersum, 2012). If agricultural areas cannot be protected against population growth, serious problems will arise. For this reason, finding and developing innovative methods in agricultural systems is becoming more and more important. In this way, strategies such as protecting natural resources such as water and soil, preventing chemical fertilization, protecting and increasing biodiversity are implemented. Precision agriculture practices developed for this purpose have many benefits such as increasing yield in agricultural areas, providing economic benefits and efficient use and protection of natural resources. One of the most important innovations in this field is IoT technology. IoT enables real-time monitoring of data such as soil moisture, weather conditions, and plant health through sensors placed in agricultural areas.

Today, the rapid advancement of technology, the increase in precision agriculture activities and the spread of applications that make life easier accordingly allow greenhouse activities to become more modern and efficient. According to the researches conducted, it has been observed that the use of technology is more preferred in the studies on agriculture in our country. The increasing difficulty of living conditions and the complexity of

problems have made the increase in intelligent system applications inevitable. Since greenhouses using technology are more advantageous than traditional structures, the transition from traditional greenhouse farming to modern greenhouse farming is increasing rapidly (Çanakçı & Yıldız, 2013).

Greenhouse farming, also known as under cover cultivation, is defined as the cultivation of any agricultural product without being affected by climate change (Vanegas-Ayala, Barón-Velandia, & Leal-Lara, 2023). In this way, products can be produced throughout the year, that is, outside the season (Chouchaine & Mami, 2020). Parameters such as heating, cooling, humidity, temperature and fogging are important in order to control the greenhouse interior climate (Labidi, Chouchaine, & Mami, 2020).

Greenhouse activities are mostly concentrated in the Mediterranean region in our country. The main reasons for the prevalence of greenhouse cultivation in this region are the favourable climate, high temperatures throughout the year and the high number of sunny days. In recent years, it is observed that the effects of global warming have been felt more in Turkey. Especially climate change and sudden weather changes affect greenhouse activities negatively. Despite these negativities, the application of information technologies in greenhouses increases continuity and efficiency in production (Ambarwari, Widyawati, & Putra, 2024; Ozguven & Tarhan, 2018).

In order to minimize the impact of greenhouse activities, which is an important branch of precision agriculture in our country, on all adverse conditions, intelligent systems developed based on fuzzy logic are also used effectively in greenhouse activities. Fuzzy logic, which is encountered in many fields such as health, medicine, education, industry, engineering, industry, etc., is one of the preferred methods in the field of agriculture in recent years. The reason for using fuzzy logic based intelligent systems is that this system imitates the human thought structure and has a learning and decision-making structure like humans.

Many studies on modern greenhouse cultivation have been carried out in our country. Hocagil and Öztürk (2025) by placing a signal sensor in the greenhouse, they ensured that the signals from the sensor are processed through the cards. The climate conditions entered by the user are recognised as commands by the cards and transmitted to the sensors to control the environment (Hocagil & Öztürk, 2005). With the help of the equipment developed in the greenhouse, the indoor temperature was reduced to the

desired temperature by Akgül et al. Temperature and relative humidity conditions were modelled with fuzzy logic and the natural ventilation system was controlled. According to this model, the opening amount of the greenhouse windows was determined according to the rules processed in the fuzzy logic system (Akgül, Kavdır, & Dayıoğlu, 2006). Soy et al. (2008) were tested the greenhouse's humidity and temperature values by controlling them with an embedded system and creating a simulation in the Proteus program (Soy, Yılmaz, & Dilay, 2008). Ödük (2010) was created a fuzzy expert system simulation for greenhouse automation. In the study, input parameters; light intensity, temperature, soil moisture, air humidity, wind speed and carbon dioxide amount were determined. Output parameters are ventilation, cooling, irrigation, heating, lighting and shading (Ödük, 2010). Öztürk et al. (2014) developed a greenhouse air conditioning mechanism using a microcontroller. They ensured that the remote control system was used actively through the web interface (Öztürk, Ökdem, & Öztürk, 2014). Ayan and Senol (2016) were developed a greenhouse control system using a fuzzy logic based and programmable controller (Ayan & Senol, 2016). In the greenhouse application developed by Alpaya (2018), ideal values for greenhouse heating, cooling, lighting, shading and irrigation were obtained with fuzzy logic systems (Alpaya, 2018). In another study, a fuzzy expert system was designed for use in tomato production by Eldem et al. (2013). Depending on the soil temperature, pH level and irrigation amount, both the amount of fertilization and the cultivation of tomatoes in a shorter time were achieved (Eldem, Başçiftçi, & Eldem, 2013). In another study by Eldem et al. (2012), a fuzzy expert system was developed to determine the amount of water to be used in order to reduce production costs in cucumber production (Eldem, Başçiftçi, & Eldem, 2012). A fuzzy irrigation controller was developed by Flores (2024) that calculated how much water the soil should be irrigated according to the soil moisture and temperature values. An arduino nano microcontroller was used to operate the system. Thanks to the developed system, excessive water consumption has also been optimized (Flores, 2024). A web interface was designed to control the greenhouse prototype by Robles et al. (2017). In addition, it is aimed to provide climate control of the greenhouse in the fuzzy logic-based application using humidity values, temperature and lighting parameters (Robles Algarín, Callejas Cabarcas, & Polo Llanos, 2017).

In this study, it is aimed to provide ideal air control with fuzzy logic in the autonomous greenhouse system. At the same time, the desired goal is to create a self-sufficient system by integrating fuzzy logic-based smart systems into greenhouse activities and minimizing the damage caused by sudden weather changes. Within the scope of the study, it was utilized that fuzzy logic has a structure that can make computer-aided decisions and produce results by imitating people's experiences. The data received from the humidity and temperature sensors were transferred to the Arduino Uno card and thanks to the fuzzy-based system developed, the hot or cool fan motors were enabled to operate at the desired speed. In this way, ideal weather conditions were created for the greenhouse and it was aimed to increase the efficiency of greenhouse activities. The developed system is given in detail in Figure 1.

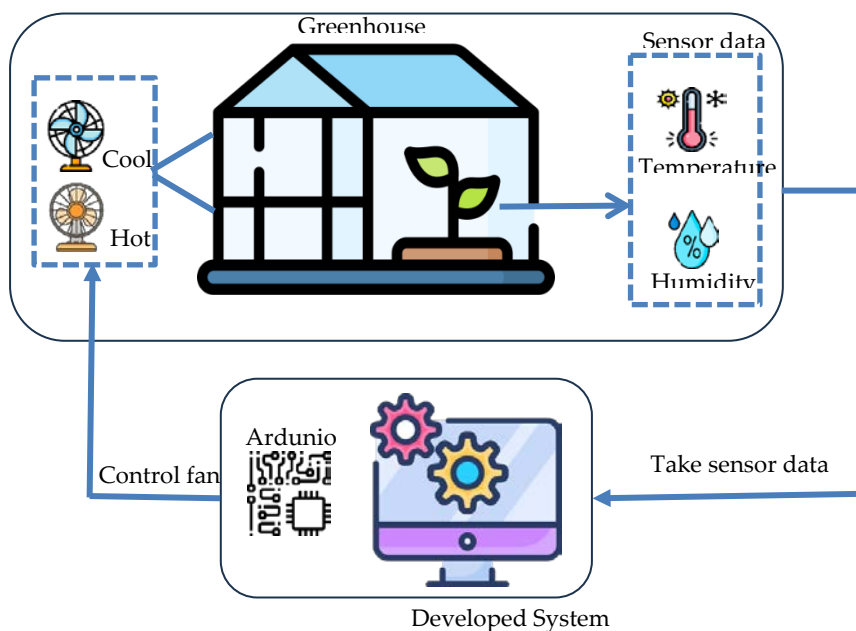


Figure 1. Fuzzy Logic Based Greenhouse Control

In the second section of the study, general information about Fuzzy Logic is given. In the third section, detailed information is given about the hardware components used in the developed greenhouse prototype, the software interface, and the input and output parameters used for the fuzzy logic based application. In the forth section, the benefits of the developed system and future work are discussed.

Fuzzy Logic

The concept of fuzzy logic was first described by Lotfi Zadeh in 1965. Fuzzy logic is compatible with the philosophical thought structure of the Eastern world and also expresses transition and continuity. The reason for this is that in classical logic, there are two opposite and definite values such as open-closed and white-black. In addition, fuzzy logic also includes intermediate tones such as gray between white and black (Keskenler & Keskenler, 2017).

Fuzzy logic applications can provide a decision mechanism that is closer and more suitable to daily life. While two definite values such as yes (1) or no (0) are used in classical logic, infinite values between 0 and 1 are used in Fuzzy Logic (Özcan & Eldem, 2020). Therefore, if the correct information is used, very accurate results can be obtained (Del Giudice, De Paola, & Cantisani, 2017). In other words, in Fuzzy logic, the aim is to find the closest value to reality. When modeling with fuzzy logic, inputs and outputs are associated with each other and rules are created. Considering these features, the fuzzy logic system can be mathematically compared to the cause-effect relationship (Zadeh, 1996).

Fuzzy logic basically consists of four components. These components are knowledge base, which consists of database and rule base, fuzzification, inference mechanism and defuzzification as shown in Figure 2. The aim of fuzzy logic is to find the closest value of a reality. When modeling in fuzzy logic, rules are created by associating inputs and outputs with each other.

In the *Fuzzification stage*, the input and output variables are determined, the value ranges of the input and output parameters are determined, they are converted into linguistic expressions, and membership functions and membership function degrees are determined.

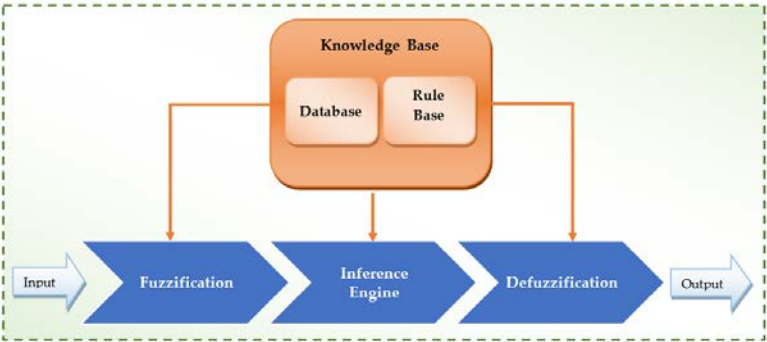


Figure 2. Fuzzy System

Inference Mechanism is the method used to determine which linguistic expression will be selected for the output parameter in the rules triggered according to the predefined rule base and to find the numerical equivalent of this linguistic expression in the membership function. The most commonly preferred inference methods of fuzzy logic are Mamdani Inference, Sugeno Inference, Tsukamoto Inference and Larsen Inference. Mamdani is the most preferred method among these. Because the Mamdani is generally considered the simplest and most understandable model. Mamdani method is more in line with people's thinking structure and is easier to design. It can better mimic human thoughts. It allows working with different types of fuzzy sets such as triangles and trapezoids. However, it can be easily used in many applications such as decision support systems and control systems.

The *Defuzzification* phase is the process of converting the linguistic expressions obtained for the output parameter into numerical data. The methods used at this stage are Centroid, Max, Weighted Average, Max Membership, Mean of Maximum and Smallest. One of the most commonly used methods is Centroid. Centroid uses weight averaging to find the center of a fuzzy output set so that the results obtained are balanced. Because, the Centroid method can work with fuzzy sets of different shapes such as triangles and trapezoids. It can be easily used in different application areas. It can be used in many various areas such as control systems, decision support systems, optimization problems.

Knowledge Base stage is the rule base created based on expert knowledge using the input and output parameters in the developed system. While creating the rule base, rules defined as if-then are used as a basis. These rules, based on expert opinion, are important for creating a successful model. The input data coming to the system is interpreted according to these rules and the output data is obtained. Thus, expert knowledge is explained based on cause-effect relationships.

Application

In this study, an autonomous greenhouse application was developed. According to the information received from the temperature and humidity sensors in the greenhouse, the fan that provides hot or cool air is activated in order to keep the temperature inside the greenhouse at the required level. The flowchart of the precision agriculture application created is given in Figure 3. As can be seen in the picture, the data from the temperature and

humidity sensors are read first. Then the readings from the sensors are displayed on the LCD screen and they sent to the proposed fuzzy logic based system. According to the values obtained from Fuzzification, Inference Mechanism, Defuzzification stages, hot and cold fans are operated according to fan operating speeds. The operation of the fans continues until the ideal conditions are met. The ideal conditions should be entered at the beginning according to the crop planned to be grown. If the conditions are met, the operation is terminated.

The prototype created to regulate the ideal weather conditions needed for the greenhouse is shown in Figure 4. In the hardware components of the proposed greenhouse application; Arduino uno, DHT11 temperature humidity sensor, L293D motor driver, 16x2 LCD screen to show the values coming from the humidity and temperature sensor, cooling fan, heating fan and thermoelectric (peltier) were used to create the system.

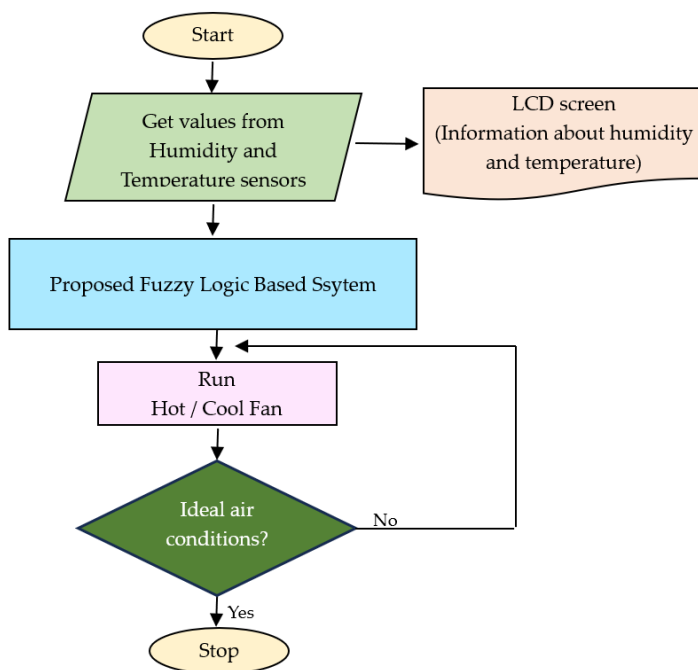


Figure 3. The flowchart of the precision agriculture application

The hardware tools used are shown in Figure 5. Arduino Uno is an open source microcontroller board designed for anyone interested in electronics to use easily. Electronic applications such as turning lights on and off and starting engines can be done using signals from many sensors with Arduino

Uno. In the developed greenhouse prototype, Arduino Uno passes the data received from the temperature and humidity sensor through the fuzzy logic system and sends the operating speed signal to the heater or cooling fan. When the heater fan is running, the peltier works and provides heating. The DHT11 Sensor, used as a temperature and humidity sensor, contains an 8-bit microprocessor. It responds quickly and with high quality.

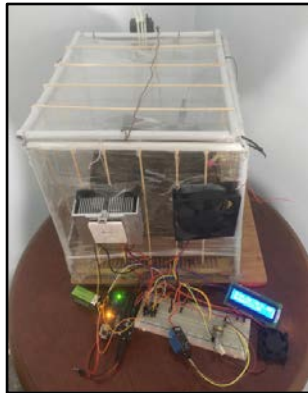
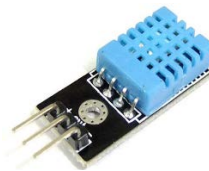


Figure 4. Greenhouse Prototype



Arduino Uno



DHT11 Sensor



L293D motor driver



Fan



Peltier



Fan



LCD screen (16x2)

Figure 5. Used Hardware Tools

The layout of the hardware components is shown in Figure 6. Figure 7 shows the placement of the heater and cooling fans inside and outside the greenhouse.

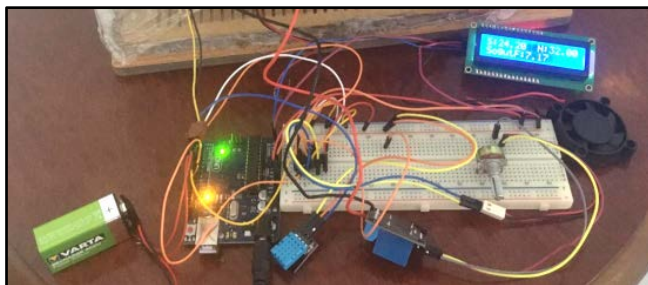


Figure 6. Developed system



(a)



(b)

Figure 7. The heater and cooling fans (a) Inside greenhouse (b) Outside greenhouse

The application developed based on fuzzy logic, temperature and humidity variables were selected to use the information coming from temperature and humidity sensors as input variables. Fan operating speeds were selected as output variables so that the hot and cool fan motors could operate at the desired speed. Triangular membership functions were preferred for the selected input and output parameters. The required value

ranges, linguistic expressions and membership functions for the input and output variables were determined and a rule table was created. At this stage, Matlab Fuzzy Logic Toolbox was used.

The input variable, the determined temperature value, was determined as the highest 32 degrees and the lowest 10 degrees in ideal weather conditions for greenhouse farming. The preferred linguistic expressions for the temperature parameter are Very Cold (VC), Cold (C), Ideal (I), Hot (H), Very Hot (VH). The value ranges of the selected linguistic expressions are given in Table 1. The mathematical membership functions to be used for the linguistic expressions of the temperature parameter are given between Formula 1 and Formula 5. The membership functions created according to the value ranges are shown in detail in Figure 8.

Table 1. Value ranges of temperature parameters

Linguistic expression	Value Ranges
(VC)	[10 15.5]
(C)	[10 15.5 21]
(I)	[15.5 21 26.5]
(H)	[21 26.5 32]
(VH)	[26.5 32]

$$\mu_{\text{verycold}}(x; 10, 15.5) = f(x) = \begin{cases} 1, & x \leq 10 \\ \frac{15.5-x}{5.5}, & 10 < x < 15.5 \\ 0, & x \geq 15 \end{cases} \quad (1)$$

$$\mu_{\text{cold}}(x; 10, 15.5, 21) = f(x) = \begin{cases} \frac{x-10}{5.5}, & 10 \leq x < 15.5 \\ \frac{21-x}{5.5}, & 15.5 \leq x < 21 \\ 0, & x \geq 21 \end{cases} \quad (2)$$

$$\mu_{\text{ideal}}(x; 15.5, 21, 26.5) = f(x) = \begin{cases} \frac{x-15.5}{5.5}, & 15.5 \leq x < 21 \\ \frac{26.5-x}{5.5}, & 21 \leq x < 26.5 \\ 0, & x \geq 26.5 \end{cases} \quad (3)$$

$$\mu_{\text{hot}}(x; 21, 26.5, 32) = f(x) = \begin{cases} \frac{x-21}{5.5}, & 21 \leq x < 26.5 \\ \frac{32-x}{5.5}, & 26.5 \leq x < 32 \\ 0, & x \geq 32 \end{cases} \quad (4)$$

$$\mu_{\text{veryhot}}(x; 26.5, 32) = f(x) = \begin{cases} 0, & x < 26.5 \\ \frac{x-26.5}{5.5}, & 26.5 \leq x < 32 \\ 1, & x \geq 32 \end{cases} \quad (5)$$

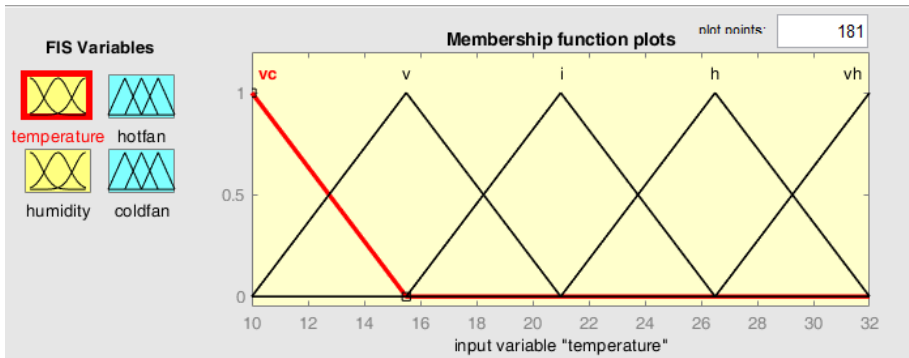


Figure 8. Membership Function Graph of Temperature Parameter

The value ranges, linguistic expressions and mathematical membership functions to be used for the other input parameter, humidity, have been determined. The value range determined for this parameter is determined as minimum 10 g/m³ and maximum 100 g/m³ under ideal weather conditions. The preferred linguistic expressions are Very Low (VL), Low (L), Normal (N), High (H), Very High (VH). The value ranges of the selected linguistic expressions are given in Table 2.

Table 2. Value ranges of humidity parameter

Linguistic expression	Value Ranges
(VL)	[10 32.5]
(L)	[10 32.5 55]
(N)	[32.5 55 77.5]
(H)	[55 77.5 100]
(VH)	[77.5 100]

The mathematical membership functions to be used for the linguistic expressions of the temperature parameter are given between Formula 6 and Formula 10. Membership functions created according to value ranges are shown in detail in Figure 9.

$$\mu_{\text{verylow}}(x; 10, 32.5) = f(x) = \begin{cases} 1, & x \leq 10 \\ \frac{32.5-x}{22.5}, & 10 < x < 32.5 \\ 0, & x \geq 32.5 \end{cases} \quad (6)$$

$$\mu_{\text{low}}(x; 10, 32.5, 55) = f(x) = \begin{cases} \frac{x-10}{22.5}, & 10 \leq x < 32.5 \\ \frac{55-x}{22.5}, & 32.5 \leq x < 55 \\ 0, & x \geq 55 \end{cases} \quad (7)$$

$$\mu_{\text{normal}}(x; 32.5, 55, 77.5) = f(x) = \begin{cases} \frac{x-32.5}{22.5}, & 32.5 \leq x < 55 \\ \frac{77.5-x}{22.5}, & 55 \leq x < 77.5 \\ 0, & x \geq 77.5 \end{cases} \quad (8)$$

$$\mu_{\text{high}}(x; 55, 77.5, 100) = f(x) = \begin{cases} \frac{x-55}{22.5}, & 55 \leq x < 77.5 \\ \frac{77.5-x}{22.5}, & 77.5 \leq x < 100 \\ 0, & x \geq 100 \end{cases} \quad (9)$$

$$\mu_{\text{veryhigh}}(x; 77.5, 100) = f(x) = \begin{cases} 0, & x < 77.5 \\ \frac{x-77.5}{22.5}, & 77.5 \leq x < 100 \\ 1, & x \geq 100 \end{cases} \quad (10)$$

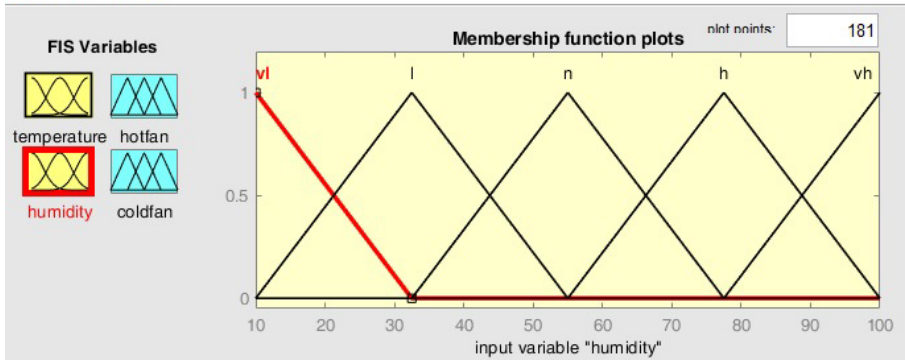


Figure 9. Membership Function Graph of Humidity Parameter

The preferred values for adjusting the speed of the fan (cool fan & hot fan), which is the output variable of the modeled system, under ideal weather conditions were determined as the lowest 0 rpm and the highest 150 rpm. The preferred linguistic expressions are Low Speed (LS), Medium Speed (MS), Full Speed (FS). The value ranges of the selected linguistic expressions are given in Table 3.

Table 3. Value ranges of fan parameters

Linguistic expression	Value Ranges
(LS)	[0 50]
(MS)	[0 50 100]
(FS)	[50 100]

The mathematical membership functions to be used for the linguistic expressions of the fan parameter are given between Formula 11 and Formula 13. Membership functions created according to value ranges are shown in detail in Figure 10.

$$\mu_{\text{low speed}}(x; 0, 50) = f(x) = \begin{cases} 1, & x \leq 0 \\ \frac{50-x}{50}, & 0 < x < 50 \\ 0, & x \geq 50 \end{cases} \quad (11)$$

$$\mu_{\text{medium speed}}(x; 0, 50, 100) = f(x) = \begin{cases} \frac{x}{50}, & 0 \leq x < 50 \\ \frac{100-x}{50}, & 50 \leq x < 100 \\ 0, & x \geq 100 \end{cases} \quad (12)$$

$$\mu_{\text{full speed}}(x; 50, 100) = f(x) = \begin{cases} 0, & x < 50 \\ \frac{x-50}{50}, & 50 \leq x < 100 \\ 1, & x \geq 100 \end{cases} \quad (13)$$

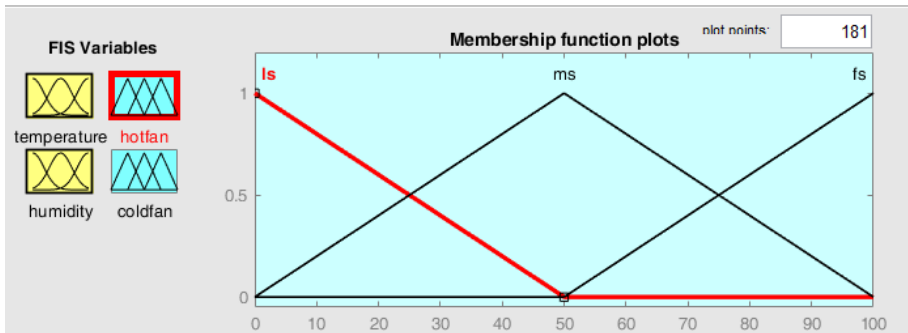


Figure 10. Membership Function Graph of Fan Parameter

In this study, since 5 linguistic expressions were used for each input parameter, 25 rules were formed in the rule table. The linguistic expressions that can be obtained for fan speed in the rule table created according to

humidity and temperature values are as shown in Table 4. Rules are defined in the Matlab Rule Editor as shown in Figure 11.

Table 4. Rule Table

Humidity Temperature	Very Low		Low		Normal		High		Very High	
	Hot Fan	Cool Fan	Hot Fan	Cool Fan	Hot Fan	Cool Fan	Hot Fan	Cool Fan	Hot Fan	Cool Fan
Very Cold	Full Speed	Off	Full Speed	Low Speed	Full Speed	Medium Speed	Full Speed	Full Speed	Full Speed	Full Speed
Cold	Full Speed	Off	Full Speed	Low Speed	Full Speed	Low Speed	Medium Speed	Low Speed	Medium Speed	Full Speed
Ideal	Medium Speed	Off	Medium Speed	Low Speed	Medium Speed	Medium Speed	Low Speed	Medium Speed	Low Speed	Full Speed
Hot	Low Speed	Off	Low Speed	Low Speed	Low Speed	Medium Speed	Low Speed	Full Speed	Low Speed	Full Speed
Very Hot	Off	Off	Off	Low Speed	Off	Medium Speed	Off	Medium Speed	Off	Full Speed

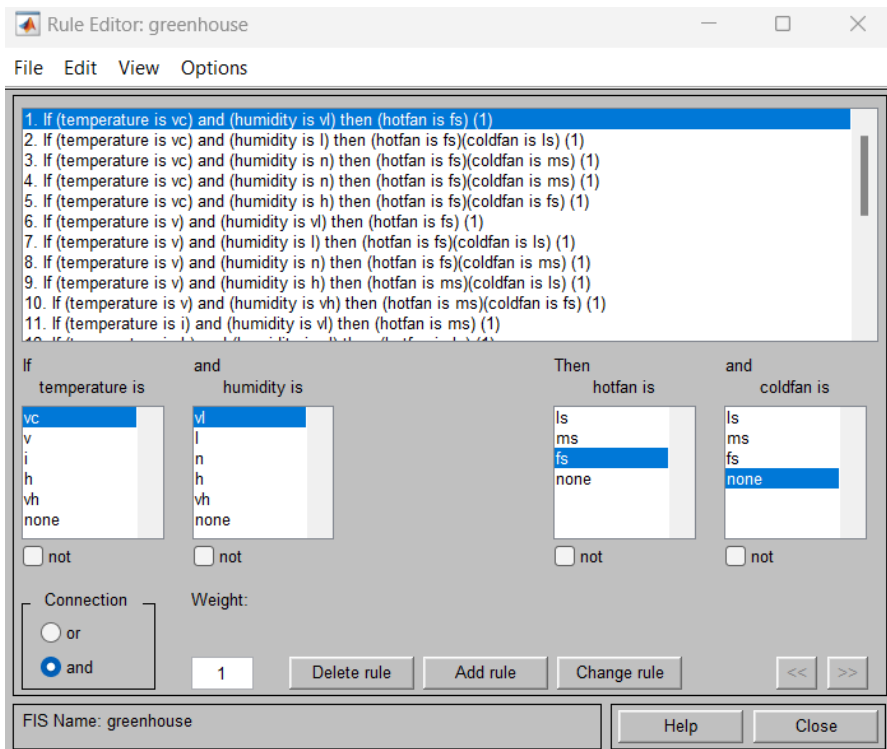


Figure 11. Rule Table

In this study, the Mamdani method was preferred as the inference mechanism and the Centroid method was preferred for the defuzzification phase, as shown in Figure 12. Figure 13 shows the Matlab interface where the results of the hot and cool fan speed obtained when data is entered for temperature and humidity parameters are shown.

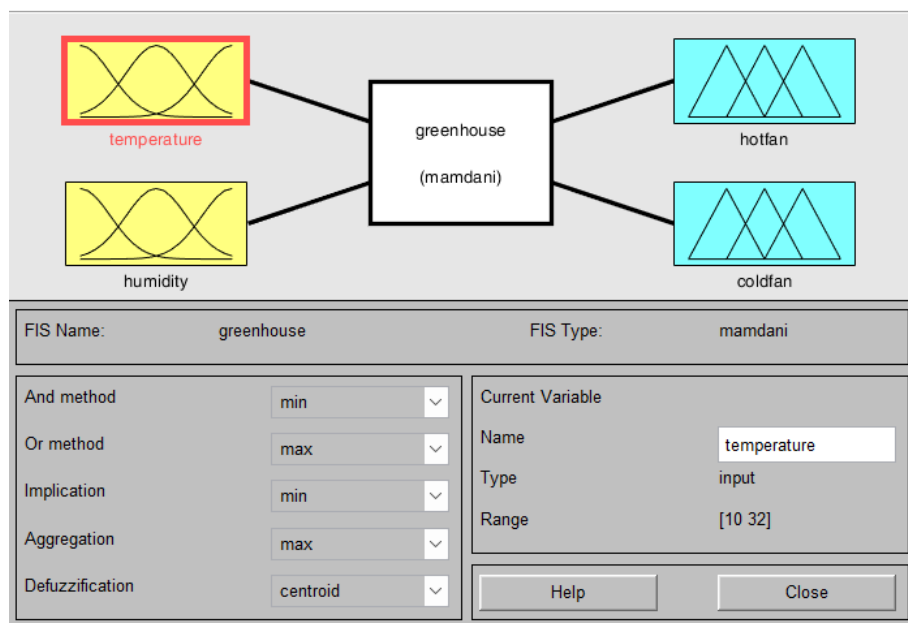


Figure 12. Matlab Fuzzy Logic Module

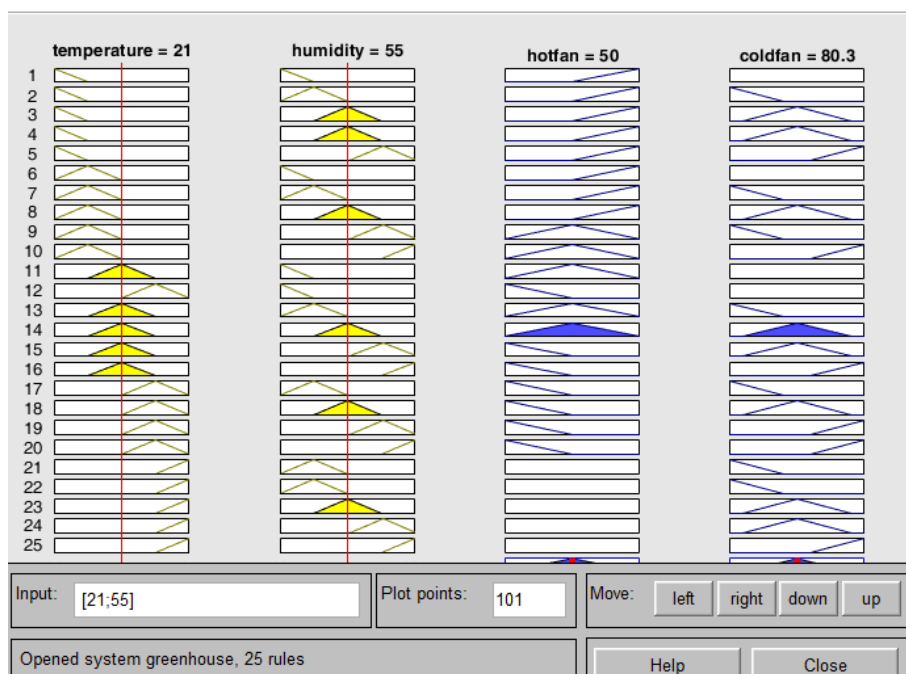


Figure 13. Matlab Interface

Detailed information on the operating speed of the cool and hot fan according to the humidity and temperature information measured in the greenhouse at different time periods is given in Table 5. There are 20 different observations in Table 5. The graph including temperature and humidity values for each observation value is given in Figure 14. Figure 15 shows the values of hot and cool fan at each observation value. Figure 16 and Figure 17 show the operation graph of hot and cool fans according to temperature and humidity parameters.

Table 5. Sample values of cool and hot fan speed calculated according to temperature and humidity parameters.

Observation Number	Temperature (°C)	Humidity (g/m ³)	Cool Fan Speed (rpm)	Hot Fan Speed (rpm)
1	29.50	95.00	63.20	19.60
2	28.00	60.00	51.30	17.40
3	28.90	50.00	48.50	18.60
4	28.70	35.00	29.50	18.30
5	27.10	30.00	16.50	16.50
6	30.00	35.50	28.90	20.50
7	32.00	35.50	28.20	50.00
8	31.50	50.00	48.70	23.60
9	30.80	58.00	50.50	22.10
10	29.15	95.00	62.70	19.00
11	27.00	100.00	83.50	16.50
12	28.50	97.00	69.50	18.00
13	22.00	45.00	45.10	48.90
14	23.60	47.00	46.50	44.50
15	27.00	75.00	73.40	16.50
16	26.50	62.00	52.40	17.60
17	31.50	58.00	50.30	23.60
18	30.00	43.00	42.90	20.50
19	32.10	45.75	45.80	50.00
20	31.25	49.80	48.60	23.10

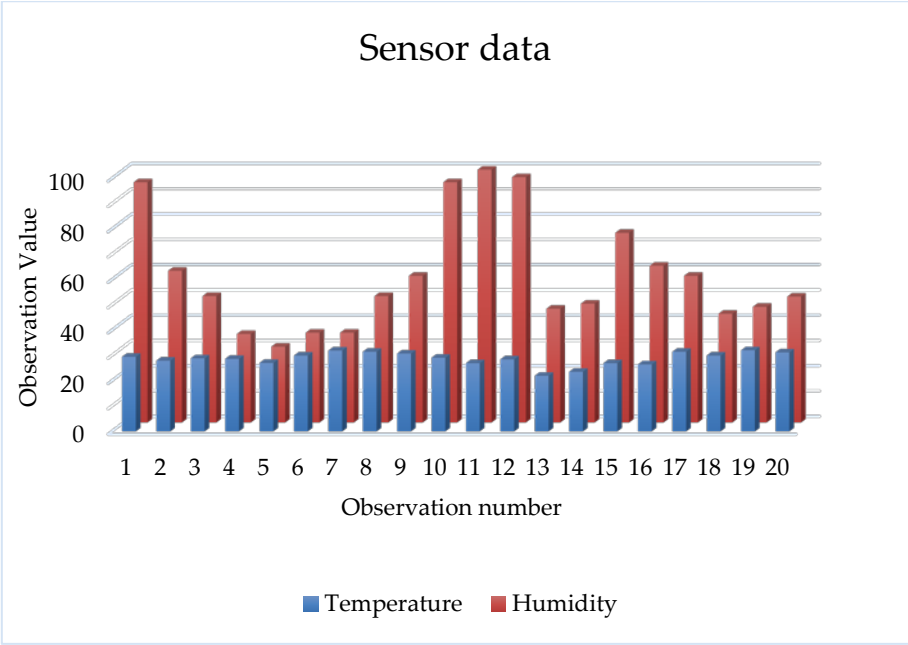


Figure 14. Observation values for temperature and humidity

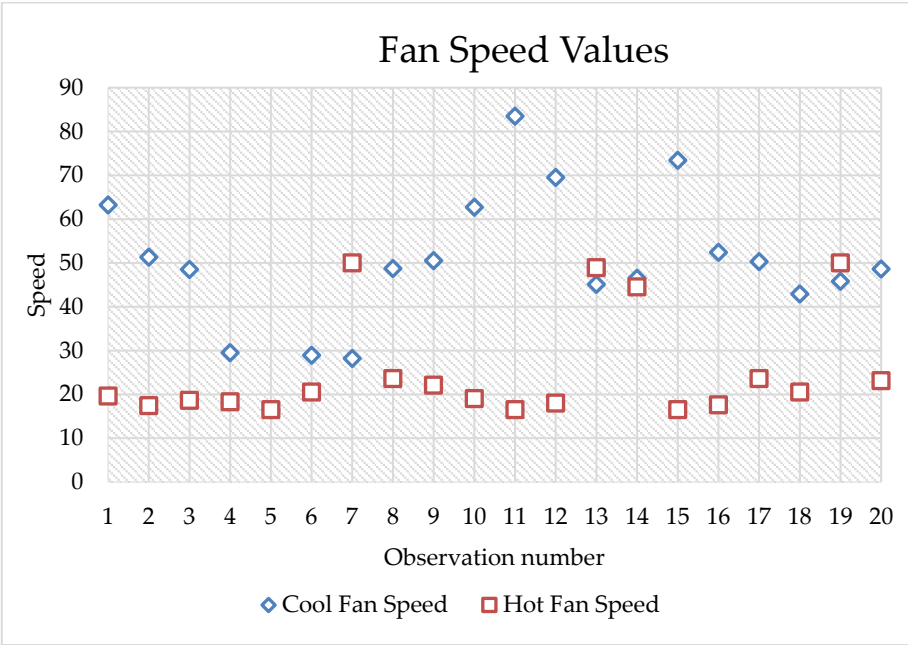


Figure 15. Values for Hot and Cool Fan Speed

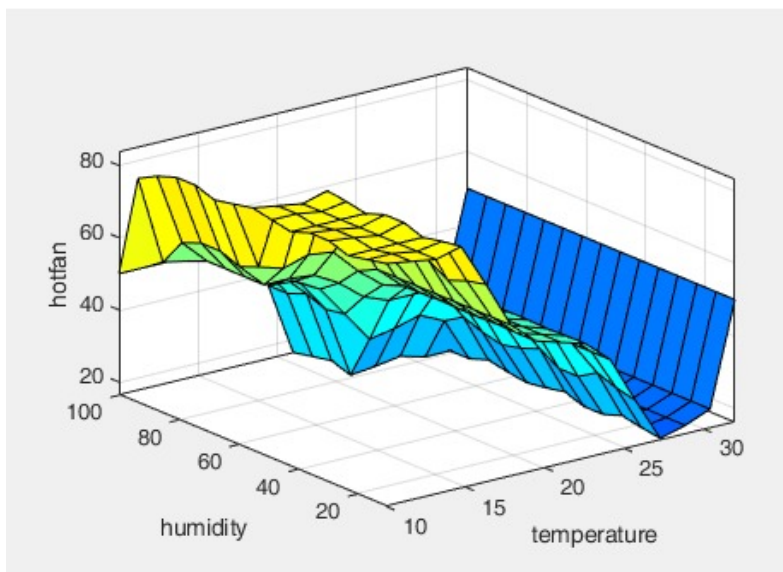


Figure 16. Hot Fan Speed surface graph according to temperature and humidity parameters

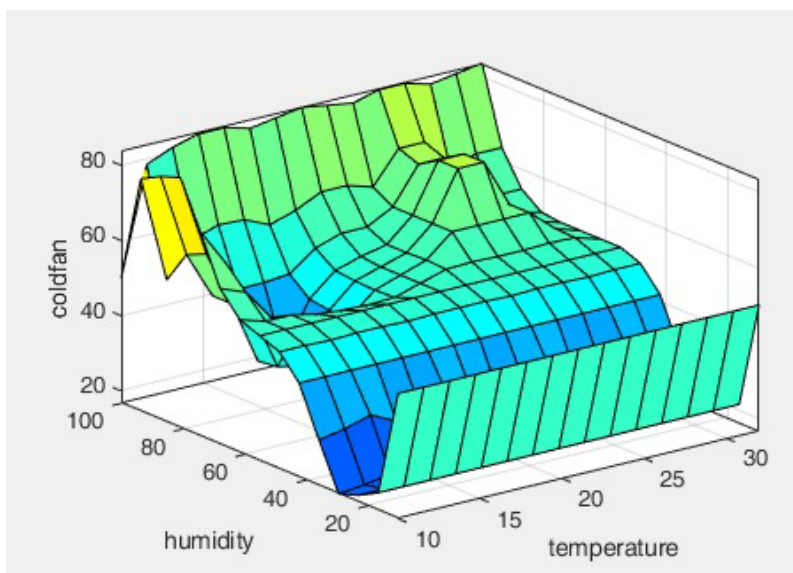


Figure 17. Cool Fan Speed surface graph according to temperature and humidity parameters

Conclusion

In this study, an application that provides ideal air control with fuzzy logic for an autonomous greenhouse system was developed. In this system, developed within the scope of precision agriculture applications, hot or cold

adjustable fan control is provided by the fuzzy logic controller according to the humidity and temperature values obtained from the greenhouse environment. The method used has changed as a result of differences in ambient humidity and temperature, and as a result of these changes, the fan system has been activated and different results have been produced. Triangular membership function was used for input and output parameters in the fuzzy logic controller and the system output was examined. The Mamdani inference mechanism and the Centroid method were preferred. In line with these results, it was revealed that the fuzzy logic controller system contributed positively to the changing weather conditions in greenhouses.

In future studies, in addition to existing temperature and humidity sensors, the integration of additional sensors such as light intensity, carbon dioxide levels, and wind speed will be important. These sensors can be used to monitor and analyze environmental conditions more comprehensively. In addition, soil irrigation systems and other applications can be controlled via web or mobile interfaces, allowing users to manage agricultural processes more effectively.

Data obtained from sensors can be processed with machine learning techniques to optimize the performance of fans and other components. In this way, energy efficiency can be increased and resource use can be made more sustainable. For example, when light and carbon dioxide levels are considered in an agricultural field, the most suitable conditions for plant growth can be provided. As a result, such data integration and analysis will help reduce environmental impact while increasing agricultural productivity. Such innovative approaches can enable agricultural practices to be smarter and more environmentally friendly in the future.

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Insect Pest Identification in Agriculture: A Lightweight CNN Architecture Proposal

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Introduction

Due to the rapid increase in the human population worldwide, increasing agricultural production has become very important in recent years. In contrast, one of the most important factors threatening agricultural production worldwide is insect pests, which cause crop losses of 20% to 40% (Kariyanna & Sowjanya, 2024; Teixeira, Ribeiro, Morais, Sousa, & Cunha, 2023). It is estimated that there are approximately 30 million species of insects worldwide, of which only 5.5 million have been identified. While only about 500 of these species are classified as pests for agricultural products, the vast majority are beneficial to agriculture (Doan, 2023; Soni et al., 2022). Beneficial insects have important functions such as protecting crops and controlling pest species.

The presence of insect pests reduces the efficiency of agricultural production and the quality of the crop, thus causing economic losses for the producer and threatening global food security. Early detection and correct management of insect pests are of critical importance in reducing the damage caused to beneficial insects (due to excessive and incorrect pesticide use), preventing economic losses, food security, and preserving the balance of the ecosystem (Kariyanna & Sowjanya, 2024; Soni et al., 2022; Teixeira et al., 2023).

Among traditional pest detection methods, trapping is very common. Sex pheromone traps, yellow sticky traps, and light traps (Figure 1) allow the detection and evaluation of pests, while also helping to make decisions on the appropriate use of pesticides. However, these methods are manual, time-consuming, and costly to implement on a large scale (Teixeira et al., 2023). In addition, subjective decisions are made by examining the traps by experts. This is also not sustainable. As a result of traditional methods, the dynamic behavior of pests cannot be effectively examined causing subjective outputs.

In addition, excessive pesticide use occurs in the process of pest control, which is harmful to nature and human health and causes the destruction of useful species (Amrani, Diepeveen, Murray, Jones, & Sohel, 2024; Zheng et al., 2023).

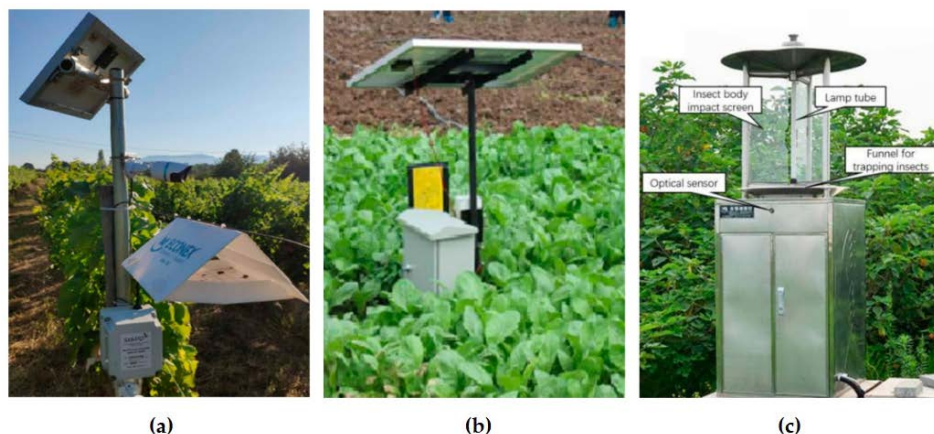


Figure 1. Insect Pest Traps (Teixeira et al., 2023). a) Pheromone trap; b) Yellow sticky trap; c) Light trap.

Modern agriculture requires more effective methods for pest management and crop protection while ensuring ecosystem sustainability. These methods are examined under the title of Integrated Pest Management (IPM). Technological approaches such as Artificial Intelligence (AI), Machine Learning (ML), Computer Vision (CV), and the Internet of Things (IoT) have a high potential for IPM strategies (Dewi, Christanto, & Dai, 2023; Kariyanna & Sowjanya, 2024; Teixeira et al., 2023). Automatic pest detection applications can be developed by using image processing and complex decision-making algorithms on images obtained through camera-equipped devices. Thanks to these applications, which are now called Smart Pest Management (SPM), the accuracy and speed of pest detection processes are increasing (Kariyanna & Sowjanya, 2024; Teixeira et al., 2023). It also supports environmental sustainability by optimizing pesticide use.

In the classification of insect pests, early detection of species, especially in the larval stage, is of critical importance for the protection of crops (Zheng et al., 2023). However, difficulties such as different background conditions (leaves, tree trunks, different plant colors), the presence of insects of the same species in different colors, and the presence of insects in a very small area in the obtained images are also disadvantages of imaging systems (Amrani et al., 2024). In recent years, deep learning models that examine the data layer

by layer without requiring preprocessing have been used to address such difficulties. Convolutional neural networks (CNNs), in particular, offer significant potential in image-based insect classification tasks. The ability of CNNs to automatically detect insect species with high accuracy rates has become an important building block in terms of efficiency in agricultural production.

In recent years, when we look at the studies conducted for automatic detection of harmful insects, Kasinathan et al. compared Artificial Neural Network (ANN), Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Naïve Bayes machine learning algorithms with the CNN model they proposed on the 9-class dataset created by Wang and 24-class dataset created by Xie. The CNN model gave 91.5% accuracy on the Wang dataset and 90.0% accuracy on the Xie dataset (Kasinathan, Singaraju, & Uyyala, 2021). In the study by Soni et al., EfficientNetB7, Xception, Mobilenet, and MobileNetV2 were trained using the Kaggle dataset. It was found that the EfficientNetB7 method had a classification accuracy of 95.15% for the dataset. Then, the decision-making mechanism was adapted to the mobile application called Kisaan, which was created using a Flutter framework, and an online pest detection system was designed via smartphones (Soni et al., 2022). In the study conducted by Doan, the EfficientNet model was adjusted and retrained on Xie24, D0, and IP102 insect pest image datasets and the Power Mean Support Vector Machine (PmSVM) machine learning classifier was designed using their activations. As a result of the study, 99%, 99%, and 72.31% classification accuracies were obtained on the used datasets, respectively (Doan, 2023). Zheng et al. focused on simple but accurate models suitable for mobile devices. In the study, a novel insect classification method based on lightweight CNNs embedded attention mechanism, PCNet (Pest Classification Network), was developed. An accuracy of 98.4% was obtained on the 30-class larva dataset they obtained. The success of the method was also tested on the IP102 dataset and an accuracy of 73.7% was obtained (Zheng et al., 2023). The aim of Syahputra et al. was to determine the best method for detecting insect pests on the IP102 dataset using pre-trained common CNN models (transfer learning + fine-tuning). According to the results of this study, when fine-tuned, DenseNet-201 model produces 70%, MobileNetV2 66%, MobileNetV3L 68%, InceptionV3 67%, Xception 69% accuracy value (Syahputra, Siregar, & Insani, 2023). In their study, Rimal et al. A Flutter-based mobile application that works both online and offline was

designed by training the proposed CNN model based on MobileNet on the IP102 dataset. The model provided 96.19% accuracy for training, 95.04% for validation, and 91.62% for testing (Rimal, Shah, & Jha, 2023). At last, unlike the others, Amrani et al. focused on a single insect species and proposed a Bayesian multi-task learning model to detect the presence of aphids and the size of aphids in their study. This structure includes the ResNet18 structure because it is robust and adaptive. Thanks to the proposed method, aphids were detected with 75.77%, 66.39%, 70.01%, and 59% accuracy rates in corn, rape, rice, and wheat images, respectively (Amrani et al., 2024).

As can be seen, Deep Learning provides great advantages in terms of accuracy in pest detection. These systems offer solutions to effective analysis of large amounts of insect pest images without human intervention when there is a shortage of experts. However, there are still gaps in the development of lightweight models for practical and online applications. In this study, a lightweight and effective CNN model is proposed. In the study, known CNN architectures were trained on the insect dataset and their performances were tested. The proposed CNN model was trained using the parameters of the architecture that gave the best results, and thus the previously acquired knowledge was used for an architecture that would be more suitable for mobile applications. The proposed model was compared with known architectures by considering the number of layers, depth, and total number of parameters, along with its success in pest detection. In this study, a solution is offered to eliminate the deficiencies of traditional insect trapping methods by using the advantages of modern technology. The proposed lightweight CNN model is aimed to contribute to environmental sustainability as a practical tool that performs insect detection accurately and quickly.

Insect Pest Dataset and Pest Species

In this study, the Kaggle dataset of Simran Volunesia was used (Volunesia). The dataset has nine insect pest classes that are harmful to agricultural products. Also, the images show the insects from their larval stage to their mature stage and the image sizes are inconsistent. First, the mode of all image sizes was calculated and resized as 220x300x3 RGB images. Then, the data (total of 917 images) were partitioned as 70% train, 15% validation, and 15% test data. Table 1 shows all the image numbers belonging

to train, validation, and test data for all nine classes. Also, Figure 2 shows sample insect images of all insect pest classes in the dataset used.

Table 1. The number of samples belonging to train, validation, and test data from all nine classes.

# of Class	Pest Type	# of Samples		
		Train	Validation	Test
1	aphids	63	18	19
2	armyworm	70	21	21
3	beetle	61	23	23
4	bollworm	82	24	25
5	grasshopper	65	25	25
6	mites	55	17	18
7	mosquito	71	25	25
8	sawfly	60	24	25
9	stem borer	89	21	22

Aphids: Aphids are among the important pests in agriculture and feed on cultivated plants. These insects damage plants and crops by sucking phloem sap. There are more than 5,500 species of aphids worldwide, of which approximately 250 species cause economic damage. Migrating aphids, which are common in crops such as corn, rice, wheat, and rapeseed, can cause huge crop losses (Amrani et al., 2024; Batz, Will, Thiel, Ziesche, & Joachim, 2023).

Armyworm: There are two races of armyworms morphologically similar but genetically different. One is a rice strain that thrives in rice and pasture habitats while the other is a corn strain adapted to corn (maize), cotton, and sorghum. Their range expands all over the world due to favorable climatic conditions (Mendesil et al., 2023).



Figure 2. Images from Insect Pest Classes in the Dataset. a) Aphids; b) Armyworm; c) Beetle; d) Bollworm; e) Grasshopper; f) Mites; g) Mosquito; h) Sawfly; i) Stem Borer.

Beetle: Beetles are major pests attacking brassica vegetable and oilseed plants. Beetle pest management is difficult to maintain because they have complex biology and ecology. Mature beetles are highly mobile so it is hard to apply pesticides. Also, they develop plant-derived chemical defenses so they can be resistant to pesticides (Li, Costamagna, Beran, & You, 2024).

Bollworm: Bollworms can inhabit more than 180 plant species, including cotton, corn, soybean, wheat and rice. They can enter pupal diapause if necessary to survive in adverse winter conditions (Jin et al., 2023).

Grasshopper: The habitats of grasshoppers are generally dry grassy areas and deserts. The reason they are different from other insects and more dangerous is that their numbers can increase catastrophically, and they can travel very long distances in a very short time. They can destroy crops, gardens, pastures and forests (Lomer, Bateman, Johnson, Langewald, & Thomas, 2001).

Mites: Some species of spider mites are important agricultural pests, targeting both annual and perennial plants. Some of these mites spin silky webs of varying densities on the leaves of their host plants. These web

structures serve as an adaptation for the mites' survival and also lead to different life types depending on their feeding habits and web density. Annual host plants are considered to be unstable habitats, while spider mites infesting these plants exhibit a stable life type. On the other hand, perennial host plants are considered to be stable habitats, and mites infesting these plants develop different life types (Mushtaq, Ali, Kamran, & Alatawi, 2023).

Mosquito: Mosquito species are pests attacking fruits and plantations. They are also dangerous to human health, carrying many diseases. They suck the sap from the inhabited plant's leaves, buds and shoots (Sankarganesh, Rajeshwaran, & Mounika, 2023).

Sawfly: Sawflies can lead to significant crop losses, particularly in wheat, by attacking the stems of the plants. Their control is challenging due to their life cycle. Mature sawflies deposit their eggs inside the host plant's stem, where the larvae develop by feeding on the plant tissue. This feeding behavior ultimately causes the seed head to drop to the ground (Peirce, Cockrell, Ode, Peairs, & Nachappa, 2022).

Stem Borer: Stem borers are significant pests affecting rice, maize, broomcorn millet and wheat production, threatening food security worldwide. A particularly destructive species, yellow stem borer, primarily targets rice plants feeding on their internal tissues from the larval to mature stages. Managing this pest is challenging due to the development of resistance to pesticides (Zhou et al., 2024).

Deep Learning and Proposed Model

Machine Learning (ML) is a field of artificial intelligence that allows automatic learning and prediction of new data based on an existing data set. Deep Learning (DL), a sub-branch of machine learning, is a field where more complex artificial neural networks are used to effectively analyze increasingly complex data. The term "complexity" here refers to the non-linearity of the data. DL is designed with inspiration from biological human decision-making mechanisms and can have hundreds of layers that determine the depth in its structure. DL eliminates the need for preprocessing stages by directly processing the raw data. Each layer of DL processes the data in a different way and is connected to each other by nodes. These nodes consist of weights that represent the relationships between the layers (Batz et al., 2023; Kariyanna & Sowjanya, 2024).

In the fields of Machine Learning (ML) and Deep Learning (DL), models are evaluated on training, validation and test sets. While training and validation sets are used in the development and training phase of the model, the test set is used in the final evaluation phase of the model. Using the validation data set in the development phase and then testing the model based on data it has never seen helps prevent the overfitting problem and allows the model to generalize more accurately. When the validation and test results are compared, it can be said that the model has made a correct generalization if these results are close to each other (Batz et al., 2023).

Deep Learning (DL) models usually require large data sets to train successfully. However, in some applications, the problem of not being able to obtain enough data due to high cost and effort may be encountered. This is where Transfer Learning (TL) comes into play. TL is a method of using a model trained on a different data set to analyze another data set. This approach is extremely effective when the distribution of the new data is similar to the distribution of the previously trained model's data. The weights of the previously trained model allow tasks to be performed by improving the learning of new data. TL thus provides better performance with limited data and significantly reduces training time (Batz et al., 2023; Syahputra et al., 2023).

Among DL methods, Convolutional Neural Networks (CNNs), which are especially popular in image classification, extract image patterns such as edges, shapes, and textures at different levels using a series of convolution layers. Then, the size of the feature maps is reduced by pooling layers to preserve the relevant information. Finally, the fully connected layer provides a connection between all layers and uses the information in each layer to make predictions (Batz et al., 2023).

In this study, several known CNN architectures trained on the ImageNet dataset were used as TL methods to classify insect pest images. The input layer, the fully connected, and the classification layer were changed according to the insect pest dataset. Later, a new, lightweight CNN model was proposed to counteract the unpractical use of these architectures in the field of agriculture.

Inception V3: Inception V3, as a variation of GoogleNet, is based on the principle of splitting 7x7 convolutions into two or three consecutive 3x3 convolution layers. This deep neural network design is equipped with Label Correction and extra classifier components, aiming to provide better

performance with less computing resources. Inception blocks consist of layers where filters of various sizes work in parallel, thus the model captures information at different scales, increasing efficiency and accuracy. It also improves accuracy depending on the input scale using the “batch normalization” technique, achieving effective results in machine learning tasks such as image classification (Doan, 2023; Syahputra et al., 2023).

ResNet18: ResNet is a network architecture designed to solve the problem of learning image activation maps. This model contains many stacked residual units where the shortcut connections add the input of the previous layer to the output of the next layer, skipping unnecessary layers and thus speeding up the training process. Its special architecture helps the network understand global image features by preventing gradient distortion in the backpropagation process (Doan, 2023).

ShuffleNet: ShuffleNet is a lightweight CNN architecture that is widely used in hardware with low processing capacity and in real-time applications where we need to get fast results. It is an efficient architecture that exhibits high performance while reducing computational costs by reducing the number of learning parameters using pointwise group convolution and by enabling the learning of various features with different inter-channel information flow with the channel shuffling layer (L. Liu, Wang, & Ma, 2024; Ma, Zhang, Zheng, & Sun, 2018; Ying, Sun, Zhou, & Lin, 2023).

Xception: The most basic feature of the Xception (Extreme Inception) CNN architecture is that it consists of both depth and point convolution operations called "Separable Convolution Blocks". This design provides an advantage because it allows better results to be obtained by using fewer parameters. Additionally, Xception employs batch normalization to address challenges related to input scale. The architecture features a deep structure comprised of three distinct stages: entry flow, middle flow, and exit flow. Despite its effectiveness across various applications, it is important to acknowledge that deep networks may lead to overfitting issues. Furthermore, determining which layers provide the most decisive information can be challenging, necessitating careful consideration during implementation (Gülmez, 2023; Y. Liu et al., 2022; Syahputra et al., 2023).

The proposed lightweight CNN architecture has a design that integrates both branch and residual structures. Following an initial Convolution Layer composed of 16 filters with a 3x3 kernel, the branch structure utilizes convolution layers with 32 filters and a 5x5 kernel, repeated five times. The

output of each repeated layer is summed with the output of the previous layer via an Add Layer. Subsequently, the output from the branch structure serves as the input for a single 32-filter convolution layer with a 5x5 kernel, which is then fed into residual blocks comprised of the same type of layers, also repeated five times. To reduce the dimensionality of features within the branch structure, a 3x3 kernel maximum pooling layer with a stride 2 is employed. Additionally, batch normalization is applied to both branch and residual structures to eliminate the problems arising from the input scale. The architectural design is illustrated in Figure 3.

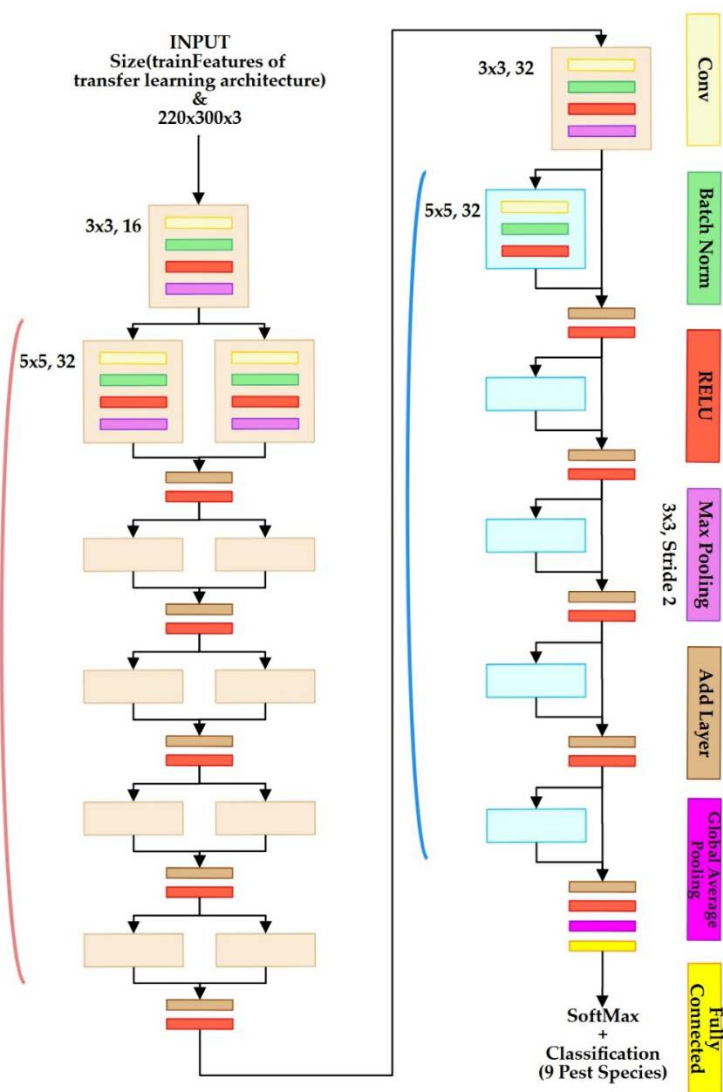


Figure 3. Proposed lightweight CNN architecture.

In this study, we first obtained transfer learning results from the Inception V3, ResNet18, ShuffleNet, and Xception networks for the insect pest dataset. Based on the validation and test accuracy results, we selected the activations from the best-performing network to serve as the input layer for the training of the proposed lightweight convolutional neural network (CNN) architecture. This approach leverages the knowledge acquired from established models to train a new model characterized by significantly fewer learning parameters, making it more suitable for insect pest classification applications that require faster decision-making and reduced computational costs in agricultural settings. Moreover, this methodology facilitates easier training of the new network with additional insect images. After the training, the new model was tested on the images with changing the size of the input layer to 220x300x3. Figure 4 illustrates the flow diagram of the study.

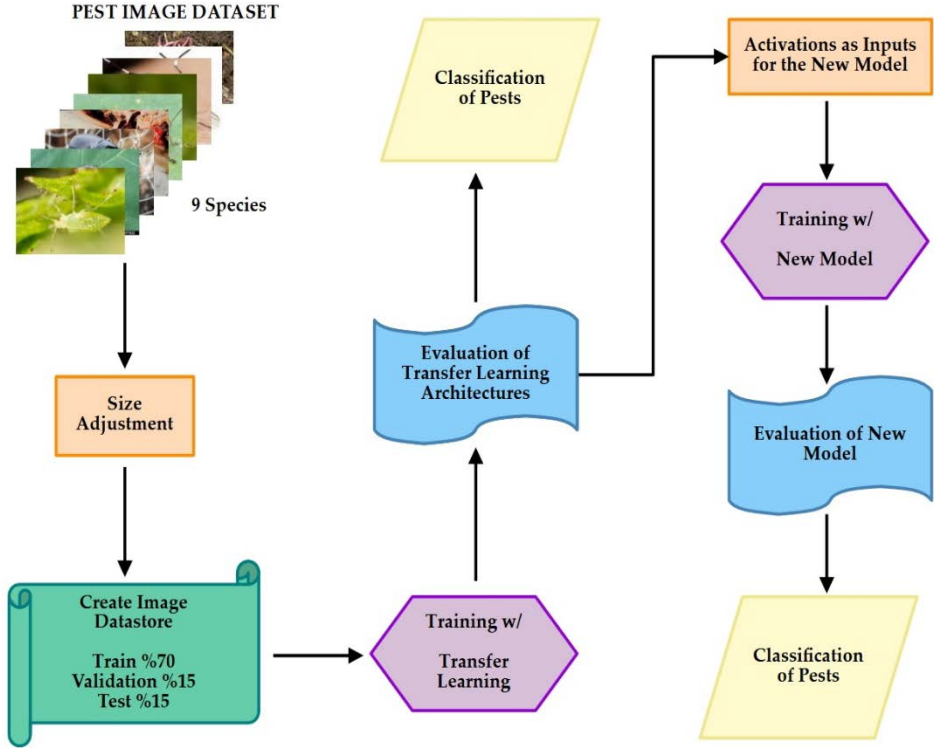


Figure 4. Flow diagram of the study.

Results and Discussion

In this study, accuracy, which is the percentage of correct predictions to total predictions is the primary evaluation parameter. Specifically, the accuracy of the validation and test sets determines the activations associated with the transfer learning method, which will be used as training parameters for the developed CNN model. In addition to accuracy, the model was evaluated by calculating precision, which shows the ratio of true positive predictions to total positive predictions, and recall, which shows the ratio of true positive predictions to actually positive examples, for validation and test data.

Inception V3, ResNet18, ShuffleNet and Xception networks was used as transfer learning methods to classify insect pest images belonging to nine insect classes. Parameter optimization was not used during transfer learning; the learning parameter was fixed at 0.01 with sgdm solver function. Mini batch size was 16. Validation frequency was 50 while the maximum epoch number was 10. All the networks except ResNet18 give the same accuracy result of 97.98% which is the highest one for the validation set. However, the highest test accuracy was obtained from Inception V3 model with 97.54% accuracy. Inception V3 also has the highest Recall and Precision results for both validation and test set. Validation accuracy and validation loss graphs for all iterations belonging to transfer learning networks is shown in Figure 5.

Because Inception V3 was found as the best performed transfer learning network for insect pest dataset, the activations obtained from the “mixed 10” layer, which is the last mixing layer located before the fully connected and classification layers, was used to train the new model. “Mixed 10” layer concatenates features from different scaled convolutions along the channel dimension. After the training process of the new model was completed, it was tested by using the test images with 220x300x3 dimensions. Parameter optimization was realized at this stage and the best result was found with 32 mini batch size, 50 validation frequency, and 0.001 learning parameter. The maximum epoch was fixed at 10. The new model yields 98.48% and 97.54% accuracies from validation and test set, respectively. Even surpassing Inception V3, it also has the highest recall and precision values for both validation and test set. Table 2 shows the accuracy, recall and precision results of all the network models including the proposed one. Figure 6 shows the training progress of the new model, while Figure 7 shows its confusion

matrix illustrating all the true and negative classifications belonging to validation and test sets.

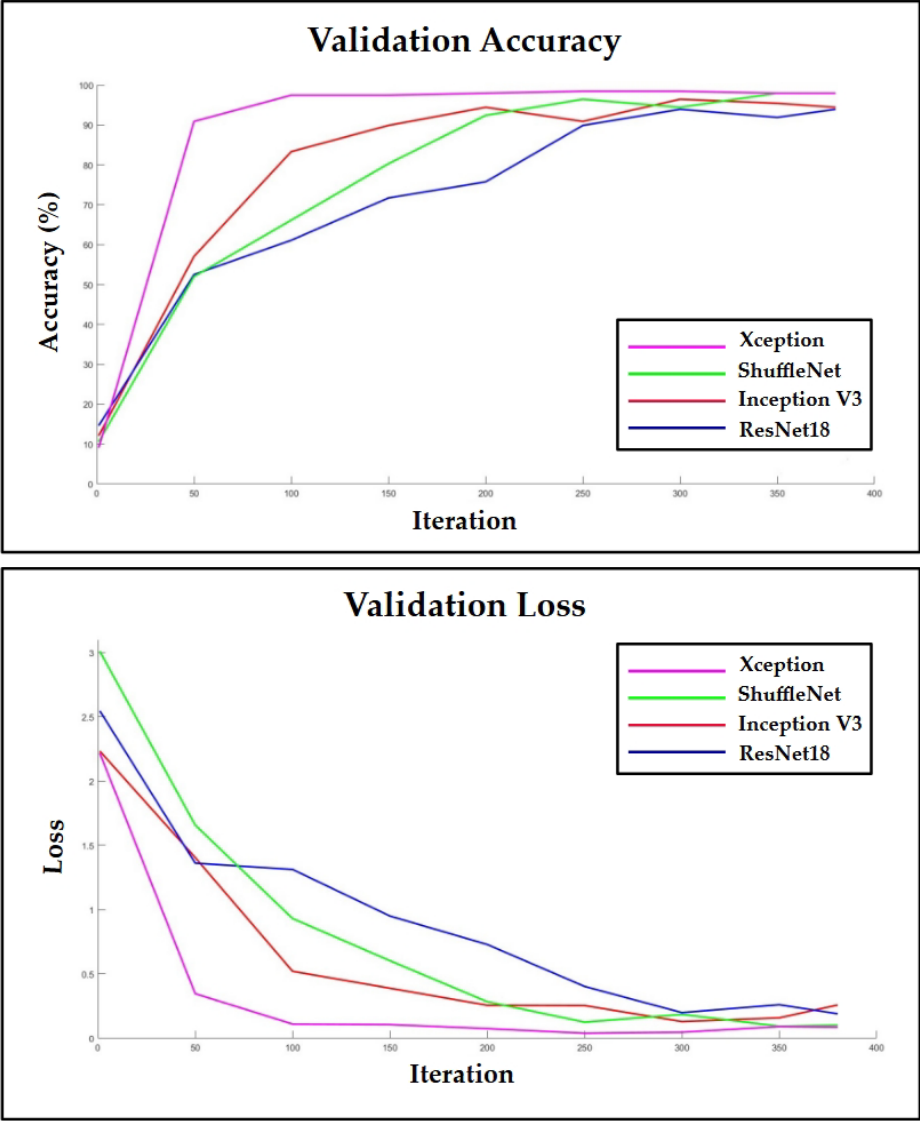


Figure 5. Accuracy and loss graphs belonging to validation process

Table 2. The evaluation results of transfer learning networks and the new lightweight CNN model.

Network	Acc Tr	Acc Val	Acc Test	Recall Val	Precision Val	Recall Test	Precision Test
Inception V3	99.03	97.98	97.54	98.07	97.95	97.34	97.68
ResNet18	99.19	96.97	95.07	96.98	96.90	95.03	95.27
ShuffleNet	100.00	97.98	95.07	97.88	97.91	95.03	95.00
Xception	100.00	97.98	96.06	97.88	97.92	96.26	96.30
New Model	99.51	98.48	97.54	98.52	98.52	97.43	97.57

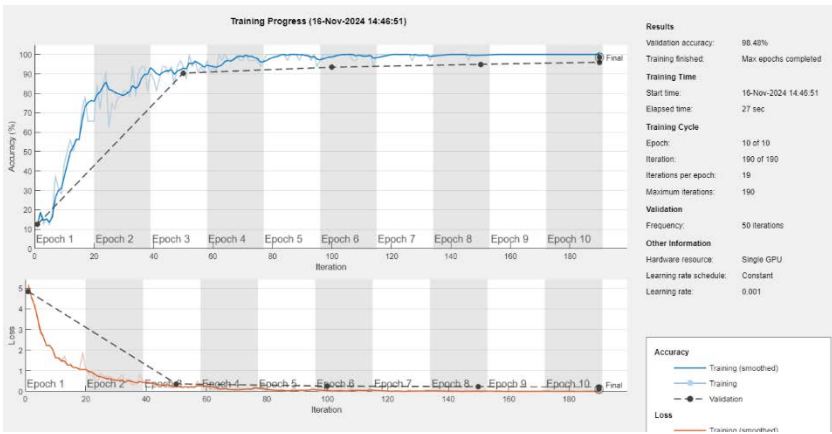


Figure 6. Training progress of the proposed CNN model.

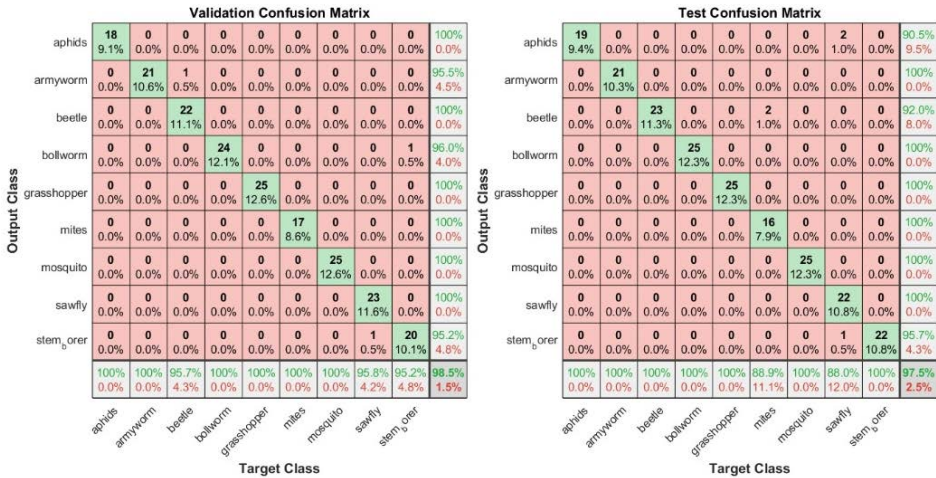


Figure 7. Confusion matrices of validation and test processes.

As seen from Figure 6, the training progress of the new model is much smoother, and the model approaches the maximum level faster. Also, it has the advantage of using the previous experience of Inception V3, so that its performance is spectacular. As additional results, confusion matrices in Figure 7 indicate that aphids, armyworm, bollworm, grasshopper, mites, and mosquito were classified perfectly for validation set. Aphids, armyworm, beetle, bollworm, grasshopper, mosquito, and stem borer were classified perfectly for test set. To highlight the success of the model, the new model was also compared to the known CNN architectures in terms of the number of layers, the depth, the total number of learning parameters, total training time and testing time of a sample, which are presented in Table 3. Xception network has the highest training and testing time, which is undesirable for real-time applications like insect pest detection in agriculture. Inception V3 has the largest number of layers (315) and learning parameters (23.8M), but its training time is approximately half that of the Xception network. This means that the depth of the network negatively affects the training and testing times more significantly, because Inception V3 has the depth of 48, while it is 71 for Xception. Among transfer learning networks, ShuffleNet is the fastest. However, the new lightweight model has the fastest training time with 27 seconds and testing time with 0.0040. Moreover, it is cost friendly and advantageous in real-time applications with 88 layers, 664.4K learning parameters with a depth of 12.

Table 3. Comparison of the lightweight CNN model with transfer learning networks in terms of the number of layers, the depth, the total number of learning parameters, total training and testing time.

Network	# of Layers	Depth	# of Learning Parameters	Training Time	Test Time (per one sample)
Inception V3	315	48	23.8M	10 min 49 sec	0.0143 sec
ResNet18	71	18	11.6M	4 min 4 sec	0.0065 sec
ShuffleNet	172	50	1.4M	3 min 47 sec	0.0051 sec
Xception	170	71	22.9M	21 min 25 sec	0.0330 sec
New Model	88	12	664.4K	27 sec	0.0040 sec

Conclusion

In this study, a high-performance lightweight CNN architecture suitable for real-time applications was designed to automatically detect and control insect pests that harm agricultural products, human health and nature without the need for experts. The proposed model was compared with complex networks such as Inception V3, ResNet18, ShuffleNet and Xception in terms of performance metrics such as accuracy, recall and precision, and it achieved superiority in all criteria. The model's validation and test accuracy rates were obtained as 98.48% and 97.54%, respectively. In addition, it was proven to be the most suitable option for real-time applications with minimum training and test times.

Table 4. Literature Comparison

Author	# of Class	Method	Acc
Kasinathan et al.	9	Proposed CNN	91.50%
	24		90.00%
Soni et al.	9	EfficientNetB7 + Kisaan	95.15%
Doan	24	EfficientNet + PmSVM	99.00%
	40		99.00%
	102		72.31%
Zheng et al.	30	PCNet	98.40%
	102		73.70%
Syahputra et al.	102	DenseNet-201	70.00%
Rimal et al.	102	MobileNet + Flutter	91.62%
Amrani et al.	Presence of one species	Bayesian multi-task learning model	75.77%
This study	9	Proposed lightweight CNN	97.54%

When compared to other studies in the literature in Table 4, it is seen that the proposed model offers significant advantages in terms of performance and applicability. For example, Kasinathan et al. and Soni et al. achieved 91.50% and 95.15% accuracy rates with their proposed CNN structure and the EfficientNet they used, respectively, while the proposed simple structure trained with the parameters of an existing system and tested with the original images of the dataset showed higher performance. These scientists used 9 classes of insect pests as in this study. Although it is difficult to directly

compare the performance of the proposed lightweight model with the methods of other authors working with different data sets, it attracts attention with its simple structure and successful results.

As a result, it is concluded that the proposed lightweight CNN model provides an effective solution for the detection and control of insect pests in the agricultural field. In cases where there are hardware constraints, it is clear that this model provides an advantage over accepted networks by requiring less computation. In order to generalize the performance of the model in a wider range, it is recommended to conduct additional evaluations on data sets with various classes. In today's world where increasing human population and food shortages are observed in the agricultural field, accurate and effective detection of insect pests is of great importance. Considering the difficulty of training producers, it is thought that this study will be a pioneer in terms of developing structures that provide fast solutions with simple hardware.

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