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DEEP LEARNING APPROACHES IN PRECISION AGRICULTURE: A COMPREHENSIVE REVIEW OF CROP CLASSIFICATION, DISEASE DETECTION, AND WEED DETECTION TECHNIQUES

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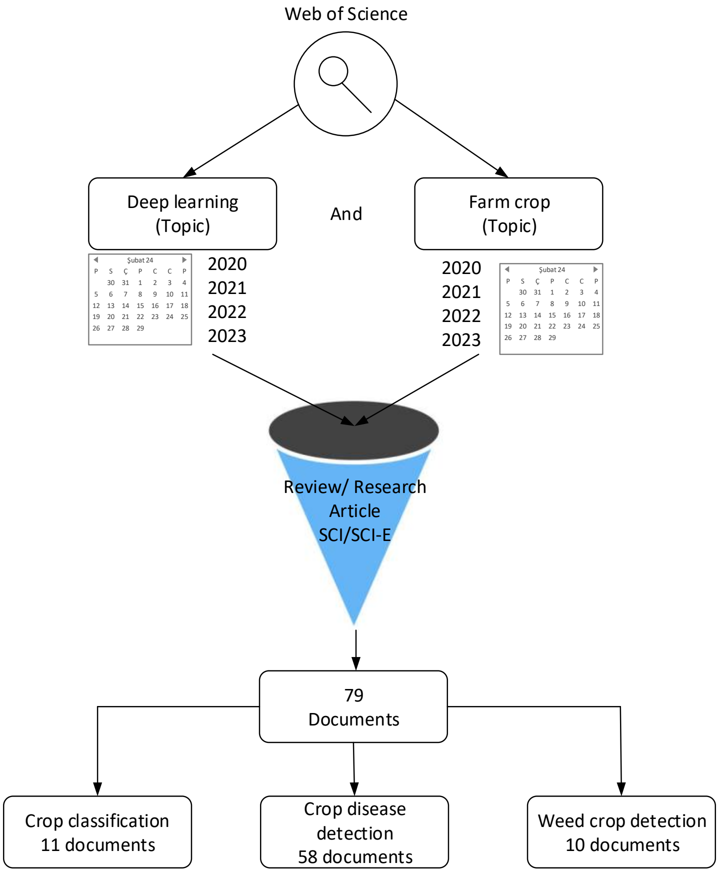
Highlights

- Research on deep learning techniques applied in the field of field crops research.
- Detailed review of 79 relevant research articles.
- Examining the uses of deep learning techniques used in the field of research.
- Examining the originality of deep learning as a technology.
- Discussion of advanced deep learning models used in various agricultural problems.
- Examining open issues, trends, and challenges facing researchers for deep learning and advanced technology use.

Graphical Abstract



Flowchart of the proposed method

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ABSTRACT: This paper presents a systematic and comprehensive review of deep learning (DL) methodologies used in precision agriculture (PA). It focuses on three critical application areas in particular: plant classification, plant disease detection, and weed detection. The study covers 93 peer-reviewed papers published between 2020 and 2025 and indexed in the SCI and SCI-Expanded indexed WoS database. Of these, 68 studies addressed disease detection, 13 focused on plant classification, and 12 examined weed detection strategies. The review describes a wide range of DL architectures, including Convolutional Neural Networks (CNNs), Residual Networks (ResNet), You Only Look Once (YOLO), Image Transformers (ViT), and various hybrid frameworks. A large number of models demonstrated exceptional performance with classification accuracies reaching up to 99.64% and precision and sensitivity values exceeding 98%. Studies have evaluated a wide range of datasets such as PlantVillage, COCO, and privately acquired RGB/UAV imagery, and a variety of sensor platforms such as drones, smartphones, hyperspectral, and LiDAR systems. Moreover, transfer learning and ensemble learning approaches have been frequently adopted to enhance generalization capabilities and model robustness. The integration of DL models with advanced technologies such as unmanned aerial vehicles (UAVs), unmanned ground robots (UGRs), depth-sensing cameras, and mobile-based platforms facilitates automation in agricultural monitoring, disease diagnosis, and yield prediction. This review not only consolidates the current technological developments, but also analyzes the emerging trends, methodological gaps, and possible directions for the advancement of sustainable, data-driven agricultural systems using artificial intelligence.

Keywords: *Precision Agriculture, Deep Learning, Farm Plant, Plant Classification, Disease Detection in Plants, Weed Detection, Artificial Intelligence, Comprehensive Review*

1. INTRODUCTION

The global human population, which was estimated as 2.5 billion in 1950, has reached 8.0 billion by mid-November 2022. 1 billion people have been added to this population since 2010, and 2 billion people have been added since 1998. It is seen that food consumption will increase in parallel with this population growth. On the other hand, it is known that approximately 821 million people have problems in terms of food supply. However, increasing food production is particularly difficult due to several factors. Especially primitive agricultural methods, poor stocking techniques, political reasons and market practices are factors that make food production difficult. International food and agriculture organizations emphasize that food production should be increased by 70% by 2050. Since the area of lands which are suitable for agriculture or have high soil quality does not increase, making plans to increase production should be a priority [1], [2].

PA is a farming method that has the potential to bring great benefits to the agri-food industry and improve environmental quality by reducing the environmental footprint [3]. PA technologies are used in important cycles in agriculture. Aerial images, robots, smart sensors, etc. technologies are important

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technologies at this point [4]. According to researches, it is thought that artificial intelligence and machine learning will remove the obstacles of HT. Software-based approaches are not new, there are approaches dating back decades and these approaches are developing [5]. However, the number of DL approaches, which is a specialized field of machine learning, is increasing day by day. DL is a subdomain of machine learning and covers more complex artificial neural networks [6]. Many different DL-based network architectures have been used for PA. IoT, wireless sensor networks, aerial images taken with the help of drones have been applied to various deep learning architectures and successful results have been achieved. For the results of some models used especially in the detection of plant diseases and plant pests, [7] can be read. PA is an approach that aims to optimize agricultural production by using technology in the field of agriculture and performing analytics of the data obtained because of the technologies used [8]. The main goals of PA include more efficient use of agricultural resources, reducing environmental impacts and increasing product productivity [9].

Technologies used in PA are used to monitor soil and plant condition, collect, and analyse data, and provide the right amount of input at the right time. These technologies include sensors, drones, and GPS [10]. Sensors are used to measure soil moisture, temperature, and nutrient (physical quality of the soil) content [11], while drones and satellite imaging can be used to detect plant stress, yield, and diseases [12], [13]. GPS is an important tool for the accurate placement and orientation of agricultural machinery and equipment [14]. The use of precision agriculture technologies allows for more targeted and effective application of agricultural inputs (e.g. fertilizer, water, and pesticides). This reduces input costs [3]. Additionally, precision agriculture practices provide higher profitability in agricultural production by increasing crop yield [15]. The methodology of the research is given in Figure 1.

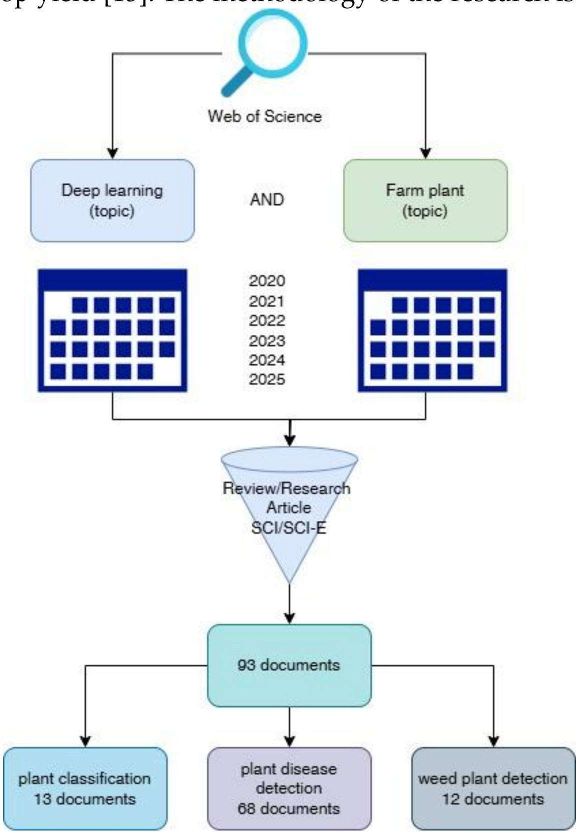

Figure 1. Methodology of the research

This study was conducted to comprehensively examine the deep learning methods used in agriculture, the machines and equipment used with these methods, and the purposes of using deep learning. The aim of this study is to provide a comprehensive literature review from many perspectives to researchers working on HT, investors who want to advance in this field, and those who want to focus on this field. In this study, not only deep learning approaches will be discussed, but also these approaches will be classified. The review and research articles listed in SCI and SCI-Expanded indexed journals for the last four years were filtered using the keywords "Deep Learning" and "Farm Plant". The literature review was conducted in the Web of Science (Wos) database. The results obtained in the literature review were analyzed and publications outside the research field of engineering, computer science, and agriculture were eliminated. In addition, the remaining results were analyzed one by one, and studies that did not comply with this study and did not provide sufficient numerical data for the metrics were eliminated. A total of 93 studies were evaluated, 13 of which were related to plant detection, 68 to plant disease detection, and 12 to weed detection. However, the study benefited from more studies in writing the text. This study focused on analyzing the intensive use of deep learning approaches, which are successfully used in different research areas today, for field crops. In this context, the research questions of this study are as follows.

Research Question 1: In which subdomains of farm plants research, are deep learning approaches used?
Research Question 2: What are the deep learning techniques used in crop classification, disease detection and weed detection?

1.1 Contribution

Today, researchers have presented many studies on the use of deep learning in agriculture. However, no studies have focused on the specific extent to which deep learning approaches are used as a technology in agriculture. This review presents a detailed discussion of deep learning approaches used in agriculture. The contributions of this study to the literature are as follows.

- This comprehensive research discusses deep learning models in agriculture. It has been investigated to what extent deep learning models are original studies in terms of the use of technology in the agricultural sector.
- In this review, an examination of the DL models used in terms of innovative datasets and new layers/new structures is presented. It is thought that the results of this review may direct the use of deep learning approaches in agriculture.
- It is discussed in which research areas deep learning approaches have been successfully applied in the agricultural sector.

General information and the motivation of the study is given in first section. Then, deep learning and deep learning approaches are mentioned theoretically in second section. Sections three gives details of deep learning methods used for PA. These approaches are categorized, and their advantages and disadvantages are also discussed. Information about the methods that are recommended for the detection of vegetative diseases, plant classification and detection of weeds and the characteristics of these methods are given. In the fourth chapter, the technologies and equipment used in PA are listed. DL approaches used in PA are explained in fifth section. In Discussion, which is the sixth section, gaps, trends and challenges in the analysis and literature on deep learning approaches used in PA are discussed. The summary of the paper and future works is given in seventh section, namely Conclusion.

2. FUNDAMENTALS OF DEEP LEARNING

2.1. Artificial Neural Network

Artificial Neural Networks (ANN) have become an important component in the field of Artificial Intelligence (AI) and Machine Learning (ML). These networks are inspired by the biological neural networks of the human brain and consist of connected nodes or artificial neurons that process and transmit data [6]. The development and improvement of ANN have significantly contributed to the solution of problems in various domains. ANN are mathematical models inspired by biological neural networks. These networks can learn complex patterns and relationships by processing data. In agricultural production, ANN can analyse data from various sensors to detect plant growth, diseases, and pests, predict crop yields and optimize agricultural processes. ANN can be divided into several categories. Feedforward and backpropagation neural networks are the most common and basic types of them.

Feedforward and Backpropagation

Feed forward refers to the network, processing input to output [16]. Backpropagation, on the other hand, refer to updating the weights and biases by using the output error of the network [17]. Figure 2 shows the feedforward and backpropagation architecture. In feedforward architecture, output of each neuron is calculated by Eq.1:

$$z = Wx + b \tag{1}$$

W refers to weight matrice; x is input vector and b is bias vector. Then, activation function (f) seen in Eq.2 is applied to z.

$$a = f(z) \tag{2}$$

By this way, the activation value (a) of the neuron is obtained. This process is performed for all layers in the network.

In the backpropagation process, the error value is calculated by comparing the output of the network with the expected value. Common error functions include Mean Square Error (MSE) and Cross Entropy. The error value is used to update weights and biases. Gradient descent optimization algorithm is used by taking the derivatives of the error value according to weights and biases [18]. The error of the weight is calculated with Eq. 3, and the error value of the bias is calculated with Eq.4.

$$\Delta w = -\eta * \nabla L / \nabla w \tag{3}$$

$$\Delta b = -\eta * \nabla L / \nabla b \tag{4}$$

η refers to learning rate; L refers to error function and ∇ refers to gradient. Δw and Δb refer to weights and bias updates. These updates are applied across iterations to optimize the performance of the network.

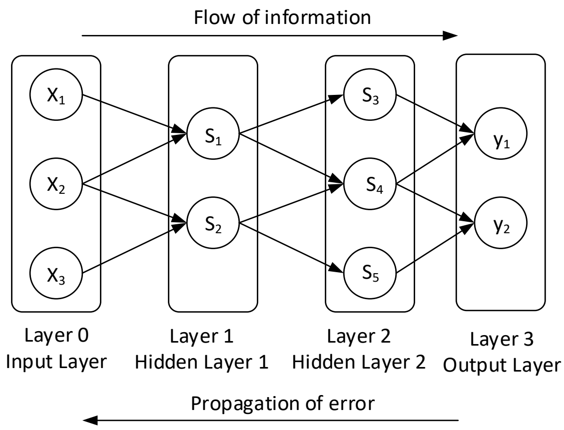

Figure 2. Traditional artificial neural networks feedforward backpropagation architecture.

Apart from the feedforward and backpropagation type of artificial neural networks, there are also recurrent neural networks, where the information calculated in the previous time step is included in the current calculations through loops within the network, convolutional neural networks for functions such as image classification / object recognition, and self-organizing neural networks that determine the output class themselves. Researchers select appropriate neural networks according to the nature of the problem.

2.2. Deep learning and Advantages

DL, which has become so popular in recent years with its ability to process large amounts of data, is a subset of ML that is a field of AI [6], [18]. However, DL differs from traditional ML in many aspects, such as the type of algorithms used, the complexity of the data that can be processed, and the performance of the models. DL is a type of ML that aims to model and solve complex problems using ANN. These networks are inspired by the structure and function of the human brain and consist of interconnected nodes that process and transmit information. The nodes in these networks are called neurons, and each layer performs a specific function. The main difference between DL and traditional ML is the depth of the network architecture. Traditional ML algorithms typically process input data to make predictions using a single layer of nodes. However, DL algorithms use multiple layer nodes to process increasingly complex features of the input data [19]. These layers allow DL models to capture more subtle and complex relationships in data, making them more powerful and accurate.

DL is a subfield of AI technology that enables significant developments, especially in areas such as computer vision and natural language processing [18]. In this study, we will evaluate the basics of deep learning and its features, especially increase accuracy and decrease modelling costs. We will also touch upon the effects of these photographs in various applications and the importance of their changes. Figure 3 shows the deep learning architecture generally.

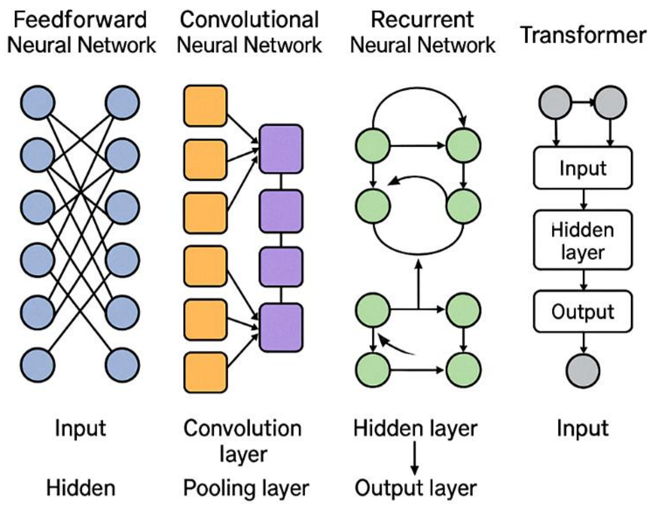

Figure 3. Deep Learning Architecture.

DL is used in many tasks related to image processing and image recognition. Its simple use makes DL models more common. Many studies in the literature, reports DL models with a success over 90% in image recognition studies in different fields [20], [21], [22], [23]. This increases the reliability of DL models. With the use of some specially developed hardware and libraries, the use of DL in image-centered problems is increasing day by day.

Deep models can be modified specifically for the problem and optimized for better results: As mentioned before, models consisting of effects such as weights, biases and many special layers can be used in different tasks by changing them. With transfer learning, the model can be classified, and its weights can be used in new tasks [12], [24], various classifications can be combined to optimize deep learning models [25], [26], [27], and new layers can be proposed to increase performance. [28], [29], [30]. DL techniques provide more reliable solutions with advanced decision-making by reducing dependence on human labour [31]. While some tasks may be time-consuming for humans, this process is quite fast for DL [32], [33], [34], [35], [36], [37]. Thus, labour costs are reduced, and more efficiency is achieved.

3. USE OF DEEP LEARNING IN PRECISION AGRICULTURE

In recent years, the agricultural sector has been experiencing a radical change with the use of DL techniques. PA has emerged as a practice that aims to optimize plant production through effective management of resources and has been promising in meeting global food demand. DL, inspired by the functioning of the human brain, enables innovative developments in the agricultural field. Using large datasets and powerful computational models, DL enables farmers to make data-driven decisions and gain valuable insights about their crops and farm operations. In the study presented by [38], they designed 260 ensemble classifiers using various pre-processing techniques, feature extraction methods and classifiers. The research then compared how effective these ensemble methods were to determine the best ensemble classifiers. During the evaluation process, the accuracy and sensitivity of the proposed method were evaluated using two datasets: PlantVillage and Taiwanese tomato leaves collected under various laboratory and field conditions. The most successful ensemble classifier was based on features such as shadow conditions, brightness changes, disease similarity, etc. and has achieved a good accuracy rate of 95.98%. Figure 4 shows the distribution of papers according to the tasks in the literature obtained.

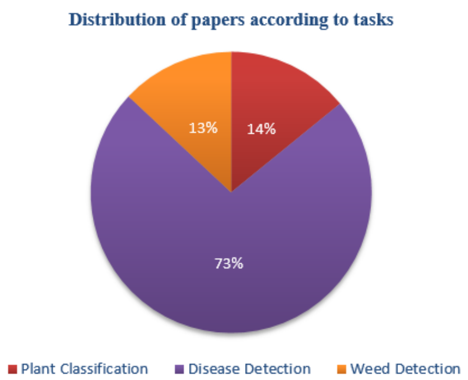

Figure 4. Distribution of papers according to tasks.

In this chapter, information about the applications of deep learning in precision agriculture and how this advanced technology provides a transformative impact on sustainable and efficient agricultural practices in areas such as plant monitoring, yield prediction, disease detection and resource management is going to be given.

3.1. Classification of Plants

In the study by Cho and friends [39], a smart agricultural robot was presented for the establishment of two infrastructures: high plant density, widespread object diversity and growth information view. After distributing solutions when measuring growth information in real-world smart agricultural fields, distributing depth information as well as RGB segments have been proposed for these distribution solutions with data enhancement methods. You can also use general measurements so that you can use growth information for two types of plants, such as plant stem diameter and the distance between a branch point and a growing point. A real-time deep learning model was used for object detection, utilizing RGB and depth information. In the study, the performance of the system was evaluated using plants grown on tomato plants. The YOLOR [40], [41] model classified with ImageNet was used together with the 2D object detector. In tomato samples, the AP value for flowers was 90.2% and the AP value for branch points was 94.8%. In the cucumber example, with the increase in data, the AP value was determined as 89.6%. These results show that the proposed method provides reliable results in target fault detection. However, the authors note that the system they designed depends on the lighting conditions, temperature, location, etc. of the mounted camera. It was emphasized that it is sensitive and weak to changes. During the experiments, a smart agricultural robot was used. This robot consists of depth cameras, LiDAR sensor, lighting devices and movement mechanisms (wheels, etc.). The authors mentioned cheaper payments in comparison of RGB-D camera sensors.

In a study conducted by [42], image data was collected regularly throughout the growing season in the environment where 30 plants of three different species were grown. Various tasks such as plant species recognition, growth analysis, health analysis, and yield stage determination have been accomplished using a deep neural network (DNN)-based technique. The study focused on modelling and interpretation of plant phenotype characteristics and aimed to develop computer vision-based analysis in the field of plant phenotyping. In the hydroponic system, optimal plant growth has been supported by artificially regulating factors such as light intensity, nutrient concentration, pH, and temperature-humidity. The created dataset contains time series measurements and information about plant growth stages, physiological states, and yield stages. YOLO-V3 model, a real-time object detection model, was used to identify and classify plant features based on the captured images. The accuracy rate, especially in terms of detecting Narcissus plants, was over 95%. The authors mentioned that collecting data was a challenging process. However, the dataset used by the authors consists of RGB images. Artificial and natural lighting were used when collecting the dataset. Photographs taken in bad lighting conditions and incorrectly were removed from the dataset. This has added an extra difficulty to the study.

The study by [43] has presented a semi-supervised DL framework for automatic pomegranate detection using a farmer robot equipped with a consumer-grade camera. The proposed system has bypassed the labor-intensive image labelling required in traditional DL methods and instead has used a novel multi-stage transfer learning approach. This method adapts a pre-trained network to the target task using controlled fruit images and then progresses to more complex scenarios for efficient segmentation of field images. The proposed framework was tested using the DeepLabv3+ (Resnet18) architecture in a commercial pomegranate orchard in southern Italy. The results were compared to those obtained with traditional manual image labelling. The proposed framework was successful in producing accurate segmentation results with an F1 score of 86.42% and an IoU score of 97.94%. The authors used a tracked robot, having an RGB-D sensor, weighing approximately 70 kg to collect the dataset. It has been observed that it can move balanced on difficult ground against vibrations. Since the captured colour and FullHD images were calibrated spatially and temporally, they also provide 3D analysis. It has been mentioned that the disadvantage of the method was that machine learning models require a large amount of data for training.

In the study by [44], a tomato detection model was developed to automatically detect all green tomatoes, regardless of whether they are covered or the growth stage of the fruit, using DL approaches. The model has used Resnet-101 with a faster region-based convolutional neural network (R-CNN) and transfer learning from the COCO dataset has also been performed. Performance on the test dataset showed a high average precision (87.83%, intercept >= 0.5 upon union) and a high accuracy in tomato counting (R^2 = 0.87). Additionally, the detected boxes were combined into a single image to create the tomato location map and estimate their size along a greenhouse row. With its ability to detect, count, location and size estimation of tomatoes, this method shows great potential for maturity and yield estimation. In the datasets used, photographs were taken using a camera. The authors mentioned the long model training period as disadvantages, the fact that some tomatoes are blocked by leaves and other tomatoes due to the 2D image, and the difficulty in estimating the size of tomatoes due to the lack of depth information.

In the study by [45], YOLOv5n and YOLOv5s – were applied and evaluated for cassava plant detection. The performances of these models were examined in different scenarios. Models have used NVIDIA Jetson AGX Orin embedded GPU for the application. Experimental results showed that YOLOv5s provides the best accuracy, but YOLOv5n has the best speed in detecting cassava plants. YOLOv5s allowed for more accurate crop counting, whereas YOLOv5n occasionally misidentified cassava plants. While YOLOv5s performed better for weed detection, it did so at lower speed. The study by [46] attempts to create a cost-effective robotic system that automates the monitoring and management of urban agriculture by addressing time constraints for modern city dwellers. Built from the ground up, the system combines a range of technologies such as the movement of Cartesian robots, computer vision, deep learning for plant recognition, irrigation scheduling according to growth stages and cloud storage. The effectiveness of the robotic platform was demonstrated by experiments with lettuce plants, precisely controlling movement and watering.

A method to remotely detect foliage and heads of broccoli plants using UAV RGB images and LiDAR point clouds was proposed by [47]. Methods using TransUNet for RGB image analysis and a point cloud transformer (PCT) network for point cloud segmentation achieve high accuracy and provide better results in terms of precision, recall, F1 score, and IoU than other studies. These results have the potential to contribute greatly to applied research about plant phenotyping and precision agriculture applications. In TransUNet RGB model images, average sensitivity of 0.917, recall of 0.864, F1 score of 0.901 and IoU of 0.895 have been obtained in distinguishing leaf and non-leafed sections. The study by [48] proposes a Yolov4_tiny-based deep learning algorithm that includes an adaptive spatial feature pyramid method to increase green pepper detection for use in complex and difficult to detect backgrounds. With 95.11% AP, 96.91% accuracy rate and 93.85% recall rate, the algorithm shows high accuracy and shows the same detection rate of the most advanced green pepper detection models. In the study by [49], a new DL image recognition approach is proposed to detect the rooting stage of Legacy blueberries. Legacy blueberries make up 80% of Chilean blueberry products. The developed model detects trays with live blueberry plants, trays without live plants, and the absence of trays using a CNN. The model's performance averages were 86% for accuracy and precision, 88% for recall, and 86% for F-1 score.

Sajitha et.al.[50] presented a comprehensive review on the use of ML and DL techniques in image-based plant disease classification. The study examined data sources, modeling strategies, and challenges in industry applications and made recommendations for future research. In strawberry cultivation, the measurement of phenotypic traits (such as crown diameter, petiole length, plant height, flower, leaf and fruit size) is important as it serves as a decision-making tool for plant monitoring and management. To date, strawberry plant phenotyping has relied on traditional approaches. Ndikumana et al. [51] developed an image-based Strawberry Phenotyping Tool (SPT) using two deep learning (DL) architectures, namely “YOLOv4” and “U-net”, integrated into a single system. SPT was developed in two steps using image data with different backgrounds captured by simple smartphone cameras as the basis. Irrespective of the complex environmental scenario of strawberry plant, the efficiency of the system in recognizing six strawberry phenotypic traits was verified. This tool can help farmers and researchers make accurate and effective decisions regarding strawberry plant management and possibly contribute to increased productivity and yield potential.

Shi et al. have introduced DFU-Net, a lightweight semantic segmentation model designed for real-time crop plant detection in complex field environments [52]. It extends the U-Net architecture by incorporating a Lightweight Crop Double-Depth Convolution (LC-DDC) backbone, an Initial Block, and a Fusion Block for multi-scale feature extraction. DFU-Net achieved over 92% PA, mIoU, and F1 scores across three datasets (cotton, seed melon, CVPPP), with peak F1 = 98.5% on the seed melon set. The model uses a composite loss function (weighted cross-entropy + Dice loss) to handle sample imbalance and runs at 10.5 FPS with only 0.975 MB parameters, making it ideal for low-power devices. It outperformed DeepLabv3+, PSPNet, U-Net, and others in both speed and segmentation quality.

Kim et al. have developed a non-destructive, image-based fresh weight prediction system for butterhead lettuce grown in commercial plant factories [53]. The study integrated a custom automatic image acquisition system with RGB, IR, and depth cameras installed on a rail-guided motion platform in a highly confined indoor environment. The system collected 376 annotated top-view images over 102 days. Three types of models were trained: conventional regression (with manual features like area and perimeter), MLPs, and CNNs using automatic feature extraction. The ResNet18-based CNN achieved the highest accuracy with R^2 = 0.95 and RMSE = 8.06 g, while MLP_2 offered faster inference (0.003

ms/image) with only a slight drop in performance (R^2 = 0.93). The solution proved suitable for on-site application with low-power devices, supporting precise harvest timing without physical contact.

Ying et al. have proposed a novel deep learning-based method called GS-NIR (Geometry-Smooth Neural Implicit Surface) to reconstruct high-fidelity 3D fruit models for phenotypic analysis [54]. The system improves NeRF-based reconstruction with two key innovations: geometric depth smoothing constraints and a random dilation sampling strategy, enhancing spatial continuity and reducing noise. A sparse segmentation network (Fuse-PointNet++) and a scale restoration algorithm are integrated to enable accurate phenotypic measurements. Compared to traditional scanners and prior NeRF variants (Instant-NGP, Instant-NSR), GS-NIR achieved the best performance on PSNR (29.74 dB), SSIM (0.812), and Chamfer Distance (0.889 mm). It was also more robust under real greenhouse conditions and outperformed even 3D scanners in measurement accuracy, with less than 1.2% error. Supporting Table 1 summarizes the articles in this section.

In [39] and [43], real-time classification was performed using RGB-D cameras and robotic systems. Cho's study achieved high AP values, while Devanna's method offers a practical contribution by reducing labeling effort through semi-supervised learning. Both studies are groundbreaking in sensor integration. However, the systems' environmental sensitivity (light, temperature) reduces their flexibility. [45] and [40] used lightweight YOLO variants, targeting real-time agricultural applications on low hardware. Models such as YOLOv5n and YOLOv4-tiny are optimized for mobile devices. These features make them suitable for widespread use in field applications, unlike larger and heavier models. Studies such as [44] and [53] include not only classification but also features such as crop counting, size estimation, and fresh weight measurement. These features directly contribute to applications such as harvest timing and yield prediction within PA. However, these systems often lack depth perception, and measurement errors can be affected by leaf overlap. In [40], the combined use of LiDAR and RGB images allowed for three-dimensional separation of plant morphology. This approach achieved high accuracy in applications such as precise phenotyping. However, the system's setup and data processing costs are high, which may limit its use. Simpler CNN models, such as those by [49], increase applicability on low-end hardware; however, their success is limited for complex plant structures or classifications requiring detailed information.

3.2. Disease Detection in Plants

In the study by [55], the authors propose a mathematical model of plant disease detection and identification based on DL. The model increases accuracy. First, the RPN was used to recognize and locate leaves in the complex environment. Then, based on the results of the RPN algorithm, the segmented images were processed by the Chan-Vese (CV) algorithm, which includes the feature of the symptoms. Finally, the segmented leaves were used as input to the transfer learning model, which was trained with the diseased leaf dataset under a simple background. Additionally, the model was tested with black rot, bacterial plaque, and rust diseases. The results show that the method has an accuracy rate of 83.57%, which outperforms traditional methods and contributes to sustainable development in agriculture by reducing the impact of disease on agricultural production. The authors obtained the data from the Chinese Plant Photo Bank. The authors mention that as disadvantages, there were no herbs such as hemp in the dataset and photos couldn’t take done under some field conditions.

In the study conducted by [56], a CCNN was designed to classify various tomato plant diseases. Compared to state-of-the-art architectures such as AlexNet and VGG-16, the proposed CCNN model consists of three convolution layers and three fully connected layers. This design reduces processing time and computational power while achieving higher accuracy in the classification of various diseases. Additionally, the number of hyperparameters of the proposed model is significantly reduced compared to existing models. The effectiveness of the CCNN model was experimentally validated with a dataset using ten tomato leaf classes and evaluated both qualitatively and quantitatively. The results show that the CCNN model achieves competitive accuracy compared to traditional models that require less computational resources. Moreover, the use of the proposed CCNN model with an accuracy rate of

98.44%, in a mobile system enables smartphone-assisted agricultural disease diagnosis, which is widely used globally.

Agricultural data were collected in the study by [57]. These images data were processed to remove noise and resizing. Features were extracted from the processed data using deep attention layer-based convolutional learning (DAL_CL). These extracted data were classified using recursive architecture based on neural networks (RNN). The proposed system can be used to categorize the obtained data and predict when a plant will contract (or not) a disease using deep learning. Experimental results show 96% accuracy, 75% F-1 score and 66% AUC value. The study by [58] offers automatic detection of lettuce with tip blight growing indoors using a deep learning algorithm based on a single-stage object detector. Images of lettuce with tip blight were captured under various lighting and indoor background conditions (under white, red, and blue LEDs). As a result of data augmentation, a total of 2333 images were produced and used for training using three different single-stage detectors: CenterNet, YOLOv4 and YOLOv5. The best result was obtained with YOLOv5 with a mAP score of 82.8%.

[59] presents ResNet v2 model and Optimal Weighted Extreme Learning Machine (CNNIR-OWELM) with a CNN selection startup for smart agrotherapy plant disease diagnosis and symptoms. The proposed CNNIR-OWELM method involves a set of IoT devices that capture rice plant images and transmit them to the cloud server over the internet. The CNNIR-OWELM method uses histogram segmentation technology to identify affected regions in the crop image. Additionally, DL with the ResNet v2 model is used to process features. In addition, in OWELM, Weighted Extreme Learning Machine (WELM) optimized by Flower Pollination Algorithm (FPA) is used to determine optimal data such as seeds. The results of the application of the presented model on a reference image dataset were compared. Simulation results show that the presented model effectively diagnoses diseases with 90.5% sensitivity, 96.1% specificity and 94.2% accuracy. The study by [60] proposes a DL model for identifying and classifying plant diseases using an open access image database of healthy and diseased leaves taken from five different varieties. AlexNet, a deep CNN model, is improved with Particle Swarm Optimization. The model achieved impressive results with 98.83% accuracy, 98.56% specificity, 98.78% sensitivity, and 98.47% F-Score, demonstrating the performance of this approach with the images taken under natural conditions.

In the study by [61], a new method called Local Feature Matching Conditional Neural Adaptive Processes (LFM-CNAPS) is proposed to overcome the limitations of existing deep learning-based plant disease detection techniques. Current methods, especially CNNs, suffer from accuracy when working with small numbers of samples and require large amounts of manually labeled data, which is not often encountered in practice due to variable plant pathogens and harsh farm environments. LFM-CNAPS which has been designed based on meta-learning, aims to detect previously unseen plant disease categories with just a few labelled examples and highlight 'important' input regions for predictions. The LFM-CNAPS model achieved 93.9% accuracy on the Miniplantdisease dataset. In the study by [62], a mobile-based lightweight deep learning model is proposed for plant disease detection to address the memory and processing power limitations generally associated with deep learning methods in mobile applications. The model managed to achieve 97%, 97.1% and 96.4% accuracy rates on apple, citrus and tomato leaves datasets, respectively. Even on a privately collected apple leaf dataset, the model achieves 93.33% accuracy, confirming its suitability for field applications. A comparative study with equivalent lightweight models proves the superiority of the proposed model.

[63] present a shuffled shepherd optimization algorithm (SSSO-based deep learning) method developed for classification of rice leaf disease and prediction of severity rate. The system uses deep maxout network for classification and deep LSTM for severity rate estimation. Training is performed with the improved SSSO algorithm, which is a combination of mixed shepherd optimization algorithm (SSOA) and social optimization algorithm. The technique achieved the highest accuracy of 0.926, sensitivity of 0.935, specificity of 0.892, and lowest mean square error and root mean square error rates of 0.106 and 0.326. The accuracy of the approach is improved by 7.24%, 5.29%, 4%, and 2.81% over

existing techniques such as BLSNet, multilayer maxout, RSW-based deep RNN, and RHGSO_DNFN + deep LSTM, respectively.

In the study conducted by [64], DL method was used in the early detection of bacterial spot disease in bell pepper plants to prevent yield loss. Using YOLOv5, the system can detect even small disease spots on leaves with remarkable speed and accuracy. The inputs to the model are random photos taken from the farm with a mobile phone. The results help farmers identify whether their plants are affected by bacterial spot disease so they can take precautions. This efficient and accessible model makes a great contribution to farmers. The confidence score of the proposed model is approximately 100%. An ensemble model consisting of pre-trained DenseNet121, EfficientNetB7, and EfficientNet NoisyStudent was presented by [65]. This model aims to classify apple tree leaves into categories such as healthy, apple rot, apple cedar rust, or multiple diseases. In this research, various image enhancement techniques were used to increase the size of the dataset and therefore increase the efficiency of the model. The proposed model achieved a 96.25% accuracy rate on the healthy dataset, and it is possible to identify those with more than one disease with 90% accuracy. The authors state that the biggest problem of the study is that they focused on only four types of leaf individuals.

In the study by [66], the Quantum Behavioral Particle Swarm Optimization based Deep Transfer Learning (QBPSO-DTL) model was proposed for the detection and classification of sugarcane leaf diseases. The model uses optimal region growth segmentation to identify affected regions in the leaf image, SqueezeNet model for feature extraction, and Deep Stacked Autoencoder (DSAE) model for classification. Hyperparameter tuning of the DSAE model is implemented by using the QBPSO algorithm. By integrating different models into the main model, accuracy rates of up to 97.50% were achieved. In the study by [67], a lightweight deep learning approach based on Vision Transformer (ViT) is proposed for real-time automatic plant disease classification. In addition to ViT, classical CNN methods and a model using CNN and ViT together have been tried for plant disease classification. Models were trained and evaluated on multiple datasets. Comparing the results, it was concluded that although attention blocks increased accuracy, they slowed down the prediction. This speed reduction can be compensated by combining attention blocks with CNN blocks.

In the study by [68], researchers found that optimization of the weights and biases in the DNN model supported by a crow search algorithm (CSA) throughout the pre-training and fine-tuning phases minimized classification errors. The DNN-CSA model used simple statistical learning methods, which guaranteed excellent classification accuracy while reducing the computational loads. The process involves initial preprocessing of rice leaf images and extraction of disease-indicative regions using a k-means clustering technique. Then, a threshold value was applied to remove regions that did not indicate the disease and then features were extracted from the previously separated diseased regions. As a result of the research, it was seen that the DNN-CSA model reached an accuracy rate of 96.96%. In the study by [69], the authors proposed a CNN model for classification of rice and potato plant leaf diseases. The model was trained on a dataset containing 5932 rice leaf images and 1500 potato leaf images. Rice leaves were classified as bacterial blight, blast, brown spot and tungro diseases, and potato leaves were classified as healthy, early blight or late blight. The proposed CNN model outperformed other machine learning image classifiers such as SVM, KNN, Decision Tree, and Random Forest by providing 99.58% accuracy on rice leaf images and 97.66% accuracy on potato leaf images.

In the study by [70], the authors state that plant diseases disrupt the food supply chain and destroy natural ecosystems, as well as worsening environmental problems. The authors argue that these problems can be alleviated by adopting deep learning algorithms to analyze and visualize the current state of products. They propose a deep neural network model using the MobileNet architecture with complex hidden layers fine-tuned on a dataset of 12318 images. The improved MobileNet model, trained on a large, combined dataset collected from smaller datasets, provides good feature extraction and representation. This model was able to separate the input into 64 different classes for 22 different product sets and achieved an accuracy rate of 95.94%. The model was later also integrated into an Android application called Plantscape. In the study by [71], the authors applied the transfer learning approach to 15 pre-trained CNN models for automatic identification of rice leaf diseases. The results showed that the InceptionV3 model outperformed others with an average accuracy rate of 99.64% and Precision, Recall, F1-Score and Specificity as 98.23, 98.21, 98.20 and 99.80, respectively. In contrast, the AlexNet model showed the worst performance with an average accuracy rate of 97.35%.

In the study conducted by [72], four Convolutional Neural Network (CNN) models, namely SqueezeNet, EfficientNet-B3, VGG-16 and AlexNet, were trained and tested to classify healthy and diseased plants to determine leaf blight disease in strawberry plants. EfficientNet-B3 and VGG-16 identified the initial and severe (advanced) stages of leaf blight disease with higher performance accuracy than AlexNet and SqueezeNet. Additionally, more accurate classification of severe disease stages has been observed. All trained CNN models are integrated with a machine vision system for real-time image acquisition under two lighting conditions (natural and controlled). It showed that the EfficientNet-B3 model achieved the highest classification accuracy (0.80 and 0.86 for initial and severe disease stages, respectively) under controlled illumination. The verification accuracy of AlexNet (0.72, 0.79) is slightly lower compared to VGGNet and EfficientNet-B3. The results suggest that trained CNN models can be used with variable-rate agrochemical spraying systems, helping farmers reduce agrochemical use, crop input costs, and environmental pollution.

[73] developed a method that aims to facilitate the analysis of large-scale mango plantations and enable timely detection of biological threats. The method developed by the authors is a technique that extends the pre-trained VGG-16 deep learning model by adding a two-layer fully connected network training to the last layer. With data augmentation, it resulted in a 73% accuracy rate on the validation dataset and 76% accuracy on the test data. Significantly, using the magnification transform function showed a 13.43% increase in accuracy in the test data. This approach proves the potential of machine learning in improving agricultural practices by providing real-time, accurate solutions.

In the study conducted by [74], the authors aim to provide an effective solution to recognize various potato diseases by presenting a deep learning approach called EfficientPNet. The authors propose a model using the EfficientNet-V2 network to recognize various potato leaf disorders. To increase the model's ability to effectively identify various infections, a spatial-channel attention method focusing on damaged areas was implemented. Considering the problem of imbalanced class distribution, the EANet model was tuned using transfer learning and improved the generalization ability of the network. Additionally, dense layers were added at the end of the model structure, which improved the feature selection of the model. The testing phase of the model was performed on PlantVillage, a dataset containing images taken under complex and diverse background conditions. A 98.12% accuracy rate was achieved on 10,800 images in classifying various potato plant leaf diseases such as late blight, early blight, and healthy leaves. The study by [75] proposes the use of InceptionResNetV2, a CNN model, with a transfer learning approach to recognize diseases in rice leaves. The parameters of this model were specifically optimized for classification and achieved a high accuracy of 95.67%.

[76] focused on the problem of late blight in potatoes, which is caused by the plant pathogen Phytophthora infestans and can lead to a significant reduction in potato yield. To determine whether late blight lesions can be extracted from unstructured field environments with high-resolution visual field images and DL algorithms, the study collected approximately 500 field RGB images from various potato genotypes showing different disease severity (ranging from 0% to 70%). At the end of this process, 2100 cropped images were obtained. It found that the intersection (IoU) values over the union of classes background (leaf and soil) and disease lesion in the test dataset were 0.996 and 0.386, respectively. In addition, an overall accuracy rate of over 99% and a class average accuracy rate of 80% were obtained in the test dataset.

In the study conducted by [77], the authors propose an IoT-based plant disease recognition system. This system used semantic segmentation methods such as FCN-8 s, CED-Net, SegNet, DeepLabv3 and U-Net together with the CRF method to identify disease segments in leaf plants. The results of the experiments, together with the comparative analysis, showed that the proposed system achieved an accuracy rate of 83.02% when combined with SegNet and CRFs. In the study conducted by [78], it is stated that large fluctuations in annual olive production due to some infectious diseases and climate change pose significant difficulties. Farmers detect plant diseases by visual inspections or laboratory tests, but these methods can be time-consuming and misleading. The presented work describes the use of deep feature fusion (DFC) strategy to combine features extracted from two modern pre-trained CNNs, ResNet50 and MobileNet. The model called MobiRes-Net aims to increase the prediction ability by using the strengths of these two models. For experimental analysis, 5400 olive leaf images were obtained from an olive grove using a remotely controlled agricultural UAV equipped with a camera. The MobiRes-Net model showed high success in overall classification accuracy with 97.08%, leaving behind ResNet50 and MobileNet models, which reached 94.86% and 95.63% accuracy rates, respectively.

In the study conducted by [79], deep transfer learning was applied to classify three maize diseases such as Cercospora leaf spot, common rust, and northern leaf blight, and to identify healthy plants. Corn leaf images were used as input and convolutional neural network models were utilized. The experiments were repeated ten times to check the validity of the experimental results. The results showed that the model could distinguish the four classes with an average accuracy of 98.6%. The study by [80] provides an application of technological advances in automatic detection of leaf diseases in potato fields to increase agricultural productivity and reduce the need for plant protection products. Problems such as early spot disease caused by Alternaria solani can be managed more effectively with the help of these technologies. The presented study has shown that UAVs equipped with near-infrared (NIR) sensitive cameras can be an important tool in disease detection by taking high-resolution images of diseased plants. In this study, eight plots containing 256 infected plants were monitored with UAVs for 16 days, and more than 15,000 lesions were detected during this period. The deep learning U-Net model was able to detect the areas where the disease was most intense by determining the density of these lesions. This technological development can help farmers combat plant diseases more effectively.

The study by [81] proposes an improved CNN and LSTM model combined with a majority voting ensemble classifier for early detection of plant pests and diseases. Tested with a dataset obtained in Turkey containing 4447 apple pests and diseases in 15 different classes, this model showed the ability to extract deep features from connected layers in pre-trained models. The study revealed that the LSTM-CNN model achieved a remarkable accuracy rate of 99.2% when compared to state-of-the-art models using LSTM, Logistic Regression (LR) and Extreme Learning Machine (ELM) classifiers. Additionally, pre-trained models such as VGG19, VGG18, and AlexNet exhibited better accuracy, especially with the fc6 layer. In the study by (Z. Zhang, Qiao, Guo, and He, 2022), the authors propose a deep learning-based approach called YOLOv5-CA, which provides automatic detection for real-time control of Grape Leaf Mildew (GDM) disease in precision viticulture. YOLOv5-CA improves detection performance with a coordinate attention (CA) mechanism that focuses on mold disease-related visual features and achieves 85.59% detection sensitivity, 83.70% recall, and mAP@0.5 compared to popular methods such as Faster R-CNN, YOLOv3, and YOLOv5. It achieves 89.55%. This approach is a model that can perform inference at 58.82 frames per second and meet the need for real-time disease control.

The study by [82] focused on using the Visibility Transducer (ViT) method to identify diseases in tomato plants. By developing the global ViT and local CNN structure, the method has been successful in extracting image features more efficiently and precisely than traditional manual recognition. When tested on images from different tomato fields, the approach achieved an impressive 96.30% average counting accuracy, providing a valuable resource for PA. The study by [83] introduces a cloud-based module for detecting agricultural diseases in plants using a DL model trained on more than 40,000 images. This method demonstrated a laboratory-based accuracy rate of 98.78% in diagnosing plant leaf diseases and provided users with real-time status information in less than a second on average. The study by [84] aims to address the rice misleading mold problem by using frame-based hyperspectral devices and mixed detection methods and applying various experimental cultivation conditions. Using 49 edits and more than 196 discrimination patterns between healthy and infected rice, the study achieved a diagnostic accuracy of more than 95%. Deep learning-based feature sets achieved 100%

accuracies with 100 epochs. The method has been field validated and provides a basis for future precision plant protection studies.

[79] focuses on the use of deep learning and artificial intelligence methodologies for the classification of three common grape diseases: black barberry, black rot, and isariopsis leaf spot, and focuses on healthy plants. By retraining 11 convolution network models using a dataset containing 3639 grape leaf images, the research demonstrated that it is possible to design pilot and commercial applications with accuracy that meets field requirements. The models have consistently demonstrated high accuracy performance values, exceeding 99.1%. [85] emphasize the importance of early detection of plant diseases and advocate low-cost and high-accuracy diagnostic methods. This study presented a new dataset of 2500 images representing seven varieties of strawberry diseases, facilitating the development of deep learning-based automatic detection systems that can segment strawberry diseases even under complex background conditions. Using a model based on the Mask R-CNN architecture and using the ResNet backbone, the study achieved an average precision of 82.43% for disease sampling segmentation. [86] propose a deep convolutional neural network-based method for classifying diseases of different fruit leaves. This method leverages pre-trained deep models such as VGG-s and AlexNet. The researchers introduce a multi-level fusion methodology based on a threshold value under entropy control and use a multi-SVM as the host classifier. The proposed method was tested on five different diseases and showed superior performance in terms of sensitivity, accuracy, sensitivity, and G-measure; all values are above 97%.

In the study conducted by [87], Reconstructed Disease Awareness-Convolutional Neural Network (RDA-CNN) is recommended for classification of rice plant diseases. This network improves disease identification by converting low-resolution rice plant images into super-resolution images. Compared to baseline architectures, RDA-CNN improved classification performance by approximately 4-6%. In the study by (Srinivasa Rao et al., 2022), two linear convolutional neural networks (Bi-CNN) were proposed for the identification and classification of plant leaf disease. Second, the optimized VGG and pruned ResNets were used as feature extractors by connecting them into fully connected dense networks. The largest model achieved 94.98% accuracy for 38 different classes. In the study conducted by [88], it was aimed to automatically identify infected regions and extract features for disease classification using RNN. Compared to traditional CNN approaches, the RNN-based method is more robust and has a higher generalization ability to previously unseen plant species and diseases. The Seq-RNN model proposed by the authors achieved 98.17% accuracy. The study by [89] introduces AgroLens, a new architecture that supports a mobile Smart Farm application using environment friendly devices and can work without an internet connection. The system shows high disease classification performance with real-time AI-based analysis of leaf images on a smartphone. AgroLens can connect to thousands of smart farm sensors without creating computational overhead, offering the potential for large-scale Smart Farm applications with low-cost devices. DenseNet, one of the models the authors tried for disease detection, reached an accuracy rate of 98.45%. The study by [90] presents a hybrid model called SpikingTomaNet, which integrates a deep convolutional neural network and a sputtering neural network for effective disease identification in plants and energy efficiency in UAVs. The model outperformed established models, achieving 97.78% accuracy on original images and 59.97-82.98% accuracy on augmented datasets.

The study by [91] used hyper-spectral imaging technology to identify and classify virus infections in grapevine veins in the early stages. Using statistical analysis and DL architectures, the research used support vector machines (SVM), RF classifier and automatic 3D convolutional neural network to classify grapevines based on collected image data. As a result of experiments conducted with 5-fold cross-validation, a high accuracy rate of 96.75% was achieved with SVM. A new approach presented in the study by [92] uses a CNN to simultaneously detect and geolocate plantation rows while counting plants even in high-density plantation settings. Through tests in both corn fields and citrus groves at different growth stages and densities, the robustness and efficiency of the proposed method, surpassing other deep networks, have been verified. The study presents a CNN approach that accurately detects and positions plantation rows and individual plants in high-density fields using images captured by UAVs. The method outperforms other deep networks, showing excellent performance with low mean absolute errors (MAEs) of 6,224 for corn fields and 1,409 for citrus groves.

The study by [93] presents attention-driven extended CNN logistic regression (ADCLR), an advanced approach for the detection of tomato leaf diseases. The proposed method incorporates pre-processing techniques such as bilateral filtering and Otsu segmentation and uses a Conditional Generative Comparative Network (CGAN) to deal with imbalanced data and noise. The extracted features are normalized and classified by logistic regression. Experimental results show the high performance of the proposed method, achieving 100% training, 100% testing, and 96.6% validation accuracy on the plant village dataset. This study highlights the potential for future applications for model development and cloud-based automatic foliar disease classification for different plant species.

[94] presents a deep CNN approach based on the tiny YOLOv3 architecture for the detection of C. sepium and sugar beet. The developed model achieved average sensitivity (APs@IoU0.5) values of 0.761 for C. sepium and 0.897 for sugar beet and ran with an inference time of 6.48 ms per image in an NVIDIA Titan X GPU environment. The results show that it provides a better average precision (mAP) compared to using only field images, highlighting that the model is effective for accurate and efficient weed detection.

[95] presents the Artificial Intelligence-Assisted Coconut Tree Disease Detection and Classification (AIE-CTDDC) model for smart agriculture. The aim of the presented AIE-CTDDC technique is to classify coconut tree diseases in a smart farming environment and thereby increase crop yield. First, the AIE-CTDDC model uses a median filtering-based technique for noise removal. Then, a Bayesian fuzzy clustering-based segmentation method is applied to detect affected leaf regions. Additionally, the capsule network (CapsNet) method is used as a feature extractor. In this study, GRU model with Harris Hawk Optimization (HHO) was used for disease detection in coconut trees. Experimental analysis confirms that the proposed AIE-CTDDC model outperforms existing state-of-the-art techniques. The method achieved 97.75% accuracy in coconut tree disease classification. In the study by [96], the authors introduce AIE-ALDC, an AI-assisted technique for classifying apple leaf diseases in precision agriculture. The technique includes elements such as data augmentation, noise removal, CapsNet-based feature extraction, and WWO-based hyperparameter optimization. The use of BiLSTM increases the classification accuracy. Experimental results show the superior performance of the AIE-ALDC technique compared to existing methods with an accuracy rate of 99.20%. The research by [97] presented an integrated framework combining sample-based segmentation, classification, and semantic segmentation models to detect potato leaf diseases. The model achieved average accuracy of 81.87%, 97.13% in accuracy, 95.33% in accuracy, 89.91% in MIoU and 94.24% in MPA using Mask R-CNN, VGG16, ResNet50, InceptionV3, UNet, PSPNet and DeepLabV3+ at different stages. This new framework provides a reliable method for potato disease assessment and classification. [98] used the LeafConvNeXt model to classify plant diseases with over 99% accuracy. The model is suitable for use in unmanned agriculture due to its low hardware requirements, high accuracy and increased interpretability with LayerCAM.

Potato plants (Solanum tuberosum) are prone to various diseases that result in significant economic losses for farmers. A 2024 study presents a deep learning-based approach to accurately detect and classify six different diseases affecting potato leaves. These are bacteria, viruses, fungi, phytophthora, pests, and nematodes. Strategic data augmentation, L2 regularization, and transfer learning were used to improve the model performance by addressing the challenges of class imbalance. Three pre-trained convolutional neural networks, DenseNet201, ResNet152V2, and NasNetMobile, were fine-tuned on a diverse dataset of 3076 images collected under real-world conditions. DenseNet201 achieved a peak accuracy of 77.14% on the original dataset and showed further improvement with data augmentation, achieving an average accuracy of 81.31% through k-fold cross-validation, a 4.17% improvement over initial results and a 7.68% increase over previously reported findings. The findings highlight the importance of reducing class imbalance through adapted augmentation and regularization techniques, contributing to more reliable disease detection systems [99].

Bananas are among the most widely produced perennial fruits and staple food crops affected by a multitude of diseases. When not managed early, Fusarium Wilt and Black Sigatoka are two of the most damaging banana diseases in East Africa, causing 30% to 100% production loss. Elinisa et al. evaluated a U-Net semantic segmentation deep learning model for early detection and segmentation of Fusarium Wilt and Black Sigatoka banana diseases. The model was trained using 18,240 images of banana leaves and stems affected by these two banana diseases. The dataset was collected from farms using mobile phone cameras under the guidance of agricultural experts and annotated to label the images. The results showed that the U-Net model achieved a Dice Coefficient of 96.45% and an Intersection Over Union (IoU) of 93.23%. The model accurately segmented areas where banana leaves and stems were damaged by Fusarium Wilt and Black Sigatoka diseases [100].

Mulberry leaves are the primary food source for Bombyx mori silkworms, which are crucial for silk yarn production. Using computer vision for early disease detection and classification can reduce up to 90% of production losses. Salam et al. collected leaves categorized as healthy, leaf rust affected, and leaf spot affected from two districts of Bangladesh. A total of 1091 images were divided into training (764), test (218), and validation (109) sets, with 5-fold cross-validation, preprocessing, and boosting, producing 6000 images including synthetics. The study compared ResNet50, VGG19, and MobileNetV3Small on a specific task following their architecture modifications. When three pre-trained convolutional neural networks (CNNs) – MobileNetV3Small, ResNet50, and VGG19 – were augmented with four additional layers, the modified MobileNetV3Small excelled in precision, recall, F1 score, and accuracy, achieving remarkable results of 97.0%, 96.4%, 96.4%, and 96.4% in cross-validation folds, respectively [101]. [102], developed an IoT-enabled smart farming framework that addresses key agricultural tasks such as disease and pest detection, smart irrigation, and crop yield prediction. The system utilizes two advanced deep learning architectures: a Multi-scale Adaptive CNN with LSTM (MA-CNN-LSTM) for classification tasks, and a Multi-scale Adaptive 1D CNN with LSTM (MA-1DCNN-LSTM) for predictive modeling. Both models are fine-tuned using the Advanced Mountaineering Team-Based Optimization (AMTBO) algorithm to enhance accuracy and efficiency. The framework integrates multiple datasets and employs attention mechanisms to improve feature extraction, offering a robust solution without the use of transfer learning.

In [103] authors proposed a convolutional neural network (CNN)-based deep learning model specifically designed to classify potato leaf diseases using images. The model was trained on the PlantVillage dataset, focusing on three classes: healthy, early blight, and late blight. It employed standard preprocessing techniques such as image resizing and rescaling, and achieved high accuracy (98.28%) on the test set—outperforming several state-of-the-art methods. The architecture, while custom-built, was benchmarked against established models like VGG, ResNet, AlexNet, and DenseNet, showing superior precision, recall, and f-score metrics. In their 2024 study, authors have introduced a lightweight deep learning architecture named T-Net, aimed at accurately classifying tomato leaf diseases [104]. The model integrates convolutional layers with Fire modules—drawing from SqueezeNet design principles—and employs the ALVIN active learning strategy to refine feature extraction and reduce reliance on extensive labeled datasets. Training was conducted on an augmented version of the PlantVillage dataset comprising ten tomato disease classes. T-Net achieved a high classification accuracy of 98.97% and demonstrated superior performance compared to established deep learning models such as VGG16, Inception V3, and AlexNet, while also maintaining computational efficiency.

Wu et al. have proposed SAW-YOLO, an enhanced version of YOLOv8n, designed specifically for detecting small citrus pests [105]. They introduced a custom dataset, IP-CitrusPests13, with 7844 annotated images across 13 classes. The model incorporates three innovations: the SPD Module to preserve spatial detail during downsampling, the AFFD Head for better feature fusion and small object focus, and Wise-IoU v3 loss for improved convergence. SAW-YOLO achieved 90.3% mAP@0.5 and outperformed larger models like YOLOv8s, particularly in small-object detection, while maintaining a lightweight architecture of just 4.58M parameters. Daşkın et al have proposed an Ensemble Transfer Learning (ETL) approach that integrates pre-trained VGG16 and InceptionV3 models to enhance the classification of maize crops, weeds, and their growth stages [106]. They introduced a custom dataset called MaizeSet, consisting of 3330 field images—later expanded to over 6400 through augmentation—captured under diverse environmental conditions. The ensemble employed the Dirichlet Ensemble method, which assigns model weights based on performance probabilities. In weed and crop classification, the ensemble achieved 90% accuracy, outperforming VGG16 (83%) and complementing the high performance of InceptionV3 (98%). For growth stage classification, it reached 80% accuracy, improving upon VGG16's results. The trained models were successfully deployed on NVIDIA Jetson Orin hardware, demonstrating their feasibility for real-time, on-device agricultural applications.

Irmak and Saygılı have introduced a hybrid approach that integrates classical machine learning techniques with a custom convolutional neural network (CNN) for the classification of tomato leaf diseases [107]. Utilizing the Kaggle Tomato dataset comprising 18,345 images across 10 categories (9 disease types plus healthy leaves), they conducted experiments under three classification schemes: binary, 6-class, and 10-class. For the classical pipeline, they employed Local Binary Pattern (LBP) for feature extraction, followed by classification using SVM, kNN, and ELM. Their tailor-made CNN—featuring layered convolution, pooling, dropout, and dense components—achieved impressive accuracy rates of 99.5%, 98.5%, and 97.0% across the respective classification tasks, consistently surpassing classical methods. Additionally, the CNN demonstrated stable computational performance regardless of class complexity, making it both accurate and efficient.

Kim et al. have introduced a hybrid deep learning model—ANFIS-Fuzzy-CNN—for detecting bacterial infections in pepper bell leaves [108]. The model integrates the powerful feature extraction capabilities of convolutional neural networks (CNNs) with the uncertainty-handling strengths of an Adaptive Neuro-Fuzzy Inference System (ANFIS), further enhanced by Local Binary Pattern (LBP) texture features. Using 2,475 images from the PlantVillage dataset, the proposed model achieved 99.99% accuracy, precision, recall, and F1-score when LBP was applied. These results significantly outperformed both classical machine learning algorithms and popular transfer learning models like ResNet, MobileNet, and EfficientNetB4. Extensive validation through k-fold cross-validation and ablation studies confirmed the model's robustness and its potential for real-world deployment in precision agriculture.

Prashanth and friends have introduced MPCSAR-AHH, a hybrid deep learning model that detects cassava leaf diseases in real time and recommends suitable fertilizers through an augmented reality (AR) interface [109]. The system integrates a Modified Pyramidal Convolutional Shuffle Attention Residual Network with the Advanced Harris Hawk Optimization (AHH) algorithm for fine-tuning parameters. Key components include Swin-Unet for ROI segmentation and LUV color conversion for preprocessing. The model was trained on a real-time dataset of 286 images across five classes (four diseases + healthy), achieving 99.02% accuracy, 97.55% precision, and strong F1 scores. GUI support and AR visualization enhance its practicality for farmers. Extensive validation (10-fold CV, ablation, optimization comparisons) confirmed its robustness, outperforming other models like CNN, DGCNN, and PDD-Net.

Chilakalapudi and Jayachandran have proposed a two-level plant disease classification framework combining Chronological Flamingo Search Optimization (CFSA) with a CNN-based transfer learning model built on LeNet [110]. The system performs noise removal (adaptive anisotropic diffusion), segmentation (MGRA-trained U-Net++), and image augmentation using geometric and color transformations. It extracts hybrid features with OCLBP-based DWT, SIFT, and LTP before classification. Using the PlantVillage dataset (38 classes), the model achieved 95.7% accuracy, 96.5% sensitivity, and 94.7% specificity in second-level classification, outperforming baselines like Dense CNN, EfficientNet, and DPD-DS. The approach offers improved generalization and low error, making it effective for early disease diagnosis in crops.

Johri et al. have presented a comprehensive evaluation of deep transfer learning models for multi-class cotton leaf disease classification using a curated dataset of 36,000 images spanning six categories: Aphids, Army Worm, Bacterial Blight, Powdery Mildew, Target Spot, and Healthy leaves [111]. The study implemented a robust preprocessing pipeline (grayscale conversion, noise reduction, contour-based ROI extraction) to enhance image quality and model performance. Ten pre-trained CNNs—EfficientNetB0/B3, ResNet50V2/152V2, DenseNet169, MobileNetV2, Xception, VGG19, InceptionV3, and InceptionResNetV2—were fine-tuned and compared using metrics like accuracy, RMSE, loss, precision, recall, and F1-score. EfficientNetB3 emerged as the top performer with 99.96% validation accuracy, 0.149 loss, and 0.386 RMSE, while VGG19 lagged significantly in all metrics. This study demonstrates that efficient architectures, combined with advanced preprocessing, significantly boost accuracy and generalization in disease detection. Supporting Table 2 summarizes the articles in this section.

Several distinct deep learning paradigms emerge across disease detection studies. Lightweight CNN models (e.g., [56], [62]) are tailored for mobile and edge devices, enabling practical, real-time plant disease diagnostics in the field with high accuracy but sometimes limited to specific crops. On the other hand, ensemble and hybrid models (e.g., [59] [67]) integrate deep CNNs with metaheuristics or transformers, showing superior accuracy and robustness—but often at the expense of inference time and hardware requirements. Transfer learning-based approaches (e.g., Simhadri & Kondaveeti) leverage pre-trained architectures like InceptionV3 and EfficientNet, providing near-perfect classification but requiring significant computational resources. Such methods are ideal for centralized cloud-based systems or precision labs. Studies like [64] and [58] prioritize real-time object detection, focusing on early symptom identification. Although these systems are responsive, their performance may vary with image quality and lighting conditions. Lastly, segmentation-focused models such as [77] excel in localizing disease regions, offering interpretability, but lack multi-disease scalability.

3.3. Weed detection

In the study conducted by [112], it was reported that Sosnowsky's Hogweed (Heracleum sosnowskyi) is a rapidly spreading plant that poses significant risks to human health, agricultural crops, and local ecosystems, and has spread throughout Eurasia. Despite its harmful effects, there are currently no automated detection and location systems available for hogweed. This study presents a solution for rapid and accurate hogweed detection using an UAV equipped with an embedded system running various FCNN models. Based on the balance between detection quality and frame rate, the study describes the optimal FCNN architecture for the embedded system. The proposed model demonstrates high ROC AUC (0.96) in hogweed segmentation tasks and can process 4K frames at 0.46 FPS on NVIDIA Jetson Nano. This innovative system capable of recognizing hogweed at the individual plant and leaf scale opens new possibilities for obtaining detailed and up-to-date data on invasive plant spread, thereby aiding in their containment. A 550 mm quadcopter was built to capture aerial images of the farm. The data collection dates were adjusted according to the two main growth stages of hogweed: the first two dates correspond to the early growth stage, while the last date corresponds to the vegetative growth stage. The images were collected at a size of 4000x3000 under different natural lighting conditions, various growth stages of hogweed, and varying densities of weeds and leaf occlusions.

In the study conducted by [113], the methodology involves introducing two sub-networks to a traditional encoder-decoder style DNN with the aim of improving segmentation accuracy. These two sub-networks determine the differences between inter-row and intra-row pixels and provide corrections to the pre-segmentation results of the traditional DNN. The authors used a dataset captured in a wheat farm at different times by an agricultural robot to evaluate the segmentation performance. The proposed method outperformed various popular semantic segmentation algorithms. It operates at a speed of 48.95 fps with a consumer-grade graphics processing unit, enabling real-time deployment at the camera frame rate. Additionally, the models they used achieved average accuracy rates of 95% or higher for different tasks.

In the study conducted by [114], a semi-supervised, deep learning-based technique is presented to estimate the density and distribution of weeds in fields using a limited number of color images obtained from robots. The proposed method first determines the foreground plant pixels containing both crops and weeds using an unsupervised CNN segmentation. Then, areas infected with weeds are recognized using a fine-tuned CNN without the need for handcrafted feature design. This strategy has been tested on two different product/weed type datasets and achieved a maximum accuracy of 82.13% in weed density estimation. Therefore, this approach demonstrates its effectiveness in different plant species without the need for extensively labeled data.

In the study conducted by [115], a selectively pre-trained neural network model was used to differentiate between plants and weeds. Specifically, a faster R-CNN method was applied, which achieved a mAP of approximately 31% considering a learning rate hyperparameter of 0.0002. When compared to the ground truth, the prediction values ranged from 88% to 98%. On the other hand, for a completely unknown dataset of plants and weeds, the prediction range was 67% to 95% for plants and 84% to 99% for weeds. The study conducted by Kamal et al. (2022) emphasizes the accuracy of weed and crop plant segmentation using two different deep learning frameworks: FCN and ResNet. These networks were trained and tested using a readily accessible database consisting of images of 40 different plant and weed species in a carrot field. Experimental results showed a solid overall accuracy of over 90% on the validation set across both frameworks.

In the study conducted by [116], the proposed CVDL-WDC technique aims to accurately distinguish between plants and weeds. This technique involves two processes: multi-scale Faster RCNN-based object detection and optimal ELM-based weed classification. The parameters of the ELM model are optimized using the FFO algorithm for agricultural land productivity optimization. A comprehensive simulation analysis conducted on benchmark datasets demonstrated that the CVDL-WDC method achieved an accuracy rate of 98.98%. In the study conducted by [117], a study was conducted for the detection of weeds. In this study, images collected with an RGB camera belonging to the species Zea mays, Helianthus annuus, Solanum tuberosum, Alopecurus myosuroides, Amaranthus retroflexus, Avena fatua, Chenopodium album, Lamium purpureum, Matricaria chamomila, Setaria spp., Solanum nigrum, and Stellaria media were used for training CNNs. Three different CNN models, namely VGG16, ResNet-50, and Xception, were trained on a dataset consisting of 93,000 images. The training images consisted of plant material images containing a single species. During the testing phase, a Top 1 accuracy ranging from 77% to 98% was achieved in plant detection and the discrimination of weed species.

The accurate classification of weed species in field crops plays a crucial role in enabling targeted treatments and is significant in precision agriculture. Recent studies have shown promising solutions using deep learning (DL) models. In one study, an image-based weed classification pipeline was proposed, where a portion of the image is simultaneously considered to enhance performance. Images were first enhanced using generative rival networks, and operations were performed using state-of-the-art DL models. The proposed pipeline was tested on four different datasets. It was observed that the proposed approach improved the model's performance [118].

Weed management is a major challenge for agricultural engineers, especially in densely populated fields. Goyal et al. aimed to develop a computer vision-based system to distinguish potato plants from weeds at the post-emergence stage in highly congested and complex backgrounds. To achieve this, RGB dataset with real images was collected from potato farms. After extensive cleaning, data augmentation was performed. State-of-the-art deep learning techniques, namely Mask RCNN and YOLO version 8 (YOLOv8), were trained to accurately distinguish, detect and classify potato plants from weeds. Although the accuracy levels were not high, it is a testament to the capabilities of the model in weed detection in a highly complex and densely populated environment [119].

Gao et al. have has proposed a novel cross-domain transfer learning approach for weed segmentation in the context of site-specific weed management (SSWM), where a deep learning-based semantic segmentation model was developed to support precision herbicide application [120]. They implemented a deep convolutional neural network with an encoder-decoder architecture, trained exclusively on high-resolution ground-based images, and successfully applied it to lower-resolution UAV imagery. To overcome domain discrepancies, a customized preprocessing pipeline was introduced, and a weighted loss function was used to handle class imbalance. The deep learning model achieved strong performance in both domains, demonstrating the potential of transferring knowledge from ground to aerial imagery for efficient and scalable weed mapping in SSWM applications.

Hasan et al. have introduced a site-independent weed classification method that combines YOLOv7 for plant detection with a Siamese neural network for morphology-based classification [121]. Unlike traditional species-level classification, their system groups weeds into three morphological categories—broadleaf, grass, and sedge—enhancing generalizability across diverse agricultural environments. The models were trained on the Weed25 dataset and evaluated on two unseen datasets: Cotton weed, and Corn weed. YOLOv7 achieved mAPs of 91.03%, 84.65%, and 81.16%, respectively. The Siamese network, using VGG16 and cosine similarity, reached classification accuracies of 97.59%, 93.67%, and 93.35%, outperforming conventional CNNs like ResNet50 and InceptionV3. This meta-learning framework demonstrated robust generalization and fast inference (avg. 4.53 ms), making it ideal for real-time, precision agriculture applications.

Kanna et al. have presented an in-depth review of the YOLO (You Only Look Once) object detection architecture and its widespread applications in agriculture, such as crop monitoring, weed detection, fruit identification, disease diagnosis, and quality evaluation [122]. The study traced the evolution of YOLO from version 1 through version 9, highlighting advancements in detection accuracy, processing speed, feature representation, and architectural efficiency. It examined over 20 case studies involving different crops and agricultural tasks. Notable examples included YOLOv5 achieving 93% accuracy for tomato disease detection, YOLOv4 reaching 95.4% mAP in citrus disease classification, and YOLOv8L delivering 97.95% mAP@0.5 for turfgrass weed detection. While YOLO excels in real-time performance, the authors identified challenges in detecting small objects and suggested architectural enhancements—such as attention modules and resolution optimization—to improve its effectiveness in complex field environments. Supporting Table 3 summarizes the articles in this section.

The studies on weed detection reflect a variety of deep learning strategies tailored to different application scenarios. Real-time deployment in agricultural fields is a key concern; [113] and [112] address this using encoder-decoder DNNs and FCNNs, with Su's model achieving real-time performance (≈49 FPS), while Menshchikov's embedded Jetson Nano system trades speed for low-power feasibility. Hybrid and multi-stage architectures such as that by [116] combine object detection with Extreme Learning Machines and optimization algorithms, reaching near-perfect accuracy. These models are ideal where computational power is not a limiting factor. Semi-supervised and unsupervised approaches [114] are promising in data-scarce environments, needing fewer annotations but often sacrificing performance and generalizability. Similarly, [115] highlight that models trained on specific weed types can struggle with novel or unseen species, pointing to a need for transfer learning or domain adaptation. CNN-based benchmarks like those by [117] and [122] demonstrate that traditional architectures (ResNet, VGG) still perform well, especially when classifying large numbers of weed types. However, their practical deployment is limited by inference time and power consumption.

4. TECHNOLOGIES USED IN PRECISION AGRICULTURE

This section addresses the status and potential of precision agriculture technologies. The advancements in technology and increased utilization of data create new opportunities in the agricultural sector, emphasizing the importance of precision agriculture technologies. Our review encompasses various technological approaches employed to enhance the effectiveness of precision agriculture and reduce the environmental impact of agricultural production. The effects of precision agriculture technologies on plant health and productivity will be discussed, aiming to provide insights into improving the accuracy of agricultural production and enhancing agricultural sustainability. The fundamental equipment used in this section will be explained under three main headings: Sensors, Unmanned Aerial Vehicles, and Unmanned Ground Robots.

4.1. Sensors

Sensors are commonly used in precision agriculture, as in various other fields [123]. These applications range from soil sensing to detecting plant presence and determining moisture levels [124]. This section will discuss how sensors are utilized in the methods examined in this study. The fundamental uses can be categorized into four categories: distance, position, and measurement; environmental parameter measurement; and image capture [125]. Various types of sensors are mentioned in the study, such as color and image-based sensors, LiDAR sensors (and other distance sensors), soil, moisture, and temperature sensors. Additionally, GIS and navigation systems are used for mapping and other geographical operations. [123] and [126] stated that LiDAR sensors can provide robust data due to their high resolution and wide coverage area for target detection. However, it is known that LiDAR sensors can be costly at a large scale [127]. It is understood that LiDAR sensors can be used in smaller projects. [128] stated that image-based systems can reflect rich environmental features and provide navigation capabilities. Furthermore, image-based navigation systems are likely to be the most efficient and cost-effective systems in terms of cost and may be suitable for tasks such as harvesting, planting, and plant protection [129]. Therefore, it can be mentioned that systems utilizing cameras or at least image-based systems have higher potential.

In this subsection, we have categorized sensors into three categories as follows: distance, position, and depth measurement sensors; image capture-based sensors; and environmental parameter measurement sensors. It should be noted that the advantages and disadvantages of these systems are also dependent on other components.

Distance, position, and depth measurement sensors: In the study conducted by [39], LiDAR sensors and depth cameras were used together to obtain RGB images. These sensors and cameras, being attached to a robot, offer significant advantages in terms of mobility, and can mutually validate each other. IR stereo sensors proved to be useful in data collection, as demonstrated in the study by [43]. These sensors were integrated into a tracked ground robot and placed on its left and right sides, providing depth information along with color images. [47] utilized LiDAR sensors and visible light in their study. Additionally, the LiDAR sensor was connected to a real-time kinematic system to achieve higher accuracy. [82] attached a GPS for positional tracking to a drone device used for image capture.

Image capture-based sensors: [44] employed a Canon 60D camera (Canon Inc., Tokyo, Japan) with a Tamron SP10-24 mm lens (Tamron Co., Ltd., Saitama, Japan) to capture high-resolution images. [45] mounted a GoPro Hero 7 camera (GoPro Inc., California, CA, USA) with a 1/2.3-inch CMOS sensor capable of producing 12-megapixel images on a quadcopter to capture RGB images of the farm. This setup allowed capturing images from approximately 2-3 meters. [46] utilized an OV2640 camera with a resolution of 1600 x 1200 and low power consumption. [59] used IoT devices for image capture but did not provide details about the system. [60] employed smartphones for image capture, citing their high-resolution cameras, powerful processors, and built-in tools as reasons for their choice. [62] transferred their models to a mobile application that can be installed on smartphones. With the application, photos can be taken to determine the health of leaves. [49] utilized a system controlled by Raspberry Pi 3 B+ and equipped with a robotic arm to capture top-view images of plants. They obtained images with a resolution of 1920 × 1080 using a Microsoft Lifecam Studio digital camera. [82] aimed to diagnose crop diseases through images captured by a camera attached to a flying drone.

In the study conducted by [113], a ground robot was equipped with a JAI AD-080-GE multi-dimensional RGB+NIR camera mounted underneath. The robot traversed each row in the field and captured 1024x768 images of wheat at different stages (different growth cycles). [72] used a Canon PowerShot SX530 Digital camera to capture images from strawberry fields in South Punjab, obtaining color images with a resolution of 1920 × 1080 pixels. [76] employed a Sony RX100 III RGB hand camera to obtain potato images. [78] used a camera to capture images from an aerial vehicle at a height of 25-30 meters. The captured images were later sent to a cloud server for the examination of olive tree diseases. [80] obtained images by mounting a camera on an UAV. [83] placed a mobile camera in the area where plants were located to capture images. In the study by [47], hyperspectral image data within a spectral range of 450 to 950 nm with a sampling interval of 4 nm was collected in a rice field using a hyperspectral frame-based camera. Since a UAV was used to capture the images, shots taken from very close or very far distances from the ground may degrade the image quality. [85] created a new dataset by collecting around 2500 strawberry images using camera-equipped smartphones placed in greenhouses. [112] obtained images with a resolution of 4608×3456 using a Xiaomi Yi action camera with a 16 MP CMOS sensor. Similarly, images with a resolution of 4000x2250, resembling drone camera images, were also obtained.

Sensors measuring environmental values: In the study conducted by [46], an economical and low-cost humidity sensor was utilized to perform appropriate operations. The significance of the humidity sensor for irrigation was emphasized. Furthermore, this sensor was connected to a NodeMCU (ESP8266) device to facilitate future expansion of the system with different sensors.

4.2. Unmanned Aerial Vehicles

In the study conducted by [130], it was mentioned that traditionally agricultural imagery is captured by satellites and manned aircraft. However, these captured images are often expensive for farmers and do not meet the quality requirements in terms of resolution. Small UAVs, on the other hand, are seen as a feasible solution that provides high-quality images using hyperspectral and multispectral cameras. These images enable farmers to monitor plant changes and other conditions. In the study by [131], although the usefulness of UAVs is emphasized, it is stated that they have some disadvantages in terms of power and communication. The authors highlight the importance of integrating UAVs with IoT in this regard. In the study by [132], it is mentioned that various tools (sensors, cameras, etc.) can be mounted on UAVs and used together. However, the disadvantages of UAVs are discussed, including the current weather conditions and the high cost of UAVs capable of long-duration flights. The limited flight time of UAVs is also highlighted by the authors. In the study conducted by [133], the limitations of battery life and short flight durations are mentioned as disadvantages.

In the study conducted [82], a Mavic Mini Propeller type UAV was used. The drone has a speed range of 6-16 m/s and can capture images up to 12 million pixels. During the drone operation, it was flown at a height of up to 6 m since tomato diseases are more prevalent on the leaves and fruits of the plants. In the study by [45], a Quadcopter UAV was used for selective spraying and counting of cassava plants in the future. This UAV captured images at varying heights of 2-3 m under different lighting conditions. The images were captured between 11:00 am and 4:00 pm during daylight hours. In a study by [78], a remotely controlled fixed-wing UAV was used to obtain images at heights ranging from 25 to 30 m over a 30-hectare area for the detection of olive leaf diseases. [134] obtained ultra-high-resolution images from a DJI Matrice 600 (DJI, Shenzhen, Guangdong, China) drone at a height of 10 m. Additionally, images were captured at a height of 60 m using additional technologies to create a general map of the region. In the study conducted by [47], a drone was flown over an approximate area of 500 hectares. [47] captured images of broccoli using a Matrice M300 RTK (DJI Technology Co., Shenzhen, China) model UAV. The images were captured at a speed of 2.5 m/s from a height of 30 m. The mission was completed within 20 minutes.

When examining these studies, it can be observed that determining the appropriate height and speed at which the UAV will be flown is a challenging task. Furthermore, capturing images within a specific time interval, under certain conditions, and in a particular location can be considered an optimization problem.

4.3. Unmanned Ground Robots

Ground robots are advanced devices used in precision agriculture. In the study conducted by [125], unmanned ground robots (UGRs) were mentioned as an alternative to solve the image resolution problem of UAVs. UGRs are also useful for close-range sensing and are typically designed to perform specific agricultural operations such as weed removal, treatment, pruning, etc. To accomplish the main functions, the robot needs to perform various supporting tasks such as localization, obstacle avoidance, and navigation. Additionally, it is necessary for the robot to perform tasks such as object detection for processing, determining the required treatment or action, and similar tasks. In this regard, the robots used in the collected studies will be discussed.

In the study conducted by [39], a fully autonomous robot was designed. The designed robot moves on wheels and can perform tasks such as plant recognition and determining their growth status. It can move autonomously and communicate with its surroundings. It is equipped with an Intel RealSense L515 depth camera, capable of moving at a speed of 8 km per hour and lasting up to 5 hours on a single charge. It features a lifting unit to adjust its height and a robotic arm. The robot establishes communication using TCP/IP socket communication and can capture colored images with an RGB-D camera. In the study by [43], automatic detection of pomegranates was targeted, and a robot was developed for this purpose. It is a tracked robot capable of lifting weights up to 70 kilograms and moving at a speed of 0.5 m per second. The robot operates using the ROS. In the study conducted by [113], a multispectral camera was attached to a robot and was traversed along wheat beds. Images were obtained using the connected camera.

5. DEEP LEARNING MODELS USED IN PRECISION AGRICULTURE

5.1. Transfer Learning

[39] utilized a pre-trained YOLOR model on ImageNet for their study. This model aims to recognize target objects by leveraging both implicit and explicit knowledge using a unified network. The authors also mentioned that this model reduces the time cost for inference (prediction). They employed CSP-DarkNet53 as the backbone model. The main purpose of using YOLOR was to identify the measurement location for growth assessment. In the study conducted by [43] for automatic detection of pomegranates, a pre-trained DeepLabv3+ model on the ImageNet dataset was utilized. ResNet-18 was used as the backbone model. The authors based their selection of this model on its proven effectiveness in semantic segmentation of natural images. [44] employed a Faster R-CNN model trained on the COCO dataset and utilizing ResNet-18 as the backbone model. The authors expressed their preference for this model due to its high accuracy and speed. In the study by [45] for the detection of cassava plants, YOLOv5n and YOLOv5s models were used. It was found that YOLOv5s provided better accuracy, while YOLOv5n achieved the best inference speed. The authors used pre-trained weights on the COCO dataset. [46] utilized a Faster R-CNN model with InceptionV2 as the backbone, which was pre-trained on the COCO dataset. In the study conducted by [65], the proposed model was an ensemble of pre-trained DenseNet121, EfficientNetB7, and EfficientNet NoisyStudent models. The aim was to classify apple tree leaves into various categories, including healthy and diseased classes, based on their images. Image augmentation techniques were also incorporated in this research. The proposed model achieved 96.25% accuracy on the validation dataset and was able to recognize leaves with multiple diseases with 90% accuracy.

In the study conducted by [70], transfer learning was applied based on the MobileNet architecture. MobileNet is a pre-trained model specifically designed for image classification and mobile vision applications, with fine-tuning performed using deep neural networks. The main advantages of using MobileNet are its small model size, low latency, and other factors. [71] utilized 15 different pre-trained networks, including DarkNet-53, DenseNet-201, GoogLeNet, Inceptionv3, MobileNetv2, ResNet-50, ResNet-101, ShuffleNet, SqueezeNet, Xception, InceptionResNetV2, NasNetMobile, VGG16, AlexNet, and EfficientNetB0, for classifying rice leaf diseases. In the study by [75], the focus was on classification using two models: a simple CNN model and a transfer learning model based on InceptionResNetV2. InceptionResNetV2 outperformed the CNN model with an accuracy rate of 95.67%, surpassing the CNN model's accuracy rate of 84.75%. [79] employed multiple pre-trained deep learning models to detect corn diseases from corn plant leaves. The highest F1 score, and accuracy were achieved by the Inceptionv3 and ResNet101 models, with scores of 96.5% and 97.5%, respectively. In the study conducted by [135] several pre-trained deep learning models trained on ImageNet were used with the aim of classifying grape diseases. The highest average accuracy values of 100% were obtained with the Inceptionv3 and Xception models. [115] selected the Faster R-CNN Inceptionv2 and SSD Inceptionv2 models and adapted them for plant and weed detection using the transfer learning technique. The models provided reasonable detection speed with high mAP accuracies and confidence scores. The Inceptionv2 architecture was used as the feature extractor, which includes the "Inception" module that performs filter operations in parallel and widens the network, resulting in a less computationally expensive network. Predictions for plants ranged from 67% to 95%, while for weeds, the range was between 84% and 99%. In the study by [117], various weeds' images, taken with an RGB camera, were used to train CNNs for multiple plant and weed species. Three different CNN models were specifically VGG16, ResNet-50, and Xception, which were modified and trained on a dataset of 93,000 images. The trained CNNs achieved Top 1 accuracies ranging from 77% to 98% based on the evaluation of image tests for plant detection and weed species differentiation.

5.2. Proposed New Models

In the study conducted by [47], they proposed a new model called TransUNet that combines CNN and Transformer models to map broccoli canopies. This model leverages both the spatial information from CNN and the global context encoded by Transformer. The CNN-Transformer hybrid encoder consists of ResNet-50 and ViT. When an input sample is provided, ResNet-50 is initially used to generate a feature map through a three-layer subsampling process. This feature map is then divided into N different 1x1 patches used for patch embedding. The Transformer encoder consists of 12 blocks, each containing a self-attention mechanism and a multi-layer perceptron. The code of the hidden feature is decoded at the end using a stepwise upsampler that performs several upsampling steps to generate the final outputs. In the study conducted by [136], for the detection of small green peppers, a pre-trained model on the COCO dataset and the CSDarknet53_tiny model, which is the backbone model of YOLOv4_tiny, were used. The YOLOv4_tiny model provides an adaptive spatial feature pyramid method that improves the recognition of occluded and partially occluded small green peppers by combining the attention mechanism and the multi-scale prediction idea. The CCNN model proposed by [56] includes three convolutional layers and three fully connected layers, in contrast to current models such as VGG-16. This change reduces both the processing time and computational power while improving the accuracy in diagnosing various diseases. Additionally, the new model significantly reduces the number of hyperparameters compared to existing models. In the study conducted by [137], the Local Feature Matching Conditional Neural Adaptive Processes (LFM-CNAPS) method was proposed as a solution to recognize plant diseases with a small number of samples. It uses a feature extractor based on ResNet18 and employs a local feature matching classifier for robust categorization. The method also utilizes an attention mechanism TAM that reveals the focus regions of the model in input images.

The method proposed by [62] is a deep learning framework for plant disease classification. It employs a three-stage process: a Siamese network trains an embedding module to distinguish sample pairs, which then generates class prototypes through clustering, and finally, the prototypes and embedding module are used to train a classification network. This network is subsequently deployed to mobile devices using TensorFlow Lite. The classification network utilizes an experimentally determined number of prototypes per class and can handle a significant number of classes, making it suitable for single-crop disease modelling. The model developed by [49] consists of an eight-layer CNN. The authors aim to detect the presence of Legacy blueberry fruits. The method proposed by [113] comprises a main segmentation network and two sub-networks. The main segmentation network is primarily based on an encoder-decoder structure and utilizes the Bonnet architecture. It first generates a feature map using three encoder blocks, then transforms this map back to the original input image resolution using three decoder blocks and finally assigns a class label to each pixel using a linear classification layer. The encoder and decoder blocks include specialized downsampling and upsampling blocks that allow for more informative feature gathering and reduced computational cost. However, the main segmentation network often faces challenges in distinguishing between rye grass and wheat. Therefore, two newly proposed sub-networks are used to improve the initial segmentation results. Both sub-networks calculate segmentation errors and incorporate these errors into the main segmentation result to determine the final segmentation outcome. In the study conducted by [73], the authors extend a pre-trained VGG-16 deep learning model with a two-layer fully connected network to support automatic pest classification in mango farms. [78] combine MobileNet and ResNet models to create the MobiRes-Net model, which is used for diagnosing olive leaf diseases. Both models are deep learning models and pretrained. MobiRes-Net achieves an accuracy rate of 97.08%.

In the study conducted by [85], a Mask R-CNN architecture utilizing the ResNet model as the backbone was proposed to detect seven different strawberry diseases. A data augmentation approach was followed using a ResNet-based structure to enable disease segmentation under complex environmental conditions. The model was pre-trained on the MS-COCO dataset and achieved an accuracy rate of 82.43%. In the method proposed by [87], an architecture called RDA-CNN was used. This architecture consists of three stages: i) initial feature extraction, ii) super-resolution layers, and iii) classification layers for disease classification. A traditional image scaling algorithm is used to resize the input image dataset. Finally, the low-resolution image is transformed into a super-resolution image, and the performance of different image classifiers is improved. The RDA-CNN method achieved an accuracy rate of 96.595%. In the study conducted by [41], a neural network called Bi-CNN, inspired by human visual perception, was proposed. Features are extracted from images using pre-trained VGG and pruned ResNet models. These features are pooled and normalized using logarithm, signed square root, and L2-norm layers. The normalized features are then classified using a fully connected neural network. This method improves upon previous approaches by utilizing ResNet models and performing end-to-end training to extract meaningful features and accurately classify images. With Bi-CNN, disease detection achieved accuracy rates of 94.12%, 90.92%, and 91.20% for potato, corn, and tomato images, respectively, with a 70-30 train-test split. In the study conducted by [88], an attention based RNN model combines RNNs and an attention mechanism to improve the identification of plant diseases. Feature maps are extracted from plant disease images using a pre-trained CNN, and these maps are processed using an attention mechanism to focus on important regions. Bi-directional training models the relationships between different states to enhance detection performance. The proposed PV-SC model achieved a top-1 accuracy rate of 98.17% on the PlantVillage dataset. In the study conducted by [92], a novel CNN model was used. The locations are predicted using a confidence map, which is a 2D representation of the probability of the object occurring at each pixel. The model includes PPM, which adds global and local neighbourhood information to improve the prediction of the confidence map, and MSM, which refines the confidence map for more accurate object center estimation. Furthermore, two detection branches were added within MSM to understand how the rows of planted crops appear in the image and how they are related to the plant's position. This process allows our network to simultaneously return both line and point features and their relevant geographic location information. The method was verified on a test set, achieving an average precision of 95.11%. In the study conducted by [136], a deep learning detection algorithm based on Yolov4_tiny was developed to recognize green peppers. The proposed algorithm improves the Yolov4_tiny network by incorporating multi-scale detection, adaptive feature fusion, and attention mechanism to overcome challenges such as large target scale range, severe overlap, and occlusion. The method was validated on a test set, achieving an average precision of 95.11%.

5.3. Hybrid Models

In the study conducted by [59], disease detection for rice plants was targeted. The CNN-based Inception with ResNet v2 model and the Optimal Weighted Extreme Learning Machine (CNNIR-OWELM) were used. The CNNIR-OWELM method utilizes histogram segmentation technique to identify affected regions in rice plant images. Additionally, the deep learning-based Inception with ResNet v2 model is used for feature extraction. The Weighted Extreme Learning Machine (WELM), optimized by the Flower Pollination Algorithm (FPA), is employed for classification purposes. FPA is integrated with WELM to determine optimal parameters. In the study conducted by [60], AlexNet and the PSO algorithm were used together for plant disease detection. PSO was used to optimize both the parameters of AlexNet and the extracted features from AlexNet, and finally, AlexNet was used for classification. In the study conducted by [63], a technique called Social Shepherd Social Optimization-based Deep Learning (SSSO-based deep learning) was developed to classify rice leaf diseases and predict the percentage of disease severity. Classification is performed using a deep maxout network, while the prediction of disease severity is achieved using deep LSTM. The training of both deep learning techniques is carried out using an improved SSSO algorithm, which combines SSOA and social optimization algorithm. In the study conducted by [66], a novel approach called QBPSO-DTL was developed to detect and classify sugarcane leaf diseases. The proposed QBPSO-DTL technique involves several sub-processes, including preprocessing, optimal region enlargement segmentation, DSAE-based classification, and QBPSO-based hyperparameter tuning. The system first enhances the image quality for better disease detection, and then uses a region enlargement technique to segment the diseased leaf portions. The new algorithm achieves high accuracy by applying Mayfly Optimization for tuning and utilizing Deep Stacked Autoencoder for classification. In the study conducted by [67], a hybridization of CNN and ViT was performed. The study aimed to automate the diagnosis of plant diseases.

In the study conducted by [68], the authors developed a deep learning-based image classification system that performs image segmentation using k-means clustering. They identified the diseased regions in the images based on HUE (hue) values and removed irregular green pixel regions to improve classification accuracy. They performed feature extraction using various MATLAB functions to extract color, shape, and texture features. Then, they trained a DNN using a two-stage approach consisting of pre-training and fine-tuning. Additionally, a Crow Search Algorithm (CSA) was applied for optimization in a d-dimensional search space. The method proposed by [38] is a community classification method that examines the impact of diversity at the data, feature, and classifier levels. It involves a combination of various preprocessing steps, feature extraction, and different classifier models to classify 13 classes of tomato diseases with various challenges. The proposed method utilizes diverse preprocessing techniques and the selection and extraction of different features to increase diversity at the data and feature levels. Four different classifier models, namely RF, SVM, LR, and K-NN, are used, and MLP is used for combining the results. This method improves classification accuracy by increasing diversity within the community classification strategy. In the study conducted by [77], CRF method was combined with FCN-8s, CED-Net, SegNet, DeepLabv3, and U-Net for finding diseased parts in leaf plants. The method proposed by [86] for fruit disease classification involves deep feature extraction, parallel feature fusion, and classification using multi-class SVM. The method extracts deep features using pre-trained networks. The extracted features are then fused, and feature selection is performed to select the most discriminative ones. Finally, the selected features are classified using multi-class SVM, and the classification accuracy is compared with other popular classifiers. The highest success rate of 97.80% was achieved by M-SVM.

In the study conducted by [90], automatic plant disease diagnosis methods used for early detection of plant diseases and the obtained accuracy results were examined. The focus of the study was on detecting tomato plant diseases. A new hybrid detection model called SpikingTomaNet was developed, which combines deep CNN and SNN models. In the experiments, the proposed hybrid model achieved an accuracy of 97.78% on original images and obtained success rates ranging from 59.97% to 82.98% on the created datasets. Additionally, the proposed hybrid model showed better accuracy compared to other popular models and the combination of LeNet and SNN. In the study conducted by [91], the authors used the SPECIM IQ camera to obtain hyperspectral images, which were then pre-processed using the ENVI software and SVM classifiers to segment grapevine leaves from the background. Reflectance spectra of healthy and GVCV-infected vines were analyzed using t-tests. Index-based plant classification was performed based on various categories, including pigment, structure, physiology, and water content, followed by pixel-based extraction and feature reduction using PCA and kernel-PCA. A machine learning pipeline was then created to classify the processed data using SVM and Random Forest classifiers, and the performance of the model was evaluated based on accuracy scores. Finally, CNN was used for automatic feature extraction and image-based classification. The study conducted by [138] consists of several stages. It starts with preprocessing, including color transformation, filtering, bilateral filtering, and noise removal using the Otsu segmentation method. Synthetic images are then generated using CGAN to improve the prediction results. These synthetic images are fed into the proposed ADCLR model, which utilizes attention-based Dilated CNN for efficient feature extraction. The model is trained, and the images are classified using a Logistic Regression classifier. The robustness of the model is tested using various performance evaluation metrics and disease image comparisons. The proposed method achieved an accuracy rate of 96.60% on the test data. In the research conducted by [95], an Advanced Intelligent Environment-Coconut Tree Disease Detection and Classification (AIE-CTDDC) method was introduced to recognize and classify coconut tree diseases to enhance crop productivity. This method utilized a Median Filter (MF)-based technique during data preprocessing to remove noise and a Bilateral Filter-based Color Segmentation (BFCS) model to detect affected leaf regions. The Capsule Network (CapsNet) method was used for feature extraction, and the HHO algorithm with the GRU model was applied to detect diseased coconut trees. An accuracy rate of 97.75% was achieved in detecting coconut tree diseases.

In the study conducted by [139], an Advanced Intelligent Environment-Apple Leaf Disease Classification (AIE-ALDC) method is proposed, which consists of several steps. Firstly, a dataset consisting of four classes (Apple Scab, Black Rot, Cedar Apple Rust, and healthy images) is subjected to routing-based augmentation and Gaussian Filter (GF)-based preprocessing to remove noise and enhance the images. Feature extraction is then performed using a Capsule Network (CapsNet) method. The Whale Optimization Algorithm (WWO) is used for parameter tuning to optimize the solution, and a BiLSTM model classifies the images into their respective disease categories or healthy. The accuracy and efficiency of the AIE-ALDC technique are validated using the dataset. In the study conducted by [116], a novel CVDL-WDC technique is developed for accurate differentiation of plants and weeds in precision agriculture. The proposed CVDL-WDC technique encompasses a series of sub-processes, including WF-based preprocessing, multi-scale Faster RCNN-based object detection, ELM-based classification, and FFO-based parameter optimization. The proposed model reduces herbicide usage and improves efficiency by accurately detecting weeds in the field. The multi-scale Faster RCNN model is used to detect both weeds and plants in the object detection process. During weed classification, features are extracted using ELM and classified into different classes. The FFO algorithm is applied to enhance the classification efficiency of the ELM model. The combination of these methods ensures the differentiation between plants and weeds while maintaining an overall accuracy rate of over 90%.

5.4. Deep Learning Models

In the study conducted by [42], the authors utilized YOLOv3 and noted that this model produces fast and accurate results. Their objective was to evaluate factors such as plant growth and health in real-time using this model. They mentioned that DarkNet-53 was used as the feature extractor in the YOLOv3 model. In the study conducted by [55], the RPN model was used for leaf disease classification. RPN was employed to extract regions where leaves are present in complex images. The method proposed by [57] aimed to detect diseases in crops using a combination of a recursive neural network and deep attention layers (DAL_CL)-based CNN. Features were extracted using DAL_CL, and recursive networks were used to classify these features. In the study conducted by [64], the YOLOv5 architecture was employed for disease diagnosis in leaves. Bacterial regions in leaves were detected by this model. In the study conducted by [99], a deep learning-based CNN model was proposed for reliable classification of healthy and diseased potato and rice plant leaf images. The CNN model consists of various layers, including a convolutional layer, ReLU layer, pooling layer, dropout layers, and fully connected layers. Experimental results achieved an accuracy rate of 99.58% for rice and 97.66% for potato leaves.

In the study conducted by [72], the authors trained the weights of AlexNet, VGG, SqueezeNet, and EfficientNet networks from scratch and found that EfficientNet yielded the best results for leaf scorch disease detection. In the study conducted by [74], a CNN model based on VGG16 was used. The developed model employed data augmentation techniques, various parameter adjustments, and activation functions. Additionally, the images were analyzed using a layered approach. Bayesian Gaussian Process Latent Variable Model (B-GP-LVM) and deep convolutional autoencoder (cAE) were used for more complex feature extraction and classification. Through these processes, significant features were identified, and image regions were differentiated. All parameters and methods used in the study were optimized on the original dataset. In the study conducted by [76], a SegNet-based encoder-decoder neural network architecture was adopted for lesion segmentation. The proposed network operates on 512 × 512-pixel input images and produces segmentation masks of the same size as the input image. The architecture is designed in a U-shaped manner, consisting of a series of convolution and upconvolution layers. In the study conducted by [89], three different CNN architectures were selected: AlexNet, DenseNet, and SqueezeNet. These CNNs were preferred due to their success in plant disease research. The best result was achieved with DenseNet, with an accuracy rate of 98.45%. In the study conducted by [94], the proposed method addressed the challenge of data collection for deep neural network training by generating synthetic images. The original images were used to generate grayscale images and binary mask images, which were then manipulated using parameters such as rotation, zooming, and shifting. The obtained synthetic images were used for training a deep neural network based on the tiny YOLOv3 framework. The architecture comprised a series of convolution and maximum pooling blocks, and detections were performed at two different scales with modifications made for better feature fusion. Finally, transfer learning was applied using pre-trained model weights, and an Adam optimization method was used to minimize the loss function. According to the experimental results, the average precision (AP50) for C. sepium and sugar beet was found to be 0.761 and 0.897, respectively, with an inference time of 6.48 ms per image.

In the study conducted by [97], a four-step process for potato disease identification was presented. In the first stage, potato leaves were segmented from complex backgrounds using Mask R-CNN, resulting in individual leaves. These individual leaves were then used as input for a model capable of classifying healthy, early blight, and late blight leaves. In the second stage, the obtained single leaves were trained through a semantic segmentation model, which served as the input for the third stage. In the fourth and final stage, the diseases detected in the semantic segmentation process were used as disease recognition criteria in the classification stage. Furthermore, healthy, early blight, and late blight leaves were identified and labeled by an example segmentation model and classification model. The ratio of the disease area to the total leaf area was also determined for each leaf. The study conducted by [112] focused on collecting aerial imaging data from various locations in the Moscow region to create a dataset and labeling the data for the 'hogweed' and 'not-hogweed' classes. Different FCNNs were trained, and their performances were compared. The performance of the FCNN was evaluated using measurements such as frames per second (FPS), ROC AUC, the potentially covered area, and power consumption in watts. These processes were implemented on a single-board computer (SBC) that performs real-time analysis, and a ROC AUC score of 0.96 was obtained. The approach proposed by [114] operates on a single RGB image and identifies areas infected with weeds. The image pixels are divided into two classes (plant and background), creating a plant cover mask and a background mask. The plant cover mask is overlaid on the original RGB image, resulting in interest. This area is divided into smaller regions, and feature vectors are extracted from these regions. These vectors are then used to classify each region as either a crop or a weed. At the end of this process, the areas infected with weeds and the weed density in those areas can be determined. Only a part of the method was trained in a supervised manner, utilizing a CNN-based unsupervised learning method, allowing for a scalable approach adaptable to different weed and crop types. The method achieved an accuracy of 82.13%. In the study conducted by [68], the primarily used neural network architectures were AlexNet, FCN, and SegNet. The database used was obtained from a rice farm in Tamil Nadu. The value of each pixel ranges from 0 to 255 to distinguish the classes. Tests were conducted to compare the performance between the FCN and SegNet architectures and to propose and implement some modifications to the FCN architecture. The performance of the trained network for the segmentation process was measured. The results showed over 90% accuracy for both architectures during validation. The study conducted by [81] utilized an LSTM-CNN model.

6. DISCUSSION

In this study, the referenced articles were analysed based on three main criteria: innovation, dataset, and new layers and structures. Each criterion comprises sub-criteria. For example, the innovation criterion consists of three sub-criteria: innovation in architecture, innovation in optimization methods, and innovation in data augmentation methods. The dataset criterion consists of four sub-criteria: dataset source, dataset size, dataset labels, and the purpose of dataset collection/use. The third criterion, new layers, and structures, includes five sub-criteria: new layers, new connections, novel architecture, transfer learning, and unique optimization techniques. In this study, the term “new layers” refers to the addition or modification of functional layers within existing deep learning architectures, such as convolutional neural networks (CNNs), to enhance model performance. These layers may include newly designed feature extraction blocks (e.g., squeeze-and-excitation layers, spatial attention modules, dilated convolutions), or task-specific layers that are not part of the original base architecture. “New connections”, on the other hand, describe the introduction of novel ways to connect layers or modules within a network. This may include skip connections (as in ResNet), dense connectivity (as in DenseNet), bidirectional or feedback loops, or cross-stage partial connections. These modifications improve information flow, gradient propagation, and model convergence. While these changes may not always constitute an entirely new CNN architecture, they often result in a customized or enhanced variant of an existing model. In this review, such modifications are categorized under five design innovations: new layers, new connections, novel architectures, transfer learning schemes, and unique optimization strategies. The articles were analysed based on these twelve criteria, which encompass the three main criteria and their respective sub-criteria. Additionally, each examined article detailed the DL technique used or developed, aiming to determine the extent to which the studies employed original technologies (DL models).

In this section, the research questions provided in the introduction of the study are discussed. The first research question is "*In which sub-domains of field crop research are deep learning approaches being used?*" DL is used for classification and prediction purposes. A literature review was conducted, analysing deep learning and classification and prediction as keywords together. The results revealed that deep learning approaches are extensively studied in the areas of classification, disease detection, and weed detection in field crops. Table 5 provides the literature analysed for plant classification/detection purposes. Additionally, deep learning approaches are used for various purposes such as predicting crop harvest time ([39]), leaf classification in medicinal plants ([140]), yield prediction in corn plants ([141]), determining the severity of lodging behaviour significantly affecting wheat yield ([142]), and monitoring plant growth ([143]).

Another research question examined in this study is "*What are the deep learning techniques used in crop classification, disease detection and weed detection?*" Increasing agricultural production requires the use of advanced technology. Particularly, disease detection in plants using technological advancements instead of manual methods can enhance productivity and increase farmers' profits throughout the season. Table 6 presents studies conducted on disease detection in field crops, and Table 7 provides studies on weed detection in field crops. When examining the tables (5, 6, 7), it can be observed that researchers primarily focus on plant diseases. Deep learning approaches require many diseased images for disease detection. Many researchers have created their own datasets for disease detection studies. However, some studies have utilized publicly available datasets in the literature.

The innovative aspect of the reviewed studies: Under the criterion of innovation, researchers have proposed innovations in DL architectures primarily for the detection of plant diseases. This is because disease detection involves more complex features compared to plant classification and weed detection, and unique architectures are required to achieve successful results in disease detection. Similarly, optimization methods and data augmentation techniques are predominantly used in studies focused on disease detection in field crops. Specifically, there are numerous publicly available datasets for data augmentation techniques related to plant classification and weed detection. Researchers have mainly utilized these existing datasets. However, due to the specific nature of disease detection, data augmentation techniques have been more extensively employed in this area. This has contributed to the development of new data augmentation techniques.

The aspect of dataset in the reviewed studies: While researchers have used DL models for plant classification, disease detection, and weed detection, they have primarily recommended unique datasets, particularly for plant diseases. DL models have been more commonly used for object recognition in plant classification and weed detection tasks. As a result, the utilization of existing publicly available datasets in the literature has been more prevalent. However, since the detection of plant diseases is a more specific task, the number of publicly available datasets for this purpose is limited. Therefore, researchers have mostly developed their own datasets for disease detection. This has contributed to the introduction of unique datasets in the literature, but it has also made the researchers' work more challenging. Due to this challenge, the number of samples in the developed datasets is relatively smaller compared to publicly available datasets.

The aspect of new layers/new structures in the reviewed studies: Similarly to other criteria, it can be stated that researchers have developed more unique approaches in terms of new layers/new structures for the detection of plant diseases. This is because, as previously mentioned, plant classification and weed detection tasks are limited to object recognition and are relatively easier compared to the task of plant disease detection. Adapting computer vision technologies (DL) alone is not sufficient for automated disease detection. To accurately detect plant diseases with high performance, researchers have partially utilized transfer learning but have primarily proposed unique architectures (new layers, new connections, original architectures, and optimization techniques).

It is known that recommending and developing DL models is a challenging process. When examining the literature, it can be observed that researchers have used existing models, but in addition, they have also proposed/developed their own deep learning models, particularly for disease detection. Disease detection requires processing/extracting more complex features compared to plant detection (weeds or cultivated plants). Accepted deep learning models in the literature mainly focus on object detection. Therefore, researchers feel the need to develop their own models for plant disease detection. Researchers have also embraced hybrid approaches due to the high computational and setup costs of deep learning. In this approach, researchers have combined deep learning with optimization algorithms or machine learning algorithms. This reduces the complexity and cost of the experimental setup. Such solutions can also be more accessible for farmers. Monitoring plant development, early disease detection, and predicting the nutrients needed by the plant have become inevitable requirements in agricultural production. Deep learning approaches have been successfully used by researchers in all these processes.

This study analysing deep learning approaches in precision agriculture research reveals that there are still unresolved issues in related fields. Some of these issues include low data quality, the accuracy of data augmentation techniques in the case of limited data, and the scarcity of problem-specific optimization techniques. These areas are attractive research domains for researchers. Technological advancements in precision agriculture are progressing in parallel with technological developments. The increased use of technology in precision agriculture has given rise to the concept of Agriculture 4.0 ([99]). Technologies that farmers need to have, especially under Agriculture 4.0, include cloud technologies, autonomous robotic-mechanical systems, and IoT-enabled cyber-physical systems. Due to the high cost of DL-based systems, researchers have turned to cloud-based solutions ([144]). This shift can be attributed to the accessibility and ease of use of cloud platforms for everyone. Cloud technologies enable the production of edge solutions for machine learning and deep learning. Additionally, cloud technologies provide solutions for storing and processing agricultural big data generated by precision agriculture. Researchers face challenges in processing image-based data in precision agriculture when using or developing deep learning models. CNN models can perform tasks such as object recognition, texture, and color extraction with high accuracy from linear images ([145]). However, CNN models struggle to process images collected using non-linear remote sensing techniques that represent reflected energy from the surface with a narrow and contiguous set of wavelengths ([146]). Such data is described hyperspectral and is in the form of a three-dimensional data cube. The use of this type of image data in precision agriculture contributes to better planning and more precise management of agricultural production [147]). Data-driven Agriculture 4.0 applications benefit all stakeholders involved in agriculture, from farmers to consumers, financial institutions, and food processing industries. The sustainability of these benefits depends on the successful data collection step, which is the first step in precision agriculture applications. Data can be collected by almost anyone. The increasing performance of techniques like DL necessitates a certain standard for the data collection step in systems established within the scope of Agriculture 4.0. Researchers face challenges in standardizing the data collection step and ensuring the quality of the collected data. Traditional system-oriented data collection is being replaced by more user-oriented data collection in conjunction with big data. Big data tools can be used to ensure the quality of data within the scope of Agriculture 4.0.

The attributes of the analyzed studies within the scope of this review are shown as the columns of tables (Supporting Table 5, Supporting Table 6 and Supporting Table 7). As some of the names of these attributes are so long, using abbreviations of these column names are preferred. Full form of the column names and abbreviations forms are given in Supporting Table 4 below.

The types of models used in the reviewed studies and the distribution of these model types according to the number of times they are used in the studies are shown in Figure 5 below. Figure 5 shows that while popular models YOLOvXX (11), ResNet (23) and VGG (18) have been used as single models in many studies, many researchers have preferred to use several of these models (35) in the same study to obtain better performance results. In addition to this, there are also architectures that hybridize these models (13) or customize (6) in various ways.

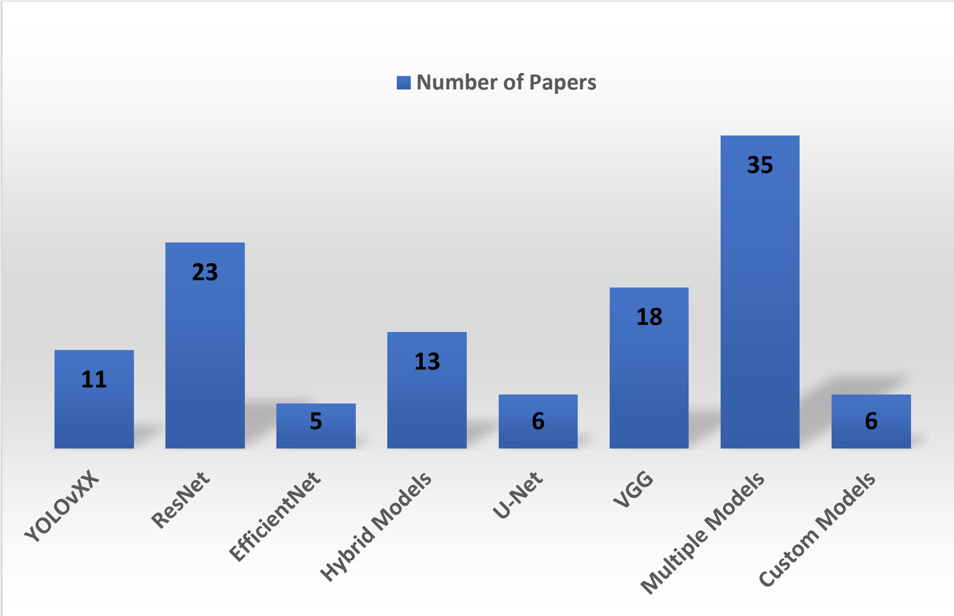

Figure 5. Distribution of Number of Papers According to Models Used in the Studies.

The results of the analysis of the studies presented in terms of which crops focused are shown in Figure 6 below. As seen in Figure 6, the top crops most frequently studied are tomatoes (14), potatoes (11), rice (8) and strawberries (6). "Others" category includes the plants which have been studied in less than three papers such as paddy plant, corn, sunflower, rye grass, mulberry, banana, coconut tree, sugar beet, bell pepper, Chile pepper, mango, blueberries in Chile and cassava plants.

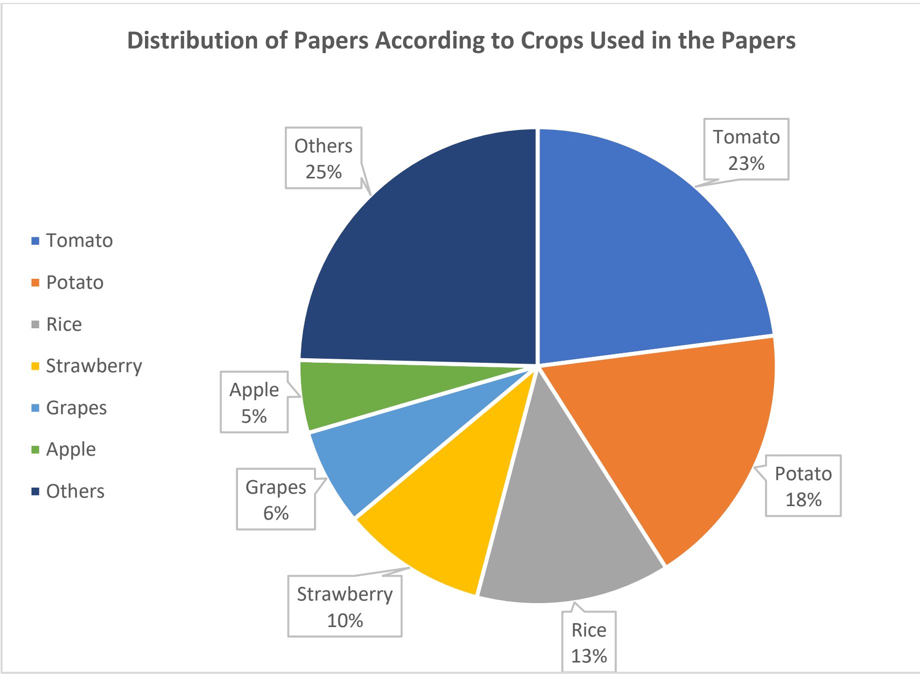

Figure 6. Distribution of Papers According to the Crops Studied in Research

Figure 7 provides a visual representation of the distribution of imaging methods utilised in the analyzed studies. As illustrated in Figure 7, the most preferred imaging methods are RGB cameras (32), drones (24), mobile cameras (12), LIDAR (10) and hyperspectral (8).

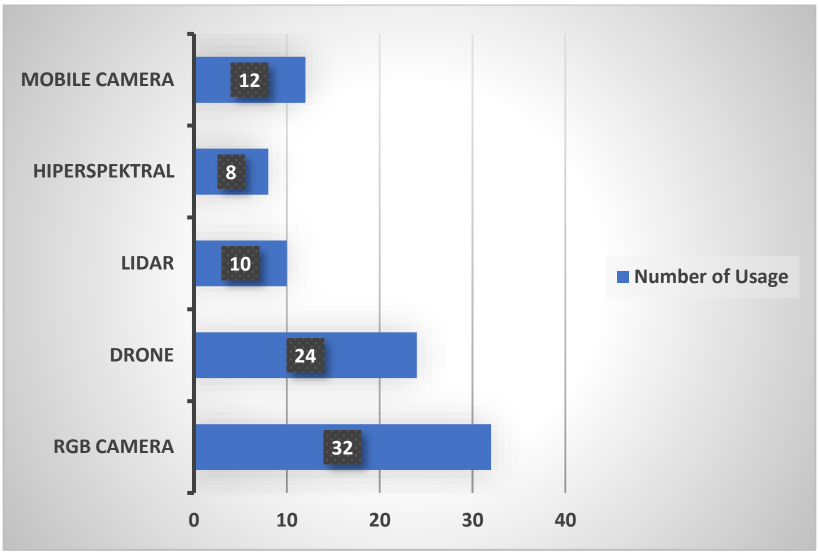

Fig 7. Distribution of Imaging Methods Used in Papers

The results of the distribution of the analyzed studies by country are also given in Figure 8. In case the authors of the studies are from different countries, the country of the first author is taken as reference. The ranking of the countries with the highest number of studies is India (23), China (11), South Korea (5) and others in descending order.

To enhance the readability of the study, a consolidated overview of the datasets used in the reviewed PA studies is provided in Supporting Table 8. Given the wide variety of crops, imagery modalities, and acquisition platforms used in the field, this table categorizes the datasets by crop type, data format (e.g., RGB, RGB-D, LiDAR), and acquisition source (e.g., UAV, smartphone, robot). Importantly, it also indicates whether the dataset is publicly available and, if applicable, its citation references and links. This categorization aims to help future researchers identify suitable, accessible, and context-specific datasets for training and evaluating deep learning models in agricultural applications.

Supporting Table 9 summarizes the DL architectures applied across plant classification, disease detection, and weed management tasks in recent PA literature. The models are grouped by architectural type (e.g., object detection, classification, segmentation) and are annotated with the number of studies using each, primary use cases, and representative citations. This structured view provides insights into prevailing trends—such as the dominance of YOLO-based detectors in real-time tasks, or the growing adoption of lightweight and transformer-based models in resource-constrained environments. The table is designed to guide researchers in selecting DL models aligned with their specific agricultural objectives and hardware constraints.

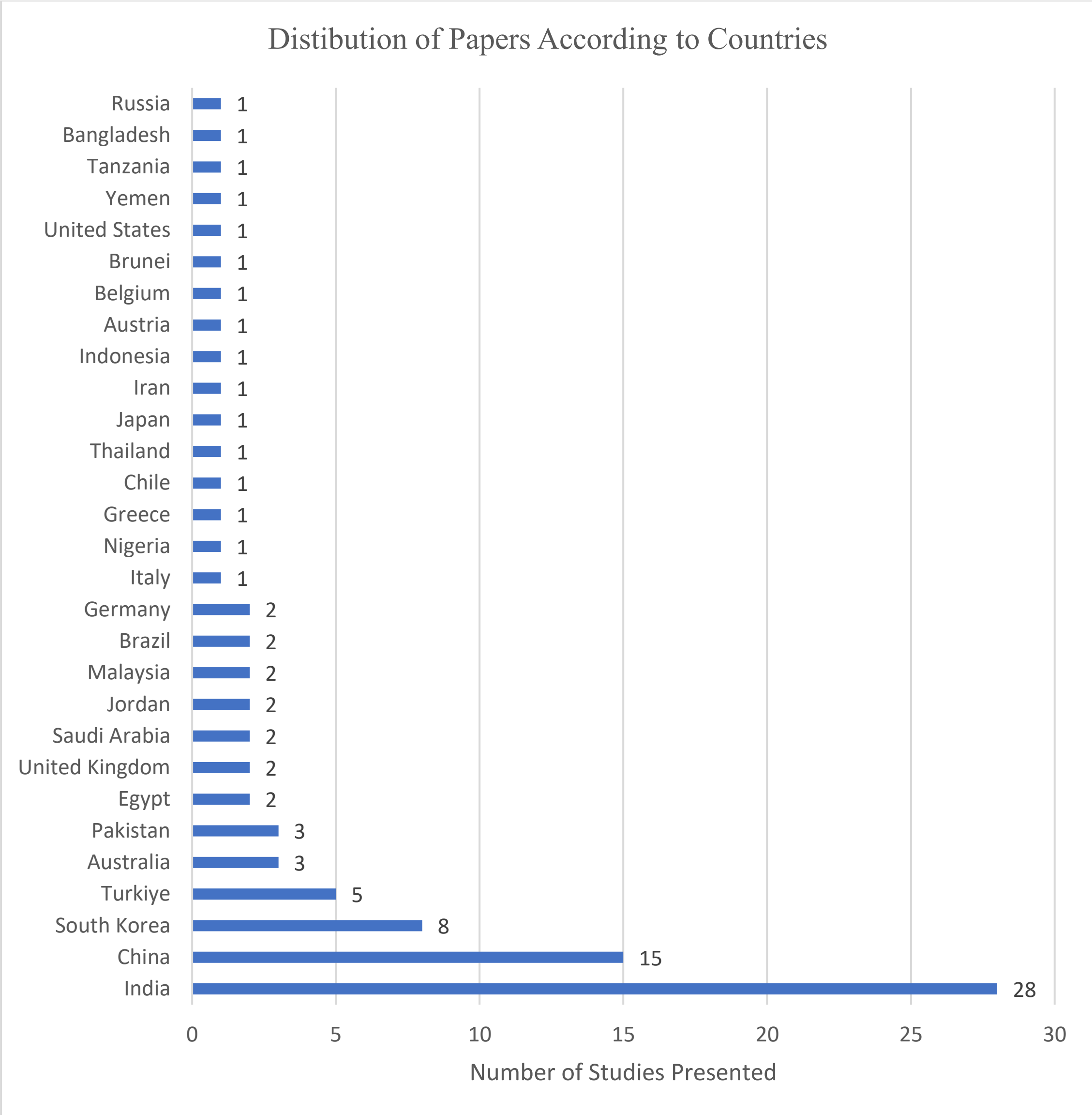

Figure 8. Distribution of Papers According to Countries

7. CONCLUSION

This article focuses on deep learning approaches used in the analysis of field crops in precision agriculture applications. The analysis of field crops is of great importance in terms of productivity and quality in the agricultural sector. Therefore, deep learning methods are being utilized as effective tools in the analysis of field crops. The article extensively examines deep learning approaches used for the analysis of field crops and how these approaches can be employed in precision agriculture applications. DL algorithms are used to detect, predict, and classify complex patterns in large datasets. When addressing critical issues such as the growth status of field crops, disease diagnosis, and yield estimation, deep learning approaches provide accuracy and precision. The various deep learning approaches discussed in the article include CNNs, LSTMs, and deep learning-based image classification methods. These techniques offer effective means to analyse and detect field crop images, as well as identify plant diseases and weeds. Most of the studies presented in the article have achieved success rates of over 90%, indicating the successful utilization of these techniques in agriculture. It is evident that the types and combinations of tools used influence the success of the approaches. Careful selection of tools, ensuring high-quality data, and efficiency in processing are crucial in this regard. The various methods examined in the article offer numerous advantages, such as increasing agricultural production, early disease detection, and more efficient resource utilization. Therefore, further exploration, development, and widespread adoption of deep learning techniques in precision agriculture applications are necessary. This way, significant progress can be achieved in terms of productivity, sustainability, and profitability in the agricultural sector.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Ethical Standards

Authors declare to comply with all ethical guidelines including authorship, citation, data reporting, and publishing original research.

Credit Authorship Contribution Statement

Ahmet Albayrak: Methodology, Data curation, Writing original draft, Editing, Visualization, Investigation, Software, Supervision.
Emre Can Kuran: Writing original draft, Data curation.
Fatih Kayaalp: Writing original draft, Visualization, Editing.

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