Towards Smart Agriculture: Deep Learning Methods for Plant Disease Monitoring

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Abstract: Plant diseases are one of the most disastrous threats to global agriculture, causing crop loss and decreasing food security. Although early and accurate detection of plant diseases is one of the most important aspects of disease management, it is often performed using traditional methods including visual examination and laboratory testing, which are time-consuming, subjective and resource-intensive. Deep learning has been a groundbreaking technology during the past few years due to its role in switching smart agriculture into an automatic, precise and scalable solution for the identification of plant diseases and monitoring.This paper aims at exploring the deep learning methods using Plant disease detection as the base but will mainly focus on image-based systems providing a comprehensive survey of modern Plant disease detection. Specifically, it investigates CNNs, RNNs, GANs and transformer-based architectures for diagnosing various diseases in different kinds of crops. The importance of transfer learning, data augmentation as well as synthetic data generation to improve the performance and generalizability of models is extensively discussed here.Paper also discusses the most commonly used datasets, such as PlantVillage, and investigates how they might help in a benchmark of model performance. Problems like lack of annotated data, overfitting, lack of adversarial robustness and going off smooth explainable models. Finally, the paper discusses stateof-the-art functionalities like edge computing, lightweight neural networks, multimodal learning, and explainable AI (XAI) that are necessary to deploy real-world applications.This review synthesizes existing work—especially recent scientific literature—and highlights gaps to provide researchers, practitioners, and policymakers a wide-ranging reference for the integration of deep learning into precision agriculture as it pertains to sustainable and resilient crop production.

Keywords: Plant disease detection, Deep learning, Smart agriculture, Convolutional neural networks (CNN), Image-based classification, Transfer learning, precision farming.

I. INTRODUCTION

Agriculture stands as a core pillar underpinning global economies [1]: it puts food on the table, creates jobs, and contributes substantially to GDP — particularly in developing regions. Nevertheless, one of the most constant, regular and destructive challenges to crop yield and agricultural sustainability is caused by plant diseases. These diseases are caused by a multitude of pathogens, including fungi, bacteria, viruses and nematodes that result in enormous yield losses or substandard foods of various types uniting parts within the value chain [1]. Based on Food and Agriculture Organization (FAO) estimates, plant diseases cause the world to lose 30% of its yields every year around the globe but in some regions this can be even higher. Yet the economic effects are staggering, particularly to resource-strapped smallholder farmers who could never afford a failed crop on that scale. With the increasing global population and climate change, early detection and management of plant diseases are now essential to maintaining agricultural resilience and food security [2].

Historically, identification of plant diseases has been largely based on human visual inspection (by expert agronomists or plant pathologists) of the symptoms shown by plants which can include lesions, discolorations, wilting and deformities. But these methods are intrinsically constrained by their reliance on human expertise, subjectivity and over a delayed appearance of visible symptoms [3]. Also, since trained professionals are not as readily accessible in rural and remote areas, early diagnosis is understandably challenging. While Polymerase Chain Reaction (PCR) and Enzyme-Linked Immunosorbent Assay (ELISA) methods have the capability to provide with species-specific diagnosis of Leishmaniasis, the associated costs; intensive human resource requirement, time-consumption and need for sophisticated infrastructure are some of its

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major limitations. However, these methods have limitations and are not practical for large-scale or real-time monitoring of disease in the field environments where fast decision-making is required [4].

Artificial intelligence (AI) [5] and deep learning in particular, have gained a lot of attraction in the recent past, superseding conventional methods practiced in agriculture. Convolutional neural networks (or CNNs), as the main category of the deep learning approach, have achieved great success in handling visual inputs and currently dominate image-based plant disease detection. The essential characteristics of these models is that they learn hierarchical features, thus obviating the need to manually engineer image features and maintain reasonable classification accuracies on a large variety of plant diseases with different environmental illumination [5]. Deep learning-based systems, in contrast to traditional methods, are large-scale capable and can provide real-time intelligence as well as edge-level deployment such as mobile devices, drones or smart cameras etc. These are vital enabler for a precision agriculture that can learn from big data sets and adjust to new disease patterns.

In this context, the purpose of this general review paper is to discuss the present situation of deep learning methods applied to plant disease monitoring. Specifically, it is designed to consolidate and evaluate state-of-the-art models, their strengths and weaknesses, as well as commonly used datasets and tools. The primary goal of this paper is to describe a collection of challenges and trends that we observe as pivotal, mainly from our experiences in developing AI systems [6] for real-world applications, and characterize those using five known dimensions and propose roadmap for future research and development directions with more concrete paths. Indeed, the insertion of deep learning practices to plant disease control could pave the way for a faster and steadier adoption of smarter, more sustainable agricultural systems across the globe.

A. Objectives of the Paper

The aim of this review paper is to present a systematic and thorough investigation of the different deep learning methods used for detecting plant diseases with a particular emphasis on their significance in realizing smart agriculture [7]. This paper attempts to connect the gap between development in technology and implementation on the ground — as AI is slowly becoming a crucial solution tool addressing major challenges of crop health management.

In short, the objectives are:

- The deep learning architectures such as the convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversarial networks (GANs) and tranformer-based models for plant disease identification.
- To evaluate the approaches in model training (such as transfer learning, data augmentation and synthetic data generation) that improve accuracy and generalization.
- The goal of this work is to investigate their utility as a source to analyze publicly available datasets for assessing the applicability and comprehensiveness in benchmarking deep learning models relative to agricultural disease detection tasks.
- This includes the major key performance metrics and evaluation protocols followed in literature to select deep learning models.
- Recognize the biggest obstacles and bottlenecks in real-world deployments especially which related to data quality issues, model explainability, etc. Emerging trends and future directions, like explainable AI, lightweight models for edge computing or multimodal data integration that could significantly contribute to scaling up deploying deep learning systems in precision farming [7].

This paper aims at providing a useful reference for researchers, practitioners and policy makers to integrate deep learning with an effective and scalable plant disease monitoring.

II. DEEP LEARNING IN AGRICULTURE: AN OVERVIEW

Among the most profound technologies in recent years, deep learning has brought about countless improvements for a variety of industries like healthcare, finance, transportation and now (rather unexpectedly) even agriculture [8]. Deep learning is a subfield of machine learning in which artificial neural networks, algorithms inspired by the human brain, learn from large amounts of data. And because of that, these networks are useful for modeling complex (nonlinear relationships) and thus they work well with unstructured data types like images, audio and text or more. In the world of agriculture, based on its nature of variability, unpredictability and real-world noise where deep learning is able to learn directly from raw data does provide an upper-hand [8].

Deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and some of the popular Generative Adversarial Networks (GANs) are just to name a few, transformer-based models have been more prominent in recent years. With agriculture such a visually-oriented field – disease identification, pest detection and crop classification are a few examples that come to mind – CNNs have therefore gained quite some following in this community. With these models, filters sweep over image pixels to recognize spatial hierarchies—perfect for finding tiny patterns like leaf spots or disease-induced browning. On the other hand, recurrent neural networks (RNNs) and their derivatives (e.g., long short-term memory [LSTM] networks) [9] are more ready for sequential or temporal patterns, such as climate records or sensor data with time-series imposed. While GANs have become a popular method for creating fake images with which to train other models, especially in situations where real data is scarce or difficult to obtain. The transformer models, popular for use in natural language processing (NLP), are being increasingly used for visual and multimodal tasks as these models are adept at capturing long-range dependencies across data [9].

There are many interesting possibilities for addressing such challenges in crop monitoring using deep learning when compared to traditional machine learning techniques. Traditional machine Learning methods (e.g., SVM, Decision trees, k-NN, RF etc.) [10]have a crucial step called feature engineering which require detailed domain specific knowledge. What this means is that raw data requires pre-processing before it can be fed into the model, which including the appropriate feature engineering approach: by human experts. This can be a time-consuming, possibly error-prone and domain knowledge-dependent process that might not always be to hand. More importantly, deep learning models implicitly learn both low-level to high-level features during the training process without human (manual) intervention. This results in models which capture dependencies over longer sequences, and hence which generalize better across more complex tasks (e.g plant disease classification) where visual symptoms may be both subtle and varied [10]. Scalability & Adaptability: Similar to the above point, deep learning development scaling because as the server resources increases it can reduce time in the computing of millions of parameters & weights. Deep learning models, once trained on huge datasets can then be deployed on devices such as smart phones, drones and embedded systems to enable real time decision making while out in the field. Deep Learning is farming becomes more flexible with transfer learning Through pre-training on large datasets such as ImageNet, followed by fine-tuning to the smaller agricultural database, high performance can be reached. This not only saves computation time, but also helps to avoid expensive and hard-to-acquire labeled agricultural data [11].

This is just one yet most popular use case out of the endless applications of deep learning in agriculture industries. For a drone or satellite, crop type classification use case is the most prevalent were images captured are used to identify the various kinds of crops in an area. Complex deep learning models may be used to identify spatial patterns within multispectral or hyperspectral images of crop types, growth stages, and soil properties. Such capability brings great value to precision farming, land use management, and yield estimation [12].Weed detection and management are also a vital part. In addition to taking valuable nutrients, water and sunlight needed for growth away from crops; weeds also reduce crop quality. The traditional methods of weed control either rely on manual labor or the indiscriminate application of herbicides, both inefficient. These models, trained on field images annotated to recognize valuable crop plants vs. weeds, can then discriminate between the two with high precision — ultimately using targeted herbicides while minimizing environmental impact from pesticide runoff [12].

Deep learning has also revolutionized yield prediction, which forms the basis of agricultural planning, resource allocation, and market anticipations. Recurrent and convolutional setups can predict crop output with high accuracy using input variables, including weather observations, soil parametrics, crop genetics, and prior yield data. Pertinently, integration of spatially discrete remote sensing data and temporally focused weather station or IoT sensor information appropriately predicts at a highly local level. Furthermore, deep learning has shown clues toward soil classification and health determination. Standard soil testing encompasses laboratory-based chemical analyses that can be costly and time-consuming. However, deep learning models trained with multispectral or hyperspectral soil images can infer moisture content, pH level, and nutrient vigor, among others. As such, the inference enables more judicious fertilizer use, better irrigation planning, and well-informed crop selection, among others. Finally, automatic harvesting and counting of fruits form a promising deep learning integration, especially in fruit orchards and vineyards. Robotic arms integrated with deep learning models can detect mature fruits, compile a yield estimate, and direct the robotic arm with pinpoint accuracy for harvest. This area is essential in labor-scarce regions and is fundamental post-harvest losses reduction [13]. Pest detection is also an important domain benefiting from deep learning. Similar to disease symptoms, pest infestations often manifest visually on leaves, stems, or fruits. CNN-based systems can be trained to detect specific pest damage and distinguish it from disease symptoms or nutrient deficiencies. This aids in timely and accurate pest management, which is crucial for minimizing crop damage [13].

Another interesting trend in the use of deep learning in agriculture is the multimodal data integration (including text, graphics and sensors). For example, leaf pictures might pair with soil moisture data, temp and humidity readings, or even farmer written notes on the probable causes of disease, enhancing diagnostic accuracy significantly. New deep learning architectures like multimodal transformers are in development to operationally process and combine these types of data streams efficiently [14].While improvements are being made in this space, there remain a few barriers between where we currently are and the full realization of deep learning for agriculture. One of the most important constraints is the lack of large, high-quality labeled datasets, especially for minority crops or rare diseases. Various models work great under controlled conditions but are not applicable in field conditions because of numerous challenges such as changes in lighting, background and leave orientation etc., due to appropriate atmosphere. Another problem is the interpretability of deep learning models. Although effective in terms of accuracy, this "black-box" aspect creates many challenges for the end-users (farmers & agronomists) to trust the predictions. Recent advancements in explainable AI (XAI) have tried to tackle such issues by giving visual or textual explanations for why a model made the decision it did.

Additionally, the computational demands for developing and employing deep learning models are high, especially in constrained environments. On the other hand, with edge AI becoming a hot trend this area focuses on deploying an extremely lightweight and restricted power consumption model directly on a mobile device, e.g., a smartphone or even a low energy capable drone. As a result, deep learning gets decentralized and taken to the edge allowing making decisions real-time and offline [15].

So, to conclude Deep learning has been already revolutionizing agriculture by automating intricate operations, augmenting decision-making precision and powering the era of data-driven farm management. The tools avail in it to process large volumes of heterogeneous data, make its differentiation in solving modern agriculture problems. Smart Farming is another prospective domain of deep learning, whose impact can turn really significant from disease detection to yield forecasting and robotic harvesting. Hopefully in the years to come, further research and better datasets help it reach its full potential with more user-centered deployment strategies.

III. DEEP LEARNING TECHNIQUES FOR PLANT DISEASE DETECTION

One of the essential tools being use for plant disease detection automation is the deep learning and many architectures have been designed to cope with the difficulties of agricultural image data. Of them are the most popular and basic models Convolutional Neural Networks (CNNs) [16]. CNNs are very specialized kind of neural networks for a particular type of problem, image classification, which are designed in such a way that they form spatial hierarchies that apply to only visual data. A typical CNN is organized as a set of convolutional layers to detect local patterns (e.g., leaf spots or lesions), pooling layers to reduce dimensionality, and fully connected layers for classification. Today, CNNs have outperformed within the tasks of plant disease detection by accurately discriminating visual symptoms if any exist solely in between healthy and diseased plant tissues. Plant disease identification at the leaf level has been a major use case, where CNNs were trained on extensive datasets such as PlantVillage to detect diseases of several crops [17]. Few popular CNN models like VGGNet, Resnet, and Inception have shown their best results in these domains. VGGNet, which is characterized by its simplicity and depth, ResNet with residual connections that address the problem of vanishing gradients allowing to train much deeper networks. Inception networks utilise multiple convolution filters at the same stride, which allows it to capture features that could be tiny in size and helps make the model stable. And while these architectures have been reworked and tweaked using transfer learning for more robust performance on agricultural image datasets [17].

Much research has been done on the use of RNNs and its variations to work with temporal aspects of agricultural data with respect to machine learning, whereas for image-based analysis Convolutional Neural Networks (CNN's) are most popular. Because RNNs have the ability to maintain an internal state that captures information about previous steps in the sequence they are good for predicting how diseases progress over time. LSTM (Long Short-Term Memory) networks are actually a special kind of RNN, capable of learning long-term dependencies in time series data — an issue which was previously almost impossible due to the limited lengths the memory inside each unit were allowed to operate for. For example, in agriculture, LSTMs have been used to study a series of crop images with weather data and sensor readings to forecast the time or extent at which diseases spread. For instance, RNNs can be used to identify early symptoms by analyzing the temporal changes in leaf colouring or plant morphology over a growth season that might be less visually obvious when they first appear. Similarly, these models are being used to predict the spread of diseases with respect to climate conditions and for better resource management through predictive containment mechanisms [18].

So far, deep learning-based plant disease detection methods have one serious limitation of the lack of large and balanced datasets before Generative Adversarial Networks [13] (GAN) were proposed. The networks that make up GANs are the generator, and discriminator, which together engage in a zero-sum game. The generator attempts to produce realistic synthetic images and the discriminator tries to separate these fake samples from real ones. This antagonistic training allows GANs to produce realistic positive and negative disease examples that can be used for data augmentation of training sets. However, it can also be a boon to generate these collections from existing data that is sparse (e.g., for rare plant diseases, which may not appear in public datasets) using generative models. Conversely, GANs can improve the quality of training data and model performance by correcting lighting, resolution or contrast problems in existing images as well. Synthetic image data generation using GANs also obviates the necessity for expensive and time-consuming manual data collection, enabling easier development of generalizing, well-balanced disease detection models [18].

Recently, transformer architecture models have also started to enter the agricultural applications pipeline, particularly for image and multimodal data analysis. Transformers are designed for natural language processing and achieve better capturing long-range dependencies in a sentence by using self-attention mechanisms to weighing the importance of each input component than traditional CNNs. Recently, the transformer architecture was adapted for image classification, called Vision Transformers (ViTs), which won competitive results in benchmark vision tasks as well and have also been studied for plant disease identification. In comparison to CNNs, transformers need less inductive biases and can consume complete images as sequences of patches decreasing the chance that they miss mild patterns for disorder due to convolutional filters. However, transformers usually require huge datasets and resources for training. As a result, hybrid models that integrate CNN feature extraction with transformer-based attention mechanisms are beginning to appear with the goal of capturing the benefits of both architectures. For example, combining plant imaging data with environmental or sensor inputs for all-encompassing disease monitoring [18].
In general, due to the evolution of deep learning architectures, automated plant disease detection algorithms become more performance. There are pros and cons to each, depending on the kind of data involved and the context in which you need to use it. While CNNs serve as the dominant model for image-based classification, RNNs are important to help model disease progression over time. On pasture collection, one of GANs helps in augmenting dataset and class imbalance problems can be mitigated while another transformer-based [19]approach represents the state of art scalable vision system in agriculture. The continued advancement of these techniques will drive them toward unification, leading to faster and smarter detection tools with the ability to work in real-world field settings.

IV. PUBLIC DATASETS FOR PLANT DISEASE

- **PlantVillage:** The most prominent dataset for plant disease identification, PlantVillage contains roughly 54,000 images of both healthy and diseased leaves. It has 14 crop species and 26 plant diseases, ultimately yielding 38 classes. Most of the images were collected under laboratory conditions, and while this makes it an ideal starting point for training models, it is not representative of the actual environments in which farmers operate [20].

- **PlantDoc:** PlantDoc seeks to provide images in situ to counter the disadvantages of lab-collected data. PlantDoc includes ~2,500 images with 13 crops and 17 disease classes. The images are taken in a more natural environment where it may include backgrounds and environments. This makes PlantDoc a rich dataset for testing models for at least real-world robustness [20].

- **Plant Pathology (Kaggle 2020 & 2021):** This dataset is produced for the Kaggle competitions with a specific focus on apple leaf diseases. This dataset includes thousands of images with expert annotation and categories such as healthy, multiple diseases, rust and scab.

- **Cassava Leaf Disease Dataset:** This dataset, which has roughly 21,000 cassava leaf images covering four major disease classes and healthy leaf samples, was developed for a Kaggle competition. Its intrigue stems from cassava being an important food crop across Africa motivating food security use cases for this dataset in casava-heavy geographic regions [21].

- **AI Challenger Agriculture Dataset (2018):** This large-scale dataset includes approximately 375,000 images covering 61 different disease and pest categories with widely diverse crops. It was acquired across varied and rich conditions and a very nice image data set to train models with possible variances across crops, diseases, and environments. The size of this dataset provides great opportunity for deep learning and transfer learning experiments [21].

V. METHODOLOGY

This review pursues a well-ordered reasonable approach like that of SLR for investigation, synthesis, and basic analysis to the plant disease detection applying deep learning-based method. The purpose of the methodology is to ensure only the most appropriate, peer-reviewed and high-ranking studies are incorporated. The review follows a rigorous process for identifying, screening and analyzing the research contributions from recognized academic sources. Below we outline how this was done in this paper.

A. Relevant Studies

We found most of the literature through credible digital libraries and academic databases including IEEE Xplore, SpringerLink, Elsevier (ScienceDirect), ACM Digital Library, Wiley Online Library and Google Scholar. Because of their wide sets of peer-reviewed journal articles, conference papers and technical research distributed in the domains of computer science and agricultural technology, such platforms were selected. Furthermore, we reviewed papers in three leading artificial intelligence/computer vision conferences (CVPR, ICLR, ICML and ECCV) to see if any state-of-the-art work has been done by using deep learning for plant disease detection.

B. Selection Criteria

The studies that were used to evaluate the specified outcome in this review were selected based on inclusion and exclusion criteria to make sure it stayed relevant and a high-quality review:

- Time Period: Related to the time period, only studies made between 2016 and 2025 were considered, allowing the review to be as contemporary as possible, and because deep learning methods are beginning to mature. i.e. it would be hard to examine a review of 10 year old deep learning studies. However, we made some exceptions to include older foundational papers that introduced concepts earlier, or have impactful datasets to the field.
- Plant Disease Detection: Because we were only interested in studies that directly apply deep learning models to plant disease detection in relation to visual or sensor data (for example, leaf images, hyperspectral images, aerial photography), studies that were only focused on other agricultural tasks (e.g. yield prediction, weed detection etc.) were excluded unless that study had a component related to disease detection.
- Deep Learning Orientation: Study analysis excluded other machine learning models, though deep learning studies or models for example that used Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Generative Adversarial Networks (GAN) or transformer methods had to be considered. We only looked at classical machine learning studies (e.g. SVM, Decision Trees) that were engaged in a hybrid deep learning framework.
- Multimodal Data Usage (optional consideration): While not a requirement, studies using more than one data type were preferred for relevancy (e.g. combining leaf image data with data from environmental sensors), as they may capture some elements of real-world complexity and other useful information to improve accuracy.

C. Keyword Strategy

A strategic search based on keywords using Boolean operators (AND, OR) was carried out, to maximize coverage without compromising on specificity. The keywords and keyword combinations were:

- "plant disease detection" AND "deep learning"
- "CNN" OR "convolutional neural networks" AND "leaf classification"
- "plant pathology" AND "image recognition"

- "deep learning in agriculture"
- "transformer model" AND "plant health monitoring"
- "GANs" AND "synthetic data generation for plant disease"
- smart farming" OR "precision agriculture" AND "deep learning"
- "plant leaf disease classification using AI"
- "transfer learning in plant disease detection"
- "multimodal deep learning" AND "crop disease"

The search strategy enabled the researcher to better sift through the literature established from the volume of articles available.

D. Selection Procedure

The selection process included three steps that provided rigor and uniformity: Keywords Search; once I searched the key terms of interest I received over 80 total studies from a variety of databases. The included studies were made up of journal articles, conference papers, and preprints, which published in high impact venues.

Short-listing: Titles and abstracts were screened by the authors to remove duplicates, out-of-scope studies, and studies that did not involve sufficient technical depth or experimentation. Studies that only described traditional machine learning procedures, or offered theoretical discussions without empirical results, were removed. At the conclusion of our process, approximately 40studies were remaining to work with.

Selection (and Critical Review): After reading the studies in full text and evaluating their merits, it was found that twenty-five peer-reviewed articles would be selected for in-depth review. All papers that were selected showed a clear contribution to novel deep learning models, use real world datasets, clearly indicated a proper approach to methodology (e.g., employing GANs for data augmentation, transfer learning, or attention mechanisms to support their pipeline), and had some concrete performance validation to substantiate claims of plant disease detection. Each paper was reviewed for their architecture, datasets used, accuracy indicators, deployment considerations, and their appropriateness for smart agriculture.

With systematic methodology described here, the review could convey a thorough, organised reflection of the contemporary research trends, technological advances, and potential application gaps in this important field of plant disease detection through deep learning.

TABLE I
SELECTION PROCESS OF LITERATURE REVIEW

Stage	Number of Papers	Description
Initial Collection	100	Papers identified through academic database searches and citation tracking using keywords related to deep learning and plant disease detection.
Shortlisting	40	Papers screened for relevance based on inclusion criteria (deep learning models, plant disease detection, image-based or multimodal approaches).
Final Review	22	In-depth review of selected papers focusing on CNNs, RNNs, GANs, transformers, and their applications in plant disease monitoring.

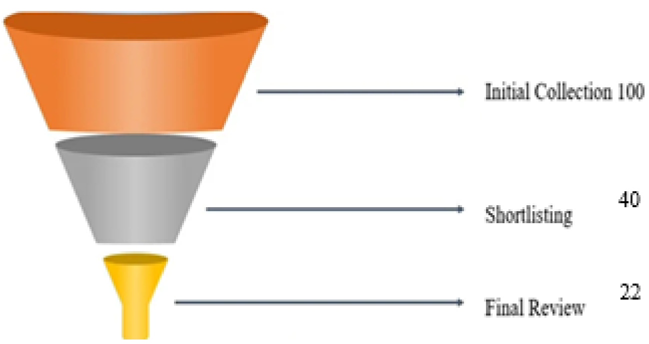

Fig 1. Funnel Diagram for Literature Review

VI. LITERATURE REVIEW

The final selected papers for literature review are as follows,

Bouacida, I., et al. (2025) [22] put forward a deep learning model that enhances the generalization of plant disease detection models. Instead of traditional leaf image-based methods which depend on whole-leaf appearance, their method is based on the detection of small diseased regions and estimation of disease severity. To handle the small leaf area with high speed, we employed a compact Inception architecture. On the PlantVillage dataset, the model was able to achieve an accuracy of 94.04% and external datasets with 97.13%, showing good results on unseen crops and diseases as well, addressing robustness and scalability in plant pathology.

Miao, Y., et al. (2025) [23] created an enhanced version of YOLOv8 referred to as SerpensGate-YOLOv8 for plant disease detection. Key improvements include Dynamic Snake Convolution (DySnakeConv) for fine-grained feature detection, SPPELAN for improved feature fusion and Super Token Attention (STA) for global modelling at large scale. The PlantDoc dataset was used to improve the modelperformance on mAP@0. 6, an increase of 3.3% from the original YOLOv8 and a precision of 0.719, suitable for real agricultural settings.

Duhan, S., et al. (2025) [24] Leveraged TL to build a light-weight plant disease predictor on edge devices with DL and introduced RTR_Lite_MobileNet. It is implemented on MobileNetV2 architecture with attention to create a light-weight attention for image classification by incorporating SENet, ECA, and Triplet Attention modules. This model achieved high validation accuracies up to 100% in different datasets with extremely low resources and it was also proven the real-time diagnose facility for IOT environment.

Ashurov, A. Y., et al. (2025) [25]depthwise CNN integration with squeeze-and-excitation blocks specialized for plant disease classification. When trained on stationary dataset and tested on the random images of the field, we obtained an average accuracy of 98% and F1-score with 98.2%. The system showed high adaptability as well as computational efficiency, fitting well with the requirements of practice in agriculture.

Roumeliotis, K. I., et al. (2025) [26] also studied the multimodal Large Language Models, i.e., GPT-4o combined with CNNs for plant disease detection using leaf images. Zero-shot Inference poor Fine-tuned GPT-4o beats ResNet-50 by 0.98% accuracy on the PlantVillage dataset (99.88%) having trained on ImageNet and using a trivial amount of agricultural data; but in zero-shot mode performance was an order of magnitude poorer, so some training is taking place during nonzero-shot inference The results demonstrate the potential of Vision-Language Models (VLMs) to enhance scalability and reduce reliance on accurate precision agriculture with high-cost resolution data and heavy labeling effort.

Demilie, W. B. (2024) [27]explored CNN and MobileNet-based models with some eXplainable AI techniques like GradCAM for transparent decision making in plant disease detection. The CNN scored accuracy of 89% with higher precision and recall where asMobileNet reached to a score of 96% but slightly lower precision. The research also illuminated that deep learning had the capability to be more effective than traditional methods, particularly when they utilized interpretability tools.

Adekunle, T. S., et al. (2024) [28] E-GreenNet: A Lightweight Deep Learning Framework For High-throughputand Efficient Plant Disease Detection Based On MobileNetV3Small The model reached accuracies up to 100%; Training on datasets: PV, PC and DRLI The new approach outperformed the state-of-the-art in terms of performance and efficiency, demonstrating its efficacy in handling low-contrast as well as complex image data.

Barman, U., et al. (2024) [29] introduction of smartphone-based detection method using Vision Transformers (ViT) and InceptionV3 to predict plant diseases on tomato. Results showed that the ViT model gave an accuracy of 90.99 and was further implemented in Android. This is an example about how transformer-based models can be utilized in mobile based smart agriculture tools as a solution.

Bhagat, S., et al. (2024)[30] introduced a fast end-to-end deep learning model Lite-MDC with Multi-kernel Depthwise separable Convolutions (MDsConv) for accurate real-time plant disease recognition. The authors fine-tune their model on a newly processed pigeon pea dataset and test it on public datasets, achieving an accuracy of 99.78% at 34 FPS on a NVIDIA P100. Meanwhile, its small footprint (2.2M parameters) makes it ideal for edge deployment with agrobotics.

Maurya, R., et al. (2024) [31] proposed a meta ensemble-based model of MLP-Mixer and fast LSTM networks for detection of plant diseases on low powered IoT.Forest Based Boosted Algorithm for Plant Disease Detection on Low-Powered IoT The ensemble outperformed CNNs and ViTs on Maize, Cotton, and PlantVillage datasets upto 98.43% accuracy offering imprassive performance improvements over standard deep networks for state-of-the-art image-based classification tasks. The given design is cost effective and low in power consumption which enables deployment on microcontrollers.

Moupojou, E., et al. (2023) [32] underlined shortcomings of PlantVillage and PlantDoc datasets because of lab conditions, poor annotations, respectively FieldPlant, a dataset of 5,170 real-field images annotated under expert supervision yielding 8,629 annotated leaves. FieldPlant logged better results on a real-world task of classifying and detecting diamond-back moth damage as well, when benchmarked.

Panchal, A. V., et al. (2023) [33] proposed a feature extraction, segment and pixel-based preprocessing system specially focused on Plant Disease classification over CNN. With training on ~87K (large RGB image dataset), the model provides a feasible solution for farmers, who need automated disease recognition especially in resource starved environments.

Archana, U., et al. (2023)[34] centered on the use of color-based features in deep CNNs with residual architectures for rice disease classification. They showed how useful deep learning methods could be for agricultural diagnostics, particularly in the case of rice diseases, with 96.35% accuracy using image-based phenotyping with ResNet-50.
Shovon, M. S. H., et al. (2023) [35] proposed PlantDet which is a deep ensemble model based on InceptionResNetV2, EfficientNetV2L and Xception for rice and betel leaf disease. Our model with multiple optimization layers and interpretability through Grad-CAM with Score-CAM gave up to 98.53% accuracy, in a state-of-the-art form of both performance as well as explainability with respect to other models

Hamed, B. S., et al. (2023) [36] Fine-tuning pre-trained CNN models (like EfficientNetV2S) on the noisy and low-resolution images for disease detection was investigated. It made their Plant Diseases Dataset (modified) into a secure-enough model for adverse conditions. This increases the flexibility and generalization of models which are crucial given the diverse real-world agricultural scenarios.

Albattah, W., et al. (2022)[37] stated that agricultural production is essential for economic development. Unfortunately, vegetable crops are plagued by plant diseases which reduce both yield and quality of products. Moreover, the agricultural sector is heavily reliant on manual inspection by plant pathologists. Even when the inspection is accurately performed, this method does not use resources economically and lacks efficiency. As a result, this can be a reason for deemed inaccurate inspection. Thus, the authors developed a robust and automated system for plant disease classification using a Custom CenterNet that makes use of DenseNet-77 as the base network. The method developed uses region of interest (ROI) annotations, feature extraction using DenseNet-77, and lastly classification using CenterNet approach. The model was tested on the PlantVillageKaggle dataset and the authors demonstrated it could deal with challenges like intensity changes, color similarities and multiple leaf shapes, which provided measured performance to existing approaches.

Akshai, K. P., &Anitha, J. (2021) [38] mentioned that plant disease detection in early stages can impact mitigating disease progression, particularly in the Indian context. As it is known, most of the plants show visible symptoms on their leaves and because of this, the researchers applied convolutional neural networks (CNN) for automatic disease classification. The study compared CNN with pre-trained models like VGG, ResNet and DenseNet, which determined that DenseNet achieved the most accuracy in classification. Their overall results showed that deep learning-based approaches can provide efficient alternatives to very manual labour, and can preserve both time and accuracy.

Guo, Y., et al. (2020)[39] proposed a mathematical model for identifying plant diseases using deep learning in order to increase identification accuracy, and adaptability in complex environments. The method included a Region Proposal Network (RPN) used to find and localize images of leaves and the images then underwent segmentation using the Chan–Vese method to capture symptomatic features. The segmented images were then classified using transfer learning models. The study demonstrated accuracy using feature images of black rot, bacterial plaque and rust with an accuracy of 83.57%. The authors noted that this study is a major step for intelligent agriculture and sustainable agricultural practices.

Saleem, M. H., et al. (2019) [40] reviewed the literature on machine learning (ML) and deep learning (DL) for plant disease detection and classification and noted that DL architectures were the better performers in the majority of cases compared to classical ML methods. The review also noted visualization methods, metrics of evaluation, and research gaps with a focus on providing more transparency and working towards enhanced earlier detection when the disease has not made visual means of detection apparent.

In the **Barbedo, J. G. (2018) [41]**article, the strengths and weaknesses of the application of deep learning to plant disease classification were researched. While deep neural networks proved effective, the author insisted that some experimental conditions sometimes neglected by researchers could affect the effectiveness in practice in real-world applications. Their study drew some conclusions with respect to designing more realistic and effective models for plant pathology applications by utilizing a database consisting of almost 50000 images.

The article by**Fuentes, A., et al. (2017)** [42] used a hierarchical meta-architecture based on deep-learning-based object detection techniques on tomato plants so that it could detect disease and pests on tomato plants. In particular, Faster R-CNN, R-FCN, and SSD were selected as their meta-architecture, which included feature extractors VGG and ResNet to analyze the groups of images containing different complex conditions in the field, varied infection status and different background conditions. They received results that indicated their proposed system had effective recognition of nine varieties of disease and pest for recognition and classification. Overall, it showed potential in agricultural applicability in real-world settings.

The work of **Sladojevic, S., et al. (2016) [43]** presented one of the first methods for plant disease identification using deep convolutional neural networks (CNNs). Sladojevic et al. (2016) [43] were able to identify 13 different diseases of the same plant species along with healthy leaves, achieving a mean accuracy of 96.3%. The model was built using a Caffe deep learning framework, which provided a functional and useful automated plant disease recognition method. This paper represented a significant step toward the application of deep learning in agriculture.

TABLE II
LITERATURE REVIEW FINDINGS

Author Name (Year)	Main Concept	Findings	Limitations
Bouacida, I., et al. (2025)	Compact Inception-based model focusing on diseased leaf regions	Achieved 94.04% accuracy on PlantVillage, 97.13% on external data; robust across unseen crops and diseases	May be limited in handling highly complex backgrounds or overlapping leaves
Miao, Y., et al. (2025)	SerpensGate-YOLOv8 with DySnakeConv, SPPELAN, and STA	mAP@0.6 improved by 3.3%; precision of 0.719 on PlantDoc; enhanced fine-grained detection	Performance improvement mainly validated on a single dataset; real-time performance not detailed
Duhan, S., et al. (2025)	Light-weight MobileNetV2 with attention modules for edge devices	Achieved up to 100% validation accuracy with real-time capability for IoT	Real-world deployment scalability and generalization to varied crop types not discussed
Ashurov, A. Y., et al. (2025)	Depthwise CNN with squeeze-and-excitation blocks	98% accuracy and 98.2% F1-score on field images; computationally efficient	Limited insight on dataset diversity and long-term deployment robustness
Roumeliotis, K. I., et al. (2025)	Vision-Language Models (GPT-4o + CNN) for plant disease detection	99.88% accuracy in fine-tuned mode; better than ResNet-50	Zero-shot performance was significantly poorer; needs some level of training
Demilie, W. B. (2024)	MobileNet and CNN with Grad-CAM for explainability	MobileNet achieved 96% accuracy; CNN 89%; better interpretability	Precision lower in MobileNet; effectiveness in real-time

		through Grad-CAM	scenarios not detailed
Adekunle, T. S., et al. (2024)	E-GreenNet: Lightweight MobileNetV3Small-based framework	Achieved up to 100% accuracy; excelled on low-contrast and complex images	Generalization beyond the tested datasets (PV, PC, DRLI) not demonstrated
Barman, U., et al. (2024)	Vision Transformer + InceptionV3 for smartphone-based detection	90.99% accuracy; implemented in Android for tomato disease detection	Limited scope (only tomato); relatively low accuracy for ViT
Bhagat, S., et al. (2024)	Lite-MDC with MDsConv for real-time plant disease detection	99.78% accuracy at 34 FPS with only 2.2M parameters	Evaluation on few crops; limited discussion on low-light or occlusion conditions
Maurya, R., et al. (2024)	Meta-ensemble of MLP-Mixer and fast LSTM for low-power IoT	Up to 98.43% accuracy; cost-effective and suitable for microcontrollers	Ensemble complexity may hinder training and updates on limited-resource devices
Moupojou, E., et al. (2023)	Critique and creation of FieldPlant dataset	More realistic field annotations (8,629 leaves); improved real-world detection	Limited scope (diamond-back moth); dataset still relatively small
Panchal, A. V., et al. (2023)	Feature extraction and pixel-based preprocessing for CNNs	Effective training on 87K RGB images; suitable for resource-constrained areas	Approach reliant on preprocessing; model scalability untested
Archana, U., et al. (2023)	Residual CNN using color-based features for rice disease	96.35% accuracy; effective for rice using ResNet-50 and phenotyping	Applicability to non-rice crops and diverse conditions unclear
Shovon, M. S. H., et al. (2023)	Ensemble with InceptionResNetV2, EfficientNetV2L, Xception	98.53% accuracy with Grad-CAM and Score-CAM interpretability	High model complexity; requires substantial computational resources
Hamed, B. S., et al. (2023)	EfficientNetV2S fine-tuning on noisy, low-res images	Improved robustness in adverse conditions with modified dataset	Generalization to unseen diseases and crops not discussed
Albattah, W., et al. (2022)	Proposed a Custom CenterNet with DenseNet-77 for plant disease classification	Achieved superior accuracy on PlantVillage dataset; effectively handled intensity variation, color similarity, and leaf shape differences	Model mainly tested on PlantVillage dataset, may not generalize well to real-world field conditions
Akshai, K. P., &Anitha, J. (2021)	Used CNN and pre-trained models (VGG, ResNet, DenseNet) for disease classification	DenseNet achieved highest accuracy; deep learning models outperformed manual inspection	Limited dataset; focus only on leaf symptoms; real-world variations not fully addressed
Guo, Y., et al. (2020)	Developed a deep learning model using RPN for leaf localization and CV algorithm for segmentation	Achieved 83.57% accuracy; improved detection of diseases like black rot, bacterial plaque, and rust	Accuracy lower than other DL approaches; segmentation step increases computational complexity
Saleem, M. H., et al. (2019)	Review of ML and DL approaches for plant disease detection	DL models showed superior accuracy; highlighted visualization techniques and research gaps	Lacks experimental validation; mainly conceptual and review-based
Barbedo, J. G. (2018)	Examined effectiveness and challenges of deep learning in plant pathology	Identified advantages of DL but also highlighted overlooked experimental issues	Dataset-specific results; highlighted that models may not perform well in practical farm conditions
Fuentes, A., et al. (2017)	Applied Faster R-CNN, R-FCN, and SSD with VGG/ResNet for tomato disease detection	Successfully recognized 9 diseases/pests in challenging field images; improved detection with augmentation	Focused only on tomato plants; high computational requirements
Sladojevic, S., et al. (2016)	Developed CNN model for leaf image classification	Recognized 13 plant diseases with ~96.3% average precision	Early-stage approach; dataset built in controlled conditions; limited to leaf images only

VII. RESEARCH GAPS DISCUSSION

Although deep learning has made a significant improvement in the detection of plant diseases, some general research issues are not fully explored. One of the more recognised problems is a focus on pre-recorded training datasets such as PlantVillage or PlantDoc that contain limited granularity and noise, not indicative of real-world agriculture. Recent studies based on Moupojou et al. Although, even datasets with field-annotations (e.g., FieldPlant) that approaches initiated the work on field-annotated dataset, but still these datasets only cover specific crops or diseases. This prevents models from generalizing in real-life farming conditions which are performed in various harsh environments with different lighting, occlusions, and complex environmental background noise.Furthermore, high-performance models with model interpretability and explainability are still not quite mainstream. Although this paper is underpinned by the "black-box" concept, some of the existing techniques have attempted to improve upon this behavior explored through Grad-CAM and Score-CAM respectively; indeed, such strategies make a strong predictive model but do abandon transparent decision-making from state-of-the-art models. This low interpretability can make it hard for agricultural practitioners to have confidence in or corroborate model outputs at a scale relevant to adoption.

Secondly, there is a technological trade-off between deploying more complex models and edge deployment feasibility. Models such as Lite-MDC (Bhagat et al., 2024) and RTR_Lite_MobileNet (Duhan et al., 2025) target on resource-constrained settings with high speed and accuracy, however many state-of-the-art architectures based on Transformers or Vision-Language Models (Roumeliotis et al., 2025) are computationally intensive for real-time, in-siloáidiagnosis in low-power IoT or mobile scenarios.
Very few people have been studying the problem of cross-domain robustness and zero-shot generalization. Is that, as lead author SteliosRoumeliotis and associates', (2025) and Vision-Language Models like GPT-4o fine-tuned shows much promise but they have poor zero-shot performance, implying that there is a present gap in generalizing to unseen or expected diseases as well as crops without requiring the models to be retrained Likewise, the vast majority of extant models do not include techniques to identify new forms of disease presentation or species with little supervision.Finally, there are few models of serious multi-modal data integration and severity estimation.While Bouacida et al. Although some work (2025) moved towards prediction severity by concentrating on small diseased regions, the plant disease detection-based models in literature assume mainly as a binary (i.e., classification) task without giving an insight about stages of progression or leveraging other sensory modalities such as temperature, humidity or soil health. This kind of incorporation could bring significant improvements to the feasibility of AI used in precision agriculture, as many decisions are not just based on visual recognition.

Collectively, future studies should look at creating models which are scalable and interpretable and perform reasonably well on diverse conditions of the real world, deployable to edge devices with severity estimation ability without reliance on large amount of annotated data through advanced few-shot or zero-shot learning approaches.

Limitation of Studies:
The limitations of the studies can be summarized in following points:
- **Dataset Dependency -** Numerous studies are predominantly dependent on demos planned data sets (i.e., PlantVillage) or crop-specific data sets, limiting generalization to field conditions.
- **Limited Crop Coverage -** Many studies only focus on singular crops in tracking Select as tomato, rice, and the diamond-back moth, resulting in limited generalization across plant species variety.
- **Controlled Environment Bias -** Many data sets are captured under controlled or simplified conditions making the models less robust and not tested in situations with complex backgrounds, and mixed crops, low-light, or occlusion.
- **Scalability -** Many studies defaults to high computational complexity (CNN, CenterNet, or ensemble methods), limiting real time networking and use on resource constrained devices.
- **Generalization -** The models perform poorly or lack confidences with unseen diseases, plants overlapping, and plant variance so therefore less reliable and certainly not trustworthy in real field conditions of agricultural applications.
- **Performance trade-offs -** Limited real-time precision, and accuracy of certain architectures (i.e., MoblieNet and ViT) versus heavier models limits real-time field use.
- **Preprocess Dependence -** Many methods are segmented or preprocessing heavy (i.e., RPN + CV algo), adding additional computation expense and limiting scalability.
- **Lack of Real-world Validation -** The majority of studies validate the models only under experimental conditions (i.e., lab or demo), which typically does not evaluate scalability, long-term deployment, and adaptability at the field-level.

- **Ensemble Complexity –** Although ensembles often improve accuracy, they complicate training, updating, and deploying models on limited-resource devices.
- **Research Gaps in Robustness –** Very few studies examine performance during diverse conditions (e.g., low-light, noisy environments, or cross-location variability).

VIII. CONCLUSION

The increasing threat of plant diseases to global food security, combined with the interest in promoting methods to engage in sustainable agricultural practices, has driven a rapid increase in the integration of advanced technologies in farming systems. One of these technological advancements is deep learning, which is becoming a powerful, flexible and automated method for detecting plant disease with unprecedented accuracy, upscalability and adaptability. In this paper, a review study was conducted of state-of-the-art deep learning algorithms, particularly, CNNs, RNNs, GANs, and transformer-based architectures, which are utilized to detect and monitor plant disease across a wide range of crops and contexts.Convolutional Neural Networks have led to excellent results for leaf image classification, and are central to most systems that detect disease from images. Recurrent Neural Networks family of models, particularly Long Short Term Memory network (LSTM), have enabled the modeling of disease progression over the time using temporal data. Generative Adversarial Networks are supporting an age-old problem of data scarcity with generative synthetic disease images that boost the performance of models. Transformer-based architectures are just emerging, but they show tremendous promise to drive the envelope for accuracy and interpretability, particularly towards complex learning in various modalities.While these advancements are impressive, there are still obstacles ahead to address, including limited annotated datasets, some models may not generalize well to all real-world scenarios, the computational burden, and the black-box that is nature of most deep learning systems. Fortunately, there is a lot of ongoing work within areas such as explainable AI, lightweight model deployment, and sensor fusion to overcome these limitations.-In conclusion, deep learning is already in a position to pave the way for smart agriculture, and if it continues to develop and is thoughtfully incorporated into solutions ready for the field, it has the potential to revolutionize plant health monitoring, diminish crop loss, and play an important role as we move towards sustainable and resilient food systems around the world.

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REFERENCES

[1] Upadhyay, A., Chandel, N. S., Singh, K. P., Chakraborty, S. K., Nandede, B. M., Kumar, M., ... &Elbeltagi, A. (2025). Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture. *Artificial Intelligence Review*, *58*(3), 92.

[2] Hari, P., & Singh, M. P. (2025). Adaptive knowledge transfer using federated deep learning for plant disease detection. *Computers and Electronics in Agriculture*, *229*, 109720.

[3] Guo, G., Lai, S., Wu, Q., Shou, Y., & Shi, W. (2025). Enhancing domain adaptation for plant diseases detection through Masked Image Consistency in Multi-Granularity Alignment. *Expert Systems with Applications*, *276*, 127101.

[4] Shoaib, M., Shah, B., Ei-Sappagh, S., Ali, A., Ullah, A., Alenezi, F., ...& Ali, F. (2023). An advanced deep learning models-based plant disease detection: A review of recent research. *Frontiers in Plant Science*, *14*, 1158933.

[5] Jafar, A., Bibi, N., Naqvi, R. A., Sadeghi-Niaraki, A., &Jeong, D. (2024). Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations. *Frontiers in Plant Science*, *15*, 1356260.

[6] Haridasan, A., Thomas, J., & Raj, E. D. (2023). Deep learning system for paddy plant disease detection and classification. *Environmental monitoring and assessment*, *195*(1), 120.

[7] Shafik, W., Tufail, A., Namoun, A., De Silva, L. C., &Apong, R. A. A. H. M. (2023). A systematic literature review on plant disease detection: Motivations, classification techniques, datasets, challenges, and future trends. *Ieee Access*, *11*, 59174-59203.

[8] Ramanjot, Mittal, U., Wadhawan, A., Singla, J., Jhanjhi, N. Z., Ghoniem, R. M., ...&Abdelmaboud, A. (2023). Plant disease detection and classification: A systematic literature review. *Sensors*, *23*(10), 4769.

[9] Chug, A., Bhatia, A., Singh, A. P., & Singh, D. (2023). A novel framework for image-based plant disease detection using hybrid deep learning approach. *Soft Computing*, *27*(18), 13613-13638.

[10] Sunil, C. K., Jaidhar, C. D., &Patil, N. (2023). Systematic study on deep learning-based plant disease detection or classification. *Artificial Intelligence Review*, *56*(12), 14955-15052.

[11] Chin, R., Catal, C., &Kassahun, A. (2023). Plant disease detection using drones in precision agriculture. *Precision Agriculture*, *24*(5), 1663-1682.

[12] Rayhana, R., Ma, Z., Liu, Z., Xiao, G., Ruan, Y., &Sangha, J. S. (2023). A review on plant disease detection using hyperspectral imaging. *IEEE Transactions on AgriFood Electronics*, *1*(2), 108-134.

[13] John, M. A., Bankole, I., Ajayi-Moses, O., Ijila, T., Jeje, T., &Lalit, P. (2023). Relevance of advanced plant disease detection techniques in disease and Pest Management for Ensuring Food Security and Their Implication: A review. *American Journal of Plant Sciences*, *14*(11), 1260-1295.

[14] Dey, P., Mahmud, T., Nahar, S. R., Hossain, M. S., &Andersson, K. (2024, January). Plant disease detection in precision agriculture: Deep learning approaches. In *2024 2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT)* (pp. 661-667). IEEE.

[15] Upadhyay, A., Chandel, N. S., Singh, K. P., Chakraborty, S. K., Nandede, B. M., Kumar, M., ... &Elbeltagi, A. (2025). Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture. *Artificial Intelligence Review*, *58*(3), 92.

[16] Dhaka, V. S., Kundu, N., Rani, G., Zumpano, E., &Vocaturo, E. (2023). Role of internet of things and deep learning techniques in plant disease detection and classification: A focused review. *Sensors*, *23*(18), 7877.

[17] Qadri, S. A. A., Huang, N. F., Wani, T. M., &Bhat, S. A. (2023, August). Plant disease detection and segmentation using end-to-end yolov8: A comprehensive approach. In *2023 IEEE 13th International Conference on Control System, Computing and Engineering (ICCSCE)* (pp. 155-160). IEEE.

[18] Ali, U., Ismail, M. A., AriyaluranHabeeb, R. A., & Ali Shah, S. R. (2024). Performance evaluation of YOLO models in plant disease detection. *Journal of Informatics and Web Engineering*, *3*(2).

[19] Ojo, M. O., &Zahid, A. (2023). Improving deep learning classifiers performance via preprocessing and class imbalance approaches in a plant disease detection pipeline. *Agronomy*, *13*(3), 887.

[20] Jung, M., Song, J. S., Shin, A. Y., Choi, B., Go, S., Kwon, S. Y., ...& Kim, Y. M. (2023). Construction of deep learning-based disease detection model in plants. *Scientific reports*, *13*(1), 7331.

[21] Sahu, S. K., &Pandey, M. (2023). An optimal hybrid multiclass SVM for plant leaf disease detection using spatial Fuzzy C-Means model. *Expert systems with applications*, *214*, 118989.

[22] Bouacida, I., Farou, B., Djakhdjakha, L., Seridi, H., &Kurulay, M. (2025). Innovative deep learning approach for cross-crop plant disease detection: A generalized method for identifying unhealthy leaves. *Information Processing in Agriculture*, *12*(1), 54-67.

[23] Miao, Y., Meng, W., & Zhou, X. (2025). SerpensGate-YOLOv8: an enhanced YOLOv8 model for accurate plant disease detection. *Frontiers in Plant Science*, *15*, 1514832.

[24] Duhan, S., Gulia, P., Gill, N. S., &Narwal, E. (2025). RTR_Lite_MobileNetV2: A lightweight and efficient model for plant disease detection and classification. *Current Plant Biology*, *42*, 100459.

[25] Ashurov, A. Y., Al-Gaashani, M. S., Samee, N. A., Alkanhel, R., Atteia, G., Abdallah, H. A., &Saleh Ali Muthanna, M. (2025). Enhancing plant disease detection through deep learning: a Depthwise CNN with squeeze and excitation integration and residual skip connections. *Frontiers in Plant Science*, *15*, 1505857.

[26] Roumeliotis, K. I., Sapkota, R., Karkee, M., Tselikas, N. D., &Nasiopoulos, D. K. (2025). Plant disease detection through multimodal large language models and convolutional neural networks. *arXiv preprint arXiv:2504.20419*.

[27] Demilie, W. B. (2024). Plant disease detection and classification techniques: a comparative study of the performances. *Journal of Big Data*, *11*(1), 5.

[28] Adekunle, T. S., Lawrence, M. O., Alabi, O. O., Afolorunso, A. A., Ebong, G. N., &Oladipupo, M. A. (2024). Deep learning technique for plant disease detection. *Computer Science and Information Technologies*, *5*(1), 55-62.

[29] Barman, U., Sarma, P., Rahman, M., Deka, V., Lahkar, S., Sharma, V., &Saikia, M. J. (2024). Vit-SmartAgri: vision transformer and smartphone-based plant disease detection for smart agriculture. *Agronomy*, *14*(2), 327.

[30] Bhagat, S., Kokare, M., Haswani, V., Hambarde, P., Taori, T., Ghante, P. H., &Patil, D. K. (2024). Advancing real-time plant disease detection: A lightweight deep learning approach and novel dataset for pigeon pea crop. *Smart Agricultural Technology*, *7*, 100408.

[31] Maurya, R., Mahapatra, S., & Rajput, L. (2024). A lightweight meta-ensemble approach for plant disease detection suitable for IOT-based environments. *Ieee Access*, *12*, 28096-28108.

[32] Moupojou, E., Tagne, A., Retraint, F., Tadonkemwa, A., Wilfried, D., Tapamo, H., &Nkenlifack, M. (2023). FieldPlant: A dataset of field plant images for plant disease detection and classification with deep learning. *IEEE Access*, *11*, 35398-35410.

[33] Panchal, A. V., Patel, S. C., Bagyalakshmi, K., Kumar, P., Khan, I. R., &Soni, M. (2023). Image-based plant diseases detection using deep learning. *Materials Today: Proceedings*, *80*, 3500-3506.

[34] Archana, U., Khan, A., Sudarshanam, A., Sathya, C., Koshariya, A. K., &Krishnamoorthy, R. (2023, April). Plant disease detection using resnet. In *2023 International Conference on Inventive Computation Technologies (ICICT)* (pp. 614-618). IEEE.

[35] Shovon, M. S. H., Mozumder, S. J., Pal, O. K., Mridha, M. F., Asai, N., & Shin, J. (2023). PlantDet: A robust multi-model ensemble method based on deep learning for plant disease detection. *IEEE Access*, *11*, 34846-34859.

[36] Hamed, B. S., Hussein, M. M., &Mousa, A. M. (2023). Plant disease detection using deep learning. *International Journal of Intelligent Systems and Applications*, *15*(6), 38-50.

[37] Albattah, W., Nawaz, M., Javed, A., Masood, M., &Albahli, S. (2022). A novel deep learning method for detection and classification of plant diseases. *Complex & Intelligent Systems*, *8*(1), 507-524.

[38] Akshai, K. P., &Anitha, J. (2021, May). Plant disease classification using deep learning. In *2021 3rd International Conference on Signal Processing and Communication (ICPSC)* (pp. 407-411). IEEE.

[39] Guo, Y., Zhang, J., Yin, C., Hu, X., Zou, Y., Xue, Z., & Wang, W. (2020). Plant disease identification based on deep learning algorithm in smart farming. *Discrete Dynamics in Nature and Society*, *2020*(1), 2479172.

[40] Saleem, M. H., Potgieter, J., &Arif, K. M. (2019). Plant disease detection and classification by deep learning. *Plants*, *8*(11), 468.

[41] Barbedo, J. G. (2018). Factors influencing the use of deep learning for plant disease recognition. *Biosystems engineering*, *172*, 84-91.

[42] Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. *Sensors*, *17*(9), 2022.

[43] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., &Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational intelligence and neuroscience*, *2016*(1), 328980