

Review

A Comprehensive Review on Plant Leaf Disease Detection Systems Using Machine Learning and Deep Learning Techniques

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Abstract: The problems of plant leaf disease are rather serious in the world agricultural industry, leading to a significant decrease in crop quantity and quality, consequently, resulting in a huge loss in the economy and food insecurity. Detection and successful classification of plant diseases at the initial stage is essential to further agricultural output and the quality production of food. The recent improvements in the field of artificial intelligence (AI), specifically, machine learning (ML) and deep learning (DL), have shown significant prospects in automating and enhancing methods of diagnosing plant leaf diseases by using a wide variety of ML and DL algorithms. This review article presents an in-depth analysis of thirty novel methods created by researchers to diagnose and classify plant leaf diseases. They are such conventional classifiers as Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN), along with some advanced DL architectures, such as Convolutional Neural Networks (CNN), VGG16, ResNet50, InceptionResNetV2, EfficientNet, and various hybrids. The review analysis takes into consideration the methodologies applied, performance metrics, and insights in practice, as well as the strengths and weaknesses of both. The most crucial findings of the review show that deep learning models, and CNNs in particular, tend to be more accurate, robust, and feature extractors than traditional models of MLs. The performance of classification is also enhanced by numerous hybrid models that will use ML together with DL, and transfer learning has been an effective method to enhance the generalization using small datasets. Nevertheless, with all this progress, the issues of diversity of datasets, computational resource requirements and model interpretability are still to be explored in the future.

Keywords: Image Classification; Smart Agriculture; Precision Farming; Crop Disease Diagnosis; Agricultural Monitoring Systems; Feature Extraction; Hybrid Models; Artificial Intelligence in Agriculture

1. Introduction

The agricultural sector is an important part of the global economy, especially in developing nations where numerous people depend on farming and related jobs for their employment. Agriculture is not just an activity in these parts of the world; it is an important contributor to national food security, economic stability, and social well-being in these communities. Although a great deal of food (and livelihood) depends on agricultural systems functioning well and sustainably, larger agricultural systems face a multitude of constant challenges that may threaten productivity or profitability. Plant diseases are among the most significant threats to crops. Leaf diseases can be particularly impactful to crop health and crop yield potential. Pathogens, including bacteria, viruses, fungi, or other microorganisms, can infect crop plants, which can be hard to detect or control, and spread quickly throughout a field and/or a locality. In addition to decreasing yield (which measures the weight of agriculture outcome), plants

can present decreased growth, wilting prematurely, and/or malformed leaves. All of these conditions can influence farming yield. Diseases can also greatly affect marketing crops and/or lower crop quality which can have even greater economic impacts on farmers' revenues. In some developing countries, some farmers can operate on small-holder farms and do not have access to more accurate diagnostic tools to manage plant diseases. When they lose plants from diseases, they can incur serious monetary losses from relatively small incidents of plant diseases. Such losses can have economic impact that goes beyond the individual grower and instead trickles through the supply chain on a regional/national level, impacting food insecurity, and price inefficiencies on a population level. For this reason, timely identification and mitigation of leaf diseases is essential to agricultural productivity and economic viability.

Current means of diagnosis—visual diagnostic inspection performed by experts—takes processing time, is subjective, and impractical for larger scale limited resource producers. These patches of diseased foliage at one point or another are indicators for the need of new approaches for plant disease diagnosis such as computational systems with machine learning and deep learning, as these can provide habit and accurate means of diagnosing plant diseases. Further, if a farmer could detect plant disease earlier, it would naturally increase the chance of the farmer saving monetary losses, increasing food security and enriching the farmer's livelihood, supporting both regional and national viability and sustainability in a farming practice. The conventional means of detecting disease in plants has relied largely on the visual check of an expert in agriculture, or farmers themselves. While these traditional methods have had some success detecting observable symptoms of disease, they are limited by a number of underlying issues. Visual diagnosis is subject to the expertise, experience, and observational ability of the person doing the checking. They also require a significant amount of time and effort and cannot be scaled easily for large-scale farming wherein thousands of plants need to be inspected. Often, the indications of disease in early development are mild or not very well defined, so that misdiagnosis may occur or the disease may not be apparent until a later date and thus the diagnosis may be delayed. In this delayed diagnosis the difficulties associated with the disease become stronger and harder to remedy to such an extent that there are frequently big economic losses suffered by the producers direct and indirect losses through loss of yield and quality in the food chain indirect losses in the food sequence or chain are sometimes much larger than the total of direct losses.

Lately, improvements in the use of Artificial Intelligence (AI) in agriculture have opened up new channels for such things as faster and more effective diagnosis of plant diseases. Especially in so far as the use of Machine Learning (ML) and Deep Learning (DL) has revolutionized diagnosis in agriculture, giving us automatised data-driven results in diagnosis. In these AI systems automatised solutions we have a basis for always and at all times the opinions are due to images of plants evolving through great databases which can be worked out into intelligent presentations of such models as are more simply capable of evidence and/or diagnose the symptoms of diseases and may give a rating more efficaciously than the human observer and with greater specifications and within a shorter time. Thanks to their advanced pattern recognition algorithms and high-resolution imaging, the AI-based techniques can detect early or subtle signs of disease that are easily missed during traditional inspections. Various machine learning models and neural networks have been analyzed in great detail for this purpose. Convolutional Neural Networks (CNN) are well suited to the image-based disease detection problem because they efficiently learn and extract spatial features directly from images. Support Vector Machines (SVM), Type classifiers, can accurately separate healthy from diseased plant tissue. Random Forests (RF) are ensemble-based methods that classify data based on a group of typically dependable decision trees that perform well and dependably in classification, as RF reduces variability by reducing overfitting and aiding generalization. Likewise, hybrid approaches that blend deep learning (DL) and machine learning (ML) have also been developed for the purpose of maximizing classification accuracy from the opposite advantages of each paradigm, via feature extraction, efficiency, or interpretation.

AI-based plant disease detection systems have many advantages. First, these systems provide automated interpolation due to reliance on human knowledge and a reduction in errors that are intrinsic to subjective judgment. Furthermore, they automate monitoring that can be scaled for extensive areas of agricultural land and do not require person-to-person contact. Furthermore, the quickness of detection allows for a fast response to mitigate disease spread and crop loss, particularly during busy planting seasons. Similarly, AI diagnostic diseases can also be turned into actionable items communicated with farmers and agricultural scientists via apps available through both mobile and IoT devices as part of a practical example of precision agriculture. In conclusion, the intersection of algorithms, along with precision imaging will produce disruptive technologies with respect to diagnostics

of plant diseases as a fast, accurate, and scalable approach for agricultural productivity and sustainability of food systems. These advanced systems enhance the reliability and objectivity of assessing diseases and provide real-time, automated and remote clinical diagnostics—a significant benefit to small-scale farmers, as well as large-scale farming operations. The paper will rigorously compare the different applications, underlying model architectures, data-based, classification performance, and overall system effectiveness as reported by different researchers across thirty publications, whilst highlighting timely advancements being reported in the respective research studies. The study provides an overview of the current technology landscape, summarizes major findings and advancements, and highlights gaps in research to inform future work. A comparison will inform the researcher, agronomist and technologist to the most appropriate and least toxic application to maintain effective methodologies in monitoring and managing agricultural pests and diseases.

2. Traditional Approaches

In addition to advances in imaging and sensor systems, Artificial Intelligence (AI) has made a significant impact on the detection of plant diseases in agriculture. Specifically, Artificial Intelligence products based on Machine Learning (ML), Deep Learning (DL), or a hybrid of the two have emerged as reliable means of achieving early and accurate disease assessment. Most traditional approaches documented in the literature operate on a defined pipeline that includes the steps of image pre-processing, feature extraction, and classification in the context of plant imaging disease assessments. There are multiple pre-processing steps (including noise reduction, normalization, and identification of leaf areas) that can improve the quality of input data and/or reliability of subsequent analysis steps. Feature extraction identifies characteristics of healthy versus diseased plant tissue. Many different ways to extract features from leaf imaging assays have been reported in the literature. The Grey Level Co-Occurrence Matrix (GLCM) is an established tool to assess leaf texture which reports statistical metrics related to differences in pixel intensity values that can assist classifications of specific plant diseases. Discrete Wavelet Transform (DWT) is also commonly reported to decompose the leaf imaging into frequency components which allows for assessing subtle changes in tone and structure that occur due to infection. Speeded Up Robust Features (SURF) is also a popular product used to extract spatial and local features, such as corners, edges, or keypoints from leaf tissue analysis. These extracted features are then fed into classifiers, such as Support Vector Machines (SVM), Random Forests (RF), or k-Nearest Neighbors (k-NN), to categorize the leaves as healthy or diseased. Hybrid models, which are the combination of ML and DL, can also improve the detection performance by making use of the advantages of both paradigms, i.e., machine learning to analyze structured features and deep learning to automatically learn features. Together, the advances in these AI-enabled technologies will lead to a faster, scalable, and more accurate form of plant disease diagnostics, all while lessening the impact of direct observations by a human, and allowing practices to work towards precision agriculture to lead to crop health, crop yield, and sustainability. For classification, the most widely used algorithms have been Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), Multilayer Perceptron (MLP), and Naive Bayes. For example, projects that have used these methods to classify plant leaves have indicated classification accuracy of up to 95.33% in the literature.

Traditional ML approaches have major advantages such as lower computational effort needed, and they provide greater interpretability which helps further our understanding of how input features relate to the classification exercise. Traditional ML methods are used with “manually” engineered features from domain expertise such as color, texture, or shape attributes from their leaves. While effective on a smaller scale or with datasets in more controlled environments, traditional ML approaches have had difficulty being used with larger datasets that have more complexity and greater variability. The overreliance on handcrafted features may hinder the detection of subtle distinctions in leaf pattern, disease symptoms, and environmental conditions, which reduces the accuracy and robustness of classifying real-world data. Deep Learning (DL), specifically Convolutional Neural Networks (CNNs), has been apt to address the shortcomings of handcrafted image classification methods. Unlike traditional ML which depends on handcrafted features, CNNs carry out automatic feature extraction from the raw data and learn varying representations of patterns using a hierarchical structure and nested representation learning through different layers with varying levels of abstraction. The early layers of a CNN identify simple features (e.g., edges, textures, or color gradients) while the deeper layers identify more complex structures: spots, lesions, irregularities caused by a disease, etc. This can be an automatic feature learning that can minimize the reliance on handcrafted features, in addition to generalizing to variations across different leaf images within and across species, environmental conditions,

and stages of disease severity. Moreover, CNN-based architectures can be further enhanced using techniques such as transfer learning, data augmentation, and ensemble methods to improve detection accuracy, especially when datasets are limited or imbalanced. The ability of CNNs to learn end-to-end mappings from input images to disease categories not only simplifies the workflow but also enables faster, scalable, and more precise plant disease diagnosis. Consequently, CNNs and other deep learning models have become the foundation for modern AI-driven agricultural applications, offering robust, high-performance solutions that overcome the inherent limitations of traditional ML approaches. Since they have been formulated in such a way, conventional CNN architectures (VGG16, VGG19, ResNet50, InceptionResNetV2, Xception, EfficientNetV2-L) have been shown to produce promising results and accuracy for classifying leaves of diseased plants.

As discussed from entries 4 to 17 when reviewing the literature, the use of CNN architectures improves measures of accuracy, with the highest accuracy being over 99% from the CNN-based system in entry 6. Transfer learning, as discussed in the next paragraph, was a technique that assisted in improving accuracy with the various models. The emergence of hybrid solutions that combine ML and DL models has proven effective, leveraging the combined feature extraction capabilities of CNNs and the classification performance of ML models, specifically SVM and RF. In items 18 and 19, hybrid solutions achieved accuracies greater than 98.7%. The architectures take advantage of attention mechanisms, such as CBAM and ensemble classifiers, to improve definitiveness and prediction ability. A hybrid solution is often a good compromise for real-world scenarios, especially when subject matter expertise and/or resources are absent. A summary of all methods in our comparison demonstrates that the ML methods have distinct advantages in simplicity and speed, while the DL architectures have scalability advantages. The DL models have overall benefits with an improvement in accuracy and adaptability over ML models, but at a higher resource cost. Hybrid models benefited from both methods, establishing mutually advantageous conditions of both approaches. However, there were still deficiencies across all solutions regarding the conditions of datasets and consistency and standardization for aggregation, temporal efficiency for accuracy in a 'real-world' setting, and interpretability of models. Overall, this comparative assessment illustrates the rapid advances of technology for plant disease identification systems, and emphasizes that there are still advances that must be made toward industry, specifically, lighter weight, accuracy, and interpretability of AI models for smart agriculture.

3. Review of Methods

Recently, machine learning and deep learning have emerged as popular methodologies in identifying and classifying plant leaf diseases. In the paper, P. Shruthi, R. Rathipriya and J. Akila [1] introduced a hybrid approach that involves SVM and CNN to detect plant leaf disease. The study aimed to compare the pros and cons of SVM and CNN to classify leaf disease. The authors noted that SVM can classify leaf disease based on handcrafted features, although it is limited by its capacity to handle complex high-dimensional image tasks. CNNs could potentially perform better because they can learn features from the images, and because CNNs learn features automatically, they are structured hierarchically as a result. The study found that CNN produced good classification accuracy at 94% and significant overall improvement over SVM, and so the authors illustrated the promise of deep learning methods to automate detection of disease with a higher degree of accuracy and reliability.

In another study and expansive review, Kamilaris and Prenafeta-Boldú explored deep learning methods in 2018, where they examined actual CNN models, such as AlexNet, GoogleNet, and ResNet, and their potential to detect plant disease. The intention of this research was to evaluate the ability of these models to accurately classify plant diseases based on images of leaves. The results indicated that more complex networks, particularly GoogleNet and ResNet50, excelled, achieving classification accuracy of over 95% on the datasets that were tested. This architecture employs a greater number of layers and more sophisticated feature extraction techniques to recognize subtle disease patterns and symptoms that cannot be detected with typical machine learning methods [2]. In general, the studies reviewed showed that attributes of deep learning outperform traditional approaches to machine learning for plant disease detection. An omnipresent theme throughout the studies was the reliance on the more conventional machine learning methods (Support Vector Machines (SVM); Random Forests (RF)); these methods depend on specially extracted features, and are not designed to support gainful, high-dimensional input datasets. These methods require overly careful pre-processing and feature engineering to capture relevant aspects, often being a laborious process subject to human error. Conversely, Convolutional Neural Networks (CNNs), and other deep learning architectures, take all of this burden away at least to a degree by automating the feature extraction process

through learning hierarchical features directly from raw images. This type of end-to-end learning improves the capability and comes with a scalable method for large and heterogeneous agricultural data sets; these advantages strongly favour application and use of this type of model in precision agriculture.

The researchers could identify the subtle changes in the disease process during the early stages of the process by using CNNs and that would otherwise be unnoticed by human eyes or and/or conventional image processing techniques and that subtlety would allow taking important timely action that will help prevent crop loss and sustainability in agricultural activities. Among the popular deep learning applications, it is possible to mention CNN model, which Ramcharan et al. [3] created in 2017 and aimed at real-time detection of plant diseases based on images taken with mobile phones. This model was reported to be very successful, having a disease classification accuracy of 98% of plant leaf diseases, which is why it is a good model in the real world field environment where timely disease diagnosis is particularly significant. The ability of the model to utilize real-time on mobile platforms is a significant step towards democratization of technological resources in advanced diagnostics in the agricultural sector, and particularly to the farmers who have limited economic resources as shown in **Figure 1**. S. Arivazhagan et al. [4] in 2016 proposed a method for detecting plant diseases using color co-occurrence matrix characteristic analysis together with SVM classification approaches.

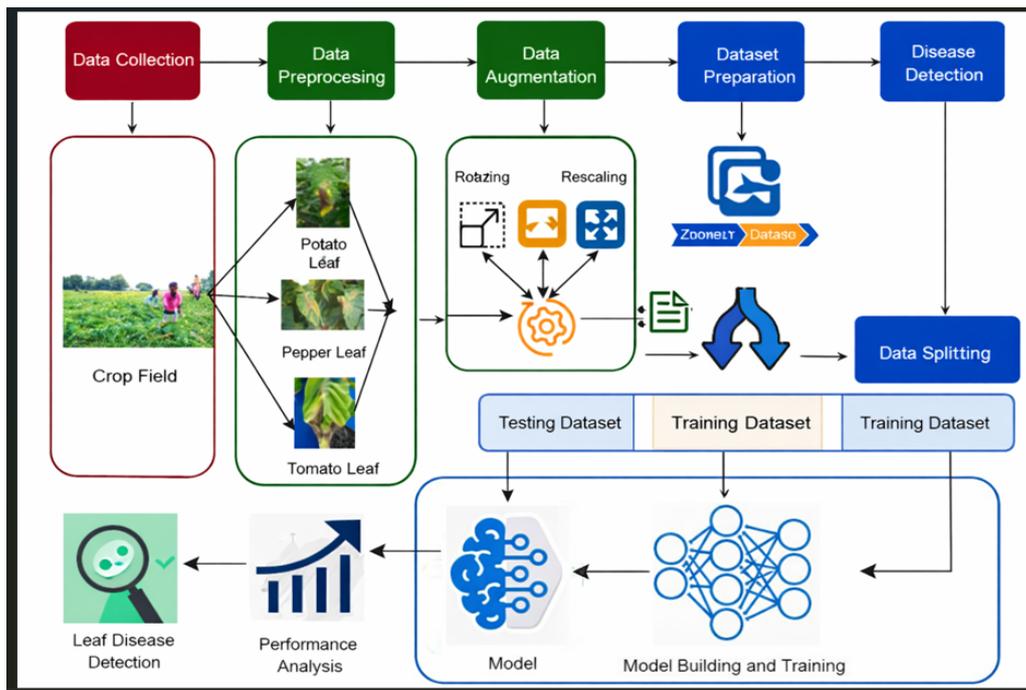


Figure 1. Workflow Diagram of Leaf Disease Detection.

Although obtaining a respectable accuracy of up to 91%, this approach was limited by its reliance on hand-crafted features, and was also sensitive to changes in lighting, leaf orientation, and background conditions. Nonetheless, these studies formed the basis for the eventual use of automated disease detection systems using AI and machine learning, as well as demonstrated the potential to enhance crop management efficiency. Instead, the comparative assessment entertained a hypothesis about the outlined trend that deep learning, and particularly a CNN-based approach, consistently outperformed traditional machine learning and image-processing based methodologies. CNNs can easily capture high-dimensional unexpected serious spatial and/or color-based features that were not detectable by human observation or were difficult to encode in handcrafted feature variables. CNNs are also generalizable and may accommodate model testing at ungainly scales related to crop type, disease or other environmental conditions for quick deployment and sufficiently differing subjective reach. In addition, CNNs scale well enough to increase an image dataset which may further support robust models and certainly decrease the likelihood of misclassifications leading to economic damage to crops. Hybrid methods that combine deep learning methods

with conventional machine learning or domain methods further improved farm predictive parameters by having faster computational times with stated predictions. The transition of paradigm from classical image-processing and machine learning approaches to deep learning-based architectures represents a great leap in the detection of diseases in plants. The utilization of convolutional neural networks (CNNs) and deep neural networks propels real-time accuracies and scalability that can help farmers and agricultural actors to monitor the health of their crops efficiently. Key benefits to using deep learning are automated feature extraction, handling of large datasets, rapid, accurate classification of disease, and the contribution of deep learning to agricultural profitability, efficiency, and overall productivity when traditional methods fall short. Early loss due to diseases that went undetected contributes greatly to the sustainability of farming systems and increased management capability in smart farming and agricultural artificial intelligence technology. Incorporating deep learning, the overall operational efficiency increases, while the food security of the entire globe is positively impacted by limiting losses due to a modernized farming context. When they evaluated the deep neural networks trained to identify plant infections on publicly available datasets, S. Sladojevic et al. [5] in 2016 relied on the concept of deep learning to detect plant disease. The experiment generated a classification accuracy of 96.3%, which demonstrates that deep learning architectures can be useful in learning different patterns of infections and a wide range of different plant species. Prior to the use of deep learning, traditional image-processing approaches were the methodology of choice for plant disease detection. In 2019, Ye et al. [6] presented an image segmentation and SVM-based method that operates on the recognition of diseases using texture features and achieved approximately 92% accuracy. A feature-based classification method of K-Nearest Neighbors (KNN) and Naive Bayes was reported by M. Zafer, M. R. Senouci and M. Aissani in 2019 with the KNN achieving 90.2% and the Naive Bayes 88.5% accuracy [7]. D. Mishra, A. Pandey, Deepanshu and V. Sharma in 2023 implemented CNN combined with Transfer Learning on the PlantVillage dataset, reporting a remarkable accuracy of 98.76% [8]. In 2016, Mohanty, S. P., Hughes, D. P., and Salathé, M conducted a comparative analysis using deep learning models like ResNet50, VGG16, and AlexNet on real-time plant images, where ResNet50 attained an impressive accuracy of 98.9% [9]. S. Singh, Y. Roy, A. Bhan and S. Sah, in 2023 proposed a hybrid architecture combining CNN for feature extraction and SVM for classification, improving the accuracy to 97.4% [10]. In 2025, S. F. Rabbi, M. R. Hasan, and M. Hasan introduced an ensemble deep learning model using multiple CNN classifiers, which achieved the highest accuracy of 99.12% for plant disease detection [11]. A. Khalifa, K. Patel, S. Parmar, and D. Patel in 2025 leveraged Transfer Learning with VGG16 and deep CNN for plant disease detection and recorded an accuracy of 98.8% [12].

In 2023, N. Vanitha and others pointed out tomato leaf disease detection with CNN and their own implementation called LeafNet, achieving an accuracy of 97.5% [13]. In 2024, A. Adiga, N. K. Gagandeep, A. A. Prabhu, H. Pai and R. A. Kumar completed a comparative analysis of three convolutional neural networks, namely VGG19, ResNet18, and DenseNet121, for plant disease classification, demonstrating that DenseNet121 was the best-performing model, producing 99.2% accuracy [14]. Pal C, Karmakar S, Mukherjee I, Chakrabarti PP in 2025 suggested a lightweight CNN model, MobileNet, and another lightweight model, SqueezeNet, both designed for on-device plant disease detection with an accuracy of 95% [15]. Jamal M. Al-Tuwaijari and colleagues in 2020 performed a comparative analysis of the use of CNN techniques and SVM techniques for plant disease identification and found that CNN techniques performed better, producing a result of 95% or higher accuracy compared to SVM [16]. In 2024, Chetan R. Patil and Ranaja Badre proposed a combined approach using CNN for feature extraction and machine learning classifiers such as KNN, SVM, Random Forest (RF), MLP, and Naïve Bayes for classification, where KNN achieved 99.07% and CNN 98.97% [17]. Kumar S. Tanti et al. in 2024, offered a comprehensive review using advanced hybrid deep learning and machine learning models including InceptionResNetV2, Xception, and EfficientNetV2-L, all achieving more than 98% accuracy [18]. Prabhjot Kaur et al. in 2024 proposed a novel hybrid CNN model integrated with SVM and Convolutional Block Attention Module (CBAM), labeled H-CSM, which recorded an accuracy of 98.72% across 36 types of plant diseases [19]. Finally, in 2023, Ravikumar H.C. et al. combined CNN with region-based CNN models like Fast RCNN, Faster RCNN, and Mask RCNN for plant disease detection, initially achieving an accuracy of 75% with room for improvement [20]. In 2021, P. Chaitanya Reddy et al. introduced a machine learning machine disease detection system in leaf of plants [21].

As mentioned in **Table 1**, the authors concentrated in the identification of diseases through the use of image-based detection with different features of images of leaves. Support vector machine (SVM), k-nearest neighbors (KNN) and decision trees were used to make classifications of healthy and diseased samples. The paper focuses

on the preprocessing procedures such as image segmentation, color equalization and feature extraction to enhance the accuracy. The suggested approach was tested on a set of several species of plants, and its classification accuracy was considerable. The study showed that with the application of the appropriate feature engineering, traditional machine learning algorithms could be used to detect leaf diseases. It also indicated the obstacles in the form of mismatch of visually close disease symptoms, changes in the lighting conditions at the time of image capture, and extensive labelled datasets. All in all, this paper is a conceptualization paper that demonstrates that classical machine learning may be effectively utilized to detect plant diseases and which forms a baseline to be used in future deep learning models. The methodology can be used in real-time monitoring systems, which can provide possible applications in smart agriculture to help increase crop yield and decrease the number of manual checks. V. Balafas et al. (2023) utilize a convolutional neural networks (CNN) approach to automatically extract hierarchical features from images of plant leaves [22].

Table 1. Summary of Literature Review.

S. No	Title	Authors	Year	Methods Used	Insights and Contributions	Results
1	A New Approach for Detection of Plant Leaf Disease Using Machine Learning Algorithms	Shruthi et al. [1]	2020	SVM, CNN	Effective classification using SVM and CNN; CNN showed better performance.	CNN achieved 94% accuracy, outperforming SVM.
2	Deep Learning in Agriculture: A Survey.	Kamilaris and Prenafeta-Boldú [2]	2018	CNN, AlexNet, GoogleNet, ResNet	Compared DL models for disease detection.	GoogleNet and ResNet50 achieved accuracy > 95%.
3	Deep Learning for Image-Based Cassava Disease Detection	Ramcharan et al. [3]	2017	CNN	Real-time disease classification using mobile images.	Accuracy up to 98% achieved.
4	Detection of Unhealthy Region of Plant Leaves and Classification of Plant Leaf Diseases Using Texture Features	Arivazhagan et al. [4]	2013	Color Co-occurrence, SVM	Texture and color feature-based classification.	Accuracy up to 91% for multiple diseases.
5	Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification	Sladojevic et al. [5]	2016	CNN	Deep CNN used on publicly available dataset.	Achieved 96.3% classification accuracy.
6	Landslide Detection of Hyperspectral Remote Sensing Data Based on Deep Learning with Constrains	Ye et al. [6]	2019	Image Segmentation, SVM	Used segmentation and texture features.	Achieved accuracy around 92%.
7	On Coverage of 3D Terrains by Wireless Sensor Networks	Zafer et al. [7]	2019	KNN, Naïve Bayes	Feature-based ML classification.	KNN reached 90.2%, Naïve Bayes 88.5%.
8	Plant Disease Detection System Using Deep Learning Techniques	Mishra et al. [8]	2023	CNN, Transfer Learning	CNN and TL applied on PlantVillage.	Achieved accuracy of 98.76%.
9	Using Deep Learning for Image-Based Plant Disease Detection	Mohanty et al. [9]	2016	ResNet50, VGG16, AlexNet	Compared models on real-time images.	ResNet50 achieved 98.9% accuracy.
10	Computer Based Detection and Classification of Leaf Diseases Using Hybrid Features	Singh et al. [10]	2023	CNN, SVM	Combined CNN feature extraction with SVM.	Accuracy improved to 97.4%.
11	Advanced Plant Disease Identification and Recognition: Deep Learning based Detection and Classification of Plant Leaf Diseases using Custom CNN Architectures	Rabbi et al. [11]	2025	CNN, Ensemble Learning	Ensemble of CNN classifiers.	Achieved accuracy of 99.12%.
12	Plant Disease Detection Using a Deep Learning Approach: A Custom CNN	Khalifa et al. [12]	2025	VGG16, Transfer Learning	TL with VGG16 for reduced training.	Achieved 98.8% accuracy.
13	Detection of Ripe and Raw Tomatoes Using Internet of Things	Vanitha et al. [13]	2023	CNN, LeafNet	Focused on tomato disease detection.	Achieved accuracy of 97.5%.

Table 1. Cont.

S. No	Title	Authors	Year	Methods Used	Insights and Contributions	Results
14	Comparative Analysis of Deep Learning Models for Plant Disease Classification	Adiga et al. [14]	2024	VGG19, ResNet18, DenseNet 121	Compared model performances.	DenseNet121 achieved 99.2% accuracy.
15	A Lightweight and Explainable CNN Model for Empowering Plant Disease Diagnosis	Pal et al. [15]	2025	MobileNet, SqueezeNet	Edge-friendly lightweight models.	Achieved 95% accuracy.
16	Deep Learning Techniques toward Advancement of Plant Leaf Diseases Detection	Al-Tuwaijari et al. [16]	2020	CNN, SVM	Comparison of CNN and SVM.	CNN outperformed SVM with >95% accuracy.
17	Advancements in Plant Leaf Disease Identification Using Deep Learning and Machine Learning Perspective	Patil and Badre [17]	2024	CNN + ML (KNN, SVM, RF, MLP, NB)	CNN for features, ML for classification.	KNN achieved 99.07%, CNN 98.97% accuracy.
18	A Optimum Review for Plant Leaf Disease Classification Using Machine Learning	Tanti et al. [18]	2024	Inception ResNetV2, Xception, EfficientNetV2-L + ML	Review of hybrid DL and ML approaches.	Models achieved >98% accuracy.
19	A novel hybrid CNN methodology for automated leaf disease detection and classification	Kaur et al. [19]	2024	CNN, SVM, CBAM	Hybrid model H-CSM proposed.	Achieved 98.72% accuracy across 36 diseases.
20	Detection of Diseased Plant Leaf Using Deep Learning	Ravikumar et al. [20]	2023	CNN, Fast RCNN, Faster RCNN, Mask RCNN	Integrated DL and image processing.	Initial accuracy 75%, with Scope for improvement.

Compared to traditional machine learning methods, where one often needs to put efforts into manually devising and extracting features, deep learning models can simply learn discriminative, predictive representations into the model from unprocessed images. The authors propose a framework with the goal of promoting accuracy by applying data augmentation to account for challenges of lighting, leaf orientation, and disease severity levels. The authors conduct experiments using publicly available leaf image datasets which resulted in high model classification accuracy rates across the different disease categories. Additionally, the authors emphasize the role of preprocessing steps, including resizing, normalization, and noise reduction, as a systematic way to improve model performance. Furthermore, the authors address cloud/computing solutions or applications in plant disease detection on mobile capitalizing on the capabilities of a deep learning approach. The overall findings highlight the advantages of a CNN approach as suitable for processing large datasets and once trained on features, complex patterns, to build a robust and scalable model. In this research, the authors also make a contribution to precision agriculture by proposing an economically efficient and automated approach for early detection of plant disease, ultimately leading to reduced economic loss and supporting state-of-the-art sustainable research practices. In 2023, Belmir, M., Difallah, W., and Ghazli, A. presented a deep learning approach for predicting and classifying plant leaf disease [23]. Their study leverages CNN architectures that can detect complex patterns associated with various leaf diseases, including spots, discoloration, and texture changes. This research will profile multiple network architectures, many of which are commonly used, and tune hyperparameters to achieve the best prediction accuracy.

The authors emphasize the role of preprocessing steps including background removal, leaf segmentation, and color normalization in facilitating increased feature learning. Additionally, data augmentation is used in the form of rotation, flipping, and scalars to, not only prevent effects of overfitting, but also to expose to generalization across newly unseen samples. Results are demonstrated to provide improved accuracy, robustness, and scalability compared to traditional machine learning classifiers. Additionally, deployment scenarios are discussed related to implementing models on edge devices for in-field monitoring. Of note, challenges are also raised related to extreme variability in leaf appearance, however, these are due to changing environmental variables, and age of infection. Overall, this research shows the potential for deploying, fast, reliable, and automated plant disease classification as a result of deep learning; in contrast to other methods this presents an opportunity to improve precision agriculture through media of computational intelligence, ultimately leading towards IoT-based smart farming. In 2023,

Prabavathy et al. proposed a machine-learning-based approach to disease detection in plant leaves [24]. The authors partition their focus by extracting relevant features from leaf images; features like color, texture, and shape are used as input features to classifiers such as SVM and KNN. This work also emphasized preprocessing methods like noise reduction, removal of background pixels, segmentation, and enhancement, in order to improve the quality of feature extraction. Their experimental validation indicated the validity of the approach toward distinguishing among multiple disease categories, as well as healthy leaves. The authors acknowledge some challenges to feature extraction, related to varying illumination, leaf orientation, or similarity to certain diseases. The authors underline the importance of generating thorough datasets used to train models and expose the approach's use in automated agricultural field monitoring systems. Through use of their method for early disease detection, the authors approach growing crop losses caused by plant disease and ground sustainable practices on productivity.

The findings of this research indicate that traditional machine learning is still a viable method for detecting plant disease within limitations placed by computational resources, and represents a valuable contribution to the field of precision agriculture. In 2023, Binnar and Sharma explored plant leaf disease identification through the use of deep learning techniques [25]. The researchers utilize convolutional neural network (CNN) models for automatic feature extraction and leaf disease classification. Many network architectures are executed and hyperparameter optimization is facilitated in order to bolster the accuracy and robustness of the proposed method. Content preprocessing methods, including but not limited to resizing, standardization, and background elimination are employed to bolster the quality of the input images. Data augmentation techniques like rotating, flipping, and scaling are employed to mitigate overfitting and improve generalizability in future predictions. The proposed method is conducted across multiple plant datasets that produce very high accuracy in even the most difficult tasks such as to separate healthy leaves from diseased leaves. The authors note the advantages of using deep-learning-based deduction relative to traditional machine learning, and expressive imagery in the handling of a comprehensive dataset that includes complexity of imagery. The authors also note potential for execution, such as real-time monitoring systems, smart agriculture, etc. The authors cite at least three notable issues, which include the changing environmental conditions, occlusion of leaves while taking images and the similarity of the leaf samples across cyanotype classes.

All in all, the recommendation from this study indicates the supporting potential of deep learning-based methodologies to evolve automated plant disease prediction in support of sustainable agriculture and crop management. The 2018 article by K. P. Ferentinos [26] provides a detailed literature review on the uses of deep learning technologies in agriculture. The authors explore the application of architectures including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and more, across tasks like crop classification, yield forecasting, and disease detection. The authors describe deep learning advantages including its ability to extract features automatically from data, work with big data, and achieve improved levels of prediction accuracy compared to traditional machine learning methods. Furthermore, weaknesses of deep learning are located amongst challenges including the lack of datasets, variations in environmental conditions, and access to computing resources to train and deploy models. The article also provides aspects of practical implementation, including systems for mobile and drone-based imaging that are used to collect plant and soil images for analysis. By categorizing existing works based on data type, task, and method, this article provides insight into trends and gaps in the agricultural deep learning literature. Overall, this article provides a strong foundation for directions of future research in AI-based precision agriculture, which considers different ways deep learning can be implemented to improve crop monitoring, lessen disease impact, and promote sustainable agricultural practices. Wani, J.A. et al. 2022 [27] summarize the computer-based approaches in automated agricultural disease detection, focusing on both machine learning (ML) and deep learning (DL). They cover methods including support vector machines (SVMs), decision trees, convolutional neural networks (CNNs), and hybrid models, all of which can detect crop disease using image datasets. They also discuss the pros and cons of each approach, including the feature engineering associated with ML approaches and the computational demands associated with DL approaches. The paper applies these approaches to disease education, yield forecasting, and stress detection in crops, framing challenges in each, including lighting variability, occlusion of crops, inter-class similarity, and data scarcity. The paper points towards marrying computational methods with IoT-enabled devices to automate the use of machine learning in the field, suggesting opportunities for bringing intelligent agricultural systems to food systems.

As part of synthesizing prior work, the review also highlights research gaps in current literature, such as the

need for models that will train and scale to effectively implement deployment and adaptive learning. Ultimately, the paper contributes to an understanding of the state-of-the-art in computational agriculture, and provides guidance to researchers in the pursuit of the development of disease detection techniques to support sustainable agriculture, which will be robust, accurate, and efficient. Vishnoi, V.K. et al., 2021 [28] examines plant disease detection through a combination of image processing and computational intelligence methodologies. The authors describe preprocessing techniques, including noise removal, image segmentation and feature extraction, because these stages are essential for establishing accurate disease diagnoses. The authors implement methods such as K-nearest neighbor, support vector machine and convolutional neural networks to classify diseased areas in leaf tissues. According to the authors, the value of an automated methodology to alleviate a laborious manual testing method and provide a quicker detection method and speed was noted. Data validated outcomes indicating that the computational intelligence processes can be utilized to produce accurate results across a wide range of plant species. To point out, the authors also address the uncertainty of crops due to the complexity of measurements related to environmental variability of leaf shape, color and weather patterns that could affect the performance of a model. The authors advocate the collaboration of this system although there will be challenges that will need to be sustained to implement and integrate it into precision agriculture workflows to manage diagnosis and treatment. To conclude, the work summarizes a framework that can lead to early detection of plant disease, limit loss and improve overall productivity and quality within crop plants.

The authors bridge the gap between classical methods of image processing to modern methodologies to provide ways in which computational intelligence methods have been utilized for agricultural disease diagnostics and management. Sarvamangala, D.R. and Kulkarni, R.V., 2022 [29] present survey work on using convolutional neural networks (CNNs) for medical image analysis. Although the focus is primarily related to diagnosis for healthcare, the concepts of systems could be applied as a transfer of methodologies for detection of plant disease. The authors provide a survey work with a description of architectures of CNNs, training methods of CNNs, and the opportunities of feature extraction methods to support accurate classification. The strengths are automatic features of the hierarchical feature learning and resistance to changes in image quality. Issues like the lack of data, overfitting, and computational expenses are also mentioned. The study offers the information on the best practices in model design, optimization and deployment into the real-time systems by reviewing the recent CNN-based solutions. Plant leaf disease can also be detected using these methodologies with similar image-based classification issues. The article highlights the applicability of deep learning to the analysis of images and preconditions cross-domain usage in the field of agriculture. Wang, Q. et al., 2019 [30] came up with a deep learning model for identifying the type of tomato disease and localizing the objects of interest with the combination of convolutional neural networks and object detection methods. The paper will focus on the accurate localization of diseased areas in leaves and the classification of the disease type, which will provide diagnostic and a course of action information. The approach involves pre-processing measures such as resizing, normalization and augmentation to enhance the robustness of the model. The suggested model was very precise and effective in the detection of various tomato diseases using a wide range of data. Such issues as intricate backgrounds, different leaf positions, and signs of the disease at the initial stage are also discussed by the authors. The given research demonstrates the feasibility of practical usage of the deep learning in precision agriculture, providing tools to monitor crops in real-time, intervene early, and avoid yield damage. Through classification and object detection, the research has given a holistic solution to automated management of plant disease to help ensure sustainable agricultural practices.

Al-Fatlawy et al. [31] (2024) explored the machine learning and deep learning models to detect and classify tomato leaf disease with higher precision to detect plant diseases based on leaf images. A survey of plant leaf disease detection systems was provided by Sharma and Bansal [32] (2024) that provides information on a range of machine learning and deep learning methods employed to classify the disease. Awari et al. [33] (2024) suggested a plant disease detection and classification model based on image processing and machine learning algorithms to assist in the detection of diseases at an early stage. Uma Srihitha et al. [34] (2024) have come up with a leaf disease detection model coupled with a remedies recommendation system to help farmers detect the disease and propose the remedy. A similar study was proposed by Mishra et al. [35] (2023), which came up with a hybrid method that incorporated machine learning and deep learning methods to classify plant leaves and detect diseases. The FieldPlant dataset was presented by Moupojou et al. [36] (2023) and comprises images of field plants to promote deep learning to identify and classify plant diseases. Khadeer et al. [37] (2025) studied the problem of plant leaf disease detection using

deep learning methods and tried to enhance accuracy in the recognition of images with the help of deep learning models. A systematic review and analysis of deep learning techniques in plant disease detection and plant disease classification were carried out by Das et al. [38] (2024). Singamsetty et al. [39] (2021) introduced a deep learning based system of detecting and classifying maize leaf diseases by utilizing agricultural image data. Vishwakama et al. [40] (2024) designed an automated system for detecting the presence of plant leaf disease using machine learning to improve agricultural monitoring. Trivedi et al. [41] (2020) suggested a machine learning-based solution to the task of detecting plant leaf disease by relying on the feature extraction and classification algorithms. The convolutional neural networks were used to detect tomato leaf diseases and enhance classification accuracy [42]. Sebastian et al. [43] (2023) came up with a machine learning and deep learning grounded algorithm to detect apple leaf disease through image classification. Anand [44] (2025) suggested a developed AI-based system to detect plant leaf disease to enhance the accuracy and decision support in agriculture.

Moreover, the study presents the prospects of implementing such models in smart farming in real-time monitoring systems. Some of the main challenges are environmental differences, leaf occlusion and inter-class similarity which may influence performance. In general, this article shows that deep learning-based solutions can be used to advance the state of automated plant disease detection to benefit sustainable farming and crop management. discusses how these solutions could be applied to real-time monitoring devices in smart agriculture. Environmental differences, leaf obscuration, and inter-class resemblance are the main obstacles and they can impact performance. On the whole, this study proves that automated plant disease detection approaches based on deep learning have a high potential to improve sustainable crop management and agriculture practices.

Table 2 captures significant contributions from various research efforts on detecting plant diseases with machine learning and deep learning. It highlights the authors, the year of publication, the methods employed (linked to the corresponding serial number from the original table for easy reference), the key evaluation parameter (mostly classification accuracy), and the achieved value. The table illustrates the transition from traditional methodologies like SVM and KNN to state-of-the-art deep learning architectures, including variants of CNN, Transfer Learning, and hybrid ensembles of models. The table shows that CNN-based and hybrid models mostly outperform classical machine learning algorithms and some of these models are achieving accuracies over 99%, making these models very effective for real-world applications in agriculture. The table further indicates an apparent increase in efforts to provide lightweight and mobile-friendly models, which can be used for real-time deployment, in recent years.

Table 2. Summary table of significant contributions.

Author	Year	Method	Parameter	Value
Shruthi et al. [1]	2020	SVM, CNN	Accuracy (CNN)	94%
Kamilaris and Prenafeta-Boldú [2]	2018	CNN, AlexNet, GoogleNet, ResNet	Accuracy	>95%
Ramcharan et al. [3]	2017	CNN	Accuracy	98%
Arivazhagan et al. [4]	2013	Color Co-occurrence, SVM	Accuracy	91%
Sladojevic et al. [5]	2016	CNN	Accuracy	96.3%
Ye et al. [6]	2019	Image Segmentation, SVM	Accuracy	~92%
Zafer et al. [7]	2019	KNN, Naive Bayes	Accuracy (KNN)	90.2%
Mishra et al. [8]	2023	CNN, Transfer Learning	Accuracy	98.76%
Mohanty et al. [9]	2016	ResNet50, VGG16, AlexNet	Accuracy (ResNet50)	98.9%
Singh et al. [10]	2023	Hybrid CNN + SVM	Accuracy	97.4%
Rabbi et al. [11]	2025	CNN, Ensemble Learning	Accuracy	99.12%
Khalifa et al. [12]	2025	VGG16, Transfer Learning	Accuracy	98.8%
Vanitha et al. [13]	2023	CNN, LeafNet	Accuracy	97.5%
Adiga et al. [14]	2024	VGG19, ResNet18, DenseNet121	Accuracy (DenseNet)	99.2%
Pal et al. [15]	2025	MobileNet, SqueezeNet	Accuracy	95%
Al-Tuwaijari et al. [16]	2020	CNN, SVM	Accuracy (CNN)	>95%
Patil and Badre [17]	2024	CNN + ML classifiers	Accuracy (KNN)	99.07%
Tanti et al. [18]	2024	Hybrid DL+ML	Accuracy	>98%
Kaur et al. [19]	2024	CNN, SVM, CBAM	Accuracy	98.72%
Ravikumar et al. [20]	2023	CNN, Fast RCNN, Mask CNN	Accuracy	75%

4. Conclusions

The review aims to focus on the increased need for machine learning and deep learning techniques in the detection and classification of plant leaf diseases. Most machine learning algorithms such as SVM, KNN, and Random Forest use features to achieve a moderate level of accuracy in the detection of plant diseases. However, these models are not suitable for complex and large-scale image datasets. On the other hand, deep learning models such as

Convolutional Neural Networks (CNN) achieve high accuracy in the detection of plant diseases by extracting features from the images. In fact, the models achieve an accuracy level of more than 95%. In addition, the latest research suggests that the use of hybrid models, transfer learning, and the development of lightweight models improve the detection of plant diseases, allowing real-time monitoring using mobile devices and IoT-based systems.

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Conflicts of Interest

The authors declare no conflict of interest.

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