



Emerging Trends in Deep Learning based Plant Disease Detection: A Review

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ABSTRACT

Deep learning, an advanced branch of artificial intelligence, has gained significant attention due to its successful applications in fields such as image analysis, speech recognition and natural language processing. More recently, deep learning techniques have been increasingly adopted in agricultural research, where they play a crucial role in plant disease identification, pest detection and the analysis of their spatial and temporal patterns. Unlike traditional approaches that rely heavily on handcrafted features and expert knowledge, deep learning models automatically learn discriminative features from large-scale data, enabling more objective, robust and accurate analysis. This capability not only reduces human intervention but also enhances detection accuracy and overall research efficiency, thereby accelerating technological innovation in smart agriculture. This review focuses on recent progress in the use of deep learning methods for detecting diseases and infections in crops, leaves and entire plants. It presents an overview of current methodologies, popular architectures, available datasets and application trends, while also highlighting the strengths of deep learning based approaches compared to conventional techniques. In addition, the review discusses existing challenges, including data scarcity, model generalization, computational complexity and real-world deployment issues. The insights provided aims to support researchers and practitioners in the domain of plant disease and pest detection, while identifying key research gaps that require further exploration and effective solutions.

Key words: Convolutional neural network, Deep learning, Machine learning, Plant disease detection.

Indian economic development is closely linked to agriculture, a sector that faces numerous critical challenges. Rapid population growth, unpredictable weather patterns and limited resources make it increasingly difficult to meet rising food demands (Simane *et al.*, 2025). Compounding these issues, the growing frequency and severity of crop diseases pose a serious threat to agricultural productivity and food security (Savary *et al.*, 2019; Gai and Wang, 2024). Continuous monitoring is therefore essential to prevent yield losses caused by such diseases (Delfani *et al.*, 2024).

Precision agriculture has emerged as a promising approach to improving agricultural sustainability. Within this domain, machine learning (ML) offers significant potential by enabling systems to learn and improve autonomously without explicit programming (Balafas *et al.*, 2023). Numerous studies have utilized ML techniques to identify and classify plant diseases using images of plants or leaves (Mohanty *et al.*, 2016; Ferentinos, 2018; Too *et al.*, 2019) distinguishing between healthy and infected samples or performing multiclass classification across various disease types (Sladojevic *et al.*, 2016; Brahimi *et al.*, 2017). Deep learning (DL) methods, in particular, have been widely applied for these tasks (Balafas *et al.*, 2023).

However, relatively fewer studies have focused on simultaneously determining the type of infection and pinpointing the specific regions of the plant affected (Li *et al.*, 2021; Abade *et al.*, 2023; Chougui *et al.*, 2024). This capability is especially important when dealing with multiple diseases or when precise localization is required

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in large crop images (Liu and Wang, 2021; Balafas *et al.*, 2023). Object detection is inherently more complex than classification and DL models often face challenges in uncontrolled environments with noisy backgrounds (Kamilaris and Prenafeta-Boldú, 2018; Vishnoi *et al.*, 2021; Alhwaiti *et al.*, 2025).

This paper reviews the application of DL techniques for plant disease classification and detection, evaluating their effectiveness using metrics such as accuracy, precision, recall and F1-score. This paper also presents a comparative analysis of various models and their performance in Table 2 of identification and classification of plant diseases section. It also gives overview of the various corpuses used in this study of plant, leaf and crop disease classification and detection.

Deep learning: Historical and current trends

Deep learning (DL), a subset ML, has emerged through decades of continuous advancement. ML originated in 1943 and has since progressed through three major developmental stages (Li *et al.*, 2021). The first generation of neural networks (1943-1969) was limited to handling linear classification tasks. The second generation (1986-1998) marked by the introduction of the back propagation (BP) algorithm (Li *et al.*, 2021) enabled the training of multi-layer perceptrons (MLPs) (Li *et al.*, 2021) allowing neural networks to address nonlinear learning problems and reigniting interest in the field.

The third generation (2006 onward) ushered in the era of deep learning, which rapidly surpassed earlier models in capability and performance. Since then, DL architectures have evolved significantly, giving rise to advanced models specialized for tasks such as image recognition, segmentation and classification. These advancements have been widely adapted for detecting diseases in plants, crops and leaves.

The literature review carried out at the Research Center of Sreenidhi Institute of Science and Technology, Hyderabad, during the year 2025.

Categories of plant diseases

For effective research in plant disease detection and classification, a solid understanding of plant diseases and their types is essential. Algorithm 1 (Vishnoi *et al.*, 2021) illustrates the major categories of plant diseases, which arise from abnormalities in plant behavior or physiology. These abnormalities may be caused by either biotic or abiotic factors. Biotic diseases result from infectious agents, whereas abiotic diseases develop due to non-infectious environmental or physiological factors. Since abiotic diseases are non-transmissible and generally less harmful, they are often preventable. Therefore, this review primarily focuses on biotic diseases.

Algorithm 1: Categories of plant diseases.

Input: Observed plant symptoms and environmental conditions.

Output: Disease category and probable cause.

- 1: Begin.
- 2: Observe visible symptoms on the plant.
- 3: Determine whether the symptoms are infectious.
- 4: If non-infectious then.
- 5: Classify as abiotic disease.
- 6: Analyze environmental and physiological factors:
- 7: Nutrient imbalance, temperature stress.
- 8: Water stress (drought or water logging).
- 9: Chemical injury and soil conditions.
- 10: Else.
- 11: Classify as biotic disease.
- 12: Identify pathogen type.
- 13: If bacterial then.
- 14: Check for water-soaked lesions and necrosis.
- 15: Else if viral then.
- 16: Note subtle or absent symptoms.

17: Else if fungal then.

18: Identify spots, rots, blights, or rusts.

19: Confirm specific symptoms (e.g., Late Blight)

20: End if.

21: End if.

22: Output disease category and cause.

23: End.

Bacterial plant diseases typically begin as water-soaked spots that appear as small green lesions, which gradually expand and dry into necrotic patches. Viral diseases are the most difficult to diagnose, as their symptoms may be subtle, absent, or easily confused with herbicide injury or nutrient deficiencies. Fungal diseases affect different plant parts and include conditions such as sclerotium wilt, common crown rot, stem rust, eyespot, leaf blight, ergot and kernel bunt or black point in seeds. Late blight, a well-known fungal disease, initially manifests as gray-green spots on the lower leaves, often triggered by alternating wet and dry weather. As the infection advances, these spots darken and white fungal growth becomes visible on the leaf surface (Vishnoi *et al.*, 2021; Liu and Wang, 2021; Kamilaris and Prenafeta-Boldú, 2018; Li *et al.*, 2021; Abade *et al.*, 2023; Balafas *et al.*, 2023; Metagar and Walikar, 2024).

Corpus

Plant disease detection and classification typically involves several key stages, including image acquisition, image pre-processing, segmentation, feature extraction, classification and validation. In the image acquisition stage, researchers collect field images using digital cameras, mobile devices, or other imaging tools to build their own datasets. These images may include healthy plants, diseased plants, or samples exhibiting multiple infections. Other researchers make use of publicly available image repositories such as the plant village dataset, Kaggle datasets and similar sources. Table 1 presents a list of commonly used datasets for plant disease detection and classification.

Methods used in plant disease analysis

Since the 1980s, plant disease detection methods have undergone substantial evolution, progressing from traditional manual practices to advanced intelligent systems driven by artificial intelligence (Liu and Wang, 2021). In the early 1980s, disease identification relied predominantly on visual inspection by farmers and plant pathologists, who diagnosed infections based on observable symptoms such as discoloration, lesions, wilting and abnormal growth patterns (Demilie, 2024). Although this approach was simple and inexpensive, it was subjective, labour-intensive and highly dependent on expert knowledge. To improve diagnostic accuracy, laboratory-based methods such as microscopic examination, pathogen culturing and serological techniques like enzyme-linked immunosorbent assay (ELISA) were widely adopted during this period, particularly for identifying

Table 1: Available corpuses for automated plant, leaf and crop disease analysis (Balafas *et al.*, 2023).

Dataset	Crops	Images	Classes
Plant village	Soybean, apples, blueberries, raspberry, cherries, potato, grapes, strawberry, oranges, peach, bell-pepper, tomato and other crops	54309	38
iBean	Bean	1296	5
Plant leaves	Various crops	4502	22
Plant pathology	Apples	3651	4
Kaggle	Various crops	22031	5
Crop deep	Various crops	31147	31
Custom	Cordia dichotoma	5400	2
Soybean	Soybean	6410	3
New plant disease	Various crops	87000	38
Flower recognition	Various flowers	4200	4

fungal, bacterial and viral pathogens (PubMed, 2023). While these methods provided reliable and pathogen-specific results, they were time-consuming, destructive and unsuitable for real-time field applications.

During the late 1980s and 1990s, non-destructive sensing techniques began to gain attention, with spectroscopy-based approaches playing a key role (Chougui *et al.*, 2024). Visible, near infrared and thermal spectroscopy were used to analyze physiological changes in plants caused by disease stress, often enabling detection before visible symptoms appeared. Hyperspectral imaging further enhanced disease detection by capturing detailed spectral signatures across numerous wavelength bands, although high equipment costs and complex data processing limited its widespread adoption (Liu and Wang, 2021). The 1990s and early 2000s saw the introduction of digital image processing techniques, facilitated by improvements in camera technology and computing power. Researchers employed image pre-processing, segmentation and handcrafted feature extraction methods based on colour, texture and shape, followed by rule-based or statistical classification to identify diseased plant tissues (Demilie, 2024). These methods improved automation but were sensitive to environmental variations and relied heavily on carefully designed features.

Between 2005 and 2015, machine learning algorithms became prominent in plant disease detection research. Techniques such as support vector machines, artificial neural networks, k-nearest neighbours, decision trees and random forests were used to classify diseases using extracted features, offering better accuracy and adaptability than traditional image processing methods (PubMed, 2023). However, their dependence on handcrafted features and limited generalization to complex field conditions remained challenges. A major breakthrough occurred from around 2012 onward with the emergence of deep learning, particularly convolution neural networks, which enabled end-to-end learning directly from raw images (Mohanty *et al.*, 2016). Deep learning architectures such as AlexNet, VGG, ResNet and DenseNet achieved high accuracy in

disease classification and eliminated the need for manual feature engineering (Liu and Wang, 2021). More recently, advanced approaches including object detection, semantic segmentation, vision transformers, mobile-based detection and explainable artificial intelligence have further enhanced robustness, interpretability and real-world applicability, establishing intelligent disease detection as a cornerstone of modern precision agriculture (Chougui *et al.*, 2024).

Identification and classification of plant diseases

This section presents a detailed review of recent research that applies well-established deep learning (DL) architectures for the identification and classification of crop, leaf and plant diseases. With the rapid evolution of computer vision and artificial intelligence technologies, deep learning has become a dominant approach in plant disease diagnosis due to its capability of automatically learn discriminative features from complex image data (Mohanty *et al.*, 2016; Ferentinos, 2018). In contrast to traditional machine learning techniques, which depend heavily on handcrafted features and expert knowledge, DL-based models enable end-to-end learning, leading to improved robustness, scalability and classification accuracy (Li *et al.*, 2021). In addition to studies employing standard DL architectures, this section also examines research efforts that introduce modified or hybrid models to enhance performance, optimize computational efficiency and address real-world deployment challenges (Adnan *et al.*, 2023). Furthermore, the development of software tools and mobile-based systems for automated disease identification highlighting the practical applicability of these approaches in precision agriculture is discussed (Salam *et al.*, 2024).

A hybrid model is proposed (Tabbakh and Barpanda, 2023) that integrates a transfer learning-based convolution backbone with Vision Transformer (ViT) architecture, referred to as TLMViT. In this framework, the ViT component is responsible for extracting high-level and global feature representations from plant images, while a multilayer perceptron (MLP) employed for the final classification task. By leveraging the complementary strengths of transfer

learning and transformer based attention mechanisms, the proposed model effectively captures both local and contextual information associated with disease symptoms. Experimental results demonstrated that the TLMViT model achieved a classification accuracy of 98.81%, indicating its strong potential for accurate plant disease detection.

Farah *et al.* (2023) conducted a study on the detection of infestation related symptoms in soybean crops. In their work, the authors employed a transfer learning strategy using the VGG19 convolution neural network. By fine-tuning a pre-trained VGG19 model on soybean leaf images, the proposed system was able to efficiently classify healthy and infested leaves. The study reported balanced accuracy values ranging from 93.71% to 94.16%, demonstrating that transfer learning can be an effective solution for crop-specific disease and pest detection, particularly when labeled training data are limited.

Shrotriya *et al.* (2024) proposed a hybrid methodology that integrating clustering techniques with neural networks to improve disease classification performance. In addition to classification, the authors introduced a damage assessment mechanism by calculating the proportion of diseased leaf area relative to the total leaf area. This quantitative measure provides valuable information regarding disease severity, which is critical for effective crop management. The experimental results showed that the proposed approach achieved accuracy between 96% and 97%, outperforming several conventional classification methods and demonstrating the benefits of integrating unsupervised and supervised learning techniques.

Metagar and Walikar (2024) focused specifically on machine learning models for plant disease prediction and detection, presenting an in-depth review of algorithms including support vector machines (SVM), random forests, k-nearest neighbors and neural networks. Their study highlighted the role of feature extraction techniques and image preprocessing in improving model performance. While acknowledging the effectiveness of ML models, the authors noted limitations related to model generalization under varying environmental conditions, emphasizing the need for diverse training datasets and hybrid modeling approaches.

Taji *et al.* (2024) introduced advanced ensemble based classification framework. Their approach utilizes two pre trained deep learning models for feature extraction, which are subsequently optimized using metaheuristic algorithms, including the binary dragonfly algorithm (BDA), Ant Colony Optimization Algorithm and Moth Flame Optimization Algorithm (MFO). These optimization techniques are employed to select the most discriminative feature subsets, thereby improving classification performance. The proposed ensemble hybrid framework achieved a remarkable accuracy of 99.8%, highlighting the effectiveness of combining deep feature learning with metaheuristic optimization strategies.

Ayaz *et al.* (2023) addressed the challenge of early disease detection in real field environments. The authors

developed a custom dataset comprising 1,784 images of *Cordia dichotoma* leaves collected under natural conditions. To overcome data scarcity, offline augmentation techniques were applied to expand the dataset to 5,400 images. A modified YOLOv4 deep learning model was trained to detect dome gall symptoms at an early stage. The proposed model achieved an accuracy of 95% and an F1-score of 95.8%, demonstrating the suitability of object detection frameworks for early-stage disease diagnosis.

The use of lightweight deep learning architectures for bean leaf disease classification is investigated in (Elfatimi *et al.*, 2022) and the authors utilized a publicly available dataset of bean leaf images and implemented the MobileNet architecture using TensorFlow. The model was evaluated on 1,296 images and achieved an average training accuracy exceeding 97% and a test accuracy above 92% across two diseased classes and one healthy class. These results indicate that MobileNet-based models are well suited for deployment in resource-constrained environments, such as mobile and edge computing platforms.

DenseNet-121 to analyze the progression of citrus canker disease is employed by (Zainab *et al.*, 2023). The disease was classified into six distinct stages, including water soaking, yellow chlorosis/initiation, chlorosis, blister formation, canker development start and canker infection. By modeling temporal changes in disease development, the study provides valuable insights into disease severity assessment. The DenseNet-121 model achieved an accuracy of 98.97%, demonstrating its effectiveness in capturing subtle variations across different disease stages. Vishnoi *et al.* (2023) trained a CNN model using the plant village dataset to identify apple leaf diseases such as Scab, Black Rot and Cedar Rust. The experimental evaluation revealed that the proposed model achieved a classification accuracy of 98%. Moreover, the model required less storage space and exhibited shorter execution times compared to several deep CNN architectures. These characteristics make it particularly suitable for deployment on handheld devices, where computational and memory resources are limited.

Adnan *et al.* (2023) evaluated the performance of several pre trained CNN models, including Xception, InceptionResNetV2, InceptionV3 and ResNet50, in conjunction with the EfficientNetB3-AADL framework. The study analyzed the impact of hyperparameters such as batch size, dropout rate and number of epochs on performance metrics, including accuracy, precision, recall and F1-score. The EfficientNetB3-AADL model outperformed both traditional feature-based methods and competing DL architectures, achieving an accuracy of 98.71%.

Amin *et al.* (2022) explored an “End-to-End Deep Learning Model for Corn Leaf Disease Classification,” employing EfficientNetB0 and DenseNet121 as feature extractors. The deep features extracted from both networks were concatenated to form a unified representation, enhancing the model's ability to learn complex disease

patterns. Additionally, data augmentation techniques were applied to increase dataset diversity and improve generalization. The study demonstrated that feature fusion significantly improves classification performance in multi-class corn leaf disease detection.

Latif *et al.* (2023) introduced an extracted feature ensemble (EFE) framework for coffee leaf disease classification. The proposed approach combines transfer learning based CNN features with custom-designed features and evaluates different feature combinations using dimensionality reduction techniques. Their ECNN method, which concatenates features from five CNN models, achieved a classification accuracy of 93.45%.

Ahmed *et al.* (2024) investigated the application of real time computer vision techniques for defect detection in supply chain management. The study focused on the Detection Transformer (DETR), a Vision Transformer-based object detection model and compared its performance with YOLO and other AI models. Using a dataset of commodity images, the authors demonstrated that DETR achieved a detection and classification accuracy of 96%, highlighting its effectiveness in real-time inspection scenarios.

Nigar *et al.* (2024) proposed an explainable artificial intelligence (XAI) framework for plant disease classification. The system was capable of identifying 38 distinct plant diseases and achieved an accuracy of 99.69%, along with precision and recall values of 98.27% and 98.26%, respectively. The study emphasizes the importance of explainability in DL-based agricultural systems, enhancing trust and interpretability.

Masood *et al.* (2023) proposed an enhanced Faster R-CNN model with a ResNet-50 backbone and spatial-channel attention mechanisms. The model accurately localized and classified various maize leaf diseases, achieving an average accuracy of 97.89% and a mean Average Precision (mAP) of 0.94.

Salam *et al.* (2024) developed a mobile-based disease detection system. Among MobileNetV3Small, ResNet50 and VGG19, the modified MobileNetV3Small achieved the best performance, with accuracy, precision, recall and F1-score values of 96.4%, 97.0%, 96.4% and 96.4%, respectively.

Hosny *et al.* (2023) proposed a lightweight CNN model combined with local binary pattern (LBP) feature fusion for multi-class plant leaf disease classification. The approach was evaluated on apple leaf, tomato leaf and grape leaf datasets, achieving validation accuracies of 99%, 96.6% and 98.5%, respectively and demonstrating strong generalization performance.

Peyal *et al.* (2023) introduced a lightweight 2D CNN architecture for dual crop disease classification in cotton and tomato plants and classified 14 categories across cotton and tomato crops using a lightweight CNN model. Implemented in an Android application named "*Plant Disease Classifier*", the model achieved an accuracy of 97.36%, outperforming several pre-trained models despite having fewer parameters and implementing the system in an Android application.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have significantly transformed agricultural research, particularly in the domain of plant disease detection and management. The rapid integration of AI-powered techniques for plant disease detection and classification (Mehta *et al.*, 2025a), emphasized the dominance of deep learning approaches, especially convolutional neural networks (CNNs), due to the superior performance in image-based disease recognition. Complementing this work, (Mehta *et al.*, 2025b) further explored the application of AI in disease diagnosis across a wide range of agricultural crops and provided a comparative analysis of traditional machine learning algorithms and advanced deep learning models, demonstrating the improved accuracy and robustness of AI-based systems over conventional diagnostic methods. The authors stressed the importance of integrating AI tools with precision agriculture technologies such as IoT sensors and mobile platforms to enhance early disease detection and reduce crop losses, particularly in developing agricultural economies.

Reddy and Kumari (2026) study underscores the extensive application of deep learning in tackling critical challenges such as dataset diversity and model scalability, which are pivotal to the advancement of agricultural technologies. As a comprehensive knowledge resource, the survey provides researchers and scholars with an in-depth overview of both conventional and state-of-the-art approaches to fruit disease diagnosis.

Table 2 summarizes recent work on plant disease detection and classification using evaluation metrics such as accuracy, precision, recall and F1-score.

Agronomic management

In contrast to AI-driven disease detection, (Krithika *et al.*, 2025) investigated agronomic management practices, particularly integrated plant nutrient management based on soil test crop response (STCR) and its effect on nutrient uptake and quality parameters of blackgram cultivated on Alfisols in Tamil Nadu, India. Their findings demonstrated that optimized nutrient management significantly improved primary nutrient uptake and crop quality. Although not directly related to AI-based disease detection, this study highlights the importance of holistic crop management strategies that can complement technological interventions for sustainable agricultural productivity.

Similarly, Oiuphisittraiwat *et al.* (2024) examined the field efficacy of antagonistic fungi for controlling black spot disease in Chinese kale. Their results showed that biological control agents were effective in suppressing disease incidence, offering an eco-friendly alternative to chemical fungicides. This study reinforces the relevance of integrated disease management approaches, suggesting that AI-based disease detection systems could be effectively combined with biological and nutrient management strategies for timely and sustainable crop protection.

Table 2: Summary of deep learning techniques employed on plant diseases identification.

Source	Plant	Dataset	Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
(Elfatimi <i>et al.</i> , 2022)	Bean leaves	Public dataset	MobileNet	94.74	92.97	92.97	92.91
(Amin <i>et al.</i> , 2022)	Corn plant leaves	Subset of (CNNs) plant village	EfficientNetB0 and DenseNet121	98.56	97	98	97
(Tabbakh and Barpanda, 2023)	Bell peppers potatoes and tomato leaves	Plant village	TLMVT	98.81	98.72	98.76	98.73
(Farah <i>et al.</i> , 2023)	Soybean leaves	Soybean images dataset	VGG19	93.71	95.19	97.62	96.39
(Peyal <i>et al.</i> , 2023)	Tomato cotton	Plant village	2D CNN	97.36	97	97	97
(Ayaz <i>et al.</i> , 2023)	Cordia dichotoma	custom	Yolov4	95	96.56	94.34	95.8
(Zainab <i>et al.</i> , 2023)	Citrus canker on fruits	Bacterial strains X. citri	DenseNet- 121.	98.97	97	98	97
(Vishnoi <i>et al.</i> , 2023)	Apple crops	Plant village	Deep CNN	98	98	97	97
(Adnan <i>et al.</i> , 2023)	Plant leaves	Kaggle	EfficientNetB3- AADL	98.71	98.85	98.71	98.72
(Masood <i>et al.</i> , 2023)	Maize	Corn disease and severity (CD&S)	Maiz Net	97.91	9.8	97.7	97.9
(Latif <i>et al.</i> , 2023)	Coffee leaf	RCD	ECNN/HLGGM	99.49	-	-	-
(Hosny <i>et al.</i> , 2023)	Apple leaf	Plant village	Deep Feature + LBP	98.0	97	97	97
	Tomato leaf	Plant village	Deep Feature + LBP	96.5	96	96	96
	Grape leaf	Plant village	Deep Feature + LBP	98.3	97	97	97
(Ahmed <i>et al.</i> , 2024)	Wheat crop	Self	Detection transformer [DETR]	96	92	90	-
(Nigar <i>et al.</i> , 2024)	Plants	New plant diseases	EfficientNetB0	99.69	98.27	98.26	-
(Shrotriya <i>et al.</i> , 2024)	-	Plant leaf images	VGG16	97.41	-	-	-
(Salam <i>et al.</i> , 2024)	Mulberry leaves	Self	MobileNetV3Small	96.4	97	97.4	96.4
(Taji <i>et al.</i> , 2024)	Multiple	Plant village	Hybrid	99.80	99.99	99.80	99.80
(Bouacida <i>et al.</i> , 2025)	14 crop kinds	Plant village	CNN	94.04	95.05	93.95	94.5
(Alhwaiti <i>et al.</i> , 2025)	Strawberry, Peach	Plant village	YOLOv4	98	96	98	98
(Roumeliotis <i>et al.</i> , 2025)	Apple Leaf	Plant village	ResNet-50	98.12	98.2	98.12	98.11

Evaluation measures

In this study, we evaluated model performance using four key metrics: accuracy, precision, recall and F1 score. These metrics were used to compare the effectiveness of various models. The definitions of the metrics are as follows:

Accuracy

Measures how frequently the model correctly predicts both positive and negative outcomes.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

Precision

Assesses how accurately the model predicts the positive class. It is computed as the ratio of true positive predictions to the total number of instances predicted as positive (true positives + false positives).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall

Evaluates how effectively the model identifies actual positive instances. It is calculated as the ratio of true positives to the total number of actual positive samples (true positives + false negatives).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 score

Represents the harmonic mean of precision and recall, providing a balanced assessment of model performance, especially when dealing with imbalanced datasets.

$$\text{F1 score} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}$$

The underlying components for these metrics include:

- **True positive (TP):** Correctly predicted positive instances.
- **True negative (TN):** Correctly predicted negative instances.

• **False positive (FP):** Instances incorrectly predicted as positive.

• **False negative (FN):** Instances incorrectly predicted as negative.

Discussion: Comparative analysis of techniques

Analysis of deep learning models using benchmark plant leaf disease corpuses

The PlantVillage dataset is one of the most widely used public datasets for plant disease detection and classification. Numerous researchers apply different deep learning models to various plant species for disease identification. The accuracy, precision, recall and F1 score reported in these studies depend on several factors, including the number of healthy and diseased images, training duration and the preprocessing techniques used at different stages. Fig 1 presents the performance of various models applied to the PlantVillage dataset. Among these the hybrid model (Taji *et al.*, 2024) achieves outstanding performance with a precision of 99.99%, a recall of 99.99% and an F1-score of 99.80%.

Plant disease detection and classification involve several key processing stages. The first step is selecting an appropriate dataset or creating a custom dataset using real-world images. During image collection, factors such as illumination, camera angle and environmental conditions must be carefully considered. The next stage is data augmentation, which increases the dataset size by applying random transformations to existing images. This process improves model generalization and helps reduce overfitting by exposing the model to multiple variations of the same image.

In the feature extraction stage, essential information such as edges, corners, textures and shapes is identified and extracted from raw images, forming the input for the classifier model. After these stages, researchers must choose a suitable deep learning model for further analysis. Fig 2 shows performance of plant diseases on various deep learning models. Fig 3 illustrates accuracies obtained by various researches with different deep learning methods

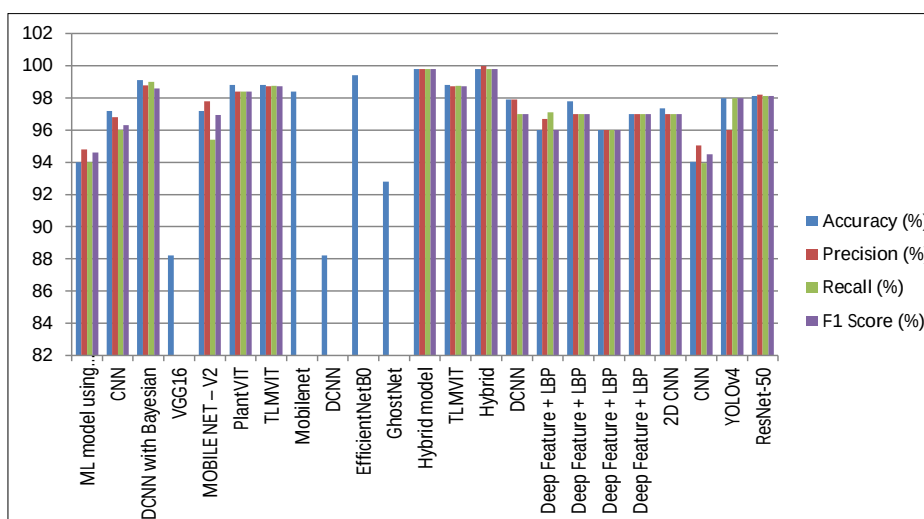


Fig 1: A comparative analysis of deep learning models using performance measures on the PlantVillage corpus.

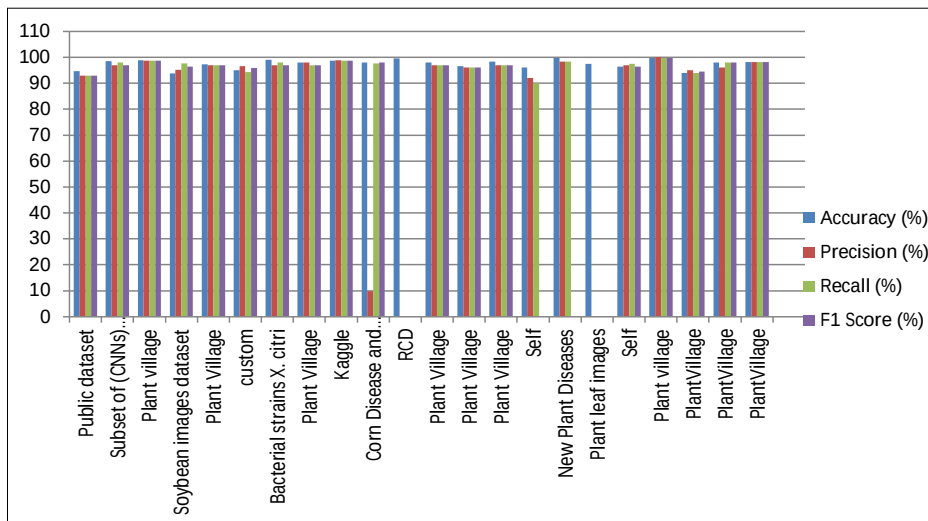


Fig 2: Performance comparison of plant diseases with deep learning models on various corpuses.

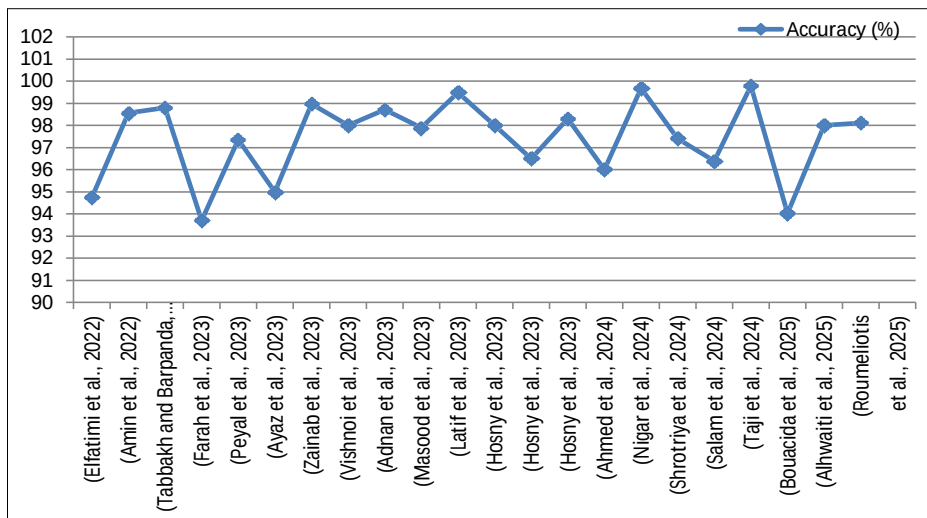


Fig 3: Accuracy comparison of plant diseases by researchers on various corpuses.

on variety of plant disease corpuses. These results highlight the importance of carefully choosing the dataset, preprocessing techniques, model architecture, training strategies, computational resources and parameter variations such as the number of layers in deep learning models.

Overall, this study demonstrates the effectiveness of deep learning models in addressing agricultural challenges and contributes significantly to the successful development of deep convolution neural network (CNN) models for plant leaf disease detection and classification.

LIMITATIONS AND FUTURE WORK

Limitations

- The performance of deep learning models is strongly influenced by the quality of input leaf images (Li *et al.*, 2021). Variations in resolution and lighting conditions, as

well as image artifacts, can negatively impact the accuracy of disease detection and classification (Vishnoi *et al.*, 2021).

- Implementing deep learning models often requires significant computational resources, including high processing power and memory (Li *et al.*, 2021). This can be challenging for researchers or practitioners who lack access to advanced computing infrastructure.
- The deep learning models used in the study primarily emphasize automated detection and classification of plant diseases from leaf images (Li *et al.*, 2021). However, they may fail to account for other critical factors affecting disease occurrence and spread, such as environmental conditions, genetic influences and agronomic practices (Vishnoi *et al.*, 2021).
- Scalability challenges may occur when deploying such systems across regions with varying geographical and climatic conditions.

- Many research studies assume controlled conditions during image capture, which may not be achievable in real-world agricultural environments. Additionally, model performance is highly dependent on image quality and biased datasets may further reduce accuracy.
- Economic feasibility may also be a concern for small-scale farmers, as the initial investment and ongoing maintenance costs of these systems may be relatively high (Vishnoi *et al.*, 2021).

FUTURE DIRECTIONS

The future scope of severity analysis on plant leaves and fruits using deep learning presents numerous promising advancements. Key areas with strong potential for further development include:

- Future studies can work toward enhancing the precision and robustness of disease detection algorithms by utilizing more advanced clustering techniques capable of better distinguishing patterns between healthy and diseased leaves. Progress in neural network architectures such as attention mechanisms, ensemble models and adversarial training may further improve detection accuracy (Taji *et al.*, 2024). Additionally, advanced image preprocessing methods like adaptive thresholding, shadow correction and highlight adjustment can help normalize images captured under varying lighting and angles. Incorporating adaptive exposure and autofocus features in cameras may also strengthen performance in diverse illumination conditions (Krithika *et al.*, 2025).
- Advancing algorithms to detect and classify multiple diseases simultaneously would add considerable value. This requires training neural networks to differentiate between various disease types, enabling comprehensive plant health assessments by assigning leaves to multiple disease categories.
- Developing real-time disease detection systems for mobile or embedded devices would enable on-site diagnosis and faster decision-making. Achieving this would necessitate optimizing models to operate efficiently in resource-limited environments.
- Expanding the use of transfer learning techniques could allow models to benefit from pre-trained networks and domain knowledge. Adapting models trained on one species to diagnose diseases in others may reduce the need for large annotated datasets and improve cross-species generalization.
- Integrating disease detection models with precision agriculture tools such as drones, remote sensing technologies and IoT sensors could support large-scale and continuous monitoring of crop health. This combination would help guide targeted interventions and improve the efficiency of agricultural resource management.
- Improving the interpretability of disease detection models can strengthen user trust and understanding. Developing approaches that explain model predictions and highlight the features influencing disease identification can support wider adoption in practical agricultural settings.
- Extending research to include long-term monitoring and disease forecasting can facilitate proactive disease management. By leveraging historical data, environmental variables and disease progression trends, predictive models can provide early warnings and guide preventive actions to minimize crop loss.
- Establishing shared data repositories and collaborative platforms can encourage knowledge exchange and support the creation of stronger detection algorithms (Taji *et al.*, 2024). Making annotated datasets and benchmark results publicly available would foster innovation and accelerate progress. Such initiatives can significantly improve the accuracy, efficiency and applicability of deep-learning-based plant disease detection. Continued collaboration among plant pathologists, data scientists and agricultural professionals will be crucial for advancing and effectively deploying these developments (Krithika *et al.*, 2025).

CONCLUSION

This study provides valuable insight into existing research that employs deep learning (DL) techniques in agriculture. It highlights various methodologies used for detecting and classifying plant, leaf and crop diseases. The review presents an overview of the datasets commonly used for plant disease detection and classification, offering details about their classes, characteristics and suitability for either classification or object detection tasks. The PlantVillage dataset is the most widely used dataset in this domain. CNN and their modified versions consistently demonstrate strong accuracy across multiple datasets. However, most existing research relies on laboratory controlled datasets, which may lead to reduced performance in real-world environments. To improve practical applicability and support farmers more effectively, researchers should focus on developing and evaluating models using real-world datasets. Their effectiveness can be further enhanced when integrated with sustainable crop management techniques, thereby supporting resilient and precision driven agricultural systems. Overall, this comprehensive analysis intends to offer meaningful insights and direction for researchers working in the field of agricultural deep learning towards accurate disease detection.

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Conflict of interest

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