Identification and classification of plant diseases using a deep learning approach: a survey

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Abstract. The loss of agricultural yields is often attributed to plant diseases that affect crops.Early detection and effective control of these diseases remain a major challenge for farmers, leading to substantial yield losses that pose a threat to a growing population. This study aims to identify gaps in the use of deep learning for early detection and classification of plant diseases. Deep learning techniques can help farmers quickly identify diseases, thereby increasing agricultural productivity. Better early detection can help developing countries mitigate food insecurity and economic challenges. The results show that despite promising progress in plant disease identification, several challenges and limitations persist in the literature over the past five years and deserve to be addressed. A critical analysis was conducted to identify the limitations and challenges of existing solutions to serve as a basis for future research on the improvement, early identification and classification crop diseases.

1 Introduction

Plant disease diagnosis involves both detection and identification while providing a comprehensive understanding of the disease. Performed early, it helps prevent production losses and, consequently, improves crop yields and boost countries's economies. The main causes of plant diseases can be biotic or abiotic in nature [1] , posing a major threat to global food security [2]. Various phytopathological techniques are used to identify these diseases, including methods related to the chemical analysis of infected areas of the plant and indirect approaches such as the use of physical techniques, such as spectroscopy [3]. Traditional phytopathological techniques remain reliable for identifying plant diseases; however, they require the physical presence of experts in the field. Therefore, diseases can spread rapidly due to the delayed intervention of agricultural specialists. Also, inexperienced use of pesticides can cause the development of prolonged resistance of pathogens, significantly reducing the ability to control these plant diseases [1] . Every year, these diseases considerably reduce global agricultural production. Countries's economies have also suffered disastrous consequences, especially those of smallholder farmers who represent 85% of global farmers [4]. With a global population estimated at 8.5 billion by 2025, according to United Nations forecasts [4], global food production must increase accordingly to meet the growing demand. Can artificial intelligence solutions be effectively used to analyse images of diseased plants accurately and reliably to identify diseases? Deep learning solutions have been used for early detection and automatic identification of plant diseases. Plant disease identification has progressed considerably thanks to applications developed by artificial intelligence researchers, allowing for faster intervention by famers in the field, and, ultimately, increased production for a constantly growing global population. These solutions cover a wide variety of plants and crops, including beans, tomatoes, corn, cassava, wheat, rice, potatoes, soybeans, strawberries, apples, coffee, mangoes, peanuts, pigeon peas, cowpeas, chickpeas, peas, bananas, etc ... . The objective of this article is to present a review of deep learning-based plant disease identification and classification solutions proposed by researchers over the past five years and identify the shortcomings of these solutions. Specific contributions of this article include:

- The advantages of early and accurate identification of plant diseases, along with the assessment of disease severity.
- A comparison of recent related work on deep learning models widely used over the past five years, utilizing datasets from various sources, as well as an overview of the limitations of proposed solutions and the potential challenges in plant disease identification and classification.

The paper is organized as follows: Section 2 discusses the advantages of early and accurate identification of plant diseases in agriculture. Section 3 outlines the plant species covered in this study. Section 4 presents the plant diseases treated. Section 5 describes the data source and research approach used for the identification of plant diseases as well as the inclusion criteria through the use of keywords. Section 6 focuses on plant disease identification based on deep learning. Section 7 explores the analysis and synthesis of the study. Section 8 addresses the limitations of current solutions and potential challenges. The final section concludes the paper.

2 The advantages of early and accurate identification of plant diseases

Early detection of plant diseases is crucial to prevent pathogens or pests from developing resistance to specific treatments in certain regions. Moreover, timely and accurate diagnosis can greatly reduce the spread of plant infections. Once a disease is identified, appropriate agricultural measures can be implemented—such as proper soil preparation, removal of infected crop residues that could contaminate healthy plants, use of disease-resistant seed varieties, correct seed treatment and selection, and adherence to recommended planting density and spacing. These strategies help minimize disease transmission within farms and prevent the introduction of more severe pathogens [5]. Additionally, accurate disease identification enables informed and targeted application of plant protection products for effective control.

3 Plants covered by our study

Approximately four hundred thousand plant species have been identified worldwide, of which around thirty thousand are utilized by humans for purposes such as medicine, food, and construction materials [6].

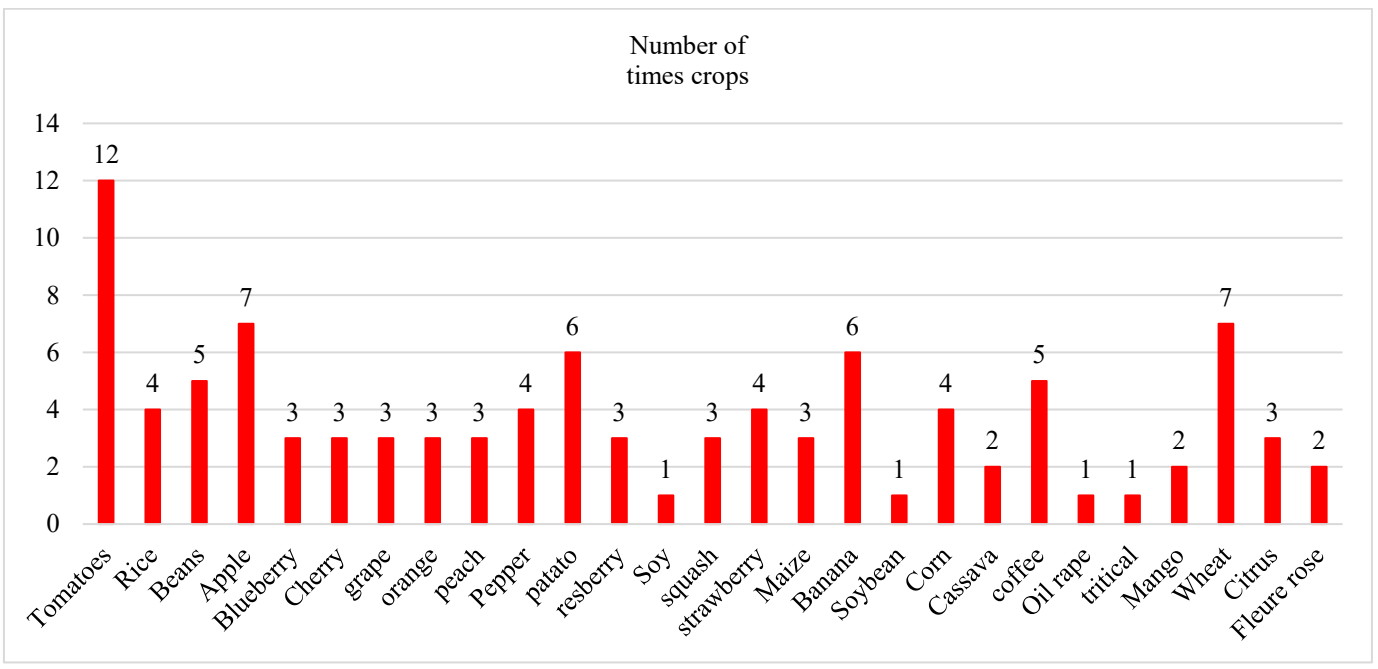

Fig.1. Graph showing the frequency of crop treatment in the 40 reviewed articles.

Human food sources derive from these plants either directly, as starches, fruits, and vegetables, or indirectly through livestock that consume them. However, only about thirty cultivated plant species constitute the foundation of the human diet, with five of them being particularly dominant.

These crops are highly adaptable and can thrive in diverse climatic conditions. In this research, we analyzed 40 articles. Various plant species were examined based on the frequency of their inclusion, as illustrated in Figure 1 above.

4 Plant diseases treated

Plant diseases can be classified in various ways, primarily based on the type of pathogen involved. They generally fall into two categories: biotic and abiotic diseases. Farmers are tasked with detecting and preventing these conditions, which pose a significant threat to overall agricultural productivity. Effective disease management is crucial to meet the demands of an ever-growing global population. The progression of a disease is influenced by three key factors: the presence of a susceptible crop, a pathogen, and favorable environmental and climatic conditions that facilitate disease spread **[7]**. Identifying these factors is crucial for assessing

disease severity and determining the appropriate dosage of fungicides and pesticides to be applied [8]. There are five primary types of plant diseases: bacterial, fungal, nematode, viral, and those caused by parasitic plants. The plant diseases discussed in this paper are detailed in Tables 1, 2, 3 and 4.

5 Data Source and Research Approach Used

In the scientific literature, a variety of methods have been developed for the detection and classification of plant diseases. These methods are generally catego-rized into two main types such as Machine learning–based approaches, and Deep learning–based approaches. For this article, we analyzed 40 research papers on the detection and classification of plant diseases using deep learning approach. The articles were sourced from multiple scientific databases, including Google Scholar, Springer Link, Web of Science, IEEE Xplore and Scientific Reports, using the keywords: "Identification, Classification, Plant diseases, Machine Learning, Deep Learning, severity level plant diseases, CNN models, public dataset, private dataset, combined dataset, plant diseases identification and classification." The annual distributions of studies published on this topic from 2020 to 2025 were presented in Figure 2, while Figure 1 highlights the variety of agricultural crops covered in these 40 studies.

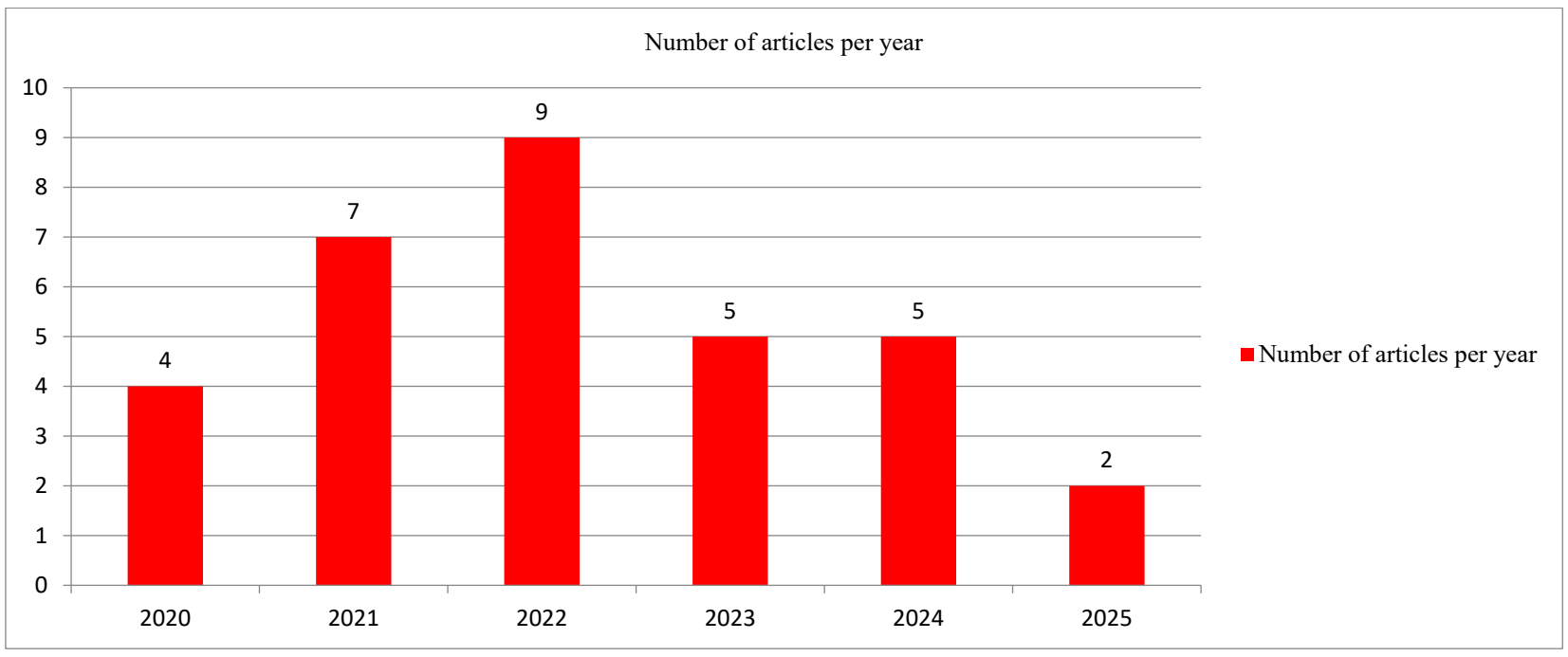

Fig.2. Graph showing the distribution of publication years for 40 articles based on the keywords ": Identification, Classification, Plant diseases, Machine Learning, Deep Learning, severity level plant diseases, CNN models, public dataset, private dataset, combined dataset, plant diseases identification and classification" from Google Scholar, Springer Link, Web of Science, IEEE Xplore, Scientific Research, etc.

The inclusion criteria for the models studied were to consider models that specifically use DL models. The reason for this criterion is that DL models offer fast and accurate analysis, adapted to real-world conditions, and form the basis of modern artificial intelligence systems dedicated to plant pathology [10]. Traditional machine learning approaches, such as Support Vector Machines (SVM), Random Forests (RF), and Decision Trees (DT), have been widely applied in plant disease identification over the past decade. Machine learning is a reliable artificial intelligence (AI) technology that has proven successful in detecting and identifying diseases in various plant parts, including leaves and fruits. However, it has faced certain limitations. But, Deep learning (DL) has emerged as a more powerful tool for plant disease identification and classification, offering enhanced accuracy in image recognition tasks [10] . This subfield of machine learning employs artificial neural networks to learn from large datasets, and AI-based deep learning techniques have significantly advanced computer vision capabilities in recent years [11].

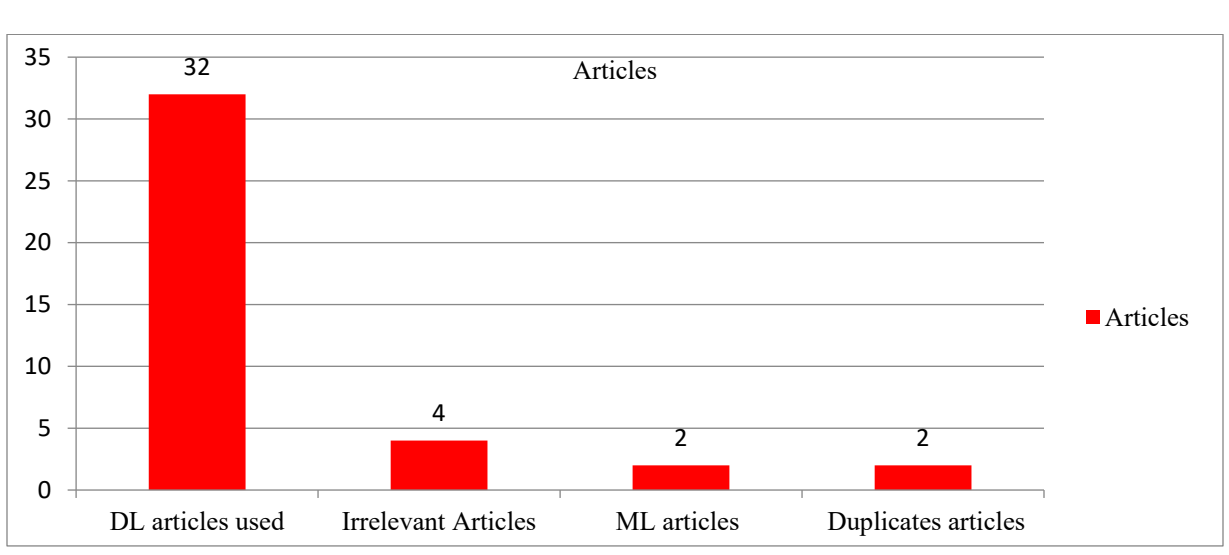

Fig.3. Graph showing the inclusion and exclusion criteria of the 40 articles reviewed.

Among the 40 articles initially reviewed, four related to deep learning were excluded as they were deemed irrelevant to the study. two duplicate records were subsequently removed, along with two additional articles whose performance relied on outdated machine learning models. In total, 28 articles employing deep learning models were considered relevant and included in the analysis, as illustrated in Figure 3. Convolutional Neural Networks (CNNs) have made substantial contributions to crop disease identification [9], as well as to improving crop recognition accuracy [10].

Several deep learning architectures are commonly used in this domain, including VGG, AlexNet, GoogleNet [11], Inception [1], ResNet , DanseNet [11], EfficientNet, MobileNet [12], SqueezeNet, YOLO, and others. These models, however, require significant computational resources due to the vast amounts of data involved. The 28 selected studies constituted the sample for the analysis. Data were extracted and organized into tables using Microsoft Excel 2013 to synthesize the publication characteristics, methodological approaches employed, obtained performance results, plant disease severity levels, and datasets used in deep learning models for the identification and classification of plant diseases.

6 Plant diseases identification based on Deep Learning

Several effective DL solutions have been employed for the identification and classification of plant diseases, utilizing advanced DL architectures [8].Deep Convolutional Neural Networks (DCNNs) are the most commonly used deep learning architecture for image recognition and classification tasks related to plant disease detection [9] .

6.1 CNN solutions trained on public dataset.

Recent research has shown that deep learning methods significantly outperform older machine learning techniques. Deep learning (DL) models have been widely used in the identification and classification of plant disease images, particularly for plant leaf diseases, over the past five years as shown in figure 3.The CNN architecture is widely used because it's capable of automatically extracting essential visual characteristics from plants in order to effectively detect plant diseases. The convolution, normalization, pooling, and dropout layers promote good generalization while reducing the risk of overfitting [13].

For example, in the identification and detection of apple plant diseases, the authors in [14] introduced a mobile version of the CNN model, MobileNet-based [12], trained on an apple leaf disease dataset. They compared the proposed model with ResNet152 and Inception v4 [15], and found that MobileNet achieved an accuracy of 73.50%. However, system performance could be further improved by applying dataset augmentation techniques.

In [13], a CNN model was developed and trained on a highly imbalanced public dataset, as well as on an augmented dataset, for the identification and classification of cassava plant leaf diseases. The results with the augmented dataset showed a validation accuracy of 90%.

The authors in [16] proposed deep learning models for the detection of tomato diseases, focusing on four main diseases: healthy, blossom and rot, splitting rotation, and sun-scaled rotation. YOLOv5 and YOLOv8 algorithms were trained separately to evaluate the accuracy and efficiency of each algorithm on an augmented dataset. The results showed a better accuracy of 97.9% in detecting tomato fruit diseases. The model architecture should incorporate an attention mechanism and multi-scale feature fusion to increase disease-specific focus and capture important patterns.

As reported in [17], a simple and optimal YOLOv5 model was trained on a pre-processed and augmented image dataset of four rice leaf disease for 100 epochs. The model yielded impressive results with recall, precision, and mAP scores of 94%, 83%, and 62%, respectively, in disease detection and classification of rice plant leaf images. However, the sample size of 400 images used in the study was too small to thoroughly evaluate the proposed method.

In the identification and classification of banana leaf disease, the authors in [18] proposed a CNN method trained on a pre-processed public dataset. Compared to existing machine learning models, the CNN model showed better results, achieving an accuracy of 95%. However, the model did not take into account climatic factors such as temperature, humidity, water levels, and soil conditions within the dataset.

The embedded system based on a ResNet model were designed in [19] to help producers automatically diagnose four coffee plant diseases. Using a set of 1,250 pre-processed and resized images, the ResNet50 model was trained over 300 epochs and achieved an accuracy of 96.5%. The system correctly detects diseased leaves in more than 91% of cases and identifies the specific disease with an accuracy of approximately 64%.

In [20], the authors proposed the CNN ResNet50 [21] network, which was trained on a combined public dataset, MandeleyData, as well as an augmented dataset. The ResNet50 CNN model showed excellent performance with an accuracy of 97.8% and an F1-score above 90% in detecting mango plant leaf disease. However, the public dataset did not reflect the actual environmental conditions of the study areas, which limited the model's applicability.

The authors in [11] proposed an improved DenseNet model, utilizing a channel attention mechanism, trained on the pre-processed PlantVillage dataset. When compared to other versions of DenseNet, the AB-SE-DenseNet model demonstrated an exceptional accuracy of 99.4% in identifying and recognizing rice leaf plant diseases. However, the solution's limitation lies in the fact that it has not been deployed on mobile platforms, which would allow for real-time assessment of rice disease severity.

In detecting and classifying tomato plant leaf disease images, three DCNN models VGG-19, MobileNet-V2, and ResNet-50 were proposed in [21], and trained on an enhanced PlantVillage dataset. The ResNet50 model outperformed the others with an impressive accuracy of 99.53%. Although they achieved good results with a small dataset, they could have achieved better results with a larger dataset captured in their specific environment.

In [22], the authors proposed a pre-trained AlexNet model, trained on the PlantVillage dataset with image acquisition and pre-processing [15], and optimized using SGD. The results showed joint performance of 99.56%, with perfect accuracy for identifying cedar apple black rot and rust classes (100%), 98.57% accuracy for the healthy apple class, and 99.68% accuracy for scab in identifying and classifying of apple plant leaf disease. However, the small dataset of 112 images used in the study limited the evaluation of the proposed method, and the model's performance could improve with a larger dataset and more epochs.

In [23], the authors employed a lightweight CNN based on the VGG16 architecture, trained on the PlantVillage dataset, to rapidly identify 9 tomato leaf diseases. The model achieved an impressive average accuracy of 98.7%. So far, most crop disease detection models have predominantly focused on foliar disease symptoms, as these are the most easily identifiable.

In [24], the authors combined Support Vector Machine (SVM) [3] and CNN models, trained on a pre-processed and augmented public dataset, achieving a remarkable accuracy of 100% in detecting and classifying apple diseases. However, CNNs, with their reduced number of parameters, typically require less learning time.

As proposed in [25], a Deep Learning approach was used to diagnose tomato diseases by using Conditional Generative Adversarial Networks (C-GAN). The DanseNet151 model was pre-trained in a refined manner using transfer learning on synthetic images. After comparison, the trained model yielded impressive results, achieving an accuracy of 99.7% in tomato leaf disease image classification. This marks a significant advancement, as real-time data acquisition, which was previously costly, time-consuming, and labor-intensive, has now become feasible thanks to generative networks.

Table.1. Comparison of solutions based on public dataset.

Numbers	Authors	Years	Crops	Diseased part the plant	Diseases	Datasets	used models	results
[14]	Chongke et al.	2022	Apples	Leaves	Alternaria leaf spot and apple rust	AppleLeaf : 668 images	MobileNet-ResNet152 -ResNet-Inceptionv4	MoblileNet of accurancy:73.5%
[16]	AHMED et al.	2024	Tomato	Fruits	Blossom end rot,splitting rotation, and sun-scaled rotation	Public Dataset:3200 images	YOLLOv5 et YOLLOv8	Accurancy 97.9%
[22]	Olanrewaju et al.	2023	Apple	Leaves and fruits	Apple scab, black rot, cedar rust	PlanteVillage:3171 images	CNN-SGD-BSIF	CNN accurancy :98.5%
[21]	HOSSAIN et al.	2023	Tomato	Leaves	Early Blight, Septoria Leaf Spot, and Yellow Leaf Curl Virus	PlanteVillage:7000 images	DCNN,VGG19,MobileNet v2 and ResNet50	Accurancy of Resnet50:99.53%
[11]	JIANG et al.	2023	Rice	Leaves	Rice blast, blight, brownspot, sheath blight, and tungro	PlanteVillage:1352 images	AB-SE-DenseNet, SEDenseNet, and DenseNet	AB-SE Accurancy:99.4%
[26]	Eunice et al.	2022	Apple,patato,soybean,squash,strawberry,tomates,blueberry,cherry,corn,grape,rassberry,orange,peach,pepper	Leaves and fruits	Several deseases	PlanteVillage:54305 images	CNN,DanseNet 121,ResNet50,VGG 16 et Inception v4	DanseNet accurancy:99.81%
[20]	Faye et al.	2022	Mango	Leaves	anthracnose, Gall Midge, Powdery Mildew and Sooty Mold	MangoLeafBD:862 images	CNN-ResNet50	Accurancy:97,8%f1_Score: 90%
[13]	ANITHA et al.	2022	Cassava	Leaves	CBB,CBSD, CGM CMD	Public Dataset:	CNN	Validation accurancy of CNN:90%
[18]	KRISHNAN et al.	2022	Banana	Leaves	FWB,BS, BW,YS and banana bunchy top disease.	Public Dataset:9000 images	CNN with TDVFCMS	Accurancy CNN:93.45%
[17]	JHATIAL et al.	2022	Rice	Leaves	Bacterial Bligh, Brown Spot, Blast, and Tungro.	PlanteVillage:	YOLOv5	Accurancy:83%,Recall:94% and mAP sacre 62%
[27]	ABBAS et al.	2021	Tomato	Leaves	Yellow leaf, curl virus,Septoria leaf spot,Two spotted spider mite, Bacterial spot, Leaf mold,Mosaic virus Target spot,Early blight,Late blight	PlanteVillage:4000 images	C-GAN,DenseNet151	Accurancy of DenseNet151: 99.51%, 98.65% and 99.11%
[28]	SERTTAS et al.	2023	Beans	Leaves	Healthy, Angular Leaf Spot, and Bean Rust	Public dataset 1295 images	CNN,ResNet50	ResNet50 accurancy: 98%
[23]	Mohit et al.	2021	Tomato	Leaves	Bacterial spot, Early blight, healthy, Late blight, Leaf Mold, Septoria leaf spot,Two-spotted spider mite, Target Spot, Tomato mosaic virus, j) Yellow Leaf Curl Virus	PlanteVillage:55000 images	CNN,VGG16	Accuracy of CNN: 98,7%
[19]	MARTINEZ et al.	2022	Coffee	Leaves	The leaf miner coffee, coffee leaf rust, phoma leaf spot and iron leaf spot	Public Dataset:1250 images	ResNet,ResNet50, DNN	ResNet50 accurancy of 96.5%
[24]	MARANDI et al.	2021	Apple	Fruits	Fungal	Public Dataset:	K-means,SVM et CNN	Accurancy:100%

In detecting plant leaf disease, the researchers in [26] proposed pre-trained CNNs such as DenseNet-121, ResNet50, VGG16, and Inception V4 models, trained on a PlantVillage dataset using transfer learning. Among these, DenseNet-121 emerged as the most efficient model for identifying plant leaf and fruit diseases, achieving a classification accuracy of 99.81% and an F1 score of 99.8%. However, a multi-object deep learning model is needed to detect plant diseases on multiple leaves or fruits, rather than on a single image.

The authors in [28] proposed deep learning techniques to detect and diagnose bean leaf diseases using a dataset of 1,295 field images captured with a smartphone. Transfer learning was applied to three pre-trained architectures—VGG16, MobileNetV2, and ResNet50—by adding one, two, or three additional layers before training on the dataset. After experimenting with multiple model configurations, the results showed that ResNet50 achieved the best performance, reaching a classification accuracy of 98%.

6.2 CNN solutions trained on private dataset

The development of CNN models has shown a remarkable improvement in accuracy and efficiency when compared to traditional machine learning methods. Deep learning models, however, can train and test reliable data more efficiently, especially when it is manually collected and organized for AI models while adhering to necessary quality and quantity criteria. Nevertheless, these models often require significant learning time.

In [25],les auteurs ont comparé six modèles d'apprentissage profond pour détecter la rouille et le mineur des feuilles du caféier à partir d'un jeu de données manuel de 542 images. Entraînés avec l'optimiseur Adam et des paramètres standard, les modèles ont été évalués sur une répartition 80/20. MobileNet s'est distingué comme le plus performant, atteignant une précision de 97,3 %.

In [29], researchers introduced a modified lightweight CNN architecture trained on three dataset versions collected directly from the fields. The results indicated that the version with the largest dataset achieved an accuracy of 93% in identifying and classifying wheat plant diseases. Although the sample size of 450 images

is relatively small for a thorough evaluation, the extensive collection of field images and their subsequent annotation could further enhance the model's performance through refined experimentation.

In [30], The authors proposed a deep learning–based approach for identifying and classifying 11 types of images of healthy and diseased apple fruits and leaves. They used the Field and Plant-Disease-Recognition datasets, applying various data augmentation techniques during training of the Multi-scale Dense model. Comparative analysis with other models showed that the Multi-scale Dense Inception-V4 and Multi-scale Dense Inception-ResNet-V2 models, when combined with Cycle-GAN augmentation, achieved high average accuracies of 94.31% and 94.74%, respectively, in detecting and classifying leaf and fruit images affected by diseases such as general apple scab, severe apple scab, apple gray spot, general and severe cedar apple rust, general and severe anthracnose, and ring rot.

In [31] , the authors suggested a DCNN solution to early identify various diseases and pests affecting banana leaves. The model was trained on an augmented manually collected dataset with eight convolutional layers. When compared to existing models, the proposed model demonstrated superior performance, achieving accuracy, precision, recall, and F1-score values of 98.92%, 99.13%, 99.43%, and 99.113%, respectively. These advanced deep learning technologies are poised to significantly enhance the agricultural industry and protect banana crops from diseases.

A deep learning model based on ResNet50 is proposed in [32] for the recognition of apple leaf diseases. A dataset was created from images recorded in the field, online, and in public databases, covering five common diseases. Preprocessing and augmentation techniques were applied to limit overfitting. The model was trained using a tailored learning rate and the SGD optimizer to improve convergence. The results show an accuracy of 93.19%, confirming the model's effectiveness and stability for the automatic identification of apple leaf diseases.

Table.2. Comparison of solutions based on private dataset.

Numbers	Authors	Years	Crops	Diseased part of the plantt	Diseases	Datasets	used models	results
[32]	Tao et al.	2024	Apples	Leaves	Spotted leaf drop, brown spot, gray spot, mosaic and rust	Manuelly collected:2029 images	ResNet50-SGD	Accurancy ResNet50:93.19%
[25]	ABOUHAWWAS et al.	2024	coffee	Leaves	Rust and leaf miners of leaves	Manually collected: 542 images	CNN, ResNet50, MobileNet, GoogleNet, VGG16 et VGG19	MobileNet accuracy:97.3%,precision:56.25%,recall2:57.143%, and F1-score:56.693% ,
[31]	RAJALAKSHMI, et al.	2024	Banana	Leaves	Leaf rust,leaf spot and leaf blight	Manually collected: 774 images	DCNN	DCCN accuracy:98.92%
[33]	ABUHAYI et al.	2022	coffee	Leaves	Coffee beery Disease, Coffee beery Healthy, coffee wilt disease, Leaf Healthy,Cercospora,Sooty Mold,Phom Costaricensis,Coffee Leaf Rust	Manually collected: 3288 images	CNN,GoogleNet,ReseNet,MLP,KNN,SVM,RF,DT,K-folder,K-means	Accurancy CNN: 99.08%
[34]	Abed et al.	2021	Beans	Leaves	Angular spot on healthy leaves and bean rust	Manually collected :1295 images	Densenet121, ResNet34, ResNet50, VGG-16, et VGG-19	DanseNet121 of 91.02%
[35]	Papan et al.	2025	Beans	Leaves	Cercospora leaf spot	Manually collevted: 2220 images	ANN, InceptionV3 et EfficientNet-B3	La précision de EfficientNet-B3 97.95% for V4718 et 91.72% de D5.
[36]	Sambasivam et al.	2020	Cassava	Leaves	CMD (Cassava Mosaic Disease),CBSD (Cassava Brown Streak Virus Disease),CGM (cassava green mite),CBB (cassava bacterial blight)	Manually collected:10,000, labeled images	CNN,CLAHE,Class-Weight,focal-loss et SMOTE	CMD, CBSD , Healty and CGM accurancy of 96%,93%),93%,92% and 90%
[29]	ASHRAF et al.	2022	Wheat	-	several diseases	Manually collected: 3750 images	CNN	CNN Accurancy :93%

Deep Learning models have demonstrated significant advancements in plant disease detection, as shown in [33] , where a combination of GoogleNet and ResNet was trained on manually collected datasets. Various classifiers, including MLP, SVM, KNN, RF, and DT [3,37] , were employed. When compared to existing models, the CNN models achieved an impressive average accuracy of 99.08% on the test dataset, proving their effectiveness in detecting and classifying coffee plant diseases. However, its execution time was considerably longer due to the large number of parameters.

In [34], the authors used a U-Net architecture with pre-trained models to detect bean leaf diseases, including angular leaf spot and bean rust. Five deep learning models, such as DenseNet121, ResNet34, ResNet50, VGG-16, and VGG-19, were trained on an unbalanced dataset of 1,295 images. DenseNet121 achieved the best results with an average accuracy of 91.02%.

In [35], an RNA model using the Inception V3 and EfficientNet-B3 architectures was run on 2,220 images of mung bean leaves classified according to five disease severity levels. The EfficientNet-B3 model achieved the highest accuracy, at 97.95% for V4718 and 91.72% for D5. The study suggests deploying the model in the cloud and developing a mobile application to help farmers assess disease severity using their smartphones.

The authors designed a CNN model to classify five cassava diseases from 10,000 field images in [36]. To limit overfitting and correct class imbalance, they used techniques such as class-weighting, focal loss, SMOTE, and CLAHE image enhancement. Evaluated by cross-validation, the model achieved up to 96% accuracy for CMD and over 92% for CBSD, CBB, and healthy leaves, but performed slightly worse for the CGM class (90%).

These results highlight the importance of real-time data collected in the field. This reliable data allows for the accurate identification and classification of plant diseases, thus providing farmers with crucial information for taking timely and appropriate crop health management measures.

6.3 CNN solution trained on mixed dataset.

It is generally advisable to combine public and private data sets before any training, in order to obtain a much more representative sample that will enable the network to learn well according to its performance.

To facilitate fast and automated identification of five citrus leaves and fruits diseases, the authors in [39] proposed an MLCNN-based approach using the Softmax activation function. The model was trained on a mixed dataset using various configuration parameters as referenced in [31]. The results demonstrated a strong performance, with a training accuracy of 94.55% and a testing accuracy of 95.65%.

Table.3. Comparison of solutions based on mixed dataset

Numbers	Authors	Years	Crops	Disease part of the plant	Diseases	Datasets	Used models	results
[39]	KHATTAK et al.	2024	Citrus	Leaves /Fruits	black spot, canker, scab, greening, and Melanose	Manually collected and planteVillage :2293 images	CNN	CNN Precision:94.55%,Test: 95.65%
[30]	TIAN et al.	2021	Apple	Leaves and fruits	General apple scab, serious apple scab, apple gray spot, general cedar apple rust, serious cedar apple rust, general anthracnose, serious anthracnose, and ring rot	Leaves images are from Challenger-Plant-Disease- Recognition and Fruits images are manually collected: 8483 images	Multi-Scale Danse Inception v4 et Multi-scale Dense Inception-ResNet-V2	Accurancy: 94.31% et 94.74%
[40]	Iftikhar et al.	2020	Tomato	Leaves	Late blight ,Septoria leafspot acterial speck , Bacterial spot,Early blight	Manually collected and Laboratory dataset:317 images	VGG16,VGG17, ResNet et Inception V3	Accurancy of inception :V3:99,6%, Recall:99.6% and F1-score:99.5%
[41]	GHANNAM et. al.	2020	Beans	Leaves	angular leaf spots and bean rust	Manually collected and Laboratory dataset:1296 images	CNN,EfficientNetB3, InceptionV3, and MobileNetV2	accuracy of EfficientNetB3 and InceptionV3 99.22%, precision of 99.24%, recall of 99.22%, and F1-score of 99.22%

Nevertheless, the dataset consisted of only 213 images, which is insufficient for comprehensive evaluation. Moreover, since the dataset was sourced from a single field, the findings lack generalizability across broader agricultural environments, indicating the need for further studies across multiple domains.

In [30], researchers introduced an innovative approach leveraging a Multi-scale Dense model trained on both the PlantVillage dataset and a locally collected dataset, enhanced through the application of various augmentation techniques [42]. Among the models compared, the Multi-scale Dense Inception-ResNet-V2

integrated with Cycle-GAN demonstrated superior performance, achieving average accuracies of 94.31% and 94.74% in the detection and classification of apple leaf and fruit diseases. However, the expanding the dataset and further refining the model would enhance its capacity for accurate and automated diagnosis.

Similarly, the authors in [41] proposed an ensemble-based method that clustered multiple transfer learning CNN architectures namely EfficientNetB3, InceptionV3, and MobileNetV2 [15] trained on bean leaf image datasets. By employing a deep stacked ensemble learning framework coupled with meta-learning, the system achieved an outstanding detection accuracy of 99.24% for plant leaf disease.

Another study in [40] , authors utilized both laboratory and field-collected datasets to pre-train four CNN models: VGG-16, VGG-19 [38], ResNet, and Inception V3 . Results indicated that the Inception V3 model pre-trained on laboratory data achieved the highest accuracy, reaching 99.6%, which was a 6% improvement over other models in the automatic classification and detection of tomato leaf disease.

Nonetheless, a critical observation across these studies is the predominant use of datasets obtained under controlled environmental conditions. This approach often limits the generalizability of the trained models in real-world agricultural settings, where variable conditions affect performance outcomes.

6.4 CNN solutions for assessing plant disease severity

Plant diseases, if left unchecked, can result in field-wide pandemics, severely compromising crop yields. Early identification and severity assessment are therefore crucial to inform timely and proportionate responses, such as determining the appropriate type and dosage of pesticides. Traditionally, disease severity was evaluated manually by agricultural experts to avoid misjudgments that could lead to either insufficient or excessive pesticide use both of which could exacerbate crop losses. Severity assessment typically involves calculating the ratio between the infected area and the total area of the affected plant part [8].

In [43], the authors proposed a deep convolutional classifier (DCC)-based model named Yellow-Rust-Xception for detecting and classifying the severity levels of yellow rust disease in wheat leaves. The model categorized disease progression into six levels: no disease, susceptible resistant, moderate, moderately resistant, moderately susceptible, and susceptible. By pre-training MobileNet and ResNet models, Yellow-Rust-Xception achieved a high classification accuracy of 91%.

A separate CNN-based solution was presented in [8], targeting the early and qualitative estimation of severity levels in four mango fruit diseases: alternaria, anthracnose, aspergillum rot, and stem rot. Seven models including EfficientNetBV2, InceptionV3 [41], DenseNet121, MobileNetV2 [41], NASNetMobile, VGG16, and ResNet50 [21] were trained on the SenMangoFruitDDS dataset. Leveraging transfer learning [12] , the ResNet50 model delivered superior performance, achieving an accuracy of 97.82% and an F1-score of 97.79%.

Table.4. Comparison of solutions based on the assessment of the severity of plant diseases

Numbers	Authors	Years	Crops	Diseased part of the plant	Diseases	Severity levels	Datasets	used models	results
[43]	HAYIT et al.	2021	Wheat	Leaves	Rust	resistant, moderately resistant, moderately susceptible, or susceptible	-	Yellow-Rust-Xception	Yellow-Rust-Xception Accurancy 91%
[8]	Faye et al.	2025	Mangoes	Fruits	alternaria, anthracnose, aspergillum rot, and stem rot	Helthy,early,intermediate and final	Public dataset SenMangoFruitDDS: 862 images	EfficientNetBV2, InceptionV3 , DenseNet121, MobileNetV2 , NASNetMobile, VGG16, and ResNet50	ResNet50 Accurancy: 97.82%,F1-score 98.56%
[44]	LAMBA, et al.	2023	Rice	Leaves	rice blast disease	mild, average, severe, and profound	Manually collected: 1679 images	CNN, SVM and CNN-SVM architecture	Training accurancy of hybrid CNN-SVM: 97%
[45]	ESGARIO et al.	2020	coffee	Leaves	Biotic stress: leaf miner , rust , brown leaft spot and cercospora leaf spot	healthy (< 01%), very low (01% 5%), low (51% 10%), high (101% 15%) and very high (> 15%).	Manually collected:1747 images	AlexNet 61 GoogLeNet VGG19 ResNet50	Resnet50 accuracy:94.05%
[46]	CHEN et al.	2021	Rice	Leaves	Rice bacterial leaf streak (BLS)	leaves without lesions; level 1 with less than 10% lesions; level 2 = 11 to 25% lesions; level 3 = 26 to 45% lesions; level 4 = 46 to 65%; level 5 = > 65% accordingly	Manually collected:1199 images	UNet model,BLSNet,DeepLabV3+,	BLSNet accurancy: 98%

Furthermore, in [44] , a hybrid CNN-SVM architecture was introduced to predict and classify the severity of rice blast disease across four categories: mild, average, severe, and profound. The model, trained on data sourced from both primary and secondary sources, attained a 97% classification accuracy. The study highlighted the advantages of combining deep CNNs with hybrid machine learning algorithms, which demonstrated enhanced predictive power and outperformed standalone CNN architectures as shown in [13].

Similarly, the study in [45] introduced a multi-task CNN-based system designed to simultaneously identify and assess the severity of coffee leaf disease associated with biotic stress agents. The researchers developed a new leaf dataset using standard augmentation and mix-up techniques to enhance generalization. Their CNN model achieved a classification accuracy of 94.05% for biotic stress identification and 84.76% for severity estimation, showcasing the model's potential for robust performance in complex field conditions.

For rice bacterial leaf streak (BLS) disease, a segmentation-driven approach was presented in [46] using a novel UNet-based architecture termed BLSNet. The model integrated an attention mechanism and multi-scale feature extraction to improve the accuracy of lesion segmentation. The results demonstrated high segmentation and classification accuracy in the automatic estimation of BLS disease severity. However, an advanced dataset segmentation model can be implemented for many diseases on several plant varieties with different severity levels.

7 Analysis and synthesis of the study

Tables 1, 2, 3 and 4 summarize articles published between 2020 and 2025 years on the application of deep learning (DL) to the detection and classification of plant diseases. This work covers a variety of crops, datasets, and models, providing a comprehensive overview of current trends, performance, and limitations. Leaves are the main organ studied (78.26% of cases), fruits are analyzed in 13.04% of cases, and other parts of plants remain largely unexplored.

Since 2022, there has been a notable acceleration in research, particularly around CNN, ResNet, YOLO, and DenseNet architectures as shown in figure 2. The heavy reliance on standardized datasets, captured under controlled conditions (homogeneous backgrounds, uniform lighting, used in 46% of studies), introduces a major methodological bias. Models trained on these data often perform very well (>97%) as shown in table 1 but do not generalize well in real-world conditions.

The used models were grouped into three categories: direct and variant CNNs, derived or optimized CNNs consisting of VGG, ResNet, DensNet, MobileNet, and Inception, and fast detection CNN models consisting of YOLLO, DCNN, and SqueezeNet models as illustrate in figure 4.

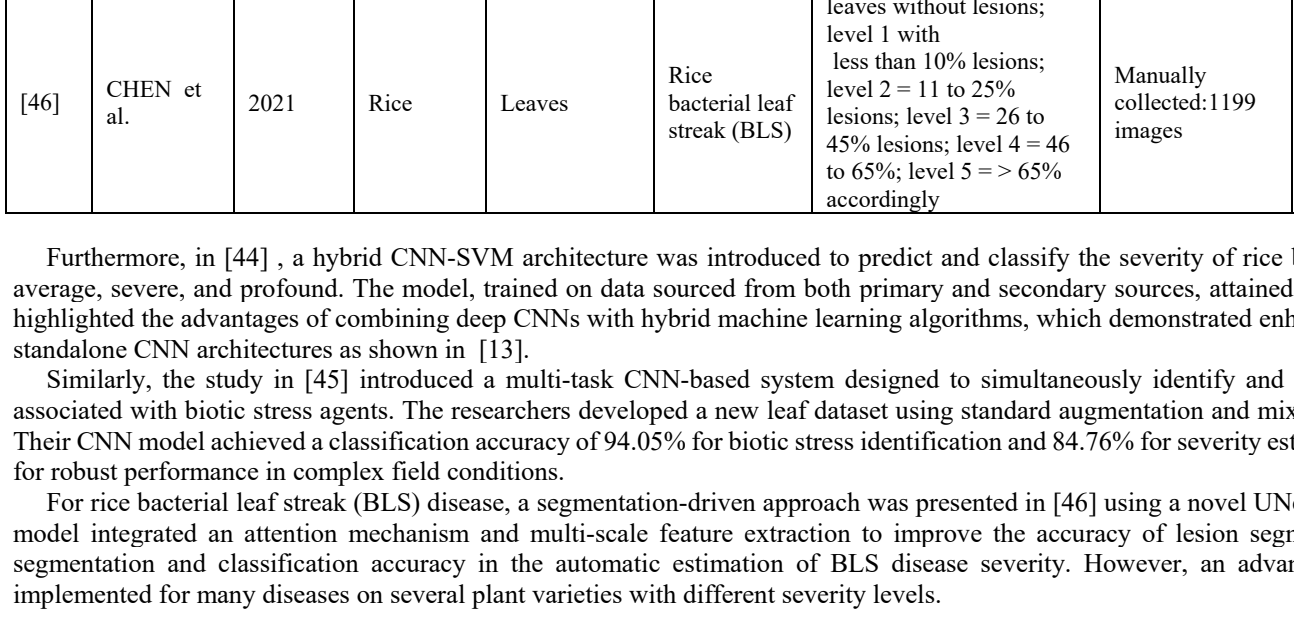

Fig.4. Models performance comparison used

The majority of studies rely on CNNs and their variants: 45.3% of articles use classic CNNs, 39.22% use derived or optimized architectures, and 8.7% use fast detection models as shown in Figure 4. CNNs remain dominant, but there is a growing adoption of lightweight and hybrid models adapted to real-world or embedded environments (drones, mobile devices, IoT sensors) as shown in figure 4. Simple YOLO and CNN models, with accuracies of 90-95%, are nevertheless better suited to early detection in real time, integrating spatio-temporal and climatic conditions.

The reported accuracies range from 80% to 100%, as shown in Tables 1, 2,3 and 4, with an overall average accuracy of 93.22%, as shown in the figure 4. However, this average precision masks the stability and variability linked to the diversity of data and metrics used. The results reveal a strong reliance on public datasets (50%), due to their accessibility and standardization. However, the low proportion of data collected under real-world conditions (31.25%) highlights a significant limitation: the models are still primarily developed using idealized images, which can reduce their robustness and performance in real and diverse agricultural environments.

A critical analysis reveals that studies based on PlantVillage achieve an average accuracy of 95.2%, compared to 96.09% for real-world data found in the study. This suggests a possible overestimation of performance due to the high standardization of public databases. While these databases remain essential for assessing model robustness thanks to their homogeneity and controlled diversity, they do not always capture the complexity of agricultural environments. Conversely, data collected under real-world conditions perform well in specific contexts but have a more limited capacity for generalization. These findings highlight the need to develop more diverse databases, conduct multi-source quantitative analyses, and strengthen field validation to improve the reliability and transferability of artificial intelligence models in agriculture. However, biases related to data variability persist.

8 Limitations of proposed solutions and potential challenges

The proposed solutions based on deep learning (DL) offer considerable potential for detecting, classifying, and assessing the severity of plant diseases. These innovations hold promise for improving crop health management by farmers, which will increase agricultural productivity and contribute to global food security in the context of population growth. However, several significant limitations must be overcome in order to improve the robustness and generalization of these solutions:

- Ensure that the models are capable of generalizing across diverse environmental conditions, including variations in light, climate, and soil.
- With advancements in agricultural tools and intelligent sensors, integrating deep learning (DL) solutions with Internet of Things (IoT) systems, smart embedded technologies, and drones can facilitate automated, real-time detection of plant diseases across vast agricultural areas, ultimately enhancing crop productivity [23, 48,54].
- Plant diseases can affect all parts of a plant, including the leaves, flowers, stems, and fruits. Most existing studies, however, have primarily focused on leaves, with only a limited number addressing fruits or considering multiple diseases that may occur on the same leaf. Furthermore, identifying the various stages of disease progression is crucial for effective monitoring and management [38] .
- Most of the studies reviewed utilized public datasets. However, due to the unavailability of such datasets and the absence of real-world fieldwork scenarios, the provided data may lack relevance compared to datasets collected directly from the field [32].
- The reviewed studies did not encompass different crop varieties [1].
- The learning models employed were designed to detect plant diseases using a single leaf rather than multiple leaves [47] .
- A key limitation of the applied models is their inability to simultaneously identify and classify plant diseases [38].
- These solutions for assessing and estimating severity should be applied to several other diseases of cultivated plants such as beans.

Conclusion and future work

Deep learning solutions are used to ensure early identification and classification of plant diseases. This helps to increase agricultural production and ensure global food security. These solutions have advanced significantly thanks to applications developed by artificial intelligence researchers, enabling farmers to intervene more quickly in the field. This article provides a focused review of plant disease detection and classification solutions developed over the past five years, highlighting the widespread adoption and effectiveness of deep learning models. It addresses a wide range of plant diseases, examines the underlying algorithms, and the benefits of early disease detection and severity assessment.

A comparison of related work using deep learning models in plant disease identification was presented, examining the impact of the dataset size in influencing average accuracy. These innovations hold promise for improving farmers' crop health management, thereby improving agricultural productivity and contributing to global food security in a context of population growth. Thus, quantitative analysis of studies published in the literature highlights significant scientific progress in the application of deep learning to plant disease detection. However, a critical analysis was conducted, highlighting the limitations of existing solutions and priority areas for improving the robustness and reliability of these research solutions. . Between 2020 and 2025, research on Deep Learning (DL) for plant disease detection has covered a wide range of crops, plant parts, and databases. Leaves are the primary focus, highlighting their key role in visual diagnosis. Since 2022, studies have increased but still rely heavily on standardized datasets, limiting real-world applicability. CNN architectures and variants dominate the field though lightweight and hybrid models are emerging for embedded use. Reported models performances range from 80% to 100% with global averaging accuracy of 93.13%, showing DL's high effectiveness in phytopathology.Despite strong results, model robustness and transferability remain challenges. Environmental variability further complicates generalization. Overall, DL shows promise but requires adaptation for practical agricultural deployment. Future research will focus on bean diseases, which are the most widely produced and traded staple food in developing countries after cereals, while examining the influence of climatic and environmental conditions. However, in order to improve the reliability of future research, it is recommended to:

- Implement standardized quantitative comparative analyses, incorporating indicators such as accuracy, precision, recall, F1 score, and mAP, in order to objectively evaluate model performance.
- Combine field data with public databases to limit biases resulting from controlled experimental environments databases and to increase the diversity and representativeness of training data.
- Design multimodal and transferable models capable of generalizing their performance to different plant species and various environmental contexts.
- Strengthen scientific reproducibility by ensuring open access to the codes, models, and datasets used.
- These solutions for assessing and estimating severity should be applied to several other diseases of cultivated plants such as beans.

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