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Towards an Improved Deep Learning Plant Disease Doctor for Sustainable Food Security: A Comprehensive Survey

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ABSTRACT
The global agricultural sector faces persistent challenges from plant diseases, which threaten food security, economic stability, and sustainable agriculture. Traditional methods of disease diagnosis, reliant on manual scouting by human experts, are often slow, labour-intensive, and prone to error. The advent of deep learning, a subset of artificial intelligence, has catalysed a paradigm shift in how plant diseases are detected and diagnosed. This paper surveys this transformation by synthesising recent advancements in deep learning architectures, primarily Convolutional Neural Networks, as well as Transformers and generative models, for automated plant disease detection and classification using visual data (e.g., leaf images). The paper meticulously outlines the standard pipeline, encompassing data acquisition, preprocessing, model training, and deployment. Furthermore, it highlights critical challenges such as the need for large, curated, and diverse datasets, model generalisation across different environmental conditions, and the path towards real-world deployment in the form of AI-powered Plant Doctor systems. Finally, future research directions, including the integration of multimodal data and explainable AI, are critically discussed. Findings show that deep learning is poised to revolutionise plant disease management, enabling precise, rapid, and scalable diagnostics for farmers worldwide.

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INTRODUCTION

Plant diseases are a significant cause of crop yield loss, estimated to result in annual global economic damages exceeding $200 billion (Savary et al. 2019). Three primary elements contribute to the development of diseases in plants: a conducive environment, the presence of a pathogen, and the host plant itself. Typically, symptoms of diseases first appear at the lower parts of the plant and then progress upwards. Once infection occurs, many diseases can spread rapidly throughout the crop, making regular crop monitoring essential. Early intervention can help control and reduce the proliferation of the disease.

In some scenarios, diseases may become apparent only later in the growing season, often after the pollination stage. Plant diseases vary widely and affect different organs, but those that manifest on leaves, classified as foliar diseases, tend to present the most recognisable symptoms that can be visually identified by plant pathologists. Notably, fungal infections are a major cause, responsible for nearly half of crop yield losses (Hosain et al. 2024). As a result, contemporary research often relies on analysing images of plant leaves using computer vision, machine learning, and deep learning techniques to detect diseases (Ochijenu et al. 2025)

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An effective diagnosis framework for plant diseases involves not only early detection within the growing season but also the ability to identify multiple diseases across various crops simultaneously, gauge the disease severity, determine the optimal amount of pesticide to apply, and suggest management practices to limit the disease spread (Hosain et al. 2024. Accurate identification of plant diseases plays a crucial role in precision agriculture and plant phenotyping, both fields that depend heavily on data, technology, and information (Li et al. 2025). Hence, early and accurate detection is the first and most crucial step in implementing effective management strategies to mitigate low plant yields. For centuries, diagnosis has depended on the expertise of agricultural pathologists and farmers visually inspecting plants for symptoms. This method, while valuable, is inherently limited by its subjectivity, scalability, and the scarcity of experts, especially in remote regions.

To address these limitations, researchers have turned to image processing approaches using plant images. One of the pioneering works in this field, dating back to 1983, employed black-and-white imaging of leaves from potted tomato and blackened fern plants for automated disease assessment (Lindow & Webb, 1983). Additionally, image analysis methods have been applied to quantify diseases, such as streak disease in corn (Martin et al. 1998), with computerised approaches proving more precise than traditional visual methods. Over the last three decades, image processing has gained traction in plant disease diagnosis because it offers an objective approach. Nevertheless, this approach requires manual extraction of features, which is time-consuming and can be subjective, as different researchers might prioritise different features.

Approximately two decades ago, machine learning began to be explored for identifying plant diseases. Early studies reviewed the potential of machine learning in agriculture, with techniques like support vector machines (SVM), random forests, and K-nearest neighbours (KNN) being used to detect diseases on crops such as tomato and soybean. These methods were employed to both detect diseases and assess their severity. For example, SVM, KNN, and Naïve Bayes classifiers were utilised for detecting tomato powdery mildew, while forecasting models were proposed for predicting disease outbreaks (Bhatia et al. 2022). Despite these advancements, classical machine learning still depended heavily on manually extracted features for training, which was a labour-intensive step.

Moreover, both image processing and machine learning approaches often performed well only under specific conditions and had limited generalizability. Hence, a paradigm shift toward deep learning techniques. Unlike classical approaches, deep learning automates feature extraction and delivers higher accuracy (Idakwo et al. 2024). This approach has become more prevalent due to advances in computational power, data storage, and the availability of large annotated datasets. Since the breakthrough success of deep learning models at the ImageNet competition in 2012, researchers from diverse fields have increasingly adopted these techniques for plant disease detection (Ferentinos et al., 2018). Furthermore, the digital revolution in agriculture, fueled by the proliferation of smartphones and drones, has generated vast amounts of visual data from fields.

Concurrently, breakthroughs in the field of deep learning (DL), particularly in computer vision, have provided the tools to analyse this data with superhuman accuracy and speed. This confluence has given rise to a new paradigm: the AI-powered Plant Doctor. These systems leverage deep learning models to automatically analyse images of plants and provide instant, preliminary diagnoses, much like a medical doctor analysing an X-ray. The contributions of this paper are highlighted:

1. **Traces the chronological shift** from traditional techniques to modern deep learning-based approaches in plant disease detection.
2. **Provides a systematic overview** of the dominant deep learning architectures and methodologies employed in recent literature.

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3. **Outlines the standard development pipeline** for building a DL-based plant disease diagnosis system, from data acquisition to model deployment.
4. **Identifies and critically discusses** the major challenges and limitations that hinder progress in the field.
5. **Proposes future research directions** aimed at addressing these challenges and enabling the development of scalable, automated Plant Doctor systems.

PLANT DISEASES SYMPTOMS AND TYPES

It is to understand the various plant disease types and symptoms before developing any model that can effectively detect and forecast the presence of disease. Plant diseases arise from abnormal behaviour or physiological changes, caused by either biotic or abiotic factors (Picon et al. 2019), as illustrated in Figure 1.

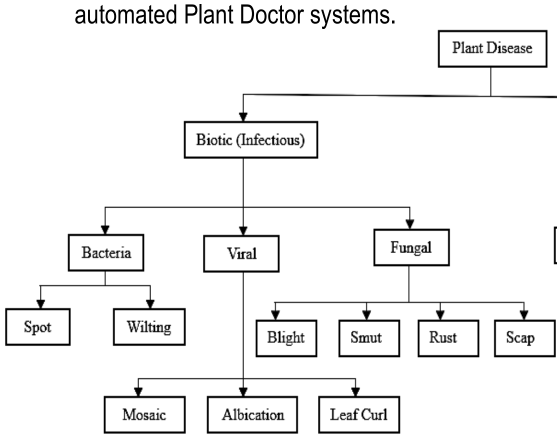

Figure 1: Plant Classification

Biotic diseases result from infectious agents, while abiotic diseases are caused by non-infectious factors. Abiotic diseases are generally less hazardous and often preventable due to their non-transmissible nature. This study focuses specifically on biotic diseases.

1. **Bacterial Disease:** Bacterial infections in plants typically start as small, water-soaked green spots that enlarge and eventually turn into dry, dead lesions, as illustrated in Figure 2(a). Examples include black or brown leaf spots and yellow halos of similar size. These blemishes often appear as speckles under dry conditions. In brinjal crops, bacterial wilt is particularly destructive, causing the entire plant to collapse (Ayaz et al. 2023).
2. **Viral Disease:** Viral infections are among the most challenging plant diseases to study. Symptoms may be subtle and mimic those of herbicide damage or nutrient deficiencies, making detection difficult (Poudel et al. 2021). Viral diseases are commonly transmitted by insects such as beetles, leafhoppers, aphids, and whiteflies. A notable example is the mosaic virus, which produces green or yellow streaks on the foliage, as illustrated in Figure 2(b).
3. **Fungal Disease:** Fungal infections can affect multiple parts of a plant, including causing sclerotium wilt, crown rot, stem rust, eyespot (on stems or sheaths), rust, leaf blight, ergot (on spikes), carnal bunt, and black point (on seeds). Late blight, caused by *Phytophthora* species, typically appears on older leaves as grey-green, water-soaked spots, as shown in Figure 2(c). This fungus thrives under fluctuating wet and dry conditions, and as the disease progresses, the spots darken and white fungal growth appears on the surface (Ayaz et al. 2023). Early blight, caused by *the Alternaria species, manifests on older leaves as small, brown spots with a*

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characteristic bull's-eye pattern of concentric rings, as shown in Figure 2(d). Rust fungi develop on mature leaves, forming lesions on the upper surface that turn black after initially appearing green-yellow, as depicted in Figure 2(e).

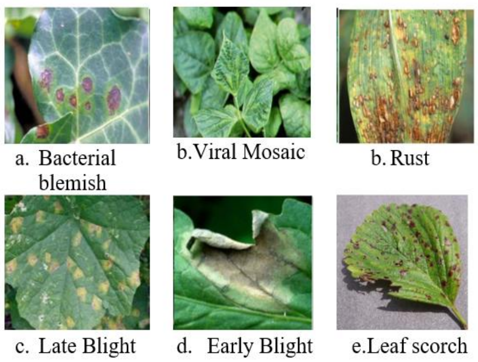

Figure 2: Various Plant Diseases

THE RISE OF DEEP LEARNING

Early attempts at automated disease detection used traditional machine learning techniques like SVMs and k-Nearest Neighbours (k-NN). The conventional approach employed in traditional image recognition processing technology to identify plant diseases is shown in Figure 3.

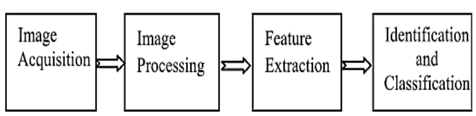

Figure 3: Classical Approach in Image Processing

Accurate identification of plant diseases through leaf images basically involves several stages. The process begins with image acquisition and preprocessing, followed by feature extraction, and concludes with applying classifiers for disease recognition.

Image Acquisition

The initial step is the acquisition of image datasets. Several publicly available benchmark datasets support plant disease research. While some are from a controlled environment, others are from the field. Unfortunately, the performance of machine learning (ML) models is significantly affected by the quality and nature of the input data, such as whether images are captured in controlled laboratory settings or in natural field conditions. Images taken under controlled conditions usually involve a single leaf placed against a uniform, artificial background, as seen in datasets like PlantVillage. These controlled datasets often enable high accuracy in classification tasks, but collecting such data is both time-intensive and expensive.

In contrast, field images present a far greater challenge due to their complexity, which includes multiple leaves, various plant parts, diverse lighting and shading, as well as heterogeneous backgrounds and ground textures (Idakwo et al., 2024). Research shows that ML models trained solely on laboratory images perform poorly when applied to field images, rendering them ineffective for practical field applications. Conversely, models trained on field images tend to perform reasonably well when tested with laboratory images. Including field images in the training process substantially improves model performance, but it is still recommended to evaluate models with images from different data sources for robust results.

Some of the widely known public plant disease datasets are PlantDoc (Ochijenu et al,2025), PlantVillage (Ahmad et al., 2024), Cassava, Hops, Cotton, and Rice.

1. **Cassava dataset** contains five classes, including cassava mosaic disease, bacterial blight, brown streak, green mite, and healthy samples, with images collected directly from field conditions (Oyewole et al. 2021). This dataset can be used to train a deep learning model for real field cassava disease detection. The images in the respective disease class are imbalanced, as shown in Table 1.

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Table 1: Cassava Dataset Summary

Class	Images
Healthy	316
Healthy blight	466
Brown Streak	1,443
Green Mite	773
Mosaic Disease	2,658

2. **Cotton dataset** comprises 2,137 images of cotton leaves at different stages of health and disease, collected from the National Cotton Research Institute field in Gazipur. The images cover both healthy leaves and those affected by bacterial blight, curl virus, herbicide-induced damage, leaf hopper (jassids) infestation, reddening, and variegation. The images were taken using a Redmi Note 11s smartphone in three resolutions: 3000 × 4000, 2239 × 2239, and 1597 × 1597 pixels, providing variation in spatial detail. Data collection was carried out through field surveys between October 2023 and January 2024, under the supervision of domain experts to ensure accurate disease identification. Furthermore, images were taken under diverse environmental conditions and at different growth stages of cotton plants, enabling a comprehensive representation of natural disease manifestations in field settings (Bishshash et al. 2024).
3. **Rice dataset** captures four disease types: bacterial blight, blast, brown spot, and tungro, collected in natural field environments with image distributions as presented in Table 2.

Table 2: Rice Dataset Summary

Leaf Disease	Images
Bacterial Blight	1584
Blast	1440
Brown Spot	1600
Tungro	1308
Total	5932

4. **PlantDoc**

Unlike PlantVillage, whose images are from a controlled environment, the PlantDoc major images were obtained from the real agricultural field environment. The PlantDoc contains 2,598 images covering 17 plant diseases across 13 crop types (Ochijenu et al. 2025). The diversity in acquisition settings provides opportunities to develop more robust deep learning models for disease detection. Nevertheless, certain images depict multiple infected leaves or even entire plants, which may hinder the models' ability to capture distinctive disease features. Moreover, PlantDoc is highly imbalanced, with many classes containing fewer than 200 samples, as outlined in Table 3. Due to these limitations, achieving high accuracy with deep learning approaches on this dataset is taxing.

Table 3: PlantDoc Dataset Summary

Crop	Disease	Images
Apple	Healthy	91
	Scab	93
	Rust	89
Bell pepper	Healthy	61
	Leaf Spot	71
Blueberry	Healthy	117
Cherry	Healthy	57
Corn	Leaf Blight	192
	Grey Leaf Spot	68
	Rust	116
Grape	Healthy	69
	Black Rot	64
Peach	Healthy	112
Potato	Early Blight	117
	Late blight	105
Raspberry	Healthy	119
Soybean	Healthy	65
Squash	Powdery Mildew	130
Strawberry	Healthy	96
Tomato	Healthy	63
	Bacterial Spot	110
	Early Blight	88
	Late Blight	111
	Leaf Mold	91
	Septoria Leaf Spot	151
	Mosaic Virus	54
	Yellow Virus	76
	Spider Mite	2

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5. **PlantVillage** dataset contains 54,309 images captured under controlled laboratory conditions, covering 38 disease classes across 14 plant species such as apple, corn, grape, tomato, and potato. It includes both healthy and diseased samples, e.g., apple scab, grape black rot, corn leaf blight, and tomato yellow curl virus. Since its release, it has become the most widely utilised resource for training and developing deep learning models aimed at plant disease detection and severity assessment (Ahmad et al.2024). Nevertheless, because the dataset does not fully reflect real-field conditions, models trained solely on these images often struggle to generalise effectively to field-based data (Ochijenu et al. 2025). Another limitation of PlantVillage is its **class imbalance (Idakwo et al. 2024)**. Visual inspection has also revealed overlapping features between certain disease categories. For instance, some images labelled as **Grey Leaf Spot (GLS)** also show symptoms of **Northern Leaf Blight (NLB),** which can introduce confusion and degrade the performance of deep learning classifiers. The PlantVillage dataset summary is given in Table 4.

Table 4: PlantVillage Dataset Summary

Crop	**Disease**	**Images**
Apple	Healthy	1,645
	Black Rot	621
	Cedar Apple Rust	275
	Apple Scab	630
Blueberry	Healthy	1,502
Cherry	Healthy	854
	Powdery Mildew	1,052
Corn	Healthy	1,162
	Grey Leaf Spot	513
	Common Rust	1,192
	Northern Leaf Blight	985
Grape	Healthy	423
	Black Rot	1,180
	Black measles	1,383
	Isariopsis Leaf Spot	1,076
Orange	Citrus Greening	5,507
Peach	Healthy	360
	Bacterial Spot	2,297
Bell Pepper	Healthy	1,478
	Bacterial Spot	997
Potato	Healthy	152
	Early Blight	1,000
	Late Blight	1,000
Raspberry	Healthy	371
Soybean	Healthy	5,090
Squash	Powdery Mildew	1,835
Strawberry	Healthy	456
	Leaf Scorch	1,109
Tomato	Healthy	1,592
	Bacteria Spot	2,127
	Early Blight	1,000
	Late Blight	1,909
	Leaf Mold	952
	Septoria Leaf Spot	1,771
	Spider Mites	1,676
	Target Spot	1,404
	Yellow Leaf Curl	5,357
	Mosaic Virus	373

6. **Hops dataset** consists of five categories, including downy mildew, powdery mildew, nutrient deficiency, pest infection, and healthy leaves, often with complex, nonuniform backgrounds (Arora & Gautam, 2023).
7. **Cotton dataset** comprises 2,137 images of cotton leaves at different stages of health and disease, collected from the National Cotton Research Institute field in Gazipur. The images cover both healthy leaves and those affected by bacterial blight, curl virus, herbicide-induced damage, leaf hopper (jassids) infestation, reddening, and variegation. The images were taken using a Redmi Note 11s smartphone in three resolutions: 3000 × 4000, 2239 × 2239, and 1597 × 1597 pixels, providing variation in spatial detail. Data collection was carried out through field surveys

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between October 2023 and January 2024, under the supervision of domain experts to ensure accurate disease identification. Furthermore, images were taken under diverse environmental conditions and at different growth stages of cotton plants, enabling a comprehensive representation of natural disease manifestations in field settings (Bishshash et al. 2024).

8. **iNaturalist & PlantCLEF:** Large-scale datasets that include a wider variety of plant species and diseases in natural environments. It contains about 859,000 images covering more than 5,000 species of plants and animals. It includes many visually similar species photographed in diverse environments across the globe. The images come from different types of cameras, vary in quality, show a significant imbalance among classes, and have been validated through contributions from multiple citizen scientists (Van Horn et al. 2018).

In addition to these standard datasets, some researchers also construct custom datasets for their studies.

Preprocessing

Preprocessing is crucial for image quality enhancement and preparing data for analysis. Basic preprocessing steps entail colour space conversion, resizing to a uniform scale, noise reduction, morphological adjustments, and disease region segmentation. Noise reduction can be achieved through filters such as Wiener, median (Park et al. 2020), or Gaussian (Tripathi et al. 2025). Multiple colour models, including RGB, HSV, CIE L*a*b* (Sghair et al. 2017), and YCbCr, are frequently applied for effective image analysis. To isolate the region of interest (ROI), segmentation methods such as colour thresholding (Chuanlei et al. 2017), Sobel edge detection (Yusoff et al. 2018), Otsu's method (Dutta et al. 2022), and K-means clustering (Javidan et al. 2023) are often used.

Feature Extraction

Feature extraction transforms visual disease patterns into numerical representations, enabling efficient classification. An ideal feature set should capture the distinct characteristics that separate one disease class from another. Features are commonly grouped into colour, texture and shape as depicted by Figure 3.

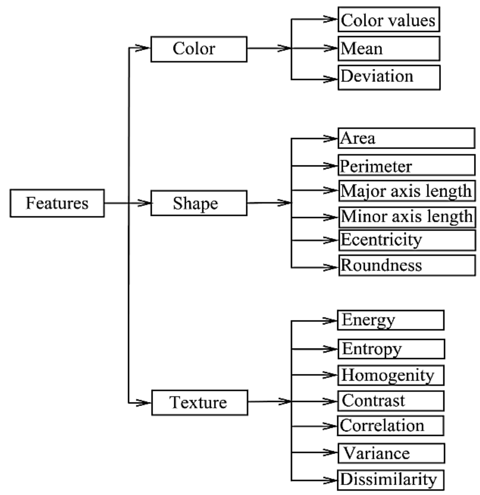

Figure 3 Common Features Categories for Plant Disease Detection Methods

Colour features-Based Disease Detection.

This method focuses on extracting chromatic attributes from infected regions of leaves. For example, Sghair et al. (2017) explored multiple colour models for plant disease detection. The plant's leaf images were converted into YCbCr, HSI, and CIE L**a**b* spaces, followed by noise reduction using median filtering. Segmentation of the diseased spots was carried out using Kapur's thresholding, applied specifically to the Cr component of YCbCr, the H component of HSI, and the A component of CIE L*A*B*. Similarly, Singh (2018) proposed a colour-slicing approach for detecting blast disease in paddy. In this approach, RGB images were first converted into the HSI colour space, and then the diseased regions were isolated through colour slicing while suppressing the unaffected parts.

When compared with edge-based boundary detection techniques such as Sobel and

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Canny, this approach achieved an accuracy of 96.6%. Furthermore, Khan et al. (2019) proposed preprocessing, spot segmentation with feature extraction, and classification as the new stage pipeline in identifying and recognising apple leaf diseases. In the preprocessing stage, a hybrid enhancement technique was employed by combining 3D box filtering, decorrelation, 3D Gaussian, and 3D median filters to improve the quality of diseased regions on the leaves. Lesion segmentation is then carried out using a strong correlation-based approach, further refined through Expectation Maximisation (EM) segmentation.

For feature representation, colour, colour histogram, and Local Binary Pattern (LBP) features were combined using a parallel fusion strategy. These features were subsequently optimised with a genetic algorithm before classification was performed using a One-vs-All Multi-class Support Vector Machine. The methodology was evaluated on the PlantVillage dataset across four categories: healthy leaves, Black rot, Rust, and Scab. The results indicated that the proposed approach achieved improved classification accuracy compared to existing methods. The study highlighted that effective preprocessing contributes significantly to feature quality, thereby enhancing overall recognition performance. Basavaiah and Arlene (2020) focused on creating an efficient approach for detecting tomato leaf diseases with an emphasis on boosting classification accuracy while minimising computational cost.

The key innovation lies in combining different feature sets to enhance recognition performance. Specifically, colour histograms, Hu Moments, Haralick features, and Local Binary Patterns were extracted and applied in both training and testing stages. For classification, decision tree and random forest algorithms were employed. Experimental findings revealed that random forest delivered superior results compared to decision trees, achieving an accuracy of 94%, while the decision tree method reached 90%.

Ahmad et al. (2021) introduced an automated system for detecting plant diseases through a structured process comprising image pre-processing, segmentation of infected regions, extraction of colour and texture features using the Grey-Level Co-occurrence Matrix (GLCM), feature selection, and classification. A total of six colour and twenty-two texture features were evaluated, with support vector machines applied for one-vs-one disease classification. The approach achieved a high accuracy of 98.79% (±0.57) under tenfold cross-validation, while testing on a self-collected dataset yielded 82.47% accuracy for disease recognition and 91.40% for differentiating healthy from infected leaves. Patil et al. (2024) presented a content-based image retrieval (CBIR) framework designed for detecting and classifying leaf diseases by combining colour and texture features. The system applied advanced image processing techniques to enhance accuracy. The developed system was tested primarily on maize leaves affected by blight and rust, two diseases known for their prevalence and impact on yield. Experimental evaluation shows a detection accuracy of 98.33%, demonstrating its reliability for precision agriculture. The dual use of texture and features enhances disease characterisation, enabling the system to distinguish between multiple diseases with high precision.

Li et al (2025) presented an automated system for identifying apple leaf diseases using image processing, artificial intelligence, and ant colony optimisation (ACO). The method involved background removal, diseased area detection, extraction of texture, colour, and shape features, feature selection with ACO, and final classification using an SVM. The results showed an overall accuracy of 92.5%, with texture features contributing most to performance. The approach demonstrates an effective and scalable solution for accurate disease detection in precision agriculture. Nevertheless, colour-based approaches often struggle with reliability because leaf colour can be influenced by external factors such as lighting conditions, camera quality, and background noise. In addition, different diseases may produce similar colour changes, making it difficult to distinguish between them using colour information alone. As a result, this method may

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lead to reduced accuracy and poor generalisation when applied in diverse real-world environments.

Texture and Shape-Based Features for Disease Detection

The shape-based characteristics of leaves are another feature used in detecting plant disease. Islam et al. (2017) proposed a method for detecting potato diseases (late blight, early blight, and healthy leaves) by first masking the background and healthy green regions using thresholds in the L*a*b* colour space. The region of interest was then isolated, and texture features from the GLCM (e.g., contrast, correlation, homogeneity, energy) along with statistical features (mean, entropy, standard deviation, skewness) were extracted. A multiclass SVM classifier was trained using the PlantVillage dataset; however, challenges included difficulties in threshold selection, a small dataset size, and uniform backgrounds, which limited its real-world applicability. Similarly, Bhimte et al. (2018) applied K-means clustering for segmentation, followed by wavelet transforms, PCA, and machine learning classifiers (BPNN, SVM) to detect cotton plant diseases. Their models achieved accuracies of 97% and 98.46%, respectively, but were trained on limited datasets, and feature selection remained a significant challenge.

Zhang et al. (2018) introduced a hybrid-based approach for plant leaf disease segmentation and recognition by integrating superpixel clustering, K-means clustering, and a pyramid of histograms of oriented gradients (PHOG). In the framework, diseased leaf images were first divided into compact superpixels, after which K-means clustering was applied to isolate lesion regions within each superpixel. PHOG features were then extracted from the colour components and grayscale version of the segmented images, and the resulting descriptors were combined into a single feature vector. Experimental validation on two plant disease image datasets demonstrated that the method achieved effective segmentation and accurate recognition, highlighting its potential as a practical solution for smart agricultural monitoring.

Furthermore, Zang et al. (2019) employed a hybrid clustering technique, where colour images of leaves were first divided into compact, uniform superpixels. These superpixels served as clustering cues that enhanced the efficiency and speed of the expectation maximisation (EM) algorithm. Using EM, diseased regions were then accurately separated from each superpixel. Experimental evaluations, along with comparisons to existing methods, confirmed that this technique achieved fast and precise segmentation, making it highly effective and valuable for practical applications in plant disease detection. To resolve the redundancy or irrelevant features which often reduce the accuracy and efficiency of plant disease models, Kumar et al. (2020) proposed an Exponential Spider Monkey Optimisation (Exponential SMO) approach for selecting the most relevant features from SPAM-generated data. The refined feature set was processed using an SVM to distinguish between healthy and diseased plants. Experimental results show that the Exponential SMO enhances both computational efficiency and classification accuracy.

Mathew et al. (2021) developed an approach for classifying three major foliar diseases in banana plants using local texture features. The process begins with image enhancement and colour-based segmentation to isolate diseased regions, followed by conversion of the segmented images into transform domains through DWT, DTCWT, and Ranklet transforms. Texture features were extracted using LBP and its variants (ELBP, MeanELBP, and MedianELBP) and evaluated with five different classifiers under a ten-fold cross-validation scheme. Results show that ELBP features derived from the DTCWT domain achieved the highest performance, recording 95.4% accuracy alongside strong precision, sensitivity, specificity, and F-score values. The combination of DTCWT and ELBP features significantly outperforms conventional feature extraction techniques, enabling accurate and early detection of fungal diseases in banana leaves.

Archana et al. (2022) presented a modified K-means segmentation approach that

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isolated infected regions in rice leaves, followed by the extraction of colour, texture, and shape features. A novel SVM-based probabilistic neural network (NSVMBPNN) was employed for classification, outperforming naïve Bayes, SVM, and PNN. Validated with fivefold cross-validation, the method achieved high accuracy, with up to 99.20% for healthy leaves and above 95% for various rice diseases. Wang et al. (2023) investigated early detection of grey mould in strawberries using hyperspectral imaging. Spectral features, vegetation indices, and textural features were extracted and refined through feature selection approaches. Machine learning models (ELM, SVM, and KNN) achieved strong results, with combined feature models reaching 93.33–96.67% accuracy. The study confirms that integrating multiple features significantly improves early and accurate recognition of grey mould in strawberry leaves. Ahmad et al. (2024) introduced a new feature descriptor, the Local Triangular-Ternary Pattern (LTriTP), for detecting plant leaf diseases from images.

The method uses triangular shape descriptors and a dynamic threshold to capture detailed texture information, while a Triangular Histogram of Gradient (T-HOG) ensures orientation invariance by analysing gradient changes in multiple directions. By fusing LTriTP and T-HOG features, the approach improves disease recognition across six tomato leaf disease classes from the PlantVillage dataset. Compared with established techniques such as Local Binary Pattern and Local Ternary Pattern, the proposed method achieved superior classification accuracy, ranging from 94.50% to 97.80%, with error rates as low as 2.03%. Tripathi et al. (2025) presented a hybrid classification model that utilises a stage-based pipeline: preprocessing with Gaussian filtering, segmentation using the MBIRCH framework, feature extraction (including GLCM, ILGBHS, colour, shape, and deep features via VGG16 and AlexNet), and classification. The hybrid model combined Bi-GRU and DCNN with transfer learning for the plant disease predictions.

Overall, shape- and texture-based disease detection methods reveal several recurring issues. Preprocessing steps are often extensive, which adds to the overall complexity of the process. Segmenting diseased regions in cluttered or natural backgrounds also remains a significant challenge. In addition, feature extraction and selection tend to be labour-intensive, particularly when working with large datasets. Furthermore, many studies rely on small, uniform datasets with limited disease categories, thereby restricting the generalisability of the results. Generally, the classical machine methods in plant disease symptom detection from their image often face challenges in recognising subtle disease symptoms, detecting early-stage infections, and handling complex, high-resolution images effectively (Idakwo et al. 2024). Thus, it was often brittle and failed to generalise to complex, real-world conditions. The breakthrough came with the application of Convolutional Neural Networks (CNNs), which automatically learn hierarchical and discriminative features directly from raw pixel data. The seminal work of Ferentinos (2018), which utilised a large dataset of leaf images (PlantVillage), demonstrated that CNNs could achieve accuracy exceeding 99% in classifying a wide range of diseases under controlled conditions. This study served as a proof-of-concept and ignited widespread research in the area.

Identification and Classification

In every plant disease detection system, identification and classification are the two interrelated tasks that are commonly performed. Identification entails determining whether a plant is healthy or diseased, while classification assigns the diseased sample to a specific category, such as bacterial blight, grey mildew, or leaf curl in cotton plants. These processes form the foundation of intelligent agricultural monitoring systems, where accurate diagnosis directly influences treatment strategies, yield protection, and resource management.

To evaluate the effectiveness of identification and classification models, a range of performance metrics is employed. The confusion matrix provides a detailed account of correct and incorrect predictions across all classes, enabling

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the detection of patterns in misclassification, especially between visually similar diseases.

1. **Accuracy** evaluates the overall proportion of correctly identified samples, making it useful for the initial healthy-versus-diseased identification stage. However, accuracy alone may be insufficient in cases of class imbalance, where certain diseases occur less frequently. Accuracy is mathematically expressed as given equation (1)

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Where Acc refers to the accuracy
TP is a true positive
TN is a true negative
FP is a false positive
FN is a false negative

2. **Precision** is particularly relevant during classification, as it quantifies how many samples predicted as belonging to a specific disease category are actually correct. This reduces the likelihood of false alarms. Precision is mathematically given by equation (2)

$$Pre = \frac{TP}{TP + FP} \times 100 \quad (2)$$

Where Pre is precision

3. **Sensitivity or Recall**: On the other hand, recall (sensitivity) is essential in disease identification, as it ensures that the majority of diseased plants are correctly detected, minimising the risk of overlooking infections. The recall is expressed as given in equation (3)

$$Rec = \frac{TP}{TP + FN} \times 100 \quad (3)$$

Where Rec is Recall

4. **F1 score:** The F1 score, as the harmonic mean of precision and recall, provides a balanced assessment, which is especially valuable when dealing with multiple disease classes that exhibit similar visual features. The F1-score is mathematically expressed in equation (4)

$$F1 - score = \frac{2 * (Pre * Rec)}{Pre + Rec} \quad (4)$$

Deep Learning Model-Based Plant Disease Detection

In recent years, deep learning (DL) has experienced rapid growth, particularly in computer vision applications such as object detection, pattern recognition, classification, and biometric systems (Idakwo et al. 2023). DL models have demonstrated remarkable success in image recognition tasks, with notable achievements in benchmarks such as the ImageNet Challenge. These advances have also been extended to agriculture, supporting applications in plant ripeness and sorting systems (Idakwo et al. 2024), disease detection (Ochijenu et al. 2025), pest recognition (Suzauddola et al. 2025), fruit classification (Wang et al. 2025), and weed detection (Goyal et al. 2025).

A key advantage of DL is that it eliminates the need for manual segmentation and feature extraction, as models can automatically learn discriminative features directly from raw images (Idakwo, 2022). For instance, Kawasaki et al. (2015) applied a convolutional neural network to detect two cucumber diseases, melon yellow spot virus (MYSV) and zucchini yellow mosaic virus (ZYMV). They used image rotation to augment the dataset and reported an accuracy of 94.9%, noting that larger datasets improved performance. Their later work, Fujita et al. (2016), extended this approach to identify seven cucumber diseases using two CNN architectures trained on images captured under varied conditions, such as different lighting, distances, and angles. Data augmentation methods, including shifting, rotation, and mirroring, were employed. CNN-2, trained on both high- and low-quality images, achieved superior robustness, with an overall accuracy of 82.3% under fourfold cross-validation.

Sladojevic et al. (2016) utilised a fine-tuned CaffeNet model for detecting 13 plant diseases from 4,483 internet-sourced images, achieving 96.3% accuracy with 10-fold cross-validation. Similarly, Rangarajan et al. (2018) applied AlexNet and VGG16 to tomato leaf disease detection, reporting accuracies of 97.49% and 97.29%, respectively. Mohanty et al. (2016)

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employed AlexNet and GoogLeNet to classify 26 diseases in 14 crops using 54,306 images. Their GoogLeNet-based model achieved 99.35% accuracy on RGB images in controlled laboratory conditions. However, performance dropped drastically (to 31%) when tested on field images, highlighting challenges in generalisation.

Other studies extended CNN-based approaches to different crops. Nachtigall et al. (2016) achieved 97.3% accuracy in apple leaf disease detection using AlexNet, while Amara et al. (2017) applied a LeNet-based CNN to banana leaf disease recognition, reporting accuracies of 98.61% on colour and 94.44% on grayscale images under complex backgrounds. Hybrid approaches, such as combining CNNs with handcrafted features, further improved performance, as demonstrated in olive leaf disease detection (Cruz et al. 2017). Comparative studies have shown that pretrained models and transfer learning significantly outperform models trained from scratch. Ferentinos et al. (2018) tested five CNN architectures (AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat, and VGG) on a dataset covering 58 plant disease classes, achieving 99.53% accuracy with VGG16. Similarly, Atole et al. (2018) applied a fine-tuned AlexNet to rice plant diseases, achieving 91.23% accuracy.

The inherent computational demand in DL models due to large numbers of parameters involved created a paradigm shift to lightweight and mobile-friendly models to ease plant disease detection, especially for small-holding farmers. Ramcharan et al. (2019) used InceptionV3 and MobileNet-based SSD for cassava disease detection in both image and video datasets, achieving accuracies of up to 98% with SVM classifiers. Similarly, Agarwal et al. (2020) presented a lightweight, efficient CNN model which outperformed the classical CNN model and pretrained models with an accuracy of 98.4% when deployed on the benchmark PlantVillage Dataset. Atila et al. (2021) demonstrated that EfficientNet outperformed traditional CNNs, achieving up to 99.97% accuracy with fewer parameters and reduced training time. Bi et al. (2022) designed a deployable MobileNet-based model for apple leaf disease detection, with competitive accuracy but much lower computational cost compared to InceptionV3 and ResNet152.

To tackle the limitations of deploying deep learning models for plant disease and pest detection on compact devices with restricted computational power. Wang et al. (2023) proposed an Ultra-Lightweight Efficient Network (ULEN) designed for image-based detection tasks. The network comprises a deep feature extraction module, which utilises residual depth-wise convolution, and a classification module that processes multi-scale features enhanced by a spatial pyramid pooling layer. With a compact structure of approximately 100,000 parameters, ULEN offers an efficient solution tailored for lightweight applications. Its performance was validated on two publicly available plant image datasets collected from both indoor and outdoor environments, and tested on compact devices to ensure adaptability across different scenarios. The results indicate that ULEN achieves superior classification accuracy compared to state-of-the-art models while maintaining the lowest computational complexity, making it a practical choice for fast and flexible deployment in precision agriculture.

Similarly, the larger data requirements of CNNs and their inability to recognise object pose and deformation have been demonstrated to lower the system's performance. Therefore, Idakwo et al (2024) utilised the equivariance property of the capsule network to resolve the inherent issues in CNNs. The developed Improved Capsule Network model was implemented in a tomato ripeness detection and sorting system. The system effectively classifies tomatoes into their respective ripeness stages with an average performance of 99.56%, 96.20%, 96.20%, and 96.40% which are 3.17%, 2.69%, 3.10%, and 2.68% average improvement over existing accuracy, precision, recall, and F1-Score, respectively.

Moreover, the developed system was subjected to defective, ripe, and unripe tomato detection and achieved a 98.74% accuracy, which was a 5.74% improvement over the state-of-the-

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art. The higher accuracy of the developed system showed that the system can automate the Agricultural sorting of tomatoes. While this system assisted the local farmers in Lokoja, Kogi State, Nigeria, the inherent plant tomato disease within the region created a further need for a low computational system that can effectively detect plant disease. Thus, Ochijenu et al. (2025) improved the capsule network by hybridising the capsule network and yolo network to form the Capsule-YOLO network architecture. The tomato images from the PlantVillage Dataset and PlantDoc Dataset were combined to form an improved dataset with images from controlled and uncontrolled environments.

The designed Capsule-Yolo network automatically segments the tomato leaf images and identifies diseases even when the images are overlapping or occluded within complex backgrounds. The model achieved outstanding results, with an accuracy of 99.31%, a recall of 98.78%, a precision of 99.09%, and an F1-score of 98.93%. These values reflect performance gains of 2.91%, 1.84%, 5.64%, and 4.12% compared to existing advanced approaches. Furthermore, a user-friendly platform was created, enabling farmers and users to upload images of tomato plants for early disease detection, along with recommendations for accurate diagnosis and suitable treatment.

Dominant Deep Learning Architectures

Among the deep learning Architectures, the dominant deep learning architecture is summarised in Figure 4.

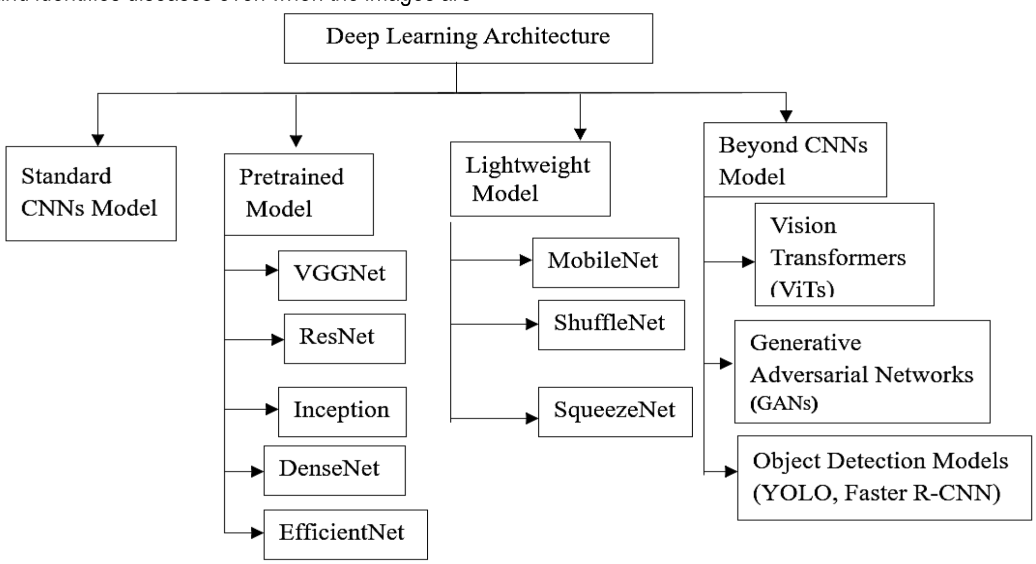

Figure 4: Dominant Deep Learning Architecture

a. **Standard CNNs:** Custom-designed architectures (e.g., with a few convolutional, pooling, and fully connected layers) are often used for smaller, specific datasets.
b. **Transfer Learning with Pre-trained Models:** This is the most prevalent approach. Models pre-trained on massive general-image datasets (e.g., ImageNet) like VGGNet, ResNet, Inception, DenseNet, and, more recently, EfficientNet, are fine-tuned on plant disease datasets. This approach significantly reduces training time and data requirements while achieving state-of-the-art performance (Ferentinos et al. 2018).
c. **Lightweight Architectures:** For deployment on mobile devices or edge computing platforms (e.g., drones, smartphones), lightweight models like

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MobileNet, ShuffleNet, and SqueezeNet are crucial. They offer a favourable trade-off between accuracy and computational efficiency (Lu et al. 2023).

d. Beyond CNNs: Several emerging architectures have been deployed in plant disease detection. Notably among them are vision transformers (Dosovitskiy et al. 2020), generative adversarial networks, and object detection models.

i. **Vision Transformers (ViTs):** Transformers, which use self-attention mechanisms, have shown remarkable performance in vision tasks, often rivalling or surpassing CNNs on large datasets by capturing global contextual information (Yu et al. 2023).

ii. **Generative Adversarial Networks (GANs):** GANs are primarily used for data augmentation, generating synthetic training images to balance datasets and improve model robustness (Cresswell et al. 2018).

iii. **Object Detection Models:** For tasks requiring localisation (e.g., not only classify disease but also find it on the leaf), architectures like YOLO (You Only Look Once) and Faster R-CNN are employed.

The summary of the core deep learning architecture in plant disease detection is shown in Table 5.

Table 5: Summary of Key Deep Learning Architectures in Plant Disease Detection

Architecture Type	Examples	Key Advantages	Common Use Cases
Standard CNN	Custom 5-layer CNN	Simplicity, low computational cost	Small-scale, specific studies
Pre-trained Models (Transfer Learning)	ResNet, VGG16, InceptionV3, EfficientNet	High accuracy, reduced training time & data needs	State-of-the-art classification
Lightweight Models	MobileNet, SqueezeNet	High speed, low power consumption	Mobile apps, drone-based scouting
Object Detection	YOLOv5, Faster R-CNN	Provides disease localisation	Precision spraying, detailed analysis
Generative Models	GANs (e.g., DCGAN, StyleGAN)	Data augmentation handles class imbalance	Enhancing dataset diversity

METHODOLOGY: THE STANDARD PIPELINE FOR A PLANT DOCTOR SYSTEM

Developing a DL-based plant disease diagnosis system follows a structured pipeline. This pipeline entails data acquisition, data preprocessing, model selection and training, and evaluation.

1. **Data Acquisition:** Collecting images from sources like lab settings, farms (via smartphones), or aerial imagery (via drones).
2. **Data Preprocessing:** Standardising images (resizing, normalisation), augmenting data (rotation, flipping, scaling, colour adjustment) to increase diversity and prevent overfitting, and segmenting the region of interest (e.g., separating leaf from background).
3. **Model Selection & Training:** Choosing an appropriate architecture (see Section 2.1). The model is trained on the preprocessed data, using a loss function (e.g., Cross-Entropy) and an optimiser (e.g., Adam) to learn the mapping from input images to disease classes.

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4. **Evaluation:** The trained model is tested on a held-out validation set. Metrics like accuracy, precision, recall, F1-score, and confusion matrices are used to assess performance.
5. **Deployment:** The final model is integrated into an application, such as a mobile app, a web platform, or an onboard drone computer, to make predictions on new, unseen data.

Deep Learning Model Open-Source Framework

There are several AI frameworks which are open source and available for practical implementation of deep learning models. The unique strength and limitations of these frameworks in terms of their core technologies, developers, hardware compatibility, functionality, programming languages, and typical applications serves as a practical guide for selecting the most suitable tool for specific AI and DL applications. TensorFlow is a robust open-source framework for dataflow and differentiable programming (Géron et al. 2022). It supports high-performance computations across diverse hardware, including memory units, GPUs, and TPUs. One of its core strengths lies in its use of dataflow graphs, which define how data is processed within a computation, making it a preferred platform for both machine learning and deep learning tasks.

In comparison, Keras serves as a high-level DL library that operates on top of TensorFlow (and other backends). It simplifies model development through an intuitive API and offers a wide range of pre-built layers and functions, such as convolutional and pooling layers that can be seamlessly integrated into models. Since TensorFlow 2.4, the framework has combined low-level model construction and training capabilities with Keras's user-friendly high-level interface, enabling efficient and accessible model development. In this research, the combined use of TensorFlow and Keras has provided a practical balance between flexibility and ease of implementation.

PyTorch, another widely adopted open-source framework, offers extensive functionality for building and training ML and DL models (Imambi et al. 2021). It is particularly popular among researchers for its flexibility and ease of use. A distinguishing feature of PyTorch is its dynamic computational graph, which allows modifications during runtime, making it highly suitable for experimentation and research. Unlike TensorFlow's earlier static graph approach, this dynamic structure provides more intuitive debugging and iterative model design. PyTorch also supports distributed training, enabling efficient scaling across multiple GPUs, and includes pre-built modules such as convolutional and recurrent layers for rapid prototyping. Its strong community support, with shared pre-trained models, datasets, and tutorials, further enhances its practicality in DL research and applications.

Caffe (Convolutional Architecture for Fast Feature Embedding), developed by the Berkeley Vision and Learning Centre (BVLC) with contributions from the open-source community, is another established DL framework. It is recognised for its speed and efficiency, particularly in computer vision tasks such as object detection, image classification, and video summarisation. Implemented in C++ with a Python interface, Caffe integrates well with scientific computing libraries like NumPy and SciPy, providing both performance and flexibility. Its strength lies in highly optimised convolutional operations, which are crucial for visual recognition tasks. Furthermore, Caffe supports a variety of DL architectures, including CNNs, RNNs, and Transformer-based networks, while also offering pre-defined layers and functions that simplify model design (Kumar & Misra, 2024).

Theano, developed by the Montreal Institute for Learning Algorithms (MILA) at the University of Montreal, was one of the pioneering open-source DL frameworks (Mohialden et al. 2024). It is designed for efficient mathematical computation, particularly in training deep models on both CPUs and GPUs. Theano's hallmark feature is symbolic differentiation, which enables precise and efficient gradient computation during model training (Shoaib et al. 2023). It also automates optimisation and differentiation processes, allowing for more scalable training of

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complex models. Implemented in Python, Theano integrates smoothly with scientific computing libraries such as NumPy and SciPy, making it both powerful and versatile for numerical experimentation. The popular artificial intelligence framework is presented in Table 6.

Table 6: Popular Artificial Intelligence Frameworks Comparison

Technology	Developer	Auxiliary Devices	Language
TensorFlow	Google	CPU, GPU, TPU, Mobile	Python
PyTorch	Facebook	CPU, GPU	Python
ONNX Runtime	Microsoft	CPU, GPU, TPU, Edge	Python
MXNet	Amazon	CPU, GPU, TPU, Mobile	Python, R, C++, Scala
CNTK	Microsoft	CPU, GPU	Python

Challenges and Limitations

Despite impressive results, several challenges impede the widespread adoption of these systems:

1. **Data Limitations:** Models require massive, high-quality, and accurately labelled datasets. Real-world data is often imbalanced (few examples of rare diseases), contains complex backgrounds, and varies greatly in lighting, angle, and leaf age. These complexities can hinder model generalisation and robustness.
2. **Generalisation and Robustness:** A model trained on one dataset (e.g., lab images on a plain background) often performs poorly on pictures from a different source (e.g., a smartphone photo in a field). Overcoming this domain shift is a major hurdle.
3. **Early Detection:** Most systems are trained to identify clear symptoms. Detecting diseases at very early, pre-symptomatic stages remains extremely challenging.
4. **Multiple Diseases and Nutrient Deficiencies:** Differentiating between diseases with similar visual symptoms and distinguishing disease symptoms from nutrient deficiencies or pest damage is a complex task.
5. **Explainability (XAI):** Deep learning models are often black boxes. Farmers and agronomists need to understand why a diagnosis was made (e.g., which parts of the leaf were most influential) to trust the system's output.

Future Directions and Conclusion

The future of the AI Plant Doctor lies in addressing current limitations and exploring new frontiers:

1. **Multimodal Learning:** Integrating visual data with other sensor data (e.g., hyperspectral imagery, weather data, soil sensors) to improve accuracy and enable earlier detection.
2. **Explainable AI (XAI):** Incorporating techniques like Grad-CAM or LIME to provide visual explanations for model predictions, building user trust and providing agronomic insights.
3. **Unsupervised and Few-Shot Learning:** Developing models that can learn from unlabeled data or require very few examples of a new disease to learn it, mitigating data scarcity issues.
4. **Edge AI and Real-Time Processing:** Optimising models for ultra-efficient inference on low-power devices, enabling real-time diagnosis directly in the field without cloud connectivity.
5. **Large-Scale Real-World Deployment:** Moving beyond academic benchmarks to large-scale field trials that validate economic and agronomic impact.

CONCLUSION

The integration of deep learning into plant pathology represents a true paradigm shift. Plant Doctor systems have evolved from a theoretical concept to a practical tool with demonstrable success in controlled environments. While challenges in generalisation, data scarcity,

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and explainability persist, the trajectory of research is clear. By fostering collaboration between computer scientists, agronomists, and farmers, the future promises robust, accessible, and trustworthy AI systems that will empower growers with timely and precise diagnostic capabilities, ushering in a new era of sustainable and productive precision agriculture.

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