Recent Advances in Computer Vision and Machine Learning for Crop Health Monitoring: Breakthroughs in Plant Disease Classification and Explainable AI

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Abstract: Plant diseases continue to undermine global food security, with their prevalence intensified by climate change, monoculture practices, and the rapid spread of pathogens. Conventional diagnostic methods are often manual, time-consuming, and reliant on expert knowledge, resulting in delayed or inaccurate detection and substantial yield losses. Recent advances in Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), have transformed plant disease detection by enabling early, accurate, and automated diagnosis. This review critically examines recent developments (2023–2025) in AI-based plant disease identification, spanning the entire diagnostic pipeline: advanced pre-processing techniques (e.g., optimized filters, GAN based data augmentation), segmentation models (e.g., U-Net variants and lightweight architectures), feature extraction (e.g., deep CNNs, Vision Transformers, handcrafted descriptors), and classification approaches (e.g., ensemble CNNs, hybrid deep models). Empirical studies report high classification accuracies (often above 95%) across diverse crops using benchmark datasets such as PlantVillage and domain-specific collections. While these advancements mark a significant leap toward precision agriculture and real-time monitoring through mobile and drone platforms, challenges remain in addressing data heterogeneity, model explainability, and scalability in resource-constrained environments. This review emphasizes AI's pivotal role in advancing sustainable agricultural practices and outlines future research directions to enhance robustness, accessibility, and real-world deployment.

Keywords: Plant Disease Detection, Deep Learning, Machine Learning, Precision Agriculture, Vision Transformers

I. INTRODUCTION

Crop diseases are threatening worldwide agricultural production, making food security one of humanity's biggest issues. Climate change, monocultures, and pathogen movement across borders have increased production losses, straining the agricultural sector's ability to feed a growing global population. Subjectivity, reliance on specialised expertise, and labour- and time-intensive field surveys hinder manual inspection and symptomatic diagnosis-based crop protection methods. Therefore, late or erroneous plant disease outbreak detection leads to significant economic losses for farmers and increased food supply chain hazards. Recently, AI, particularly ML and DL, has revolutionised plant disease diagnosis, enabling early, accurate, and scalable detection across varied agricultural systems. AI-driven solutions using computer vision can quickly and objectively analyse visual symptoms on plant tissues like leaves using enormous image datasets to discover disease phenotypes that conventional methods may miss. Mobile devices or drones can deploy these technologies in the field, giving farmers real-time disease surveillance and actionable knowledge to intervene. AI, developing sensing technologies, remote monitoring, and IoT platforms signal the transition to “Agriculture 5.0,” with precision crop protection, data-driven management, and autonomous decision-making. Despite these dramatic breakthroughs, technological and operational hurdles remain. Data heterogeneity, environmental variability, and lack of annotated datasets for rare diseases and crops limit diagnostic model adoption [1].

In addition, on-farm integration, AI model interpretability, and technological accessibility in resource-limited settings remain issues. This research critically analyses AI-powered plant disease detection achievements and restrictions to explain how these technologies are changing crop protection and global food security.

II. PLANT DISEASES

Plant diseases disrupt plant growth, development, and function. Biotic (living) agents including fungi, bacteria, viruses, nematodes, and parasitic plants and abiotic (non-living) conditions like nutritional imbalances, drought, pollution, and harsh weather can cause these diseases. Biotic plant diseases, in particular, threaten global food security and agricultural sustainability due to their fast spread and crop damage. New and existing plant diseases have emerged and spread locally and internationally due to global trade, climate change, land use alterations, and intensified agriculture. Due to their rapid evolution and capacity to elude control methods, viral illnesses are becoming more important and causing epidemics. These advances emphasise the necessity for comprehensive surveillance and prompt diagnostics. Plant diseases are categorised by their causes [2]. Key categories, instances, and affected crops are included below,

Table.1.Overview of Plant Disease

Category	Causative Agent	Examples	Affected Crops
Fungal Diseases	Pathogenic fungi	Powdery mildew, rust, late blight	Wheat, tomato, potato
Bacterial Diseases	Pathogenic bacteria	Bacterial wilt, leaf spot, fire blight	Tomato, banana, citrus
Viral Diseases	Plant viruses	Mosaic viruses, bunchy top, blight	Banana, tomato, soybean
Nematode Diseases	Parasitic nematodes	Root-knot, cyst nematode	Soybean, potato, sugar beet
Phytoplasma/Viroid Diseases	Phytoplasmas, viroids	Little leaf, exocortis	Brinjal, citrus, coconut
Abiotic Disorders	Non-living factors	Nutrient deficiency, frost, pollution	All crops

2.1. Types and Causes of Plant Diseases

Plant diseases are caused by a range of factors that can be broadly categorized into **biotic (infectious)** and **abiotic (non-infectious)** agents. Understanding the distinction between these two types is essential for accurate diagnosis, effective disease management, and sustainable agricultural practices.

Abiotic plant diseases arise from non-living environmental stressors. These include extreme weather conditions (e.g., hailstorms, frost, and drought), soil imbalances (such as pH extremes or mineral toxicities), nutrient deficiencies, air pollution, and chemical injuries from herbicides or pesticides. Although these disorders can result in significant physiological damage and reduced crop quality, they are non-contagious and generally do not spread from plant to plant. Effective soil management, proper irrigation, and careful chemical usage can typically prevent abiotic disorders [3].

In contrast, **biotic plant diseases** are caused by living organisms that infect and multiply within plant tissues. The primary biotic pathogens include:

- **Fungi**, which are responsible for the majority of plant diseases and cause symptoms such as rusts, blights, and wilts.
- **Bacteria**, which induce diseases like bacterial spots, rots, and wilts.
- **Viruses**, which often result in mosaic patterns, leaf curling, stunting, and reduced productivity.
- **Nematodes**, microscopic roundworms that attack roots and hinder nutrient uptake.

Biotic diseases are of particular concern because they are **infectious and capable of rapid spread**, often leading to severe crop losses and economic damage. Factors such as high planting density, poor sanitation, global trade, and climate change have contributed to the increased emergence and spread of plant pathogens in recent decades.

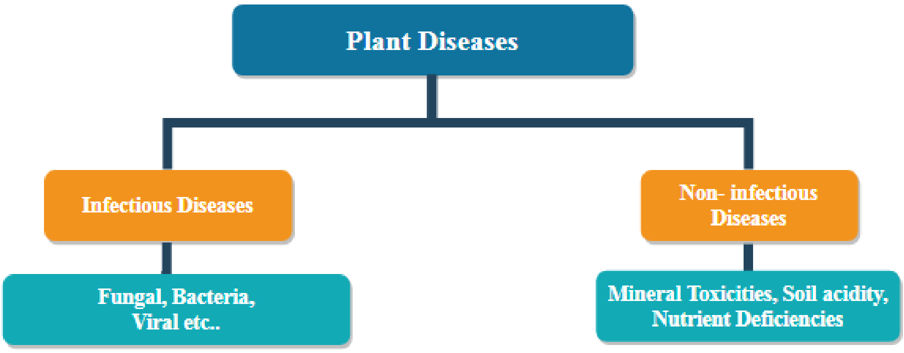

Fig.1. Types of plant diseases

This figure presents a hierarchical classification of plant diseases, dividing them into two main types: Infectious diseases caused by living organisms (e.g., fungi, bacteria, viruses) and Non-infectious diseases caused by environmental or nutritional factors (e.g., mineral toxicities, soil acidity, and nutrient deficiencies). The diagram visually distinguishes the origin of plant diseases, offering a clear overview of biotic and abiotic causes. They are classified into 3 main groups.

i. Fungal Diseases

Fungal diseases are the most widespread plant infections, accounting for nearly 85% of all plant related disorders. They are caused by a wide range of fungi and fungus-like organisms that reproduce via microscopic, airborne spores, allowing them to spread quickly between plants. Once established, they disrupt normal plant functions, leading to significant yield and quality losses.

Fungi thrive in warm, humid environments, and infections commonly present as leaf spots, blights, wilts, rots, or mildew. These diseases can devastate entire crop fields if not detected and managed early. Integrated disease management combining resistant varieties, cultural practices, biological control, and fungicides is essential for effective control [4]. The below table summarizes some common fungal diseases, their causal organisms, symptoms, and the crops they affect

Table.2. Common Fungal Diseases in Plants

Disease	Causal Organism	Symptoms	Major Affected Crops
Powdery Mildew	*Erysiphe spp.*	White powdery growth on leaves	Grapes, Cucurbits, Wheat
Late Blight	*Phytophthora infestans*	Dark lesions on leaves, fruit rot	Potato, Tomato
Rust	*Puccinia spp.*	Reddish-brown pustules on leaves	Wheat, Beans, Soybean
Fusarium Wilt	*Fusarium oxysporum*	Wilting, yellowing, vascular browning	Banana, Tomato, Cotton
Anthracnose	*Colletotrichum spp.*	Dark, sunken lesions on fruits/leaves	Mango, Beans, Chilli

Fungal pathogens remain a significant threat to global food security, especially in the face of climate variability. Continuous monitoring and adaptive management strategies are vital for minimizing crop losses.

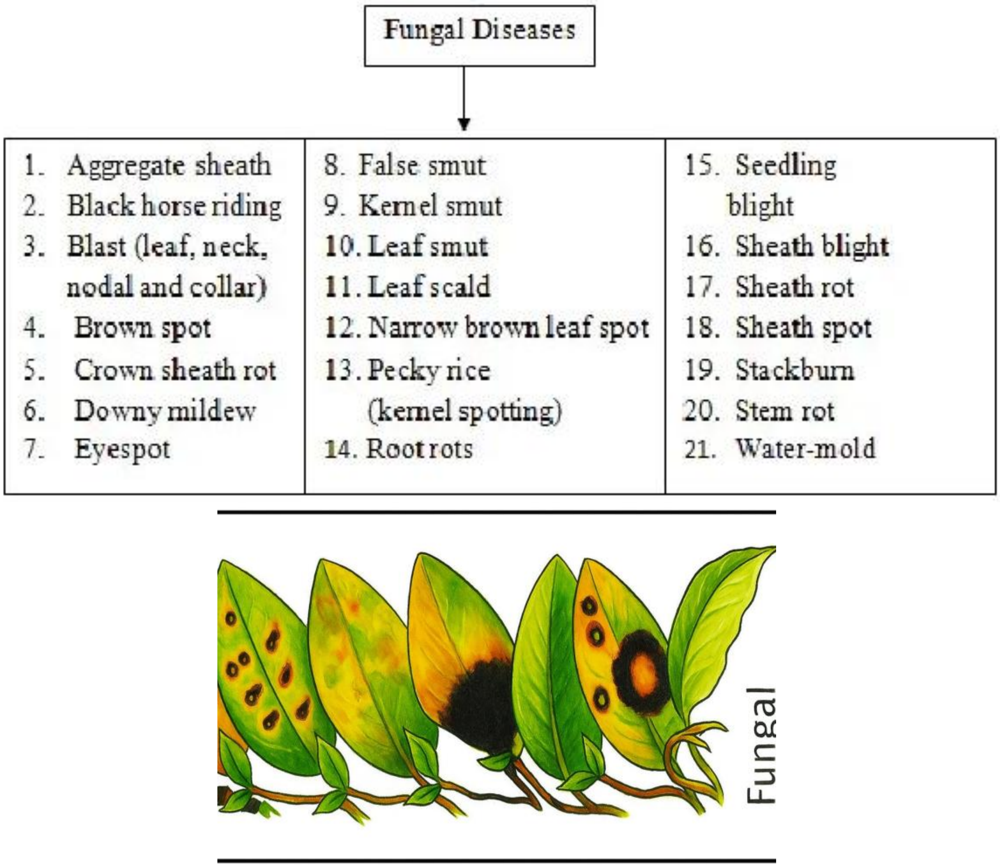

Fig.2. Fungal Diseases in Plant

The above figure lists 21 common fungal diseases arranged in three columns for clarity. Below the list, an illustration shows the progression of fungal infection on plant leaves, from healthy to various stages of damage and discoloration, visually demonstrating fungal growth. The illustration is labelled "Fungal".

ii. Bacterial Diseases

Bacterial diseases in plants are caused by around **200 known species of pathogenic bacteria**. These microorganisms invade plant tissues through natural openings, wounds, or insect vectors and can spread rapidly via **insects, contaminated water droplets, infected tools, and nearby diseased plants**.

Bacterial infections often result in symptoms such as **leaf spots, wilting, soft rots, cankers**, and **oozing of bacterial slime**. Unlike fungi, bacteria do not produce spores but reproduce quickly under **warm and moist conditions**, leading to widespread outbreaks if not managed effectively [5].

Table.3.Common Bacterial Diseases in Plants

Disease	Causal Organism	Symptoms	Major Affected Crops
Bacterial Blight	*Xanthomonas campestris*	Water-soaked lesions, wilting	Rice, Cotton, Beans
Fire Blight	*Erwinia amylovora*	Shoots appear scorched, blackening	Apple, Pear
Bacterial Wilt	*Ralstonia solanacearum*	Sudden wilting, vascular browning	Tomato, Potato, Brinjal
Citrus Canker	*Xanthomonas axonopodis*	Raised corky lesions on leaves and fruit	Citrus fruits
Bacterial Leaf Spot	*Pseudomonas syringae*	Small brown or black spots with halos	Tomato, Pepper, Lettuce

Management of bacterial diseases includes the use of disease-free seeds, crop rotation, sanitation, insect control, and in some cases, copper-based bactericides. Due to the limited availability of effective chemical treatments, early detection and prevention are crucial in bacterial disease control.

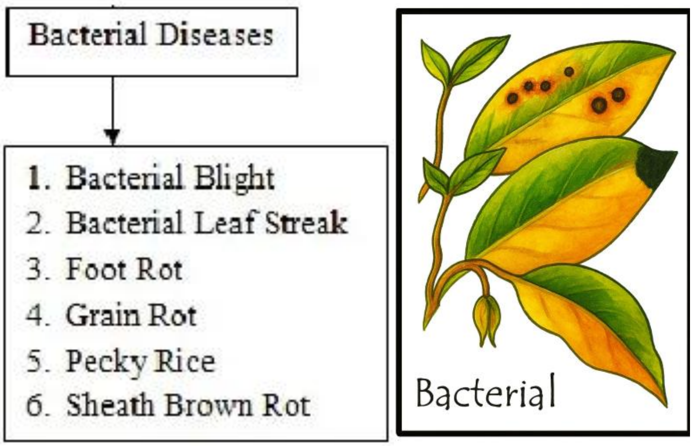

Fig.3. Bacterial Diseases in Plants

This figure lists six common bacterial diseases such as Bacterial Blight, Leaf Streak, Foot Rot, Grain Rot, Pecky Rice, and Sheath Brown Rot. A grayscale illustration beside the list shows leaf symptoms such as spots and lesions, labelled "Bacterial," highlighting typical bacterial infection signs.

iii. Viral Diseases

Viral diseases are among the **rarest but most challenging plant diseases to manage**. Caused by plant-infecting viruses, these pathogens require **physical entry into plant cells**, often facilitated by **insect vectors** such as aphids, whiteflies, thrips, or nematodes. Other transmission routes include mechanical injury, grafting, and infected seeds or planting materials.

Once a plant is infected, **there are no effective chemical treatments** to eliminate the virus. Symptoms typically include **mosaic patterns on leaves, stunted growth, leaf curling, yellowing (chlorosis), and fruit deformation**. Because viral infections can spread rapidly, **infected plants must be removed and destroyed** to prevent further transmission [6].

Table.4.Common Viral Diseases in Plants

Disease	Causal Virus	Symptoms	Major Affected Crops
Tobacco Mosaic Virus (TMV)	*Tobacco mosaic virus*	Mottled, mosaic-like leaf patterns	Tobacco, Tomato, Pepper
Tomato Yellow Leaf Curl	*Tomato yellow leaf curl virus*	Leaf curling, stunted growth, yellowing	Tomato
Banana Bunchy Top Disease	*Banana bunchy top virus*	Crowded, upright leaves at the top of the plant	Banana
Cucumber Mosaic Virus (CMV)	*Cucumber mosaic virus*	Mottling, distortion of leaves and fruits	Cucumber, Melon, Tomato
Rice Tungro Disease	*Rice tungro bacilliform and spherical viruses*	Yellow-orange discoloration, stunted plants	Rice

Management strategies focus on vector control, use of virus-free planting materials, crop rotation, and resistant varieties where available. Since viral diseases cannot be cured, prevention and early eradication remain the most effective defense.

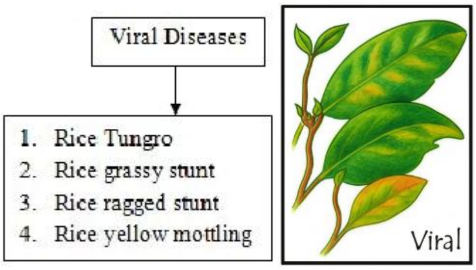

Fig.4. Viral Diseases in Plants

This figure lists four viral diseases affecting rice such as Rice Tungro, Grassy Stunt, Ragged Stunt, and Yellow Mottling. A grayscale illustration beside the list shows typical viral symptoms on leaves, labeled "Viral," highlighting disease impact.

III. METHODOLOGY

This section outlines the key stages involved in plant disease detection, including pre-processing, segmentation, feature extraction, and classification. Each step plays a crucial role in ensuring accurate and reliable identification of plant diseases from image or sensor data. A literature review is incorporated within each subsection to highlight existing research, commonly used techniques, and advancements reported in previous studies.

3.1. Pre-processing

Pre-processing Methods were used to improve image clarity, lower noise, draw attention to areas impacted by diseases, and ready datasets for strong model training. These comprised colour and intensity analysis, edge detection techniques including Canny and watershed algorithms, advanced filters for denoising and contrast adjustment, data normalisation, texture feature extraction, synthetic sample generation using GANs to address imbalance and improve classification accuracy.

Table.5. Overview of Pre-processing Techniques in Plant Disease Detection Studies

Author	Method	Dataset	Performance
Ametefe et al. (2024) [7]	DenseNet201, EfficientNetB3	Diverse leaf images	99.03% (DenseNet201), 98.23% (EfficientNetB3)
Parashar & Johri (2024) [8]	Inception v3 CNN	Apple leaf (field data)	94.76% acc., 85% F1-score
Bhujade et al. (2024) [9]	GABF + AmPel + Savitzky-Golay	Soybean, cotton	PSNR: 37.42 dB, SSIM: 0.94
Manwatkar et al. (2023) [10]	AlexNet, ResNet-50	Tomato, potato	Up to 97% accuracy
Patel et al. (2024) [11]	RNN (Moth-Flame Optimized)	Cashew, maize, cassava, tomato	Up to 98.5% accuracy
Haruna et al. (2023) [12]	StyleGAN2-ADA + Faster-RCNN, SSD	Rice (4 diseases)	mAP: 0.93 (FRCNN), 0.91 (SSD); FID: 26.67

3.2. Segmentation

This section shows how recent studies leveraged segmentation techniques, optimization algorithms, and lightweight deep learning models to enhance the accuracy, efficiency, and real-time applicability of plant leaf disease detection across diverse datasets and platforms.

Table.6. Overview of Segmentation Techniques in Plant Disease Detection

Author	Method	Dataset	Performance
Chavan et al. (2025) [13]	Hybrid DL: improved U-Net + LinkNet + LeNet	Public crop and leaf images	98.2% accuracy, 0.956 F-measure
Silva & Almeida (2024) [14]	Lightweight DL: InceptionV3, MobileNet, VGG16	Thermal images	Speedup on Edge TPU & Intel NCS2 with high accuracy
Naveenkumar & Nandagopal (2025) [15]	IRV-WSA-ETLNet (Transfer learning + metaheuristic optimization)	UCI, Kaggle, benchmark leaf datasets	94.85% accuracy, 96.07% F1-score, 24.38 ms processing time

3.3. Feature Extraction

This section shows how advanced deep learning architectures, bio-inspired optimization, handcrafted descriptors, and hybrid models have been utilized to enhance feature extraction, improve classification accuracy, and enable robust, scalable plant disease detection across diverse crops and datasets.

Table.7. Overview of Feature Extraction Techniques in Plant Disease Detection

Author	Method	Dataset	Performance
Qureshi (2024) [16]	GNut (ResNet50 + DenseNet121 + FSL)	PakNuts (Groundnut)	99% (with FSL), 95% (without FSL)
Vijayan & Chowdhary (2025) [17]	Hybrid WOA_APSO + CNN	PlantVillage (Rice)	97.5% accuracy
Alsakar, Sakr & Elmogy (2024) [18]	Handcrafted Features + SVM	Rice Leaf Diseases datasets	99.14% - 99.53% accuracy
Natarajan et al. (2024) [19]	CNN + Customized KNN	PlantVillage (38 disease classes)	99.95% accuracy, AUC=1
Selvaraj & Devasena (2025) [20]	Vision Transformer (ViT) + Hybrid FBO	Turmeric leaf dataset	97.03% accuracy
Saleem et al. (2024) [21]	AgirLeafNet (NASNetMobile + FSL)	Potato, Tomato, Mango leaf datasets	Potato: 100%, Tomato: 92%, Mango: 99.8%

3.4. Classification

The classification section presents a comprehensive review of recent deep learning-based approaches ranging from CNNs, Vision Transformers, ensemble and hybrid models, Bayesian-optimized classifiers, and GAN-augmented systems—demonstrating superior performance (up to 100% accuracy) in plant leaf disease detection across diverse crops and datasets, highlighting their scalability, explainability, and potential for real-time deployment in precision agriculture.

Table.8. Overview of Classification Techniques in Plant Disease Detection

Author	Method	Dataset	Performance
Aboelenin et al. (2025) [22]	Hybrid CNN (VGG16 + Inception-V3 + DenseNet201) + Vision Transformer	Apple, Corn (custom)	Apple: 99.24%, Corn: 98%
Sambasivam et al. (2025) [23]	DenseNet169 + EfficientNetB0	Cassava (custom)	Accuracy: 89.94%
Qureshi (2024) [24]	GNut (ResNet50 + DenseNet121 + Few-Shot Learning)	Groundnut (custom)	95% (w/o FSL), 99% (w/ FSL)
Naresh Kumar & Sakthivel (2025) [25]	Fusion Vision (VGG19 + LightGBM)	Rice (custom)	Accuracy: ~97.6%
Ramadan et al. (2024)	CNN + CycleGAN + ADASYN	Wheat (custom)	Accuracy: Up to 100%
Sharma et al. (2025) [26]	MobileNetV2 + ResNet50 Ensemble	Tomato (PlantVillage)	Accuracy: 99.91%

Tamim et al. (2025) [27]	InsightNet + Grad-CAM (Explainable DL)	Tomato, Bean, Chili	Accuracy: ~98%
Roshni & Devi (2024) [28]	YOLOv8 + DeepLabV3+ + CNN	Apple, Tomato, Corn	Training Acc: 96.97%, Validation: 92.89%
Adi et al. (2025) [29]	CNN + Bayesian SVM / Random Forest	Apple, Maize	Apple: 97.8%, Maize: 96.5%

IV. CONCLUSION

Plant diseases continue to pose a significant challenge to global food security, intensified by factors such as climate change, monoculture practices, and the rapid spread of pathogens. This review underscores the pivotal role of Artificial Intelligence in transforming plant disease diagnosis through advancements in pre-processing, segmentation, feature extraction, and classification. State-of-the-art deep learning models, including convolutional neural networks and Vision Transformers, have demonstrated exceptional accuracy, often exceeding 95% across diverse crop datasets. Furthermore, lightweight and hybrid architectures have enabled real-time deployment on mobile and drone platforms, enhancing field level applicability. However, persistent challenges such as data heterogeneity, environmental variability, limited interpretability, and infrastructure constraints must be addressed. Future research should focus on integrating multimodal data sources, expanding synthetic data generation, developing energy efficient models, and ensuring accessibility for end-users. Bridging the gap between algorithmic innovation and practical implementation remains essential for advancing sustainable, AI-driven plant disease management in agriculture.

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