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Artificial Intelligence in Plant Disease Management: Advances in Image Analysis, Spectral Diagnostics and Predictive Modelling

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ABSTRACT

Plant diseases caused by fungi, bacteria, viruses and nematodes continue to threaten agricultural productivity and food security. Conventional diagnosis involves symptom examination, microscopy, pathogen isolation, serological techniques and molecular assays. Although these approaches provide essential diagnostic evidence, they may require specialised facilities, trained personnel and considerable time. Artificial intelligence (AI) has emerged as a promising approach for analysing plant images, spectral signatures and environmental information to support disease recognition and prediction. Deep-learning models have demonstrated high classification performance using plant disease image datasets, while hyperspectral and multispectral imaging offer opportunities for detecting physiological changes associated with infection before visible symptoms appear. Predictive modelling can estimate disease risk using weather, crop and environmental variables. Recent multimodal systems and large language models further extend these applications by combining image recognition with textual and agricultural knowledge. However, performance obtained under controlled conditions does not necessarily translate into reliable field diagnosis. Similar symptoms may arise from different pathogens or abiotic stresses, and AI predictions alone cannot establish pathogen identity or viability. This short review critically examines emerging AI applications in plant disease management from a microbiological perspective, with emphasis on diagnostic limitations, laboratory validation, economic considerations and field applicability. Integrating AI with conventional plant diagnostic methods offers a more reliable approach to disease surveillance and management.

Keywords: Artificial intelligence; plant disease diagnosis; deep learning; spectral imaging; predictive modelling; plant pathogens; microbiological validation.

INTRODUCTION

Plant diseases caused by fungal, bacterial, viral and nematode pathogens are major constraints on agricultural production. Their occurrence and spread depend on interactions among the host plant, pathogen and environmental conditions. Plant diseases contribute substantially to global crop losses, affecting food availability, agricultural income and sustainability (Savary et al., 2019). Early and accurate diagnosis is therefore essential for selecting appropriate management strategies and reducing unnecessary pesticide applications.

Conventional plant disease diagnosis relies on field observation, symptom examination, microscopy, pathogen isolation, biochemical identification, serological tests and molecular techniques. Methods such as enzyme-linked immunosorbent assay (ELISA) and polymerase chain reaction (PCR) provide pathogen-specific evidence, but their application may be limited by laboratory infrastructure, cost and the availability of trained personnel. Detection of asymptomatic infections also remains challenging using visual examination alone (Attaluri & Dharavath, 2023).

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Artificial intelligence (AI), particularly machine learning and deep learning, has introduced new possibilities for rapid plant health assessment. AI models can analyse digital images, spectral measurements and environmental data to identify disease-associated patterns and estimate disease risk. Recent reviews have documented advances in deep learning, computer vision and multimodal sensing for plant disease management (Jafar et al., 2024; Pacal et al., 2024; Shoaib et al., 2025; Ghimire et al., 2026). However, the practical diagnostic value of these technologies depends on their performance under variable field conditions and their ability to distinguish infectious diseases from non-infectious disorders.

This short review examines major developments in image-based recognition, spectral diagnostics, predictive modelling and multimodal AI. It particularly considers the distinction between recognising disease symptoms and confirming the causal pathogen, an important issue from a microbiological perspective.

2. Scope and Review Approach

This article is a narrative-critical short review, not a systematic review or meta-analysis. It considers representative peer-reviewed studies and recent reviews addressing AI-based plant disease recognition, optical and spectral sensing, disease prediction and emerging multimodal applications. The literature is discussed under four principal themes: image-based recognition, spectral diagnostics, predictive modelling and integration with conventional plant diagnostic methods. Studies were considered for their relevance to plant disease detection, diagnostic performance, experimental conditions and field applicability.

The synthesis is qualitative and focuses on the strengths, limitations and biological interpretation of reported findings. The review does not claim exhaustive literature coverage, formal systematic screening or quantitative pooling of study results. This focused approach is intended to provide a concise assessment of AI applications from a microbiological and diagnostic perspective.

3. Image-Based Recognition of Plant Diseases

Image analysis is one of the most extensively investigated applications of AI in plant pathology. Convolutional neural networks (CNNs), transfer-learning models and object-detection algorithms can identify disease-associated patterns in images of leaves, stems, fruits and other plant parts. These models are trained using labelled images to classify healthy and diseased plants or distinguish among different symptom categories.

Mohanty et al. (2016) demonstrated the potential of deep learning using the PlantVillage dataset, which contained 54,306 images representing 14 crop species and 26 disease classes. Their model achieved a classification accuracy of approximately 99.35%. Ferentinos (2018) subsequently reported high classification performance using 87,848 images covering 58 plant-disease classes. These studies established the potential of CNN-based approaches for automated disease recognition.

However, high accuracy on controlled datasets does not necessarily indicate equivalent performance under agricultural field conditions. Barbedo (2018) identified factors such as image quality, background complexity, illumination, disease stage and symptom variability as important influences on deep-learning performance. The PlantDoc dataset developed by Singh et al. (2020), containing 2,598 images across multiple plant species and disease categories, addressed the need for more realistic images collected outside controlled laboratory settings. Its development also demonstrated the challenges associated with obtaining sufficiently large and accurately annotated field datasets.

Fuentes et al. (2017) investigated real-time detection of tomato diseases and pests using deep-learning-based object detection. Ramcharan et al. (2019) demonstrated a mobile-based deep-learning approach for cassava disease diagnosis, illustrating the potential for using AI in resource-limited agricultural settings. These studies represent progress towards practical disease recognition, although their results must be interpreted in relation to crop type, image acquisition conditions, dataset composition and validation procedures.

Accuracy values from different studies cannot be compared directly because they differ in the number of images, disease classes, class distribution, training and testing strategies and image environments. Evaluation should

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therefore include precision, recall, F1-score, sensitivity, specificity and class-wise performance, in addition to overall accuracy. Recent reviews have also emphasised the importance of dataset diversity, external validation and model generalisability (Attaluri & Dharavath, 2023; Jafar et al., 2024; Nyawose et al., 2025; Upadhyay et al., 2025).

From a microbiological perspective, image-based classification identifies visible symptoms rather than necessarily identifying the causal organism. Leaf spots, chlorosis, necrosis and wilting may be produced by different fungal or bacterial pathogens, viral infections or abiotic stress. Therefore, image-based AI should be considered a preliminary diagnostic aid and not definitive evidence of pathogen identity.

4. Spectral Imaging and Early Disease Detection

Conventional image analysis primarily uses visible features such as colour, shape and texture. In contrast, multispectral and hyperspectral imaging provide information across selected or continuous wavelength ranges. Infection can alter chlorophyll concentration, water content, tissue structure and photosynthetic activity, producing spectral changes that may occur before visible symptoms develop.

Mahlein (2016) described the potential of imaging sensors for plant disease detection and precision agriculture. Hyperspectral imaging combined with machine-learning methods has subsequently received considerable attention for identifying crop diseases and detecting seedborne pathogens (García-Vera et al., 2024; Ferreira et al., 2024). Ferreira et al. (2024) discussed the potential of hyperspectral imaging for distinguishing healthy and pathogen-infected seeds, while also identifying equipment cost, protocol standardisation and spectral validation as important challenges.

Tomaszewski et al. (2023) investigated the early detection of tomato diseases using temporally aggregated hyperspectral measurements and machine-learning methods. Their work included five disease conditions and measurements collected from two tomato cultivars over successive days following inoculation. The study illustrates the potential of temporal spectral information for detecting infection before extensive symptom development. De Silva and Brown (2023) investigated hybrid vision transformer and CNN approaches for multispectral plant disease detection, demonstrating the growing use of advanced architectures for integrating spectral and visual information.

Despite these advances, spectral changes are not necessarily pathogen-specific. Drought, heat stress, nutrient deficiencies and chemical injury may produce physiological responses similar to those associated with infection. Sensor calibration, crop variety, illumination, disease stage and environmental conditions can also influence spectral measurements. Consequently, spectral imaging may indicate plant stress or suspected infection, but microbiological or molecular examination is required to establish its biological cause.

5. Predictive Modelling for Plant Disease Management

Predictive modelling uses historical and real-time information to estimate the likelihood, timing or severity of disease occurrence. Environmental variables such as temperature, relative humidity, rainfall, leaf wetness and soil moisture can be combined with crop growth stage, host susceptibility and disease occurrence records to estimate disease risk.

Machine-learning approaches, including random forests, support vector machines, artificial neural networks and ensemble models, can identify relationships among these variables. Such models may assist in planning field inspections, identifying periods favourable for pathogen development and improving the timing of disease-management interventions. Their value is particularly relevant for diseases whose development is strongly influenced by environmental conditions.

However, a favourable environment does not establish that a pathogen is present in a particular field. Disease development also depends on inoculum availability, host susceptibility and pathogen-specific biological requirements. A model may therefore predict a high risk of infection without confirming an active disease outbreak. Predictive outputs should be interpreted as risk estimates rather than direct evidence of pathogen

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presence. Independent validation across locations, seasons and crop varieties is necessary before applying such models to field-level recommendations. Integration with field observations and laboratory surveillance can improve the reliability of disease-risk assessment (Jafar et al., 2024; Ghimire et al., 2026).

6. Multimodal AI and Large Language Models

Recent developments combine plant images with spectral measurements, environmental information, crop characteristics and textual descriptions. Multimodal AI systems may provide a broader assessment of plant health than models relying on a single image. Large language models (LLMs) further extend these applications by interpreting images and responding to user queries about symptoms and disease management.

Han and Kim (2024) described an AI-based plant diagnostic system using GPT-4 vision and a curated knowledge base containing information on host plants, pathogens and pesticides. Zhao et al. (2024) integrated large language models with agricultural knowledge graphs to support plant disease detection. Wang et al. (2025) developed a multimodal large language model for identifying crop diseases and pests through image and language processing. These developments indicate the potential of combining visual recognition with agricultural knowledge and interactive diagnostic support.

Nevertheless, multimodal systems may produce incorrect or incomplete interpretations when symptoms are ambiguous, images are poor quality or the disease is not adequately represented in their training data. Their recommendations should therefore be treated as preliminary guidance. A suggested disease diagnosis requires confirmation through appropriate plant pathology and laboratory procedures. The integration of curated pathogen databases and verified diagnostic information may improve reliability, but it cannot eliminate the need for biological validation.

7. Microbiological Validation of AI-Based Diagnosis

A central consideration in AI-assisted plant disease management is the distinction between symptom recognition and pathogen confirmation. AI models may identify patterns associated with a particular disease, but the presence and identity of the causal organism require appropriate diagnostic evidence.

For fungal diseases, microscopy and examination of reproductive structures can provide preliminary identification. Isolation on suitable culture media, followed by morphological, biochemical or molecular characterisation, may provide further confirmation. Bacterial diseases may require isolation, colony examination, biochemical tests and pathogen-specific molecular assays. Plant viral diseases are commonly confirmed through serological methods such as ELISA or molecular methods such as PCR and reverse-transcription PCR, depending on the virus. Plant-parasitic nematodes require extraction from soil or plant tissues, morphological examination and, where necessary, molecular identification.

AI-based image analysis can help identify suspicious plants and prioritise samples for laboratory examination. Spectral imaging may detect physiological changes, while predictive models can indicate periods of increased disease risk. These approaches can be integrated into a diagnostic workflow involving field observation, AI-assisted preliminary recognition, sample collection, laboratory examination and interpretation of the combined findings.

This integration is particularly important when symptoms overlap, mixed infections occur or infections remain asymptomatic. AI can support surveillance and sample prioritisation, while microbiological, serological and molecular methods establish the presence and identity of the causal pathogen. This distinction is essential for avoiding incorrect disease identification and inappropriate management recommendations.

8. Critical Appraisal and Field Readiness

The available literature demonstrates that AI can recognise disease-associated patterns with high performance within specific experimental datasets. However, reported accuracy depends on dataset size, class distribution, crop and pathogen diversity, image quality, disease stage and validation design. Controlled datasets may not

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adequately represent variations encountered in agricultural fields. Barbedo (2018) discussed several factors affecting deep-learning performance, while Singh et al. (2020) demonstrated the need for more realistic image datasets.

The reported accuracy of Mohanty et al. (2016) and Ferentinos (2018) should therefore be interpreted within the conditions of their respective datasets rather than treated as evidence of universal field-level diagnostic reliability. Field-oriented studies such as Fuentes et al. (2017) and Ramcharan et al. (2019) address practical imaging and deployment challenges, but independent multi-location validation remains important. Recent reviews also identify dataset bias, inconsistent validation procedures and limited generalisation as continuing limitations (Shoaib et al., 2025; Upadhyay et al., 2025; Ghimire et al., 2026).

Future studies should report dataset size, disease-class representation, training and testing procedures, image acquisition conditions, class-wise performance and external validation. They should also state whether disease labels were based on visual symptoms or laboratory-confirmed pathogen identification. Without this distinction, the diagnostic significance of reported model performance may be overstated. Publication bias towards successful models and high accuracy results should also be considered when interpreting the available literature.

9. Economic, Adoption and Policy Considerations

The practical application of AI in agriculture depends on affordability, accessibility and compatibility with existing farming practices. Smartphone-based image analysis may be relatively accessible, whereas hyperspectral cameras, multispectral sensors, drones and associated software require greater investment. Additional costs arise from image collection, expert annotation, model development, data storage, software updates and technical support. Ferreira et al. (2024) specifically identified equipment costs and the need for standardised protocols as challenges for hyperspectral seed-health assessment.

Farmer adoption also depends on ease of use, reliability, local-language accessibility and confidence in AI-generated recommendations. Agricultural extension personnel and plant diagnostic laboratories can assist in interpreting uncertain predictions and directing samples for confirmation. AI systems should communicate uncertainty and avoid presenting preliminary predictions as confirmed diagnoses.

Policy considerations include data ownership, privacy, accountability and the reliability of AI-based agricultural advice. Integration with existing agricultural advisory services and diagnostic laboratories may improve acceptance and practical utility. These considerations are particularly important when recommendations influence pesticide application and crop-management decisions.

10. Indian Context and Future Perspectives

This review considers global developments in AI-based plant disease management, with India discussed as an important regional application context. India's diverse agroclimatic conditions, crop varieties, pathogen populations and smallholder production systems create specific requirements for disease surveillance. Applications involving rice, cotton, pulses, vegetables, fruits and plantation crops could support early identification of disease-prone areas and prioritisation of field inspections.

However, models developed using foreign cultivars or controlled datasets may not perform reliably under Indian agricultural conditions. Region-specific datasets should represent locally important crops and pathogens, different disease stages, mixed infections and images collected under actual field conditions. The PlantDoc dataset developed by Singh et al. (2020) illustrates the value of more realistic image collections, while the broader challenges of data diversity and field validation remain relevant to Indian applications.

Collaboration among agricultural universities, plant pathology departments, Krishi Vigyan Kendras, extension services and diagnostic laboratories can support expert annotation and laboratory confirmation. Affordable mobile applications and local-language interfaces may improve accessibility, particularly for smallholder farmers.

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Future research should prioritise multi-location and multi-season validation, integration of image and spectral data with environmental information, explainable predictions and uncertainty assessment. Multimodal systems should be evaluated using representative field images and laboratory-confirmed disease status. Linking AI platforms with plant diagnostic laboratories would help distinguish suspected disease from confirmed infection and improve the scientific basis of management recommendations.

CONCLUSION

Artificial intelligence offers useful approaches for plant disease recognition, early stress detection and disease-risk prediction. Deep-learning models can classify visible symptoms, spectral imaging can detect physiological changes and predictive models can estimate conditions favourable for pathogen development. Multimodal AI and large language models further extend the possibilities for interactive plant-health assessment. However, high accuracy under controlled conditions should not be equated with reliable field diagnosis. Image and spectral patterns may overlap among infectious diseases and abiotic disorders, while environmental risk predictions do not establish pathogen presence. From a microbiological perspective, AI should support disease surveillance, preliminary recognition and sample prioritisation, whereas microscopy, pathogen isolation, serological testing and molecular assays remain essential for confirmation, depending on the suspected pathogen. Integrating AI with conventional plant diagnostic methods provides a scientifically sound approach to improving plant disease surveillance and management.

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