Modern Approaches and Future Perspectives for Plant Leaf Disease Identification

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DOI: https://doi.org/10.51244/IJRSI.2026.1311000167

Received: 07 November 2026; Accepted: 12 November 2026; Published: 27 November 2026

ABSTRACT

Plant leaf diseases reduce crop quality and productivity and create economic difficulties for farmers. Conventional diagnosis is often based on visual inspection, which is time-consuming, subjective, and difficult to apply across large farming areas. Recent research has investigated image processing, machine learning (ML), deep learning (DL), computer vision, and explainable artificial intelligence (XAI) to support faster and more consistent identification of plant diseases. This study presents a focused review of relevant scholarly literature published in recent years. The literature review discusses image processing, traditional classifiers, deep learning models. It also examines transformer-based methods and explanation techniques, transfer learning, and IoT-enabled monitoring. The findings highlight deep learning's effectiveness for visual disease feature learning, while traditional ML remains relevant under resource constraints. However, performance on controlled datasets doesn't ensure reliability in natural conditions. Key challenges include dataset diversity, class imbalance, model explainability, and computational cost. The review suggests future systems should integrate representative datasets, lightweight models, and practical validation for enhanced precision agriculture.

Keywords: Plant leaf disease, image processing, machine learning, deep learning, transfer learning, explainable AI, IoT.

INTRODUCTION

Agriculture supports food production, employment, and economic activity in many countries. Plant diseases are a continuing threat because infection can affect plant growth, crop quality, and final yield. Leaves are frequently used for disease diagnosis because visible symptoms such as spots, discoloration, lesions, and changes in texture may appear on leaf surfaces. Early identification can help farmers and agricultural specialists respond before disease spreads widely. Traditional diagnosis generally depends on visual inspection by farmers or experts. This approach can require considerable time and experience, and the result may vary according to the observer and the stage of infection (Bhargava et al., 2024; Katuri & Medabalimi, 2026).

Image processing and artificial intelligence have created new possibilities for automated plant disease analysis. Traditional ML systems usually follow a sequence of image acquisition, preprocessing, feature extraction, and classification. Deep learning models, particularly CNNs, can learn useful visual features directly from images and reduce the need for manual feature design. Recent reviews also examine transfer learning, object detection, vision transformers, hybrid architectures, and XAI for improving recognition and supporting interpretation (Pacal, Kunduracioglu, Alma, Deveci, Kadry, Nedoma, Slany & Martinek, 2024; Upadhyay, Chandel, Singh, Chakraborty, Nandede, Kumar, Subeesh, Upendar, Salem & Elbeltagi, 2025).

Although many studies report strong results, practical deployment remains challenging. Images captured in laboratories or against plain backgrounds may not represent field conditions. Lighting, shadows, overlapping

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue XI November 2026

leaves, camera differences, disease severity, and visually similar symptoms can affect predictions. Furthermore, farmers may need to understand why a model has produced a particular diagnosis. These issues make it important to review not only model performance but also dataset quality, interpretability, computing requirements, and real-world suitability (Sagar, Javed & Doermann, 2024; Zhao, Xu, Ma, Li, Wang, Liu & Du, 2025).

OBJECTIVES OF THE STUDY

- To review traditional ML and deep learning techniques used for plant leaf disease detection and classification.
- To summarize the datasets, image-processing steps, and model architectures discussed in the selected literature.
- To examine the role of explainable AI, severity estimation, and IoT-based monitoring.
- To identify common limitations and research gaps in existing studies.
- To suggest future directions for accurate, interpretable, and field-ready plant disease detection systems.

OVERVIEW OF PLANT LEAF DISEASE IDENTIFICATION

Plant leaf disease detection generally involves identifying whether a leaf is healthy or affected by a disease and, where possible, assigning the affected leaf to a disease category. Some systems go further by locating infected regions or estimating the proportion of the leaf affected.

Traditional image processing pipeline

A conventional image-based pipeline begins with image acquisition. The captured image is then preprocessed to reduce noise, resize the image, normalize colour, or improve contrast. Segmentation separates the leaf or diseased region from the background. Features such as colour, shape, and texture are extracted and supplied to a classifier. Common feature techniques discussed in the literature include Grey Level Co-occurrence Matrix (GLCM), colour descriptors, and local or frequency-based features. Classifiers include SVM, KNN, Random Forest, Naive Bayes, and Multilayer Perceptron (Katuri & Medabalimi, 2026; Bhargava et al., 2024).

Deep Learning and Transfer Learning

CNNs learn visual characteristics through sequential convolution and pooling operations. Early layers can learn edges and textures, while deeper layers can learn more complex patterns associated with disease symptoms. Architectures discussed across the reviewed papers include AlexNet, VGG16, VGG19, ResNet, Inception, EfficientNet, and MobileNet. Transfer learning reuses features learned from a previously trained model and can be useful when a task-specific dataset is limited. Lightweight models are also important where processing must take place on mobile or embedded devices (Katuri & Medabalimi, 2026; Salka et al., 2025; Upadhyay et al., 2025).

Explainable AI

Many deep learning models provide a predicted class without clearly showing the visual evidence behind that decision. XAI methods aim to make model behaviour more understandable. Grad-CAM and Grad-CAM++ generate visual attention or activation maps, while LIME provides a local explanation by examining changes to parts of an input. Sagar et al. (2024) explored the use of XAI for leaf-based disease detection and emphasize the need for more transparent predictions. Chihaoui et al. (2026) also connect XAI with field usability and agricultural interpretation.

REVIEW OF RELATED LITERATURE

The selected literature contains two broad evidence types. Bhargava et al., Pacal et al., Sagar et al., Salka et al., George et al., Upadhyay et al., Zhao et al., Chihaoui et al., and Katuri and Medabalimi discussed methodologies and research trends in their review and survey studies. Primary experimental papers presented by Altabaji et al., Oad et al., Gopalan et al., Mathew et al., and Khadse and Zope described specific models, datasets or proposed implementations.

Bhargava et al. conducted a review on the detection, classification, and diagnosis of plant leaf diseases with computer vision and artificial intelligence. The review covers traditional image processing, machine learning, deep learning, and newer approaches such as few-shot learning and image segmentation. Dataset requirements, computational cost, and model interpretability remain important concerns. (Bhargava, Shukla, Goswami, Alsharif, Uthansakul, Uthansakul 2024).

Chihaoui et al. reviewed AI-based crop disease detection using leaf-image classification and explainable AI. The paper brings together model explainability, field usability, and modern AI architectures for crop-disease diagnosis. Domain shift, annotation standards, and cross-environment validation remain important research gaps. (Chihaoui, Waleed, Mufleh, Alshraah, Alajmi, Altuwayjiri, 2026).

Altabaji et al. compared LeafNet, a modified LeafNet, MobileNetV2, and Xception for rice leaf disease classification using 2,658 healthy and diseased images. The Modified LeafNet model achieved 97.44% validation accuracy and 87.76% test accuracy, outperforming the other evaluated models on the reported dataset. The difference between validation and test performance also indicates that evaluation on unseen images remains important when judging practical generalization. (Altabaji, Umair, Tan, Foo, Ooi, 2024).

George et al. surveyed the past, present, and future of deep plant leaf disease recognition. The study compares widely used datasets and reviews preprocessing, feature extraction, classification, and recognition pipelines. Field-representative datasets and reliable evaluation procedures are necessary to support real-world use. (George, Thuseethan, Ragel, Mahendrakumaran, Nimishan, Wimalasooriya, Alazab, 2025).

Gopalan et al. investigated corn leaf disease classification using ResNet152 and Grad-CAM for explainable diagnosis. Their dataset contained 4,188 images across healthy, blight, common rust, and gray-spot classes; the model reported 99.95% training accuracy and 98.34% testing accuracy. Grad-CAM heatmaps were used to visualize image regions influencing predictions. The high reported scores should be interpreted in relation to the dataset split and the need for independent field validation. (Gopalan, Srinivasan, Pragya, Singh, Mathivanan, Moorthy, 2025).

Katuri and Medabalimi reviewed thirty approaches for plant leaf disease detection using traditional machine learning and deep learning. The review discussed classifiers such as SVM, Random Forest, and KNN alongside CNN, VGG16, ResNet50, InceptionResNet, and hybrid approaches. Dataset diversity, computing resources, and interpretability require further attention. (Katuri, Medabalimi, 2026).

Khadse and Zope presented an IoT-based cotton leaf disease detection system using Raspberry Pi, a camera, environmental sensors, image processing, and MobileNetV2. The proposed architecture combines image classification, disease-severity estimation, IoT sensing, and edge computing. The reported accuracy and processing targets require validation through field trials. (Khadse, Zope, 2026).

Mathew et al. developed a handheld GPU-assisted DSC-TransNet model for real-time plant leaf disease classification. The work combines deep-learning classification with a portable computing setup and evaluates the system in a real-time context, emphasizing the practical importance of inference capability beyond offline model accuracy. Hardware dependence, device cost, and validation under varied field conditions remain relevant considerations for deployment. (Mathew, Elayidom, Jagathy Raj, Abubeker, 2025).

Oad et al. proposed an ensemble-based plant leaf disease detection framework combining VGG16, VGG19, ResNet101V2, and InceptionV3. The ensemble achieved accuracy above 90% and used LIME to explain

predictions by identifying image regions that contributed positively or negatively to model decisions. The study illustrates the value of combining predictive performance with interpretability, although explanation maps and performance still need to be assessed across field conditions. (Oad, Abbas, Zafar, Akram, Dong, Talpur, Uddin, 2024).

Pacal et al. conducted a systematic review of deep-learning techniques for plant disease detection and discussed automated feature learning from leaf images and the use of different model architectures. The review provided a broad synthesis of deep-learning-based plant disease research. Model reliability depends on suitable datasets, robust validation, and performance under varied agricultural conditions. (Pacal, Kunduracioglu, Alma, Deveci, Kadry, Nedoma, Slany, Martinek, 2024).

Richter and Kim benchmarked transfer-learning models on multiple open plant leaf disease datasets to examine performance across datasets rather than relying on a single collection. Their results demonstrate substantial variation among datasets and model performance, highlighting the difficulty of transferring a classifier between crops and image environments. The benchmark supports the need for dataset-specific and cross-dataset evaluation, particularly when laboratory and field images differ. (Richter, Kim, 2025).

Sagar et al. surveyed leaf-based plant disease detection with a particular focus on Explainable AI. The study discusses common diseases, public datasets, traditional and deep-learning methods, and visual explanation techniques that can improve user trust. Disease-stage recognition, simultaneous infections, and disease-severity quantification require further investigation. (Sagar, Javed, Doermann, 2024).

Salka et al. reviewed CNN-based plant leaf disease detection and classification, covering datasets and architectures such as VGG, EfficientNet, GoogLeNet, and ResNet. The study compared commonly used CNN approaches for leaf disease classification. Small datasets, occlusion, and generalization across different environmental conditions remain limitations. (Salka, Hanafi, Rahman, Zulperi, Omar, 2025).

Upadhyay et al evaluated deep learning and computer vision technologies for detecting plant diseases in precision agriculture. Their discussion included disease detection, identification, quantification, and the integration of computer vision into agricultural applications. Field conditions, dataset quality, and deployment requirements must be considered for practical systems. (Upadhyay, Chandel, Singh, Chakraborty, Nandede, Kumar, Subeesh, Upendar, Salem, Elbeltagi, 2025).

Zhao et al. reviewed deep-learning algorithms for plant leaf disease identification, including datasets, CNN-based recognition, object detection, lightweight networks, and practical applications. The paper provided a recent overview of architectures and dataset-related issues. Generalization to real environments and balancing predictive performance with computational requirements remain challenges. (Zhao, Xu, Ma, Li, Wang, Liu, Du, 2025).

Review papers synthesize earlier studies and do not report a new experimental dataset or model score unless explicitly stated. Reported accuracy values belong to the dataset and validation protocol used in each original study; they should not be compared directly across different datasets. Where crop-wise data, validation details or hardware specifications were not available in the manuscript summary, these details must be checked in the original paper.

Table 1: Summary of the reviewed literature

Authors (Year)	Dataset Name and Crops Used	Leaf Diseases	Models Used	Key Findings and Metrics	Limitations
Altabaji et al. (2024)	Dataset: Kaggle Rice Leaf Disease Dataset (2,658	Rice Brown Spot, Rice Leaf Blast, Rice Hispa	Modified LeafNet, LeafNet, MobileNetV2, Xception	Modified LeafNet achieved 97.44% validation accuracy and 87.76% test accuracy.	Test performance was lower, and further field testing

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue XI November 2026

	images). Crop: Rice				was required.
Bhargava et al. (2024)	Dataset: Multiple datasets and diagnostic sources; no single dataset. Crops: Multiple crops	Apple Scab, Apple Black Rot, Tomato Early Blight, Potato Late Blight	Machine Learning, Deep Learning, Few-shot Learning, Hyperspectral Imaging	Discussed ML, DL and advanced imaging techniques for plant disease identification. Metrics: Not reported.	Limited labelled data and high computational requirements remained challenges.
Oad et al. (2024)	Dataset: PlantVillage Dataset (54,305 images, 14 species and 38 disease classes). Crops: Apple, Grape, Tomato, Potato and other crops	Apple Scab, Apple Black Rot, Apple Cedar Rust, Corn Common Rust, Corn Gray Leaf Spot, Potato Early Blight, Potato Late Blight, Tomato Leaf Mold	VGG16, VGG19, ResNet101V2, InceptionV3, LIME	Deep-learning models achieved above 90% accuracy, with LIME supporting model interpretation. Metric: Accuracy.	Field testing and verification of model explanations were needed.
Pacal et al. (2024)	Dataset: Multiple public plant disease datasets. Crops: Multiple crops	Tomato Early Blight, Tomato Late Blight, Potato Early Blight, Potato Late Blight, Pepper Bacterial Spot	Deep Learning Models and CNN-based Approaches	Highlighted the usefulness of deep-learning models for plant disease detection. Metrics: Not reported.	Different datasets and testing methods made comparisons difficult.
Sagar et al. (2024)	Dataset: Multiple public plant disease datasets. Crops: Multiple crops	Apple Scab, Apple Cedar Rust, Rice Bacterial Leaf Blight, Rice Brown Spot	CNNs, Vision Transformers, Grad-CAM and Explainable AI Techniques	Discussed CNNs, vision transformers and explainable AI for disease classification. Metrics: Not reported.	Multiple diseases and explanation reliability remained challenging.
Upadhyay et al. (2025)	Dataset: Multiple public plant disease datasets. Crops: Multiple crops	Tomato Early Blight, Tomato Late Blight, Potato Early Blight, Potato Late Blight, Grape Black Rot	CNNs, Computer Vision and Deep Learning Approaches	Explained the role of deep learning in plant disease detection and precision agriculture. Metrics: Not reported.	Performance under real farm conditions needed improvement.
George et al. (2025)	Dataset: Multiple plant disease image datasets. Crops:	Apple Scab, Apple Cedar Apple Rust, Rice Bacterial Leaf Blight, Rice Brown Spot, Rice Leaf Smut	Deep Learning Models	Highlighted the importance of preprocessing and feature extraction in disease identification.	Models needed testing on more diverse field images.

	Multiple crops			Metrics: Not reported.	
Gopalan et al. (2025)	Dataset: Kaggle Corn Leaf Disease Dataset (4,188 images and four classes). Crop: Corn	Corn Blight, Corn Common Rust, Corn Gray Leaf Spot	ResNet152, Grad-CAM	ResNet152 achieved 99.95% training accuracy and 98.34% testing accuracy. Metric: Accuracy.	Performance on images collected directly from farms needed verification.
Mathew et al. (2025)	Dataset: Plant leaf disease image dataset. Crops: Multiple crops	Bell Pepper Bacterial Spot, Grape Black Rot, Grape Isariopsis Leaf Spot, Grape Black Measles	DSC-TransNet, VGG19-based Feature Extraction, Transformer Encoder	DSC-TransNet combined VGG19 features with a transformer for disease classification. Metrics: Not reported.	Device efficiency and performance across different crops needed further testing.
Salka et al. (2025)	Dataset: Multiple plant disease image datasets. Crops: Multiple crops	Potato Early Blight, Potato Late Blight, Pepper Bacterial Spot, Strawberry Scorch, Tomato Early Blight, Soybean Septoria	VGG, EfficientNet, GoogLeNet, ResNet	Reviewed VGG, EfficientNet, GoogLeNet and ResNet for plant disease classification. Metrics: Not reported.	Overlapping leaves and complex backgrounds affected recognition.
Zhao et al. (2025)	Dataset: Multiple plant disease image datasets. Crops: Multiple crops	Apple Scab, Apple Rust, Rice Brown Spot, Rice Leaf Spot, Rice Bacterial Leaf Blight	CNNs, Object Detection Models and Lightweight Deep Learning Models	Reviewed CNNs, object detection and lightweight models for disease identification. Metrics: Not reported.	Lighting and image-quality changes affected detection reliability.
Richter & Kim (2025)	Dataset: Multiple plant disease image datasets. Crops: Multiple crops	Apple Scab, Apple Black Rot, Tomato Early Blight, Potato Late Blight	Transfer Learning Models	Showed that transfer-learning performance varied across datasets. Metrics: Not reported.	Different testing conditions made direct model comparison difficult.
Chihaoui et al. (2026)	Dataset: Multiple plant disease image datasets. Crops: Multiple crops	Apple Scab, Tomato Early Blight, Tomato Late Blight, Rice Bacterial Leaf Blight, Grape Black Rot	Machine Learning, CNNs, Vision Transformers and Explainable AI	Reviewed ML, CNNs, vision transformers and explainable AI techniques. Metrics: Not reported.	Unfamiliar environments and high computing needs remained challenges.
Katuri & Medabalimi (2026)	Dataset: Multiple plant disease image datasets. Crops: Multiple crops	Potato Early Blight, Potato Late Blight, Tomato Early Blight, Tomato Yellow Leaf Curl Virus, Citrus Canker	SVM, Random Forest, KNN, CNN, VGG, ResNet and EfficientNet	Discussed traditional ML and deep-learning methods for plant disease detection. Metrics: Not reported.	Dataset differences made it difficult to identify a universally suitable

					model.
Khadse & Zope (2026)	Dataset: Cotton Leaf Disease Dataset (six categories). Crop: Cotton	Cotton Bacterial Blight, Cotton Powdery Mildew, Cotton Target Spot, Cotton Aphid and Armyworm infestation	CNN, Image Segmentation, Severity Estimation and Raspberry Pi/IoT-based Technologies	Reported 98.83% accuracy with additional disease-severity estimation features. Metrics: Accuracy, Macro-precision, Macro-recall and Macro-F1.	Further testing on real farm images was required.

RESEARCH METHODOLOGY

The present study adopts a structured narrative-review methodology to examine recent developments in plant leaf disease detection and classification. The review is organized around the research problem, objectives, and major technical approaches reported in the literature. It synthesizes published findings rather than conducting a new laboratory experiment or training a disease-classification model. This approach provides a basis for identifying recurring techniques, reported contributions, limitations, and directions for future research.

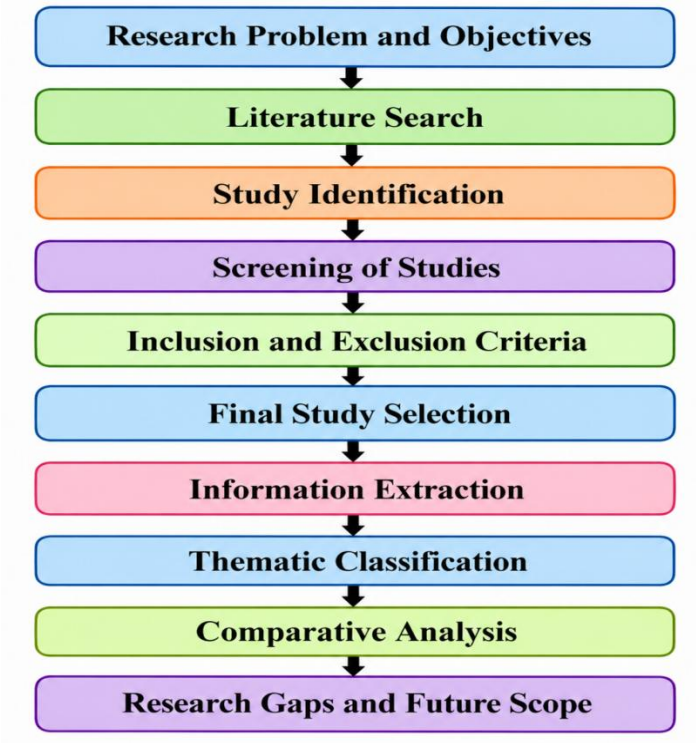


Figure1: Methodology Framework

Sources and Selection

Search strategy and reproducibility

For a fully reproducible review, the final manuscript should report the databases actually searched, the date on which each search was conducted, the exact search strings, and the number of records retrieved from each database. These details were not present in the submitted manuscript and must be completed from the authors' search records; they have not been invented in this revision.

Suggested search-string structure (adapt to the terms actually used): ("plant leaf disease" OR "crop disease detection") AND ("image classification" OR "computer vision" OR "machine learning" OR "deep learning" OR "CNN" OR "transfer learning" OR "explainable AI"). Record the final exact query separately for each database.

Screening record to complete before submission: databases searched: [insert actual names]; search date(s): [insert date(s)]; date/language limits: [insert limits, if any]; records retrieved: [insert number]; duplicates removed: [insert number]; titles/abstracts screened: [insert number]; full texts assessed: [insert number]; studies included: 15. Add reasons for full-text exclusion and describe any quality-appraisal method used. Do not retain the figure 15 unless it matches the final screening record.

The review examined the 15 publications listed in the reference section, covering plant leaf disease recognition through image processing, machine learning, deep learning, computer vision, explainable artificial intelligence (XAI), and IoT-enabled systems. The selected set includes both review articles and studies describing individual experimental or proposed systems. The review period represented by the included references is 2024–2026. The manuscript supplied for revision did not contain a complete database-search log; therefore, the exact databases, search dates and number of records screened cannot be reported as completed facts.

Inclusion and Exclusion Criteria

Studies were considered relevant when they addressed one or more of the following themes: (i) image-based identification or classification of plant diseases; (ii) feature extraction and traditional machine-learning classifiers; (iii) CNNs, transfer learning, object detection, or transformer-based approaches; (iv) disease localization, severity estimation, or multiple-disease recognition; (v) explainability and interpretation of model predictions; and (vi) mobile, edge, or IoT-based agricultural deployment.

Both review papers and primary research papers were retained when they directly addressed the objectives. Primary studies were used to describe particular datasets, models and reported metrics, while review papers were used to summarize broader research trends. Proposed architectures were not treated as proven field deployments. Where the available manuscript did not state a crop, dataset split, field-validation setting or hardware specification, the detail was marked for verification rather than inferred.

Studies outside the plant-disease image-analysis domain, publications lacking sufficient methodological or topical information for meaningful synthesis, and works unrelated to the stated review objectives were not considered in the thematic analysis. Reported performance values were not treated as directly comparable when datasets, disease categories, experimental conditions, or evaluation protocols differed.

The review is qualitative and comparative in nature. It does not calculate a pooled accuracy estimate, conduct a statistical meta-analysis, or independently verify the reported performance of individual authors. Because the studies used different datasets, disease classes, image conditions and validation procedures, their accuracy values are presented only as study-specific reported results.

Information Extraction and Analysis

For each selected publication, information was organized using a common extraction framework: author and year, research objective, crop or dataset context, image-processing or learning technique, principal contribution, application or deployment setting, and reported limitation. The extracted information was grouped into traditional image processing and machine learning, deep learning and transfer learning, detection and localization, explainable AI, and IoT/edge-based applications. The studies were compared across these themes to identify common trends, methodological strengths, unresolved challenges, and opportunities for further research.

ANALYSIS AND DISCUSSION

Traditional Machine Learning

Traditional ML methods generally require features to be identified before classification. Colour, shape, and texture descriptors can be extracted from leaf images and supplied to classifiers such as SVM, KNN, and Random Forest. These methods can be comparatively lightweight and easier to inspect, which may make them

suitable for smaller datasets or limited computing environments. However, performance can depend strongly on the quality of manually selected features and image preprocessing. Handcrafted feature design might be challenging due to complex backdrops and subtle disease symptoms (Bhargava et al., 2024; Katuri & Medabalimi, 2026).

CNN Based Deep Learning

CNNs are prominent in the reviewed literature because they learn visual features directly from image data. Architectures such as VGG, ResNet, Inception, EfficientNet, and MobileNet are used or discussed for disease classification. Transfer learning can reduce the amount of task-specific training required by starting from previously learned image representations. Nevertheless, a model that performs well on a controlled dataset may not maintain the same performance when images are captured in farms under different lighting, backgrounds, and camera conditions (Salka et al., 2025; Zhao et al., 2025; Upadhyay et al., 2025).

Object Detection and Transformer Based Methods

Classification assigns a label to an image, whereas object-detection approaches can also locate disease-affected regions. YOLO-based models and other detection architectures are discussed in recent reviews as options for faster or more localized analysis. Vision transformers and hybrid CNN-transformer systems are also emerging because they can model broader relationships within an image. However, the selection of an architecture should consider accuracy, inference speed, model size, annotation needs, and the target deployment device rather than accuracy alone (Zhao et al., 2025; Chihaoui et al., 2026).

Explainability and Trust

XAI is important because a disease label alone may not provide enough information for a farmer or agricultural specialist to assess a model's prediction. Methods such as Grad-CAM and LIME can provide visual or local explanations, but an explanation map should not automatically be treated as proof that a model has identified the biological cause of a disease. Future work should assess whether highlighted regions correspond to meaningful disease symptoms and whether explanations are stable and understandable to agricultural experts (Sagar et al., 2024; Chihaoui et al., 2026).

IoT and Edge-Based Applications

The cotton disease system described by Khadse and Zope (2026) illustrated how a camera, Raspberry Pi, environmental sensors, a lightweight model, and cloud connectivity can be combined. Such systems may support continuous monitoring, severity estimation, and timely alerts. Edge processing can reduce dependence on continuous cloud communication, but practical deployment must be tested for power use, network availability, inference speed, maintenance, and reliability under actual field conditions. The expected performance figures in a proposed design should be clearly distinguished from results measured through completed experiments.

Cross-study synthesis

The literature points to several connected issues that affect whether a model can be used outside its development dataset.

Controlled images and field performance

Images collected against plain or controlled backgrounds make classification easier because the leaf is usually clear and well positioned. Field images contain shadows, changing illumination, soil, overlapping leaves and different camera viewpoints. Altabaji et al. reported a lower test accuracy than validation accuracy on the rice dataset, while Richter and Kim (2025) found that performance varied across datasets. Together, these findings support independent field and cross-dataset testing; they do not establish a single performance ranking across studies.

Class imbalance and similar symptoms

Unequal numbers of images across healthy and diseased classes can cause a model to favour frequent classes and perform less reliably on under-represented diseases. Overall accuracy alone may hide this problem. Future evaluations should report class-wise precision, recall and F1-score, confusion matrices, and the number of images in each class. Visually similar symptoms and multiple infections create an additional challenge because the model may confuse diseases with overlapping colour or texture patterns.

Model efficiency and deployment

Large CNN and transformer models may provide strong image representations but can require more memory, processing power and energy. MobileNet-based and handheld GPU-assisted systems illustrate interest in efficient or portable deployment. However, a proposed or prototype system should not be described as field-ready unless its inference time, hardware, power requirements, connectivity and performance in farm conditions have been measured and reported.

Explainability validation

Grad-CAM and LIME can show which image regions influence a prediction, but a heatmap alone does not prove that the model has learned the biological symptoms of a disease. Explanations should be checked for stability and relevance, preferably with input from plant-disease experts. Evaluation should also establish whether explanations help users make better decisions.

Limitations of the present review

This review provides a qualitative synthesis of 15 cited publications, but the original manuscript did not record a complete database-search log, screening counts or formal quality assessment. Most included publications are review or survey papers. Consequently, the evidence base for direct experimental comparison is limited. The revised methodology marks the missing search details for author completion and avoids treating proposed systems as validated field deployments.

KEY FINDINGS

- Growing Use of Deep Learning: CNN models such as VGG, ResNet, EfficientNet and MobileNet are widely used for automated plant leaf disease classification.
- Traditional Machine Learning: SVM, Random Forest and KNN remain useful for classification using extracted image features.
- Importance of Transfer Learning: Pre-trained models and data augmentation help improve learning, especially when training datasets are limited.
- Dataset Quality: Image quality, dataset diversity and testing conditions strongly influence classification performance.
- Explainable AI: Techniques such as Grad-CAM and LIME help explain model predictions by highlighting important image regions.
- IoT and Edge Computing: Combining disease classification with IoT and edge devices offers potential for real-time plant monitoring.

Overall, reliable plant leaf disease identification requires accurate models, diverse datasets and testing under real agricultural conditions.

CHALLENGES AND RESEARCH GAPS

- Dataset coverage and class imbalance: Under-represented crops and disease classes can reduce class-wise reliability. Future work should report class distributions and class-wise metrics.
- Controlled-to-field domain shift: Models trained on plain-background images may not generalize to field images containing shadows, overlapping leaves, soil and camera variation. Independent field testing is needed.
- Similar symptoms and multiple infections: Diseases with similar colour or texture patterns may be confused. Multi-label recognition and expert-verified symptom annotations need further study.
- Severity and disease-stage assessment: More work is needed to estimate affected leaf area, recognize early stages and identify more than one disease on the same leaf.
- Explainability validation: Grad-CAM and LIME outputs should be tested for stability and biological relevance, not judged only by visual appearance.
- Model efficiency and deployment: Studies should report model size, inference time, memory, power use and device requirements, particularly for mobile and edge applications.
- Evaluation consistency: Different datasets and validation protocols prevent direct comparison of accuracy values. Dataset-wise and class-wise results should be reported using clearly described test settings.

CONCLUSION

This study reviews the recent developments in plant leaf disease detection and classification using image processing, machine learning, and IoT-based techniques. It describes the gradual transition from traditional machine learning classifiers to advanced approaches such as Convolutional Neural Networks (CNNs) and transformer-based models. The review also highlights the importance of Explainable AI (XAI) in making the decision-making process of AI systems more understandable to users. However, challenges such as limited dataset diversity and high computational requirements still need attention. Future research should focus on developing reliable systems that perform effectively under real field conditions, provide clear explanations, and require fewer computational resources. The use of diverse datasets and properly validated models can further improve the accuracy and practical application of plant disease detection systems.

FUTURE SCOPE

To enhance agricultural image analysis, develop diverse datasets covering various crops, regions, and conditions. Employ data augmentation and advanced learning techniques to optimize performance with limited labeled images. Investigate lightweight CNNs and model compression for mobile applications, merging classification with lesion segmentation and disease severity analysis. Incorporate explainable AI (XAI) methods, engaging plant pathologists for evaluations. Focus on early-stage disease recognition and links between image models and environmental sensors, ensuring robust validation of alerts. Use standardized evaluation protocols and field trials to assess reliability and generalization.

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