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Review Article

Comprehensive Review of Plant Disease Detection: Advancements in Imaging Sensors, AI Techniques, and Future Directions in Smart Agriculture

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ABSTRACT

Food safety globally is threatened by crop disease, which creates a major obstacle to yield losses, so there is an urgent need for rapid, precise, and large-scale diagnostic methods for all the global risks crops are exposed to from disease. While imaging sensors, as well as Artificial Intelligence (AI), have made great strides in recognising plant disease, most literature does not have a comprehensive analysis that combines methods, technology, and implementation. Therefore, a systematic literature review follows PRISMA methods; we review 61 excellent studies published within the last five years that outline the advancement of imaging modalities (Red, Green, Blue (RGB), multispectral/hyperspectral, thermal), deep learning architectures, augmentation of data, explanation methods and IoT (Internet of Things)-edge-cloud for managing intelligent agriculture. These modern AI-based systems (AI systems) have consistently produced accurate results above 98%. However, there are problems with the generalisability (across hybrid plant species), robustness (when exposed to environmental stresses), and interpretability of the results presented to consumers. This review represents the first compilation of using imaging sensors, artificial intelligence models, Internet of Things architecture (IoT-edge), and robotics into one comprehensive framework for the detection of plant disease in the next generation. In addition, this review suggests future research directions, including lightweight edge-deployable models, multimodal sensor fusion, interpretable AI, larger validated datasets, and autonomous robotic systems for scalable and sustainable smart agriculture.

Keywords: Artificial intelligence, deep learning, imaging sensors, internet of things (IoT), plant disease detection, robotics, smart agriculture

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INTRODUCTION

There is no substitute for agriculture in terms of food safety, economic growth, and environmental sustainability. However, various plant diseases have caused a steady decline in crop yield, resulting in significant losses in terms of money. Traditional methods of planting, generally based on human seeing and expertise, both involve delays in diagnosing disease and ineffective treatment options for plant disease (Chakrabarty et al., 2024; Nigar et al., 2024). The current demands for more sophisticated, accurate, and efficient detection systems, therefore, become vital; Figure 1 presents a selection of the most common plant diseases for different crops. Recently, advances in imaging sensors and Deep Learning (DL) models have transformed plant disease identification by offering automated high-precision analytical solutions that reduce yield losses and improve decision-making for smart agriculture. Reviews today primarily discuss either specific DL algorithms or individual sensor types rather than provide a holistic overview of combined approaches (Raval & Chaki, 2024). Current limitations relate to underexamined areas such as data set bias, use of interpretable machine learning algorithms, and the ability to identify plant diseases with data distributions typically seen in field applications (sometimes referred to as representativeness). To address these challenges, this addresses these deficiencies in an informative manner that combines information on past achievements of imaging sensors and AI-related technologies to detect and classify plant diseases while identifying new opportunities for supporting smart agriculture.

Figure 2a shows the publication trends for 2020 to 2025, while Figure 2b shows the overall circulation of the large publishers.

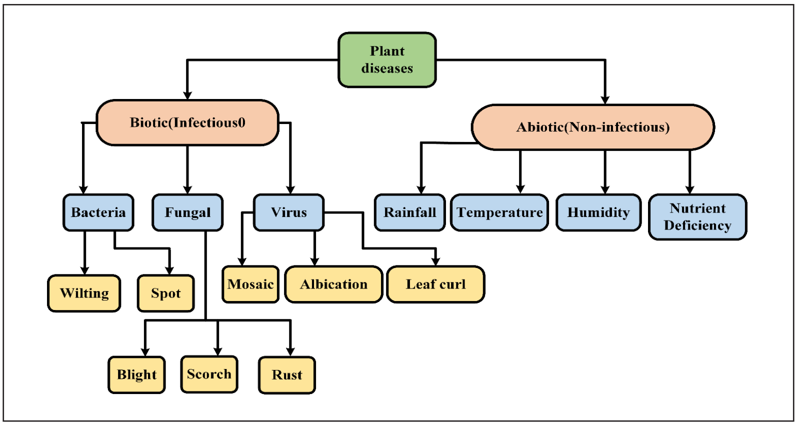
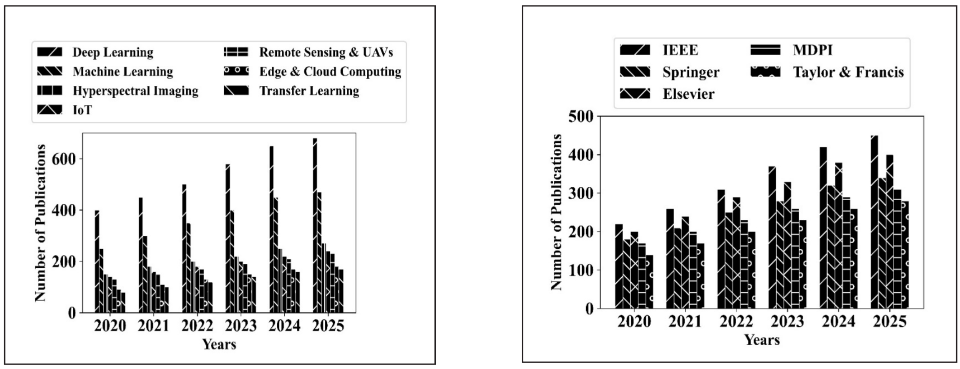


Figure 1. Overview of common plant diseases affecting various crops



(a) (b)

Figure 2. Publication trend for plant diseases (a) Different domains; (b) Different journals

Major Contributions

This review offers numerous substantial contributions to the field of plant disease detection and smart agriculture:

- The article summarises how improvements to sensors in RGB, multispectral, hyperspectral, thermal, and UAV-based systems contribute to the development of documentation for plant disease detection.
- This article compares current AI methods, CNNs, transformers, few-shot learning, ensembles, and explainable AI (XAI), for plant disease detection across different crops and environmental conditions.
- This review extends prior work by analysing how Internet of Things (IoT) sensors, edge computing devices, and autonomous robots enable scalable, real-time, in-field plant disease detection systems.
- In addition, this paper synthesises trends in performance across different plant species by documenting trends in accuracy, sensor suitability and model robustness.
- This review highlights key challenges in plant disease detection, including limited datasets, domain shift affecting transferability, and poor model interpretability, which hinder large-scale practical deployment.
- This review presents a unified framework integrating imaging sensors with AI and IoT/edge/robotic systems, offering an end-to-end approach not addressed in prior studies.

The organisation of the survey is shown in Figure 3.

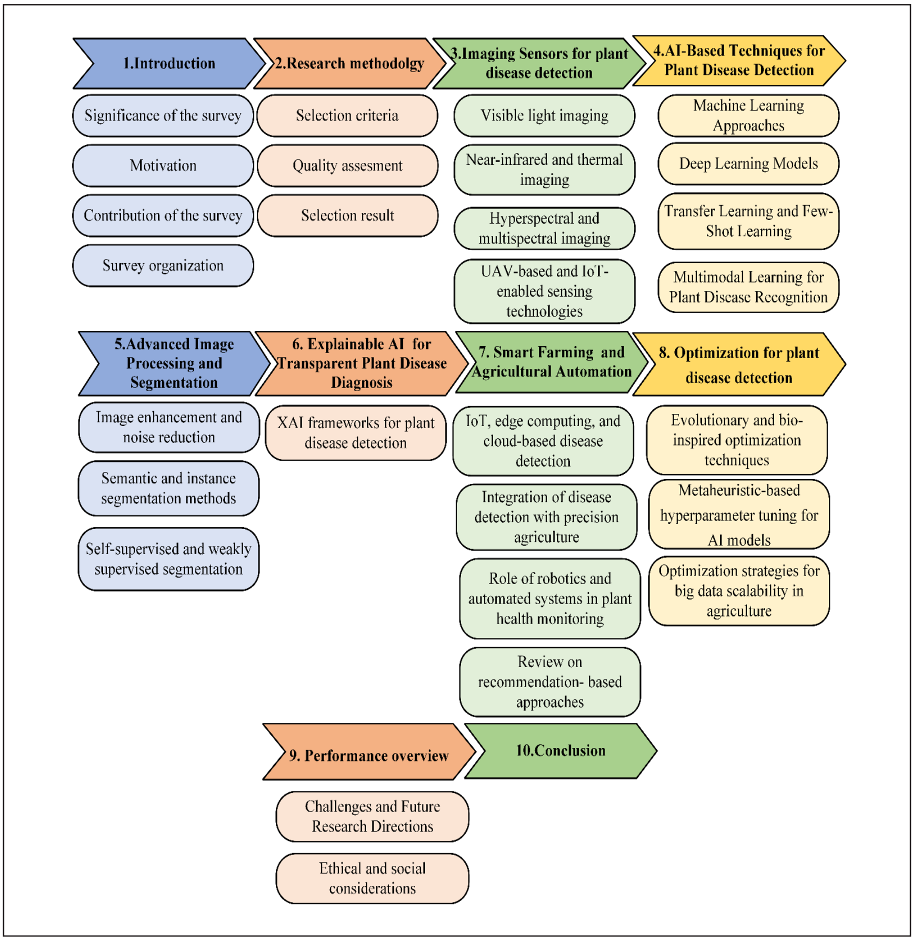


Figure 3. Organisation of the survey

RESEARCH METHODOLOGY

Research Questions

To ensure a structured and focused review, this study is guided by the following Research Questions (RQs).

RQ1 : What types of imaging sensors can be used to detect plant diseases, and how do these sensors differ in terms of how accurately they can detect plant diseases or provide early detection capabilities, and their robustness to the environment?

RQ2 : What types of AI/DL methods/algorithms appear to perform best across different crops, datasets and plant diseases, and what factors can affect the performance of these methods?

RQ3 : What are some of the major challenges (e.g., data set limitations, variations between fields, interpretability and generalisability) that have been identified in recent literature?

RQ4 : How are IoT, edge devices, and robotics integrated with AI models to enable real-time and scalable deployment of plant disease detection systems?

RQ5 : What type of future research will provide more accurate, interpretable, and easier-to-use plant disease detection systems?

Search Strategy and Databases

A systematic review of relevant research on the use of AI for identifying plant diseases was conducted across multiple databases, including IEEE Xplore, Springer, MDPI, ScienceDirect, Taylor and Francis, and PubMed. Relevant keywords involved "plant disease detection," "deep learning in agriculture," "imaging sensors for crop health," and "smart farming techniques."

Inclusion and Exclusion Criteria

The search yielded many studies, which were filtered through title/abstract screening and full-text review based on predefined criteria. Only peer-reviewed English-language articles (2020 onward) on AI/IoT-based plant disease detection were included, with duplicates and irrelevant studies removed to retain high-quality research. The full details of the inclusion and exclusion criteria for article/study selection are accessible in Table 1.

Table 1
Inclusion and exclusion criteria

S. No.	Inclusion	Exclusion
1	Available in peer-reviewed journals	Non-English papers
2	Published after the year 2020	Book chapters
3	Direct relevance to plant disease detection in AI and IoT-based agricultural domains	Little or no focus on AI-based plant disease solutions
4	Articles addressing research questions	Duplicate articles

PRISMA Process

This review followed the PRISMA 2020 guidelines to ensure a transparent and reproducible selection process. The complete selection workflow is shown in Figure 4.

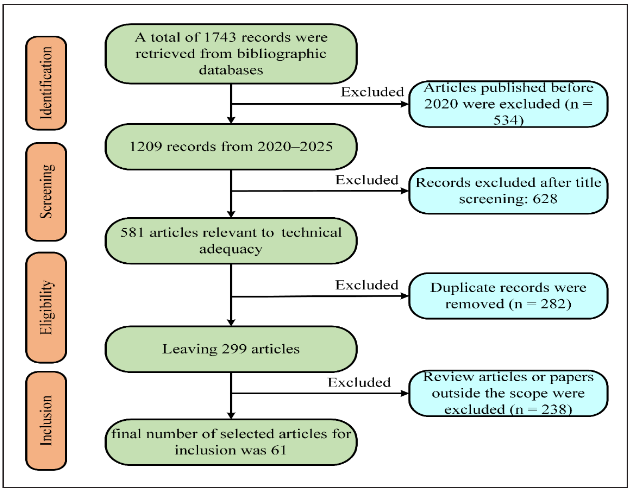


Figure 4. PRISMA process

Data Extraction and Study Categorisation

Data extraction classified studies by crop type, disease, sensors (RGB, hyperspectral, multispectral, thermal/IR), dataset details, and model architectures with performance metrics.

Performance Evaluation Metrics

Model performance was evaluated using multiple metrics, including precision, recall, F1-score, and specificity to balance false positives and false negatives, especially in imbalanced datasets. Confusion matrices further analysed misclassification patterns, providing a comprehensive assessment of plant disease classification performance beyond overall accuracy.

Quality Assessment

The excellence of the studies selected was evaluated using an assortment of criteria.

- **Application Area:** The research application for your plant disease identification is focused specifically on agriculture through imaging sensors, AI, and IoT technologies.
- **Objectives:** These articles state clearly their goals for research; they identify specific AI-related challenges to diagnosing plant diseases and present promising solutions.
- **Techniques:** These articles should utilise advanced AI techniques, including DL, Machine Learning (ML), Transfer Learning (TL) or hybrid approaches using imaging sensor technologies to improve the accuracy of the disease identification process.

- **Security Measures:** The research evaluates how models perform, scale, and can be applied to real-world situations, as well as environmental variability, diversity of the datasets, and constraints on operations being evaluated.

Imaging Sensors for Plant Disease Detection

Visible Light Imaging

RGB imaging is a low-cost, scalable method for plant disease detection, but it is limited to visible symptoms and cannot reliably detect early or differentiate stress types. ML/DL and multimodal fusion with hyperspectral or thermal data improve accuracy and early detection.

Near Infrared and Thermal Imaging

Near Infrared (NIR) and thermal imaging enable non-invasive, early plant disease detection by capturing physiological changes such as water stress, chlorophyll variation, and temperature anomalies. Table 2 presents an overview of the imaging sensors for plant diseases.

Table 2
Summary of key contributions in numerous applications of imaging sensors for plant disease diagnosis

Target	Refs	Crop	Disease	Imaging Type/ Sensors	Methods and Algorithms
Early disease detection & classification	Zhang et al., 2020	Rice	Leaf blast	Hyperspectral imaging, EM285CL EMCCD camera	Support Vector Machine (SVM)-based Spectral analysis for disease severity estimation.
	Yong et al., 2022	Oil palm	Basal stem rot	Hyperspectral imaging, a Cubert FireflEYE S185 hyperspectral camera	Region-Based Convolutional Neural Network (RCNN) based classification.
	Chen et al., 2024	Rice	Bakanae disease	Hyperspectral imaging (UAV-based)	CNN
	Zhang et al., 2024	Tomato	Bacterial leaf spot	Hyperspectral imaging	Spectral-based feature extraction + ML classifiers
	Hsiao et al., 2025	Soybean	Fungal leaf diseases	Hyperspectral imaging	CNN-based spectral-spatial classification

Table 2 (*continued*)

Target	Refs	Crop	Disease	Imaging Type/ Sensors	Methods and Algorithms
Disease severity assessment & localisation	Zhang et al., 2022	Rice	Leaf blast	Hyperspectral imaging, EM285CL EMCCD camera	Classification across multiple growth stages by the Successive Projections Algorithm (SPA) and SVM.
	Li et al., 2023	Grape	Leaf diseases	UAV-based imaging	improved U-net and Visual Geometry Group (VGG)-19 -based detection and localisation.
UAV & IoT-enabled disease monitoring	Kerkech et al., 2020	Grapevine	Various diseases	UAV-based multispectral imaging, Quadcopter drone	Optimised image registration, DL segmentation.
Advanced spectral analysis & chemometrics	Gloerfelt-Tarp et al., 2023	Cannabis sativa	N/A	NIR imaging	NIR spectroscopy, chemometric analysis.
Real-time monitoring	Rahman et al., 2025	Multi-crop	Multiple leaf diseases	RGB imaging (real-time camera system)	Deep CNN models for real-time detection
Multi-dataset detection	Krishna et al., 2025	Multiple crops	Multiple leaf diseases	RGB imaging + multi-dataset inputs	DL (CNN models)
Asymptomatic & severity grading	Chen et al., 2025	Tomato	Tomato yellow leaf curl disease	Hyperspectral imaging	3D spectral-spatial deep learning model

Hyperspectral and Multispectral Imaging

Hyperspectral imaging enables early detection via fine biochemical changes, while multispectral Imaging provides cost-effective wide-area UAV monitoring, with AI improving classification but limited by calibration and processing challenges. Chen et al. (2024) and Zhang et al. (2024) showed early rice bakanae and tomato leaf spot detection via hyperspectral imaging, while Hsiao et al. (2025) confirmed its efficacy for soybean fungal disease using CNNs. Rahman et al. (2025) built a real-time multi-crop system, Krishna et al. (2025) improved generalisation with multi-dataset fusion, and Chen et al. (2025) detected asymptomatic tomato yellow leaf curl disease with severity grading.

UAV-based and IoT-Enabled Sensing Technologies

UAV-based multispectral/hyperspectral and IoT systems enable continuous, high-resolution plant disease monitoring and early detection, while AI-driven integration improves real-time prediction and management despite challenges like battery, weather, and transmission limits.

AI-based Techniques for Plant Disease Recognition

Machine Learning Approaches

ML techniques enhance plant disease recognition by automating feature extraction and classification, with methods like K-Nearest Neighbours (KNN), SVM, and the Random Forest (RF) effectively distinguishing healthy and diseased leaves from extracted image features.

Deep Learning Models

Deep learning architectures enable high-performance plant disease recognition through advanced neural networks for accurate and efficient classification. Boyar et al. (2025) proved that the U-Net variants performed best for hazelnut leaf disease recognition from drone imagery. Yilmaz et al. (2025) reviewed recent advancements and found that CNNs, U-Net models, and transformer-based techniques consistently achieved higher accuracy in plant disease detection.

Boyar and Yıldız (2022) also confirmed that CNN (You Only Look Once (YOLOv5)) models effectively detected powdery mildew in hazelnut leaves. CNNs and their variants (DenseNet, ResNet, EfficientNet) improve leaf-image feature extraction and accuracy, while capsule networks capture spatial details (Kwabena et al., 2020). YOLO/SSD enable real-time detection, attention and transformer models enhance feature selection, and lightweight/ensemble architectures support efficient edge deployment for smart agriculture systems, as shown in Figure 5.

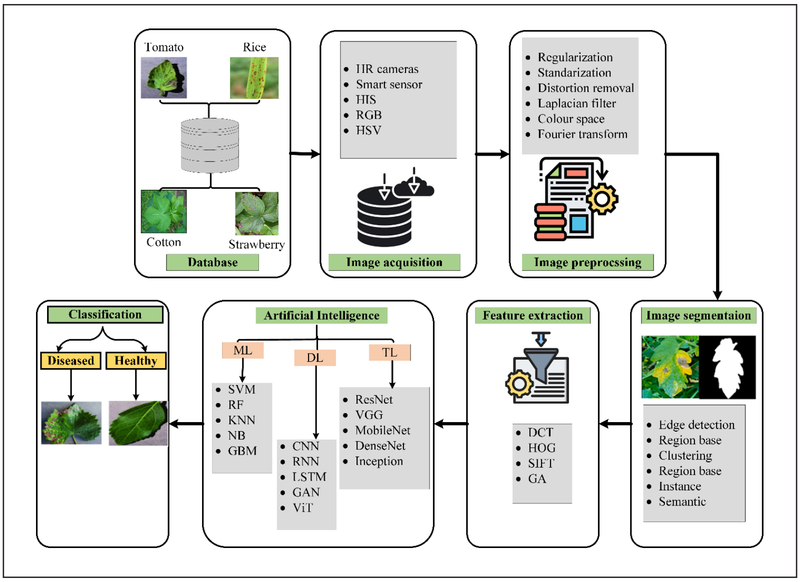


Figure 5. AI-based plant disease detection

Transfer Learning and Few-Shot Learning

Transfer learning, domain adaptation, few-/zero-shot learning, transformers, and diffusion-based models improve plant disease detection by enhancing feature extraction, handling class imbalance, enabling learning from limited data, and improving robustness in low-data scenarios. The overview of AI-constructed techniques for plant disease identification is provided in Table 3.

Multimodal Learning for Plant Disease Recognition

Multimodal fusion using RGB–hyperspectral IoT data with attention and dilated convolutions improves robustness, while rice-fusion models and multimodal Mixup further enhance real-time generalisation for large-scale plant disease detection.

Image Processing and Segmentation Techniques

Image Enhancement and Noise Reduction

Noise-removal and image-enhancement methods improve disease classification by cleaning distortions, where Leaf Artefact-Suppression Super Resolution (LASSR) (Cap et al., 2021) boosts resolution for better feature extraction, and generative lesion-simulation techniques augment data to handle lighting and background variability (Sun et al., 2020).

Table 3
Overview of AI-constructed techniques for plant disease identification

Crop	Refs	Dataset	No. of Images	No. of Classes	Algorithm Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Misclassification Insights
Corn	Noola & Basavaraju, 2022	Plant-Village dataset	3820	4	Enhanced k-nearest neighbour (EKNN)	99.60	Not reported	99.60	Not reported	Minor confusion among similar foliar diseases
Apple	Sun et al., 2021	AppleDisease5 (Custom dataset)	6,500	5	light-weight CNN	96.9	Not reported	Not reported	Not reported	Early-stage symptoms harder to classify
	Vishnoi et al., 2022	Plant Village dataset	3171	3	CNN	98	Not reported	Not reported	Not reported	Not reported
Hazelnut	Boyar et al., 2025	Drone imagery from hazelnut orchards	3,200	3	U-Net variants (U-Net++, Attention U-Net, ResU-Net)	96.8	Not reported	Not reported	Not reported	Some overlap in mild and moderate infection
	Boyar & Yıldız, 2022	Hazelnut leaf image dataset	1,050	2	YOLOv5	90	88	90	89	False positives under dense foliage
Grape	Zinonos et al., 2021	Custom dataset	5,000	3	CNN, Low-Rank Adaptation (LoRa) technology	97.8	97.5	97.3	97.4	Minor confusion in mildew subtypes
Potato	Lee et al., 2021	PlantVillage	2152	3	CNN	97.68	Not reported	Not reported	Not reported	Not reported
	Mahum et al., 2023	Plant Village dataset	2,152	3	Modified DenseNet-201	97.2	Not reported	Not reported	Not reported	Early blight misclassified in small lesions

Table 3 (*continued*)

Crop	Refs	Dataset	No. of Images	No. of Classes	Algorithm Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Misclassification Insights
Sugarcane	Srivastava et al., 2020	Custom dataset	160	4	Inception v3, VGG-16 and VGG-19	90.2	Not reported	Not reported	Not reported	Significant confusion due to a small dataset
Multi-Crop	Ganatra & Patel, 2020	plant village dataset	14956	10	RF, SVM, KNN, Artificial Neural Network (ANN)	63.20 - 73.38	Not reported	Not reported	Not reported	High confusion due to hand-crafted features
	Alirezazadeh et al., 2023	pilot dataset	3,006	4	Attention-based CNN	86.89	86.12	86.31	86.41	Misclassifications in visually similar leaves
	Ahmad et al., 2022	PlantVillage and pepper disease dataset	99,507	38	CNN with stepwise TL	99	Not reported	98	98	Confusion in rare classes
	Xu et al., 2022	PlantCLEF2022	2,885,052	1,000+	TL	99.70	98.24	98.24	98.24	Confusion among classes with similar morphology
	Li & Chao, 2021	PlantVillage	38,000	10	Semi-supervised Few-Shot Learning	97.50	Not reported	Not reported	98.1	Not reported
	Singh & Sanodiya, 2023	PlantDoc	12,345	17	Zero-Shot Transfer Learning	92.85	92.6	93.52	92.86	Difficulty with unseen classes
	Yilmaz et al., 2025	Survey-based (no single dataset)	-	-	CNNs, U-Net, Transformers	-	-	-	-	Not a dataset study

Table 3 (*continued*)

Crop	Refs	Dataset	No. of Images	No. of Classes	Algorithm Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Misclassification Insights
Field crops	Argüeso et al., 2020	Field Images (Custom)	10,000	5	Few-Shot Learning (Prototypical Networks)	93.45	94.25	93.15	94.22	Difficulty in cluttered backgrounds
Cotton	Rajasekar et al., 2024	Custom dataset	5,100	4	ResNet, ImageNet and Xception	95.4	95.2	Not reported	95.4	Confusion in overlapping leaves
Rice	Patil & Kumar, 2022	RiceLeaf Dataset	6,732	5	Multimodal data fusion framework	96.35	96.32	Not reported	97.13	Not reported
Sunflower	Zhou et al., 2025	Custom (Sunflower Disease)	9,820	6	Few-Shot Learning with Diffusion Models	97.10	97.10	97.63	97.10	Minor confusion in similar lesions
Wheat	Rezaei et al., 2024	Kaggle - Wheat Disease	5,912	5	Few-Shot Learning Model-Agnostic Meta-Learning (MAML)	94.28	Not reported	Not reported	95.21	Confusion in rust vs. mildew
Barley	Rezaei et al., 2025	Field Images (Barley)	8,214	6	Transformer-based Few-Shot Learning	96.20	95.32	96.20	96.42	Some overlap in blight categories

Semantic and Instance Segmentation Methods

DL segmentation models (e.g., U-Net, Mask R-CNN) accurately localise diseased regions, while advanced hybrid and two-stage methods improve feature extraction, lesion analysis, and overall detection precision. The overall segmentation is summarised in Table 4.

Table 4
Overview of segmentation techniques for plant disease recognition

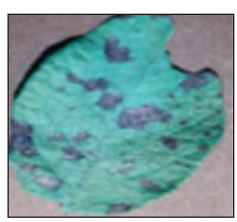
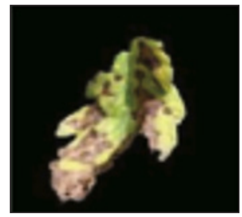
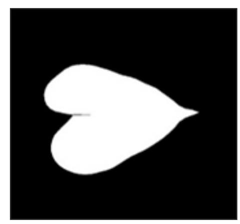
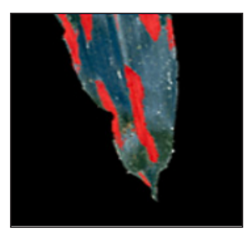
Crops	Refs	Techniques Used	Sample Image	Segmentation Output	Segmentation Accuracy (%)
Banana	Krishnan et al., 2022	Total Generalised Variation Fuzzy C means (TGVFCMS)			94.2
Strawberry	Bhujel et al., 2022	U-Net			93.5
Potato	Arshad et al., 2023	U-Net			95.3
Tomato	Shoaib et al., 2022	U-Net and Modified U-Net			92.8

Table 4 (*continued*)

Crops	**Refs**	**Techniques Used**	**Sample Image**	**Segmentation Output**	**Segmentation Accuracy (%)**
Cash crop	Xiong et al., 2020	Automatic Image Segmentation Algorithm (AISA)			81.4
Multi-crop	Zhang et al., 2021	Joint segmentation			90.1
Strawberry	Afzaal et al., 2021	Mask R-CNN			84.63
Corn	Divyanth et al., 2023	Segmented Network (SegNet), UNet, and DeepLabV3+			93.8
Apple	Storey al., 2022	Mask R-CNN			96.1

Self-Supervised and Weakly Supervised Segmentation

Self- and weakly supervised methods cut annotation needs by learning strong features from unlabelled images; contrastive learning boosts representations, LASSR improves image quality, and lesion-based augmentation increases robustness. Weakly supervised models like PLDPNet and Mask R-CNN variants enhance disease localisation, while modern segmentation frameworks further improve crop-disease quantification.

Explainable AI (XAI) for Transparent Plant Disease Diagnosis

XAI Frameworks for Plant Disease Detection

An overview of the XAI patterns is included in Table 5.

Table 5
Interpretations of explainable AI summaries across various studies

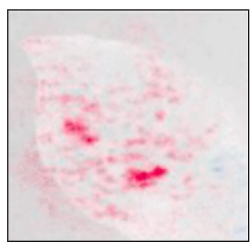
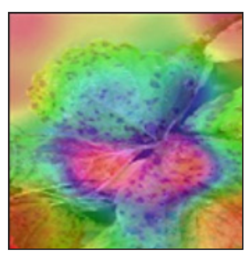
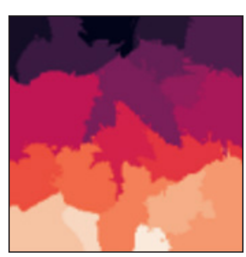
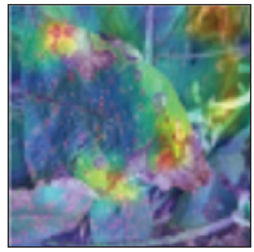
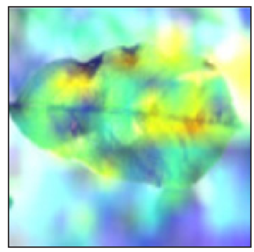
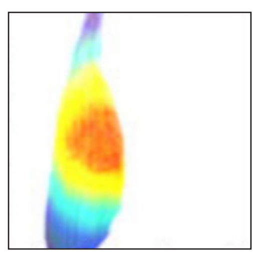
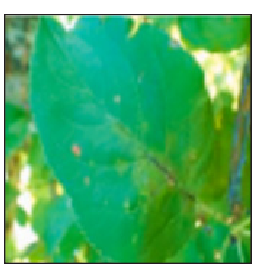
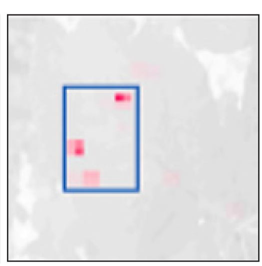
Crops	Refs	Original Image	XAI Output	Explainability Model
Potato	Anim-Ayeko et al., 2023			SHapley Additive exPlanations (SHAP)
Common leaf	Xiang et al., 2021			Gradient-weighted Class Activation Mapping (Grad-CAM)
Sunflower	Ghosh et al., 2023			Local Interpretable Model-Agnostic Explanations (LIME)

Table 5 (*continued*)

Crops	Refs	Original Image	XAI Output	Explainability Model
Various crops	Prince et al., 2024			Grad-CAM
Apple	Thakur et al., 2022			Grad-CAM
Tomato	Bhandari et al., 2023			LIME
Rice Leaf	Shovon et al., 2023			Grad-CAM
Various crops	Dai et al., 2024			SHAP

Smart Farming and Agricultural Automation

IoT, Edge Computing, and Cloud-Based Disease Detection

Edge computing enables real-time prediction, as shown in PFDI (Dhiman et al., 2023) and the IoT framework in Figure 6, with Edge AI improving scalability (Park, 2021). Faster R-CNN, ensembles, and thermal-imaging DL models also run effectively on edge devices for fast, accurate disease detection (da Silva & Almeida, 2024; Dhiman et al., 2023).

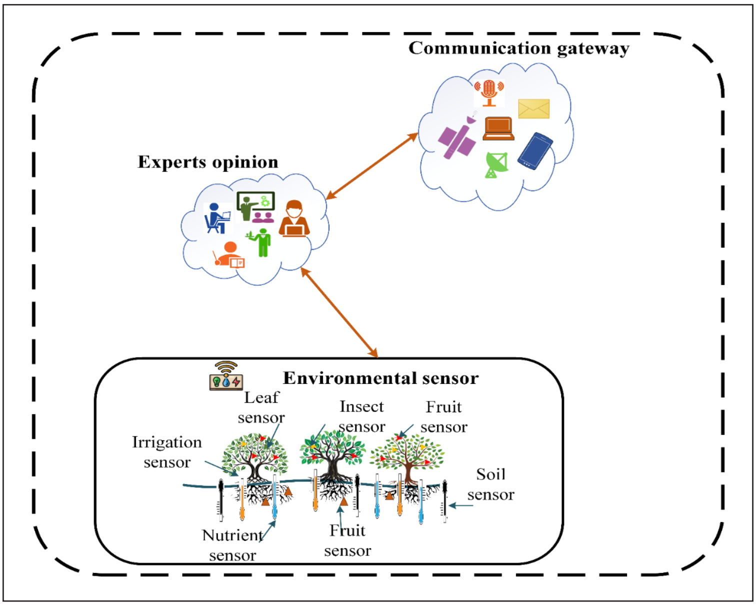


Figure 6. An IoT-based network for smart farming

ML–IoT integration boosts predictive farming, with cloud training, edge devices for on-site diagnosis, and smart IoT platforms automating irrigation and disease alerts together, enabling fast, scalable, and reliable plant-disease detection.

Integration of Disease Identification with Precision Farming

AI, IoT, and digital twins together enable fast disease diagnosis, continuous field monitoring, and predictive decision-making, with frameworks like Agrilora supporting proactive, precision crop management.

Role of Robotics and Automated Systems in Plant Health Monitoring

Robotic platforms with DL-driven vision enable rapid, accurate disease detection and real-time crop monitoring, efficiently assessing traits like stem measurements to advance precision agriculture.

Review of Recommendation-based Approaches

DL-based recommendation systems provide real-time disease diagnosis and optimised pesticide/fertiliser suggestions, with models like Transition Probability Function and Convolutional Neural Network (TPF-CNN) tailoring inputs based on crop, soil, and environmental conditions.

Optimisation for Plant Disease Detection

Evolutionary and Bio-Inspired Optimisation Techniques

This review explores different nature-inspired optimisation techniques, namely Genetic Algorithm (GA), Particle Swarm Optimisation (PSO) and Differential Evolution (DE), for improving plant disease detection models. The obtained Particle Swarm Optimisation-based Deep Neural Network (PSO-DNN) combinations proved efficient in detecting paddy leaf diseases without increasing the model complexity, but with high precision. Similarly, Machine Learning combined with a Genetic Algorithm (ML-GA) hybrid methods have been developed for crop forecasting, thus further enhancing decision-making in agricultural surveillance.

Metaheuristic-Based Hyperparameter Tuning for AI Models

Hyperparameter optimisation with methods like Bayesian Optimisation (BO), Quantum Whale Optimisation (QWO), and PSO boosts model performance by efficiently tuning network parameters, while attention-based networks paired with BO improve precision in rice disease classification. Advanced search strategies further enhance feature learning in optimised DL models.

Optimisation Strategies for Big Data Scalability in Agriculture

Agricultural big data is now managed through distributed and federated learning, supported by cloud–edge hybrids that process IoT and remote-sensing data efficiently. Metaheuristic optimisations such as parallel PSO, genetic programming, and RL improve AI decisions, while edge computing enables fast, real-time disease detection with minimal cloud reliance.

Performance Overview

Figure 7 shows the sample distribution, with Rice the most represented crop at 18.5% and Citrus the least at 1.8%, indicating that research predominantly focuses on major staple crops.

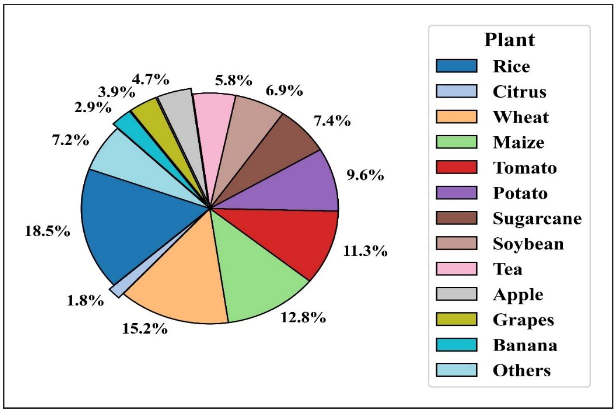


Figure 7. Percentage distribution of samples per plant across datasets

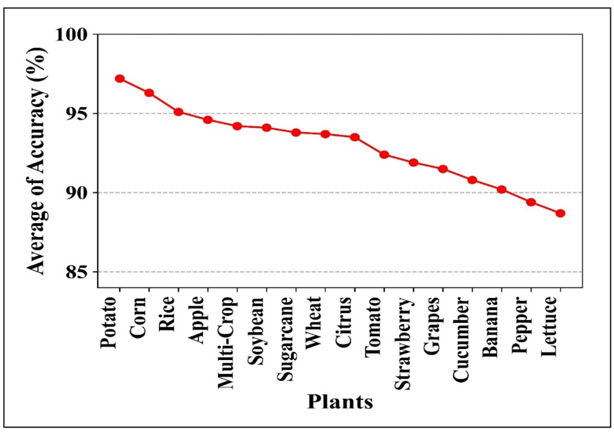


Figure 8. Average disease detection accuracy (%) achieved for each plant type based on the analysed studies

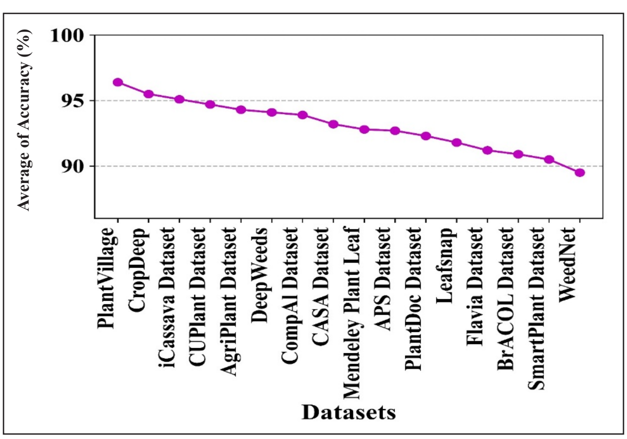


Figure 9. Average disease detection accuracy (%) of different plant disease datasets across multiple plant categories

As shown in Figures 8 and 9, detection accuracy varies across crops and datasets. Apple shows the highest performance, Banana the lowest, and strong datasets like PlantVillage yield higher accuracy than weaker ones like WeedNet, confirming that dataset quality directly influences model results.

Identified Research Gaps and Future Research Scope

Smart farming adoption remains limited due to high computational demands, real-world variability, and narrow crop/disease coverage, as highlighted in Figure 10, showing that further technical improvements are still required for practical deployment.

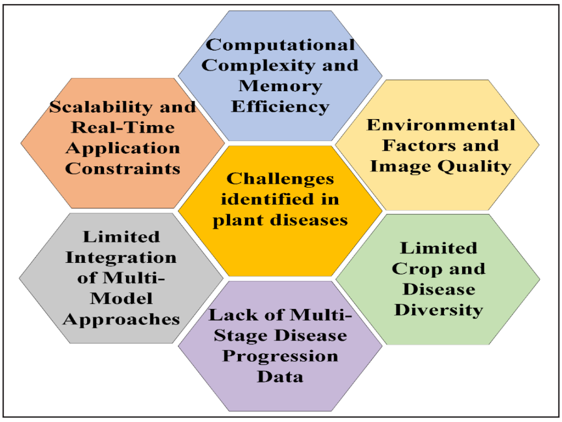


Figure 10. Challenges identified in plant diseases

To solve these problems, future research will focus on

- An efficient architecture for deep learning methods with optimised computation requirements would make practical use of systems used for agronomic monitoring systems.
- Incorporating multispectral and infrared cameras increases disease detection accuracy by filtering environmental noise from the images and improving clarity.
- Future studies will incorporate diverse crops, multiple plant parts (leaves, roots, stems), and a broader spectrum of diseases to improve model generalisation.
- A dataset with annotations for different stages of disease will allow for the creation of models to be able to estimate disease severity and provide better means of management.
- The combination of multiple pre-trained architectures in an ensemble configuration will create improved accuracy in detection, improved robustness in classification, and enhanced capability for predicting severity.
- The use of robotic applications with AI-based disease detection systems will allow for large-scale automated monitoring, reduce the need for manual intervention and provide increased precision.
- Going forward, the emphasis of future work will continue to be a holistic integration of disease detection, classification and severity assessment to provide an improved basis for making decisions in agriculture.

Ethical and Social Considerations

With smarter sensors and AI diagnostics, concerns about data privacy and misuse rise, making fairness and interpretability essential. Explainable AI shows growers how decisions are made, reducing bias and increasing trust so they can adopt AI recommendations with confidence.

Ensuring sustainable and equitable AI in crop disease detection requires farmer training, affordable tools, strong digital literacy, and supportive policies that enable widespread adoption of these technologies.

CONCLUSION

The review shows that advances in imaging sensors, AI models, and smart agricultural systems have rapidly improved plant disease detection. Analysis of 61 studies indicates that CNNs, transformers, and ensemble models often exceed 98% accuracy; hyperspectral, multispectral, and thermal imaging significantly strengthen early detection; and IoT-based monitoring with edge computing enables real-time, scalable deployment in field conditions.

Lightweight edge-AI solutions support low-latency field monitoring, multimodal sensor fusion increases robustness under variable environments, and explainable AI builds user trust. Together, these developments are driving more autonomous, faster, and resource-efficient disease management within precision agriculture.

Significant gaps persist, including domain shifts between lab datasets and real-field conditions, small or imbalanced datasets limiting generalisation, and weak interpretability, robustness, and energy efficiency in deployed models. The absence of unified evaluation metrics further restricts fair comparison across studies.

Future work should prioritise lightweight edge-AI models, diverse multi-stage field datasets, rugged multimodal sensing, stronger Explainable AI, cross-domain adaptation, and autonomous robotic monitoring supported by closer collaboration among agronomists, AI researchers, and sensor engineers.

From a business standpoint, these advancements will accelerate precision farming, remote crop monitoring, and automated early-warning systems. Integrating AI with IoT and robotics reduces labour costs, improves disease management, and stabilises yield. With advanced sensors, edge AI, and interpretable models, both large and small farmers gain scalable, cost-effective, and sustainable solutions as agriculture shifts toward fully digitised production.

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Data Availability Statements

Data sharing does not apply to this article, as no datasets were generated or analysed during the current study.

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