

Feature Engineering to Early Detection of Plant Disease Using Image Processing and Artificial Intelligence: A Comparative Analysis

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Abstract. Plant diseases are a critical barrier to agricultural sustainability, contributing to annual crop losses of 30–40% in some regions. Such diseases arise from diverse pathogens, including fungi, bacteria, and viruses, and can severely degrade crop yield and quality if undetected. Early diagnosis is crucial for timely intervention, reduced pesticide use, and long-term soil health. Traditional approaches, which rely on manual visual inspection of leaves, remain slow, subjective, and impractical for monitoring large or remote farms. In recent years, the convergence of artificial intelligence (AI), computer vision, and image-based analysis has enabled automated disease detection systems that are both scalable and real-time. Classical techniques first employed color, texture, and shape descriptors combined with machine learning models such as Support Vector Machines (SVM), k-Nearest Neighbor (KNN), and Random Forests. These methods achieved moderate success but struggled with variability in lighting, background, and leaf orientation. The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), transformed plant disease detection by allowing end-to-end feature learning directly from raw images. Modern lightweight architectures like MobileNet and EfficientNet further enhance deployability on mobile and edge devices. In parallel, segmentation-assisted and hybrid models improve robustness under complex field conditions. This review consolidates these developments, evaluating methods in terms of accuracy, generalization, computational efficiency, and field-readiness. It also identifies persistent challenges—such as limited annotated datasets and the opaque decision-making of deep models—and highlights future directions in explainable AI, multi-modal sensing, and IoT-integrated precision agriculture.

Keywords: Agricultural Disease Detection, Digital Image Analysis, Classical and Deep Learning Approaches, CNN and Lightweight Architectures (MobileNet), SVM and KNN Classifiers, Feature Extraction Techniques, Edge-AI for Smart and Sustainable Farming

I. Introduction:

With the global population steadily increasing, the pressure on agricultural productivity continues to rise, while plant diseases remain a major challenge to crop yield and food security [5], [9]. These diseases, often caused by fungi, bacteria, or viruses, can drastically reduce both harvest quality and total production if not addressed promptly [1]. Early and reliable diagnosis is crucial for sustainable farming, yet conventional practices such as manual visual inspection by farmers or field experts are slow, error-prone, and unsuitable for monitoring large agricultural areas [5], [10]. To overcome these challenges, recent advances in artificial intelligence (AI), computer vision, and deep learning (DL) have enabled automated plant disease detection [8], [17]. Earlier approaches relied on classical image processing and machine learning (ML), where leaf colour, shape, and texture features were manually extracted to identify diseases. While these techniques demonstrated moderate success, they struggled with environmental variations such as lighting changes, overlapping leaves, and background noise [6], [11].

Deep learning models, especially Convolutional Neural Networks (CNNs), now allow plant disease detection to be performed end-to-end, learning patterns directly from images without handcrafted features. Models trained on datasets like PlantVillage have achieved over 99% accuracy in controlled laboratory conditions [8], [19]. However, performance in field scenarios remains lower due to complex backgrounds, occlusions, and environmental variability [18]. To bridge the lab-to-field performance gap, researchers have developed advanced segmentation and feature-learning techniques. For example, segmentation-based methods such as the Segment Anything Model (SAM) and Fully Convolutional Data Description (FCDD) can separate infected foliage from complex field scenes, which enhances the accuracy of disease recognition in real-world environments [18]. Similarly, tensor-based methods such as Higher-Order Whitenized SVD with Tensor Exponential Discriminant Analysis (HOSVD-TEDA) offer richer multi-modal feature representation and enhanced classification robustness, especially when combined with pre-trained CNNs and transfer learning [17]. These hybrid strategies have demonstrated improved cross-dataset performance across benchmarks like the PlantVillage and Taiwan Tomato datasets.

Moreover, the use of IoT devices together with edge computing facilitates extended deep learning frameworks for real-time farm monitoring. Advanced multi-sensor IoT platforms, such as the APDDCM-SHODL system, combine DenseNet201, spiking neural networks, and optimisation algorithms to enable on-site disease detection and actionable crop management recommendations [4], [20]. These lightweight frameworks allow farmers to receive timely and precise alerts, even under dynamic field conditions. Despite these innovations, key challenges remain. Deep learning models in uncontrolled environments are limited by dataset scarcity, variation in leaf orientation, and lighting inconsistencies, while the black-box nature of DL models restricts farmer trust and interpretability. The growing field of explainable AI (XAI) offers solutions by providing visual justifications for model predictions, increasing transparency, and practical adoption [6], [22].

This review consolidates the state-of-the-art in image-based plant disease detection, categorising solutions into classical ML, CNN-

based deep learning, tensor-based approaches, and hybrid IoT-DL frameworks. It further evaluates model performance across datasets, identifies field-specific deployment challenges, and suggests future directions for building interpretable, lightweight, and scalable plant health monitoring tools [5], [17], [21].

Significance of Early Detection of Plant Diseases:

Plant diseases often begin with subtle symptoms such as tiny spots, faint wilting, or slight colour loss, which, if ignored, can rapidly spread and damage entire crops [5], [9]. For farmers, especially those managing large-scale fields or lacking timely access to expert advice, recognising these early signs is challenging. Once the disease takes hold, it becomes more difficult and expensive to manage, leading to reduced yields, economic losses, and wasted resources [10], [13].

Early detection allows for timely and targeted interventions, preventing the unnecessary treatment of entire fields and thereby saving time, reducing costs, and minimising chemical usage [5], [20]. This not only protects crop health but also promotes sustainable, eco-friendly farming practices, aligning with the principles of precision agriculture [17]. Modern technologies have made early diagnosis more practical than ever. AI-powered image analysis can detect minor, early-stage symptoms from simple leaf photographs, identifying unusual textures or subtle discolourations that often escape the human eye [8], [17]. Importantly, these tools are no longer confined to laboratories; with lightweight CNN models and IoT-based sensors, early warning systems are deployable on smartphones or portable devices, bringing real-time disease alerts to even remote or resource-limited farming communities [4], [20]. This bridges the gap between expert-level diagnosis and everyday agricultural practice, empowering farmers with field-ready decision support.

In essence, early detection is not just beneficial; it is essential. It leads to healthier crops, optimised resource use, and improved farmer livelihoods, while supporting environmentally responsible and sustainable agriculture [5], [17], [21]. As AI and edge computing technologies continue to evolve, the ability to deliver affordable, scalable, and field-ready plant disease detection will define the future of smart farming [6], [22].

A Description of Plant Diseases and Their Visual Symptoms:

Plant health is frequently compromised by pathogenic infections caused by bacteria, viruses, and fungi, each producing distinct visual symptoms on leaves that serve as critical indicators for early detection. Timely recognition of these visual cues enables farmers and agronomists to implement disease management strategies before the infection spreads to neighboring plants. Figure references provided below illustrate typical symptoms observed in affected crops.

Bacterial Diseases:

Bacterial infections often manifest as small, water-soaked lesions that are pale green in the early stages. Over time, these lesions enlarge and turn brown or black, forming necrotic patches with dry, brittle tissue. In many cases, a yellow halo develops around the affected area, which helps distinguish bacterial infections from other leaf damage. A classic example is bacterial leaf spot, which appears as evenly sized black or brown dots with a water-soaked appearance, particularly under moist conditions (Fig.1a). Another prominent bacterial disease is fire blight, where leaves and stems exhibit a scorched, blackened look as if burned by fire, giving the infection its name (Fig.1b).



Fig. 1. (a) Bacterial leaf spot showing water-soaked lesions; (b) Fire blight causing scorched tissue appearance.

Viral Diseases:

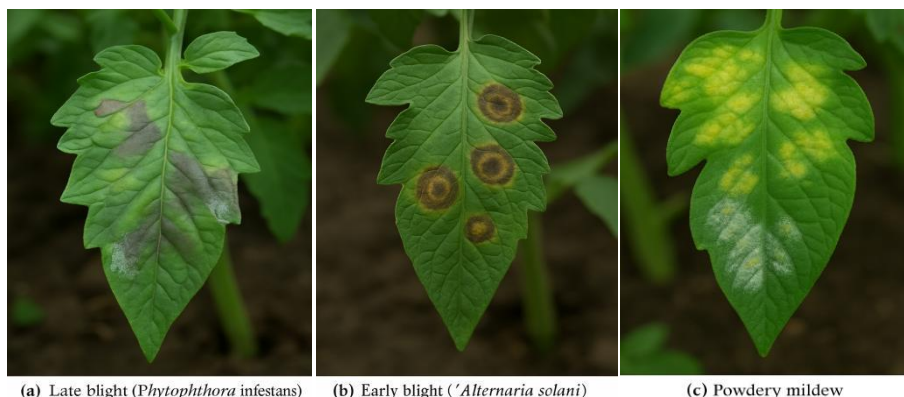
Detecting viral diseases is difficult because their leaf symptoms are often subtle and lack clear patterns. They are typically spread through insect carriers, including aphids, whiteflies, cucumber beetles, and leafhoppers. Affected leaves may develop mosaic-like patterns of light and dark green or yellow, often accompanied by leaf curling, wrinkling, and stunted growth (Fig.2). Mosaic virus, a well-known viral disease, illustrates how subtle these symptoms can be, frequently leading to misdiagnosis as nutrient deficiency or herbicide injury. Unlike fungal or bacterial infections, viral symptoms are dispersed and not confined to well-defined lesions.



Fig. 2. Viral disease symptoms on plant leaves showing mosaic patterns with mottled green and yellow discoloration.

Fungal Diseases:

Fungal pathogens are among the most destructive agents in crop production, often producing distinct spots, rings, or powdery growths. Late blight, which is caused by *Phytophthora infestans*, starts as gray-green patches on the lower leaves that are drenched in water. As the infection advances, the lesions enlarge and the lower leaf surface often develops a thin layer of white spores, indicating that the fungus is actively reproducing (Fig. 3a). Early blight typically forms circular brown lesions with a layered pattern, giving the appearance of rings on older leaves. This disease results in progressive yellowing and the outward spread of necrosis (Fig. 3b). Powdery mildew, another frequent fungal infection, appears as pale yellow patches on the upper side of leaves, accompanied by a fine white dusting of spores beneath (Fig. 3c). Recognizing such early visual patterns across bacterial, viral, and fungal diseases is critical for timely diagnosis and effective crop protection. As demonstrated in Figures 1–3, careful observation of lesion shape, color changes, and surface growth patterns allows for timely diagnosis and containment of plant diseases, significantly reducing the risk of large-scale crop loss.



(a) Late blight (*Phytophthora infestans*)

(b) Early blight ('*Alternaria solani*)

(c) Powdery mildew

Fig. 3. Common fungal diseases on plant leaves: (a) Late blight with gray-green water-soaked lesions; (b) Early blight showing concentric brown ring spots; (c) Powdery mildew with white fungal growth.

II. Literature Review:

The detection and classification of plant diseases have evolved significantly over the last three decades, transitioning from conventional image processing techniques to advanced deep learning and IoT-based systems. This section reviews the progression of research in this domain, emphasizing feature engineering, machine learning, and deep learning approaches, as well as modern advancements in explainable and sustainable agriculture technologies.

Early Image Processing Approaches

The earliest methods for plant disease detection were rooted in digital image processing and classical machine learning. Kulkarni and Patil [1] proposed one of the pioneering techniques using Gabor filters for feature extraction combined with Artificial Neural Networks (ANN) for classification, achieving a modest accuracy of around 91%. Similar early studies, such as Argenti et al. [2], focused on texture analysis using co-occurrence matrices, laying the foundation for feature-based disease recognition.

During the same period, researchers explored edge detection and segmentation methods for localizing diseased regions. Revathi and Hemalatha [3] demonstrated edge detection techniques, including Canny and Sobel filters, for identifying cotton leaf spot diseases. Jaware et al. [4] leveraged k-means clustering for image segmentation to isolate diseased areas efficiently. Dhaygude and Kumbhar [5] extended these approaches by utilizing Spatial Gray-Level Dependence Matrices (SGDM) to extract probabilistic texture features, enabling simple classification in agricultural applications.

The integration of fuzzy clustering and auto-cropping marked an evolution in pre-deep learning methods. Al-Tarawneh [6] implemented fuzzy c-means clustering for olive leaf spot detection, while Zhang et al. [7] introduced fuzzy feature selection techniques to reduce the dimensionality of cotton leaf disease datasets. Texture-based methods using Gabor filters and co-

occurrence matrices were further advanced by Grigorescu et al. [9], enabling robust classification in controlled environments.

These early approaches collectively established the importance of feature extraction and segmentation in automated plant disease detection. However, their accuracy and robustness were limited by environmental noise, lighting variations, and the manual tuning of features.

Machine Learning-Based Detection

With the rise of classical machine learning, studies began to leverage Support Vector Machines (SVM), Backpropagation Neural Networks (BPNN), and K-Nearest Neighbor (KNN) for more reliable classification. Arivazhagan et al. [10] employed texture-based features in combination with SVM to achieve high accuracy in multi-class plant disease classification. Al Bashish et al. [11] and Song et al. [12] extended this approach to maize and other crops using BPNNs and co-occurrence matrix-based feature extraction.

H. Al-Hiary et al. [13] combined k-means clustering with neural networks to achieve faster and more accurate classification, while Menukaewjinda et al. [14] implemented hybrid intelligent systems combining ANN with genetic algorithms for grape leaf disease detection. Wang et al. [15] explored Principal Component Analysis (PCA) to reduce dimensionality before feeding data into BPNN and Probabilistic Neural Networks (PNN), improving computation efficiency. Gavhale and Gawande [16] summarized these methods as the first generation of automated plant disease detection, emphasizing segmentation, texture analysis, and classical machine learning as the key pillars.

Deep Learning and Modern Advances

The advent of deep learning revolutionized plant disease detection by eliminating the need for manual feature engineering. Early adoption was demonstrated by Mohanty et al. [8], who applied Convolutional Neural Networks (CNNs) to leaf images and showed that deep learning outperformed traditional machine learning in classification accuracy. Recent studies have expanded into state-of-the-art deep learning, IoT integration, and explainable AI:

CNN-based architectures: Ouamane et al. [17] introduced knowledge pre-trained CNN with tensor subspace learning for tomato leaf disease detection, significantly improving accuracy and feature efficiency. Ramalingam et al. [19] developed a deep CNN for citrus leaf diseases, highlighting the role of task-specific architectures.

Advanced segmentation and multi-disease recognition: Moupojou et al. [18] applied the Segment Anything Model (SAM) combined with Fast Contextualized Disease Detection (FCDD) to detect multiple diseases under real-world conditions, addressing challenges of overlapping and ambiguous symptoms.

IoT and Edge AI for field deployment: Abdelbagi et al. [20] designed an IoT-enabled sustainable crop monitoring system with edge intelligence, enabling real-time inference on resource-constrained devices.

Surveys and explainable AI: Loey et al. [21] and Demilie et al. [23] presented comprehensive reviews and comparative analyses of deep learning techniques, whereas Seelwal et al. [22] emphasized explainable AI (XAI) for precision agriculture, ensuring that automated systems can provide transparent and interpretable decisions to farmers.

Table I presents a comparative overview of classifier families used in plant disease detection, highlighting that deep learning-based CNNs and hybrid DL methods consistently achieve the highest accuracy in both lab and field conditions.

Table I. Comparative Performance of Major Classifiers for Plant Disease Detection

Classifier Type	Common Algorithms	Typical Accuracy Range (%)	Strengths	Weaknesses
Traditional ML	SVM, KNN, Decision Trees	80–92	Simple, interpretable, low computation	Poor generalization in complex backgrounds
ANN (Shallow)	BP Neural Network, Hybrid ANN+GA	88–94	Learns basic nonlinear patterns	Needs manual feature extraction
CNN (Deep Learning)	AlexNet, VGG, ResNet	94–99	Automatic feature learning, high accuracy	Requires large datasets & GPUs
Hybrid DL + Segmentation	CNN + SAM/FCDD, Tensor Methods	96–99	Handles complex field images, robust	Higher computational cost
IoT + Edge AI Systems	CNN + IoT Sensors	90–97	Real-time detection in field	Limited by network and edge resources

In order to give a comprehensive picture of how plant disease detection systems have evolved, a comprehensive summary of related studies is presented in Table II. This table illustrates the progression from early image-processing approaches to classical machine learning and, more recently, deep learning and IoT-based frameworks. For each study, the dataset used, the core methodology, the achieved accuracy, and the key contribution are highlighted. This structured summary helps identify trends in classifier performance and emphasizes the transition from handcrafted feature-based methods to robust, end-to-end deep learning solutions for real-world applications.”

Table II. Summary Table of The Studies

Ref.	Dataset	Technique / Approach	Accuracy (%)	Key Contribution
[1]	Local crop images	Gabor filters + ANN	90.8	Early ANN-based method for plant disease detection using texture features.
[3]	Cotton leaves	Edge Detection	N/A	Classified cotton leaf spot diseases via edge-based segmentation.
[4]	Local field images	K-means segmentation	N/A	Applied simple clustering for crop disease region isolation.
[5]	Local leaf images	SGDM texture features	89.5	Early probabilistic texture analysis for automated leaf disease detection.
[6]	Olive leaves	Auto-cropping + Fuzzy C-Means	92.1	Detected olive leaf spot disease with improved segmentation.
[7]	Cotton leaves	Fuzzy Feature Selection	N/A	Reduced feature dimensionality for cotton leaf disease classification.
[8]	Wheat & grape leaves	Backpropagation NN	91.3	Applied neural networks for early leaf disease image recognition.
[10]	Local dataset	Texture + SVM	91.2	Multi-class plant disease classification using texture features.
[11]	Leaf & stem images	ANN Framework	93.7	General framework for detecting and classifying plant leaf and stem diseases.
[12]	Maize leaves	BP NN + CCM	90.5	Recognized maize disease images using color & texture features.
[13]	Tomato & grape leaves	K-means + NN	92.8	Fast and accurate disease classification using clustering and neural nets.
[14]	Grape leaves	Hybrid ANN + GA	93.2	Introduced hybrid intelligent system for grape disease detection.
[15]	Local leaf dataset	PCA + NN	94.0	Dimensionality reduction enhanced ANN performance for disease recognition.
[17]	Taiwan Tomato & PlantVillage	Pre-trained CNN + Tensor Subspace	98.7	High-accuracy tomato disease detection with tensor-based learning.
[18]	Real field images	SAM + FCDD	97.1	Multi-disease detection under real-world conditions with segmentation.
[19]	Citrus Leaf Dataset	Deep CNN	96.5	Accurate citrus disease classification with deep CNN model.
[20]	IoT-enabled crop monitoring	IoT + Edge AI	N/A	Sustainable real-time disease monitoring using deep learning and IoT.
[21]	Survey study	Deep Learning Survey	N/A	Provided an extensive survey of recent deep learning approaches applied to identifying plant diseases.
[23]	Multi-crop datasets	Comparative DL	97.4	Conducted a performance comparison of multiple deep learning models for recognizing crop diseases across datasets.

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III. Future Research Directions:

With rapid advancements in AI, plant disease detection is expected to become progressively promising but there are still many areas that need deeper attention. Building systems that are not only accurate but also accessible, explainable, and field-ready will be critical in the coming years. One major area of focus is the creation of more diverse and field-based datasets. Many current datasets are taken in ideal lab conditions, which limits the robustness of trained models.

Future research should prioritize image collection in real farming environments across different seasons, lighting conditions, and crop stages. This would help models generalize better when deployed outside the lab. Another important direction is multi-modal learning. Instead of relying on leaf images alone, combining data from weather sensors, soil conditions, GPS, and crop calendars could improve disease forecasting and early warning systems. This fusion of visual and environmental data could be especially helpful in predicting disease outbreaks before symptoms fully develop. Explainable AI (XAI) will also play a bigger role. As more farmers and field technicians use mobile apps or decision support systems, it's important that the AI doesn't just give a prediction it must also explain why it thinks a leaf is diseased. Research into user-friendly visual explanations or confidence scores will help build trust in these tools.

In addition, there's growing interest in self-supervised and few-shot learning. These methods aim to reduce dependency on large labeled datasets, which are hard to collect in agriculture. Being able to train effective models with just a few examples would be a game-changer for rare or emerging diseases.

Lastly, integrating AI with low-cost edge devices and IoT platforms will be crucial for adoption in rural areas. This means building lightweight models that run offline, on low-power smartphones or solar-powered edge boards ensuring that even farmers without internet access can benefit. Prioritizing these research directions will lead to the development of plant disease detection systems that are intelligent, widely deployable, and capable of delivering meaningful benefits to farmers and sustainable agriculture.

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