From Traditional Methods to Cutting-Edge Deep Learning: Advances in Plant Disease Detection and Classification

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**Abstract.** Plant diseases significantly threaten global agricultural productivity, leading to major yield losses and impacting food security, especially in resource-constrained regions. Timely and accurate detection is essential for effective intervention and sustainable farming. This paper surveys the evolution of plant disease detection methods, from traditional manual inspections and lab-based assays to advanced machine learning and deep learning techniques. While conventional methods provided early insights, they lacked scalability and reliability. Classical machine learning introduced partial automation but relied heavily on manual feature extraction. The advent of deep learning, especially convolutional neural networks and vision transformers, has enabled real-time, large-scale, and accurate analysis. The paper also explores the use of transfer learning, multimodal data fusion, and synthetic data generation to address dataset limitations. Through a synthesis of research from 2000 onward, we highlight current applications, technological advances, and key challenges, offering insights into the future of precision agriculture through AI-driven plant disease detection and classification.

# INTRODUCTION

Plant diseases, caused by things like fungi, bacteria, viruses, and nematodes, are a huge problem for farmers, wiping out 20 to 40% of crop yields every year, according to global agricultural groups [1]. These losses don’t just hit farmers’ wallets; they mess with food security, especially in places where resources are tight. Getting a quick and accurate diagnosis is key to stopping diseases early, cutting down on unnecessary pesticides, and keeping crops healthy. The way we detect plant diseases has changed a ton, going from farmers eyeballing their fields to slick AI-powered systems. This survey takes you through that shift, from traditional hands-on methods to modern deep learning tricks [2]. It highlights how these changes are shaking up farming and laying the groundwork for precision agriculture.

Saving crops is only part of the story. Plant disease detection ties into bigger economic, environmental, and social issues. When diseases strike, they slash harvests, raise food prices, and leave farmers struggling. Major outbreaks, like wheat rust or banana wilt, can devastate entire areas and threaten food supplies [3]. Catching diseases early lets farmers zero in with targeted treatments, sparing the environment and people from harmful pesticides. Climate change is making things trickier by changing weather patterns, which helps pathogens spread faster and makes reliable detection tools more important than ever. Early detection means farmers can save more crops, work more efficiently, and adopt practices that line up with global environmental goals. Folding AI and digital tools into disease management is helping make farming stronger and more sustainable.

This survey digs into the world of plant disease detection and classification, looking at how we’ve moved from old-school techniques to AI-based solutions. It compares past and present methods, breaking down what works, what falls short, and how they fit into precision farming. We explore how detection has evolved from manual field checks and lab tests to machine learning and deep learning models that deliver sharper accuracy and can tackle big-scale challenges. The paper also touches on real-world cases, available datasets, and what’s hot in the field to paint a full picture. By mixing technical know-how with practical impacts, this work hopes to be a handy resource for researchers, agronomists, and policymakers working to improve farming and food security with smart technology.

# OVERVIEW OF TRADITIONAL AND AI-BASED APPROACHES

Plant disease detection has progressed from traditional visual inspection by farmers to advanced automated systems. While laboratory techniques like PCR offered accurate analysis [4], they demanded specialized expertise and costly infrastructure. The field transformed with machine learning adoption in the 2000s, particularly through support vector machines that improved diagnostic speed and objectivity. Deep learning now represents the cutting edge, utilizing extensive datasets and neural networks to identify minute disease patterns with unprecedented accuracy. This technological evolution demonstrates how foundational manual and PCR methods enabled today's AI solutions that continue redefining agricultural diagnostics.

## Traditional Methods for Plant Disease Detection

Traditional plant disease identification depended on labor-intensive field scouting and basic lab techniques. Farmers and pathologists would systematically examine crops for visual symptoms - leaf spots, wilting, or discoloration requiring extensive phytopathological knowledge [5]. While effective for known diseases under controlled conditions, these methods proved unreliable for emerging pathogens or subtle early-stage infections. The limitations of manual detection created demand for more objective, scalable solutions. But it was easy to miss early or tricky symptoms, and it took way too much time for big farms. Even so, visual checks still matter in places with few resources, showing we need solutions that are both affordable and able to handle large-scale farming.

Laboratory techniques like PCR and ELISA enabled accurate pathogen identification at the molecular level. These methods provided diagnostic precision beyond visual inspection but required specialized equipment, trained personnel, and long processing times. Their high cost also limited access for smallholder farmers [6]. While still relevant for re- search and confirmation, their routine use in daily farming is constrained. Sensor-based and spectroscopic techniques marked progress toward automation. These systems detected physiological changes through reflectance, fluorescence, or thermal emissions. Hyperspectral imaging, for example, identified stress signals invisible to the human eye. Reported accuracies ranged from 60–80%, depending on the crop and pathogen. However, environmental variability and high equipment costs hindered widespread use.

## Transition To Machine Learning Techniques

The emergence of machine learning (ML) in the early 2000s introduced a new paradigm for plant disease detection, as shown by the scholarly works in this field illustrated in Figure 1, leveraging computational algorithms to analyze complex datasets with greater efficiency and objectivity.

Machine learning (ML) algorithms, including support vector machines (SVM), random forests, and k-nearest neighbors, were among the earliest used for plant disease detection. These machine learning models used images and sensor data to figure out plant diseases by looking at things like color, texture, and spectral patterns. Studies showed they got accuracy rates between 70 and 85%, a solid step up from older methods [7]. For example, support vector machines did a great job spotting fungal infections in wheat. But their success depended a lot on having good-quality data and experts picking the right features, which made it tough to use them widely [8].

Early machine learning relied heavily on manual feature engineering. Experts would pull out details like leaf texture, color patterns, or edge shapes to feed into the models. This worked decently but took a ton of time and needed people who knew both plants and tech [9]. Plus, these handpicked features often couldn’t handle the full range of disease symptoms, making it hard for models to work well across different crops or environments.

Classical machine learning also had trouble with inconsistent data and scaling up. Changes in lighting, crop types, or image quality could throw them off, and they sometimes struggled with overfitting when dealing with bigger datasets. These challenges opened the door for deep learning, which handles feature extraction automatically and offers tougher, more scalable solutions for detecting plant diseases.

A screen shot of a graph

AI-generated content may be incorrect.

**FIGURE 1.** Evolution of plant disease detection: a machine learning perspective (2000–2026)

# DEEP LEARNING TECHNIQUES FOR PLANT DISEASE DETECTION AND CLASSIFICATION

Deep learning (DL) has emerged as a game-changer in plant disease detection, leveraging advanced neural architectures to achieve unprecedented accuracy and efficiency. The rise in scholarly works can be clearly seen in Figure 2 over the past 10 years.

A graph with different colored lines

AI-generated content may be incorrect.

**FIGURE 2.** Detecting disease, growing intelligence: deep learning in plant health (2015–2026)

Convolutional neural networks (CNNs) have become the cornerstone of DL-based disease detection, automatically extracting hierarchical features from plant images [10]. A CNN’s operation can be described as in Equation (1).

|  |  |
| --- | --- |
|  | (1) |

where σ is a non-linear activation function, W is the weight matrix, ∗ denotes convolution, and b is the bias. By stack- ing convolutional and pooling layers, CNNs learn complex patterns, such as lesion shapes or discoloration, directly from raw images. Recent studies reported accuracies exceeding 90% for CNN-based models in classifying diseases across crops like tomatoes, rice, and maize. The ability of CNNs to eliminate manual feature engineering has made them a powerful tool for scalable and robust disease detection.

Transfer learning has greatly advanced the practicality of deep learning (DL) in agriculture by leveraging pre- trained models such as ResNet, VGG, and EfficientNet, originally trained on large datasets like ImageNet. These models are fine-tuned using plant-specific datasets, which reduces training time and data requirements while still achieving high accuracies—typically between 95–98% [11]. For example, fine-tuned ResNet models have detected potato leaf blight with near-human precision. This is especially beneficial in agricultural contexts, where labeled data is often scarce, allowing strong performance even in low-resource settings.

Recent DL innovations include vision transformers (ViTs) and generative adversarial networks (GANs), which tackle complex challenges in plant disease detection. ViTs use attention mechanisms to model long-range dependencies, achieving over 97% accuracy in wheat rust detection [12]. GANs enhance dataset diversity by generating synthetic images, improving model generalization. These approaches push the boundaries of current detection systems.

Multimodal methods that combine image data with sensor inputs, like hyperspectral or thermal data, further boost accuracy. Integrating RGB and hyperspectral data, for instance, has led to 5–10% improvements in detection performance [13]. Such models are resilient to environmental variability and hold great promise for precision agriculture through comprehensive, data-driven disease diagnostics.

# DATASETS, DATA CHALLENGES, DATA GENERATION, AND BENCHMARKING

High-quality datasets are the backbone of effective DL models, but their creation and maintenance present significant challenges.

Public datasets like PlantVillage, AgriVision, and RoPlant provide labeled images for training and benchmarking DL models. The PlantVillage dataset, for example, includes over 54,000 images covering 38 different disease types for crops like tomatoes and apples. Table 1 breaks down the main datasets and their key features.

**TABLE 1.** Common public datasets for plant disease detection

|  |  |  |
| --- | --- | --- |
| **Dataset** | **Images** | **Classes** |
| PlantVillage [14] | 54,000 | 38 |
| Agriculture Vision [15] | 21,000 | 27 |
| PlantDoc [16] | 2,598 | 17 |

Standardized datasets enable performance benchmarking but often focus on specific crops or regions, necessitating more diverse data collection. Compiling representative datasets requires collaboration between farmers, agronomists, and data scientists to account for variables like lighting, soil conditions, and crop varieties. Accurate labeling remains challenging, as it demands expert identification of subtle disease characteristics, and non-representative data often reduces field performance.

Recent solutions employ GANs to generate synthetic disease images, improving model accuracy by 5–9% when real data is scarce [17]. This approach helps address regional data gaps and enhances model generalization across different cultivars and environments, making detection systems more practical for agricultural use.

# APPLICATIONS AND CASE STUDIES

Deep learning (DL) has emerged as a transformative technology in plant disease detection, with applications spanning smallholder farms to large-scale agricultural operations. The integration of DL models with unmanned aerial vehicles (UAVs), and mobile. Smartphone apps using CNNs can check plant photos and give instant diagnoses, cutting crop losses by up to 20% in early trials. Drones with hyperspectral imaging can sweep over huge fields to pinpoint disease spots with great accuracy [18]. These AI tools bring high-tech solutions right to the farm, connecting cutting-edge research with everyday farming.

Real-world examples show how well DL works. One CNN-based system hit 96% accuracy in spotting tomato leaf blight, letting farmers use fungicides precisely and save more of their crops [19]. Another study used vision transformers to detect wheat rust with 98% accuracy, helping farmers act early to protect crop quality [12].

By catching diseases quickly and accurately, DL boosts crop yields and strengthens food security [20]. In places with limited resources, DL tools give small farmers affordable, scalable options. Their ability to stop crop losses helps keep food supplies steady. As deep learning keeps improving, it will play a huge role in tackling farming challenges tied to climate change.

# CONCLUSION

This survey dives into how plant disease detection has changed over time, starting with old school visual checks and lab tests, then moving to the game changing impact of deep learning. Early methods gave us a solid starting point but couldn’t keep up with the need for speed or scale. Machine learning brought in automation, and deep learning took things to a new level with its advanced neural architectures, delivering top notch accuracy and efficiency. Sure, there are hurdles like high computational costs and a lack of enough data, but new trends like explainable AI and edge computing are stepping up with smart solutions. By pushing these technologies forward, we can boost global food security and build a greener future for farming.

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