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A Review of Plant Disease Detection using Image Processing and Artificial Intelligence

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***Abstract*—Automated plant disease detection from images has progressed from classical image processing pipelines to modern deep learning and transformer-based computer vision. This review summarizes key stages of image-based disease diagnosis (acquisition, preprocessing, segmentation, feature learning, classification/detection), compares traditional machine learning with deep models, and discusses practical challenges such as domain shift, field deployment, explainability, and data scarcity. We highlight public datasets (e.g., Plant Village and in-the-wild sets), evaluation practices, and emerging trends including vision transformers, multimodal sensing, edge/IoT, and privacy-preserving learning. The review concludes with recommended research directions for robust, deployable systems.**

***Keywords*—Plant disease detection, image processing, machine learning, deep learning, vision transformers, Plant Village.**

I. Introduction

Plant diseases reduce crop yield and quality, motivating automated diagnosis tools that can assist farmers and agronomists. Early work relied on handcrafted color/texture descriptors and classical classifiers. In recent years, deep learning—especially CNNs and vision transformers—has become dominant due to strong performance on large labeled datasets and improved feature learning.

II. Review Scope And Methodology

This review focuses on image-based plant disease detection and classification, including (i) classical image processing pipelines, (ii) machine learning with handcrafted features, and (iii) deep learning approaches (CNNs, transformers, and hybrids). We also discuss datasets, evaluation metrics, deployment constraints, and open research problems.

III. Taxonomy Of Approaches

Fig. 1 presents a high-level taxonomy covering classical image processing, machine learning with handcrafted features, deep learning, transformer-based approaches, and practical deployment considerations.

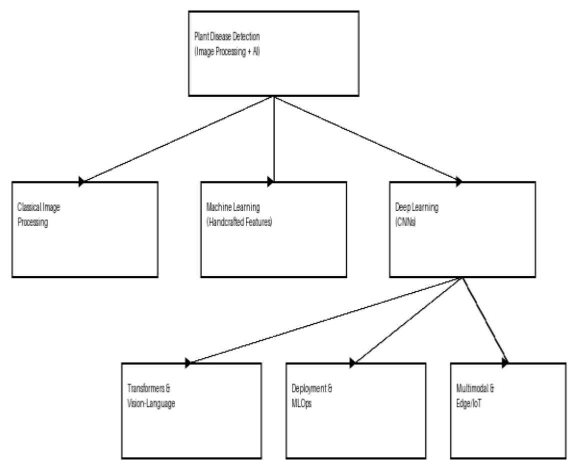

Fig. 1. Taxonomy of image processing and AI approaches for plant disease detection.

IV. Classical Image Processing Pipelines

Traditional pipelines typically include preprocessing (denoising, illumination correction, color space conversion), segmentation (thresholding, clustering, region growing), feature extraction (color moments, GLCM/LBP texture, shape descriptors), and classification (SVM, KNN, decision trees). These methods are interpretable and computationally light but can be brittle under field conditions and varied illumination/backgrounds.

V. Machine Learning With Handcrafted Features

Handcrafted features combined with classifiers (SVM, Random Forest, Gradient Boosting) remain useful when datasets are small or when edge deployment requires low compute. However, performance depends heavily on segmentation quality and feature design, and may not generalize across cultivars, cameras, and environments.

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VI. Deep Learning: CNN-Based Methods

CNNs learn discriminative features directly from images and have achieved strong results on benchmark datasets such as Plant Village. Transfer learning (e.g., VGG, ResNet, EfficientNet, MobileNet) is common, reducing data requirements. Ensemble strategies and augmentation can further boost accuracy, though high laboratory accuracy may not translate to field settings.

VII. Transformers And Emerging Models

Vision Transformers (ViT) and detection transformers (DETR variants) are increasingly applied to plant disease classification and detection. Transformers may offer better global context modeling and localization capabilities. Vision-language and multimodal models are emerging for richer diagnosis using images plus metadata (weather, soil sensors) and for improved generalization.

VIII. Datasets And Benchmarking

Plant Village is a widely used public dataset for leaf disease classification; however, it is often captured under controlled conditions. In-the-wild datasets (e.g., Plant Doc and field-collected sets) are important for evaluating robustness. Cross-domain testing (train on lab images, test on field images) is recommended to measure real-world generalization.

Table I
Common datasets used in plant disease detection (illustrative).

Dataset	Type	Typical Use	Notes
PlantVillage	Lab/controlled	Classification	Large, popular benchmark; limited field variability
PlantDoc	In-the-wild	Detection/Classification	Complex backgrounds; domain shift challenge
Field-collected sets	In-the-wild	Deployment validation	Most realistic; labeling is costly

IX. Evaluation Metrics And Practices

For classification, accuracy, precision, recall, and F1-score are standard; for detection/segmentation, mAP and IoU are common. To avoid inflated results, studies should report: dataset splits, cross-validation where appropriate, class imbalance handling, and experiments under varying illumination and backgrounds. Robustness checks include cross-dataset testing and ablations.

X. Deployment: Edge, Mobile, And Mlops

Practical deployment requires models that are accurate, fast, and energy-efficient on mobile/edge devices. Lightweight CNNs (e.g., MobileNet/EfficientNet-Lite) and quantization/pruning can reduce latency. In production, data drift monitoring, periodic re-training, and user feedback loops are important. Privacy-preserving approaches such as federated learning can be useful when farm data cannot be centralized.

XI. Open Challenges And Future Directions

Key challenges include domain shift (lab-to-field), limited labeled data for rare diseases, symptom similarity across diseases, multi-disease co-infection, early-stage subtle symptoms, and explain ability for farmer trust. Future research directions include:

(i) robust training with domain adaptation,
(ii) self-/semi-supervised learning,
(iii) multimodal fusion (image + sensors + weather),
(iv) uncertainty estimation and calibrated outputs, and
(v) standardized benchmarks reflecting field diversity.

XII. Conclusion

Image processing and AI have enabled significant progress in plant disease detection, moving from handcrafted pipelines to deep learning and transformers. Future work should prioritize robustness, transparency, and deployment readiness to maximize real-world impact.

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