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Ai For Plant Disease Detection: A Systematic Review Of Machine Learning, Deep Learning And Vision Transformers With Field Deployment And Dataset Bias

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Abstract—Crop diseases remain a serious threat to food security, causing substantial yield losses and economic hardship for farmers. Traditional detection depends on manual field inspection by experts, which is slow, subjective and often unavailable in rural regions. This paper systematically reviews AI-based approaches for crop disease prediction. It covers classical machine learning algorithms such as support vector machines, random forests and k-nearest neighbours applied to colour, texture and shape features, and deep learning architectures including convolutional neural networks, transfer-learning models and vision transformers. The complete pipeline is discussed: image acquisition through smartphones, drones and IoT sensors; preprocessing and segmentation; feature extraction; classification; and deployment on mobile and edge platforms using lightweight architectures and quantization. Commonly used datasets including PlantVillage are examined together with evidence of their background bias and the resulting gap between laboratory and field accuracy, and field datasets such as PlantDoc and the Plant Pathology challenge. Evaluation metrics of accuracy, precision, recall and F1-score are reviewed, as is the integration of environmental parameters such as temperature, humidity and soil conditions with image data for forecasting. A five-stage architecture is proposed, with research gaps, objectives, a comparison of techniques and challenges including limited real-field data, class imbalance, lighting variation, computational cost and poor generalization. Future directions identified are explainable AI, lightweight models, multimodal fusion and federated learning.

Index Terms—Plant disease detection, crop disease prediction, convolutional neural networks, vision transformers, transfer learning, PlantVillage, edge deployment, explainable AI

I. INTRODUCTION

A farmer who notices spots on leaves must decide quickly whether they indicate a fungal infection, a nutrient deficiency or pest damage, because the correct treatment differs in each case. Expert advice is often unavailable, and a wrong spray wastes money and harms the environment.

Smartphone cameras and deep learning make automatic diagnosis feasible. Mohanty *et al.* [1] trained deep CNNs on the PlantVillage dataset [2] and reported accuracy above 99 percent on held-out laboratory images, a result that attracted wide attention. Field performance, however, is much lower, and understanding why is central to building usable tools.

This paper systematically reviews AI techniques for plant disease detection across the full pipeline and identifies what is required for reliable field use.

II. RELATED WORK

Deep learning on curated data. Mohanty *et al.* [1] showed very high accuracy on PlantVillage, and Ferentinos [3] extended this to 58 plant–disease combinations. Too *et al.* [4] compared fine-tuned architectures and found deeper networks such as

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DenseNet most accurate. Brahimi *et al.* [5] classified tomato diseases and visualized symptom regions, improving interpretability.

The field gap and dataset bias. Barbedo [6] analysed the factors limiting deep learning for plant disease recognition, including limited variability and image capture conditions. Noyan [7] showed that models can achieve high accuracy on PlantVillage using background pixels alone, demonstrating that the dataset's uniform backgrounds leak class information. Singh *et al.* [8] released PlantDoc, collected in real fields, and Thapa *et al.* [9] released the Plant Pathology apple foliar disease dataset with natural variation. Ramcharan *et al.* [10] deployed cassava disease detection on smartphones in the field and reported lower accuracy than laboratory tests.

Modern architectures and deployment. Vision transformers [11] match or exceed CNNs given sufficient data, EfficientNet [12] balances accuracy and size, and quantization [13] allows deployment on low-power devices. Liu and Wang [14] reviewed deep learning for plant disease and pest detection. Grad-CAM [15] highlights the image regions driving a prediction, and federated learning [16] allows training across farms without sharing images. Table I summarizes these works.

Sr. No.	Ref.	Year	Methodology	Findings	Research Gap
1	[2]	2015	PlantVillage repository	Large labelled leaf dataset	Uniform backgrounds
2	[1]	2016	Deep CNN classification	>99% on curated data	Poor field transfer
3	[5]	2017	Tomato disease CNN	Symptom visualization	Single crop
4	[10]	2017	Cassava mobile detection	Field deployment	Accuracy drop in field
5	[6]	2018	Limiting factors analysis	Identified data constraints	Analytical
6	[3]	2018	58 plant–disease classes	Broad coverage	Lab images
7	[8]	2020	PlantDoc field dataset	Realistic imagery	Smaller, noisier
8	[7]	2022	PlantVillage bias study	Background leaks labels	One dataset

TABLE I Summary of Literature Survey

III. PRELIMINARIES

1. Detection Pipeline

Fig. 1 organizes the pipeline into acquisition, preprocessing and segmentation, feature extraction and classification, and deployment.

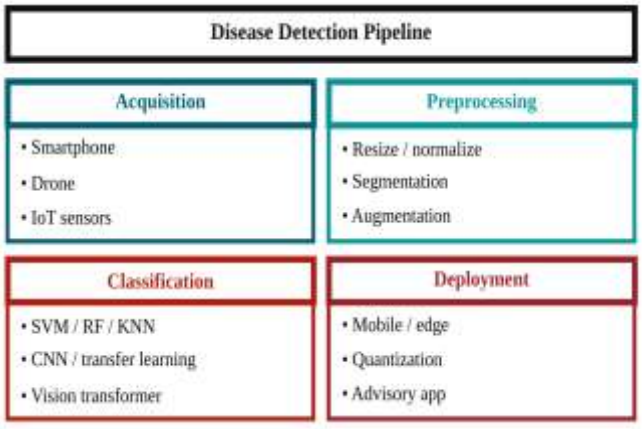


Fig. 1. Pipeline for AI-based plant disease detection.

2. From Handcrafted Features To Learned Features

Classical methods extract colour histograms, texture descriptors and lesion shape features and classify them with SVM [17], random forest [18] or k-nearest neighbours. Deep networks learn features directly from pixels, removing manual feature design but requiring more data.

IV. PROBLEM STATEMENT AND OBJECTIVES

1. Identified Research Gaps

- Public datasets are dominated by uniform-background laboratory images.
- Class imbalance leaves rare diseases poorly detected.
- Lighting, occlusion and multiple simultaneous diseases degrade accuracy.
- Large models are too heavy for low-end smartphones used by farmers.

• Few systems combine images with weather and soil data for forecasting.

2. Objectives Of The Review

1. 1) To systematically review machine learning and deep learning for disease detection.

2. 2) To examine the full pipeline from acquisition to edge deployment.

3. 3) To analyse datasets, bias and the laboratory-to-field accuracy gap.

4. 4) To propose a field-oriented detection architecture with explainability.

5. 5) To identify future directions including multimodal and federated learning.

3. Proposed Framework

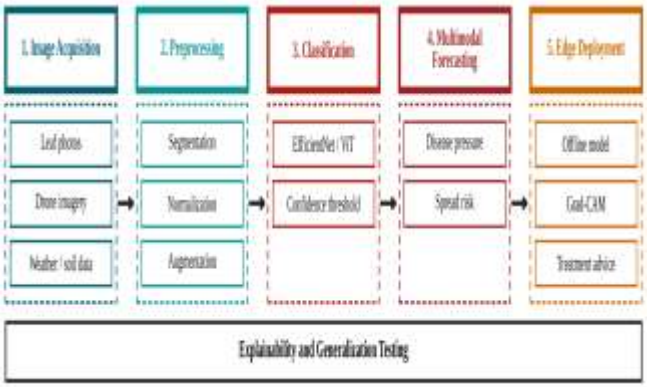


Fig. 2 presents the proposed architecture.

Fig. 2. Proposed field-oriented plant disease detection architecture.

4. Image Acquisition Stage

Farmers photograph affected leaves with a smartphone; drones provide field-scale imagery; IoT sensors record temperature, humidity and soil moisture.

5. Preprocessing And Segmentation Stage

Images are resized and normalized; leaf regions are segmented to suppress background; augmentation with rotation, colour jitter and blur improves robustness.

C. Feature Extraction and Classification Stage

A transfer-learning backbone such as EfficientNet, or a vision transformer when data permit, classifies the disease; a confidence threshold triggers a request for a clearer image.

6. Multimodal Forecasting Stage

Environmental data are combined with detection history to estimate disease pressure and the risk of spread in the coming days.

7. Edge Deployment And Advisory Stage

The quantized model runs offline on the phone; Grad-CAM shows the regions that led to the diagnosis; advice includes the disease name, confidence, treatment options and a referral to extension services for uncertain cases.

V. WORKING METHODOLOGY

Fig. 3 describes the workflow. Models are evaluated with

$$Precision = TP/(TP+FP), \quad Recall = TP/(TP+FN) \quad (1)$$

$$F1 = 2 \cdot Precision \cdot Recall / (Precision + Recall) \quad (2)$$

and must be tested on field images from different locations than the training data to measure generalization.

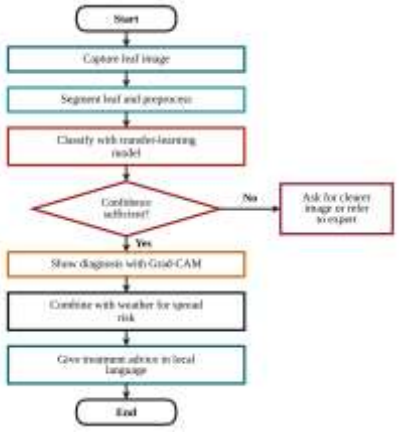


Fig. 3. Plant disease detection and advisory workflow.

VI. DISCUSSION

1. Comparison Of Approaches

Table II compares techniques by data requirement, field robustness and suitability for mobile deployment.

TABLE II Comparison of Detection Techniques

Technique	Data Needed	Field Robustness	Mobile Suitability
SVM / RF on features	Small	Low	Very good
CNN from scratch	Large	Medium	Poor
Transfer learning (EfficientNet)	Medium	Medium–High	Good
Vision transformer	Very large	High (with data)	Limited
Quantized lightweight CNN	Medium	Medium	Excellent

2. Open Challenges And Future Work

Table III summarizes challenges. Future directions include large field datasets for Indian crops, explainable and uncertainty-aware models, multimodal fusion with weather and soil data, federated learning across farms and integration with advisory services.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Lab-to-field gap	Field datasets; strong augmentation
Class imbalance	Resampling; weighted loss
Lighting and background	Segmentation; capture guidance
Compute limits	Quantized lightweight models
Trust	Grad-CAM; confidence and referral

VII. CONCLUSION AND FUTURE WORK

AI enables early, accurate and scalable plant disease detection, with deep learning clearly outperforming handcrafted features on curated data. The reviewed literature shows, however, that high laboratory accuracy does not transfer to fields, largely because of dataset bias and capture conditions. Progress requires realistic field data, lightweight explainable models and fusion with environmental information so that timely, reliable and affordable advice reaches farmers and supports sustainable agriculture.

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