Crop Disease Detection Using Machine Learning Techniques: A Review

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Abstract
Crop diseases substantially lower agricultural output, endangering food security and farmers' livelihoods globally. Early and precise detection of diseases is critical to apply timely interventions, minimize loss of yield, and curtail pesticide consumption. Recent developments in machine learning (ML), deep learning (DL), and computer vision have made it possible to automatically classify plant diseases at high accuracy levels. This review article consolidates the literature on conventional image processing methods, ML-based classification, DL structures like convolutional neural networks (CNNs) and transformers, and IoT-based integrated systems for real-time identification. A comparative review identifies the merits and demerits of different approaches, stressing issues like data limitations, model generalizability, computational complexity, and explainability requirements. In addition, newly developing trends in research—such as multimodal methods, light models for edge deployment, and federated learning—are considered as possible directions towards scalable, field- deployable solutions. The survey seeks to provide researchers and practitioners with an integrated view of the state-of-the-art and open up research directions leading towards reliable, efficient, and trustworthy crop disease detection systems.

Keywords: Crop disease detection, plant pathology, machine learning, deep learning, computer vision, IoT, precision agriculture.

1. Introduction

Crop diseases represent one of the most urgent threats to worldwide food security and agricultural economies. Yearly, plant diseases and insects cause about 25% of worldwide total crop losses, the burden of which disproportionately affects developing regions, whose yield losses are greater than 20% Wikipedia. For example, wheat leaf rust alone results in mean global losses of 8.6–18.3 million metric tons annually, equivalent to economic losses of US$1.5–3.3 billion APS Journals. In the same way, soybean diseases in the United States accumulated more than US$95 billion in losses from 1996 to 2016 Penn StatePMC, whereas recent estimates for 2015 to 2019 place losses at US$19.5 billion throughout the
U.S. and Ontario APS Journals.

These jaw-dropping statistics speak to a twin story: rampant yield decline and devastating economic impacts region-wise and crop-wise. This speaks to the need for early, reliable, and scalable disease detection systems, which can stem losses before infections run out of control.

Traditionally, disease detection depended on scounting and laboratory-based diagnostics—such as polymerase chain reaction (PCR) and spectral sensing methods ScienceDirect.
Although accurate, they tend to be sluggish, time-consuming, and not amendable to field deployment in real time. The arrival of image-based analytics, driven by advances in deep learning (DL), provides powerful alternatives: mobile- convenient systems have even reached 99.3% classification accuracy on polished datasets, albeit with significant performance decreases in non-lab settings arXiv+1.
Recent literature reflects a rich tapestry of approaches:

- Surveys and meta-studies highlight the predominant use of PlantVillage-type datasets, the limitations of hand- engineered features, and the growing shift toward transformer models and IoT-ready algorithms [1] through [10].
- Crop- and context-specific advances are evident in custom detectors like YOLO-Wheat [8], as well as frameworks combining Swin Transformers with attention-based modules for multi-scale symptom recognition [3].
- Deployment-aware strategies, such as lightweight model architectures and on-edge inference pipelines, cater to real- time disease monitoring needs [2].
- Interpretability and validation layers, including XAI (e.g., LIME) [5] and Formal Concept Analysis (FCA) [6], are emerging to foster trust and empower decision-making— especially where management interventions hinge on model outputs.

Supporting this body of work are ongoing challenges— most particularly, realism of dataset, generalization of the model over conditions, consistency of evaluation, and farmer- friendly usability. Detection frameworks of the future should not only be highly accurate but also multimodal sensing enabled, robust under field variability, explainable, and low- latency edge-supported deployment enablement.
This review paper aims to integrate the state of art in crop disease detection, bring into focus the most important technological developments, and outline a course toward next- generation systems that are accurate, robust, deployable, and interpretable.

2. Literature Survey

The algorithmic and data environment for image-based crop disease diagnosis was built by early work that was compiled into large surveys. For plant disease classification and detection, Balafas et al. [1] offer a comprehensive overview of machine learning (ML) and deep learning (DL) approaches. They cover handcrafted features like color and texture with SVM, k-NN, and RF through contemporary CNNs and transformers, and they map them to common pipelines (acquisition → preprocessing/augmentation → model → evaluation). They list publicly available datasets, draw attention to the prevalence of leaf photography in the style of Plant Village, and emphasize gaps related to field variability, class imbalance, and domain shift problems that still influence method design and benchmarking.
The agenda is then pushed toward crop specificity and deployment context by targeted, current syntheses. In their evaluation of state-of-the-art DL for IoT-based disease and pest detection, Nyakuri et al. [2] make the case that energy- aware models, wireless integration, and on-edge/near-edge inference are essential for prompt decision support. In addition to summarizing lightweight backbones, pruning, and quantization techniques that allow embedded inference without compromising accuracy, they also list system requirements (latency, bandwidth, and model size). In their systematic review, Shafik et al. [7] cover motivations, datasets, taxonomies (classification, detection/segmentation), and difficulties(reproducibility,

label quality, and cross- domain resilience). They also frame future trends like explainability, self-supervision, and multimodal sensing.

Crop-focused reviews demonstrate how model selection is influenced by problem structure. According to Sahu et al. [9], who curate machine learning strategies around banana agronomy (from disease/ripeness to quality assessment), traditional ML performs well when features are designed for tasks with constraints, but DL has a performance and resilience advantage when variability increases. Additionally, they promote protocol standardization and highlight the scarcity of datasets in particular banana morphologies. In their study of potato diseases, Kaur et al. [10] compiled datasets and models from 2007 to 2024 and connected algorithm selection to management measures like targeted sprays. Their synthesis focuses on the requirement for explainability when suggestions impact chemical usage and yield, as well as a developing path from lab to field photography.

In terms of methodology, recent primary works address multi-scale symptoms and crowded backdrops by moving away from simple CNNs and toward transformers, attention mechanisms, and task-specific detection heads. For the classification of joint diseases and pests, Karthik et al. [3] suggest a Swin Transformer backbone with a dual-attention multi-scale fusion module. In order to improve categorization in visually diverse conditions, the design specifically aggregates characteristics across scales while drawing emphasis to lesion-salient patterns. By improving the neck/head and training strategy, Yao et al. [8] modify YOLOv8s into YOLO-Wheat for wheat, reporting improved real-time detection. Crucially, they publish tangible mAP gains against robust baselines, and the paper exemplifies the trend of tailoring general detectors to crop-specific morphology.

An additional line of research examines in-situ sensing configurations that match model capabilities with the location and method of data collection. In order to identify powdery mildew and leaf blotches, Khan et al. [4] equip vineyards with carefully positioned cameras. They show that precise camera placement and customized machine learning (ML) lower false alarms and enhance early detection in the presence of field lighting and occlusion, bringing us closer to actionable monitoring systems as opposed to post-hoc lab classification.

Two overarching requirements become more important as models achieve high accuracy: explainability and verification/validation. In order to determine whether salient regions match actual lesions rather than background cues—a crucial step for trust, adoption, and dataset debugging—Nigar et al. [5] combine explainable AI (XAI) techniques like LIME with a DL classifier that detects dozens of plant diseases. By organizing the links between features, classes, and rules, Tussupov et al. [6] present Formal Concept Analysis (FCA) as a verification layer for pest/disease recognition. This aids in auditing model outputs, comprehending confounders, and directing agronomic interpretation.

Across these works, several technical patterns recur:

- Generalization and data realism. Surveys consistently show a discrepancy in performance between field situations (many leaves, mixed backdrops, and overlapping symptoms) and carefully chosen leaf images. Multi-scale and clutter are specifically addressed by more recent detectors (such YOLO-Wheat [8]) and attention-rich classifiers (Swin + dual attention [3]). Given the variety of cultivars and settings, domain augmentation and adaptability are still poorly understood [1], [7].
- Being prepared for the edge. Lightweight backbones, compression, and latency/energy restrictions are highlighted in IoT-focused assessments [2]. In order to maintain the viability of on-device inference, this forces design decisions toward smaller detection heads, effective transformers, and training-time strategies like knowledge distillation and quantization-aware training.

- The thoroughness of the evaluation. Consistent metrics (accuracy vs. mAP@0.5:0.95), more transparent train/test splits, and cross-dataset tests to assess robustness are also recommended by a number of reviewers. Alongside accuracy, application papers are increasingly reporting deployment-relevant metrics (memory, throughput) [7], [8].
- Human-centred AI. XAI [5] and FCA [6] exemplify movement beyond raw accuracy to interpretability, enabling agronomists to inspect model focus, reconcile predictions with visible symptoms, and codify knowledge. This is pivotal for prescription (e.g., fungicide timing) and for regulatory/extension-service adoption.

curated, representative datasets covering growth stages, cultivars, sensors (RGB, multispectral, thermal), and geographies; (ii) spatiotemporal modelling for tracking progression and early detection; (iii) standardized benchmarks for field deployment, such as weather/lighting robustness; and

(iv) responsible AI practices—explanations connected to agronomic ontologies, uncertainty quantification for risk- aware recommendations, and lifecycle monitoring after models are deployed all represent open challenges. A synthesis is proposed by the reviewed literature: combine deployment-aware engineering (compression/edge) with crop-tailored, attention-enhanced backbones, instrument fields to record informative perspectives, and wrap models with verification/explainability layers to facilitate reliable, real-time decision-making.

4. Existing Methodologies

The evolution of crop disease detection systems spans from traditional manual inspection to advanced artificial intelligence pipelines. The methodologies can be broadly grouped into conventional methods, classical machine learning approaches, deep learning models, and emerging IoT-enabled, explainable, and validation-focused frameworks.

A. Conventional Methods

Historically, plant disease identification has relied on visual inspection by farmers or experts and laboratory-based diagnostics such as polymerase chain reaction (PCR) and enzyme-linked immunosorbent assay (ELISA) [11]. While accurate, these methods are time-intensive, labor-dependent, and impractical for large-scale or real-time monitoring [1]. Additionally, symptom manifestation may be delayed relative to infection onset, reducing the timeliness of interventions..

B. Machine Learning (ML) Approaches

The shift toward automated detection began with feature- engineered pipelines, where handcrafted descriptors such as color histograms, Gabor filters, local binary patterns (LBP), and histograms of oriented gradients (HOG) were extracted from leaf images, followed by classification using Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Random Forests (RF), or Decision Trees [1], [9]. These methods demonstrated high accuracy in controlled environments, but performance degraded under field variability due to sensitivity to lighting, occlusion, and background noise [7], [9].

C. Deep Learning (DL) Approaches

The introduction of Convolutional Neural Networks (CNNs) revolutionized plant disease detection, enabling end- to-end feature extraction and classification [12]. Transfer learning with pretrained architectures such as VGGNet, ResNet, and Inception allowed models to generalize better with limited agricultural datasets [1], [7]. More recent innovations include:

- Attention Mechanisms: Dual-attention multi-scale fusion, as in Karthik et al. [3], improves focus on lesion-specific regions while handling varying symptom sizes.

- Transformer Architectures: Vision transformers, such as Swin Transformer, capture long-range dependencies and improve robustness to cluttered backgrounds [3].
- Specialized Detectors: YOLO-Wheat [8] adapts YOLOv8s for wheat morphology, optimizing the neck/head structure for field conditions.

D. Detection and Segmentation Models

Beyond classification, object detection and semantic segmentation allow localization of disease symptoms on plant parts:

- Detection: Faster R-CNN, YOLOv5/v8, and SSD frameworks excel in identifying multiple disease instances in complex backgrounds [8].
- Segmentation: U-Net, DeepLabV3+, and Mask R- CNN extract pixel-level disease regions, aiding in severity estimation [7].

Such models support actionable agronomy by quantifying infection spread, although they demand higher computational resources.

E. IoT and Edge-Based Systems

For real-time, scalable deployment, IoT integration is critical [2]. Low-power embedded boards (e.g., NVIDIA Jetson Nano, Raspberry Pi) run lightweight CNNs or pruned transformer models to deliver on-field, low-latency inference. Nyakuri et al. [2] emphasize model compression (pruning, quantization) and energy-efficient communication protocols to reduce costs and prolong sensor life. Khan et al. [4] demonstrate strategic camera placement to optimize data capture for grapevine monitoring.

F. Explainable AI (XAI) and Validation

Accuracy alone is insufficient in agricultural decision support; models must be interpretable to ensure trust. Nigar et al. [5] employ LIME-based saliency maps to verify that CNN predictions correspond to actual lesion patterns, reducing the risk of spurious correlations. Tussupov et al. [6] leverage Formal Concept Analysis (FCA) to formalize relationships between features and classes, enabling structured verification of outputs before dissemination to end-users.

5. Challenges and Future Directions

Despite significant advancements in crop disease detection, multiple challenges limit large-scale, real-world deployment. These challenges span data-related issues, model generalization, computational constraints, and practical adoption barriers.

A. Data-Related Challenges

A major bottleneck is the availability of high-quality, annotated datasets covering diverse crops, disease stages, and environmental conditions [1], [7]. Many models are trained on controlled datasets (e.g., Plant Village), which fail to capture variations in lighting, occlusion, background clutter, and mixed infections common in real agricultural fields [9]. Data imbalance, where certain disease classes are overrepresented, further skews predictions [3]. Emerging solutions include data augmentation, synthetic image generation via GANs, and crowdsourced labeling platforms [13].

B. Model Generalization and Robustness

Domain change between training and deployment environments frequently results in performance decreases, even when deep models can attain near-perfect accuracy in lab settings [2], [8]. Variations in leaf morphology, pest co- occurrence, and seasonal variations necessitate cross-domain generalization models. Frameworks for domain adaptation and transfer learning show promise, but they need to be systematically benchmarked [14].

C. Computational and Deployment Constraints

Low-latency inference and energy efficiency are necessary for on-field deployment [2], [4]. Model compression approaches (pruning, quantization, and knowledge distillation) are necessary because high-performing CNNs and transformers may be too computationally demanding for edge devices [8]. Furthermore, cloud-based processing is not feasible in rural locations due to wireless network limitations, which is driving the trend toward edge AI [4].

D. Explainability and Trustworthiness

Explainability is just as crucial to agricultural advice systems as accuracy. Before implementing expensive preventive or remedial measures, farmers and agronomists need to have faith in model outputs [5]. Model reasoning is aligned with human expertise and decision boundaries are shown with the aid of techniques like LIME, Grad-CAM, and FCA [6]. Still a research problem, though, is striking a balance between interpretability and prediction power.

E. Integration with IoT and Precision Agriculture

Real-time, scalable solutions are promised by the combination of IoT-based monitoring networks and AI-based illness detection [2], [4]. The robustness of detection can be improved by sensor fusion, which combines RGB, hyper spectral, and thermal imaging [8]. However, in areas with limited resources, adoption is slowed by interoperability problems, maintenance requirements, and hardware expenses.

F. Future Directions

- Large-Scale Benchmark Datasets – Initiatives to collect geographically diverse, multi-season datasets will improve model generalization.
- Lightweight Transformers – Research on efficient attention-based models can deliver accuracy without computational overhead.
- Multimodal Approaches – Combining visual, spectral, and environmental data could improve early-stage detection accuracy.
- Federated Learning – Enabling model training across distributed devices without centralizing data will address privacy and data scarcity issues.
- Policy and Extension Integration – Bridging AI outputs with agricultural extension services can ensure technology adoption at the farmer level.

5. References

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