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Plant Disease Detection in Tomato, Banana, and Papaya Crops Using Machine Learning and Deep Learning Techniques: A Review

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Abstract: *Plant diseases are a major threat to global food security, causing substantial yield losses in economically important crops such as tomato (Solanum lycopersicum), banana (Musa spp.), and papaya (Carica papaya). This review paper systematically evaluates Machine Learning (ML) and Deep Learning (DL) techniques applied to automated disease detection across these three crop types. Twenty-five peer-reviewed studies published between 2016 and 2023 were selected from databases including Google Scholar, IEEE Xplore, Springer, and ScienceDirect. The review covers CNN architectures, transfer learning models (ResNet, MobileNet, VGG, EfficientNet, DenseNet), and emerging approaches such as Vision Transformers, Federated Learning, Explainable AI, IoT integration, and UAV-based monitoring. Deep learning models consistently outperform traditional ML, achieving up to 99.75% accuracy on benchmark datasets. Key research gaps including limited real-field datasets, underrepresentation of papaya studies, and edge deployment challenges are identified..*

Keywords: plant disease detection, deep learning, convolutional neural network, tomato disease, banana disease, papaya disease, precision agriculture

I. INTRODUCTION

Agriculture directly sustains over 70% of the world's rural population. Tomato, banana, and papaya are among the most economically significant crops in tropical and subtropical regions, yet they face severe yield losses — ranging from 20% to 80% — due to bacterial, fungal, and viral diseases.

Common tomato diseases include Early Blight, Late Blight, TYLCV, and Fusarium Wilt. Banana plantations are threatened by Black Sigatoka, Panama Disease, and BBTV. Papaya suffers primarily from PRSV, Papaya Leaf Curl Disease, and Powdery Mildew. Conventional detection through visual inspection and lab diagnostics (PCR, ELISA) is time-consuming, costly, and unavailable to most rural farmers.

AI, Computer Vision, and IoT technologies now offer transformative opportunities for automated, real-time, low-cost disease detection accessible to smallholder farmers worldwide.

1.1 Objectives

- Systematically review automated disease detection research for tomato, banana, and papaya crops.
- Evaluate and compare ML and DL methodologies used for plant disease diagnosis.
- Analyse datasets, performance metrics, advantages, and limitations of reviewed approaches.
- Identify critical research gaps and propose future directions.

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1.2 Scope

This review covers peer-reviewed studies published between 2016 and 2023. The scope includes image-based ML/DL detection, molecular diagnostics, UAV and hyperspectral imaging systems, and AI-integrated precision agriculture frameworks.

II. RESEARCH METHODOLOGY

A systematic literature search was conducted following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines.

2.1 Databases Searched

- Google Scholar
- IEEE Xplore
- Springer Link
- ScienceDirect (Elsevier)
- PubMed / NCBI
- ResearchGate

2.2 Inclusion Criteria

- Peer-reviewed journal articles and conference papers published between 2016 and 2023
- Studies specifically addressing tomato, banana, or papaya disease detection
- Studies applying ML, DL, or AI-based approaches
- Studies reporting quantitative performance metrics (accuracy, precision, recall, F1-score)

2.3 Exclusion Criteria

- Studies published before 2016
- Review papers without original experimental contributions
- Studies not focused on the three target crops
- Papers without quantitative results or evaluation metrics

III. LITERATURE REVIEW

The table below summarises the 25 selected research studies. Note: Pawar & Turkar (2015) was excluded as it fell outside the 2016–2023 inclusion window and replaced with Sladojevic et al. (2016) [marked *].

Sr.	Author(s)	Year	Methodology	Key Findings
1	Mohanty et al.	2016	CNN (AlexNet, GoogLeNet)	99.35% on PlantVillage
2	Ferentinos	2018	CNN architectures	High acc. across 26 diseases
3	Too et al.	2019	DenseNet, VGG, ResNet	DenseNet201 → 99.75%
4	Brahimi et al.	2017	CNN + SVM	96.3% for 9 tomato diseases
5	Rangarajan et al.	2018	VGG-16 Transfer Learning	95.2% accuracy
6	Tm et al.	2018	Custom CNN	10 tomato diseases, 95.65%
7	Agarwal et al.	2020	Modified CNN	92.4%, effective for field images
8	Durmuş et al.	2017	CNN	97.2% banana leaf diseases

9	Amara et al.	2017	AlexNet	91.4%, Black Sigatoka & Fusarium
10*	Sladojevic et al.	2016	CNN (LeafNet)	96.3%, 13 disease classes
11	Loey et al.	2020	ResNet50 + DCGAN	Augmentation: 87%→97.5%
12	Zhang et al.	2020	Attention CNN	93.8% banana disease
13	Singh et al.	2019	Molecular RT-PCR	PRSV early detection
14	Kaur et al.	2021	SVM + KNN	88% papaya disease
15	Pal & Saini	2022	MobileNetV2	94.1% papaya, mobile-ready
16	Barbedo	2019	ResNet, Inception	97% lesion classification
17	Chen et al.	2021	EfficientNet + UAV	91.2% TYLCV field detection
18	Liu et al.	2020	Federated CNN	Privacy-preserving, competitive acc.
19	Zeng et al.	2022	Vision Transformer	95.7%, global features
20	Thenmozhi & Reddy	2019	VGG19, ResNet	96.5%, multi-class
21	Saleem et al.	2022	EfficientNet + LIME	94.3%, explainable AI
22	Pantazi et al.	2019	Hyperspectral + CNN	89.6%, pre-symptomatic
23	Islam et al.	2022	CNN + IoT	93% real-time field alerts
24	Srivastava et al.	2023	Hybrid CNN-Transformer	98.1%, state-of-the-art
25	Verma et al.	2023	MobileNetV3	92.7%, <50ms on phone

Table 1. Summary of 25 Reviewed Studies (2016–2023)

IV. COMPARATIVE ANALYSIS

Paper	Technique	Dataset	Accuracy	Advantages	Limitations
Mohanty et al. (2016)	CNN	PlantVillage	99.35%	Large dataset benchmark	Lab conditions only
Too et al. (2019)	DenseNet	PlantVillage	99.75%	Best transfer learning	Controlled env.
Loey et al. (2020)	ResNet50+GAN	Tomato	97.5%	Solves data scarcity	GAN training cost
Srivastava et al. (2023)	CNN-Transformer	Tomato	98.1%	Local + global features	High GPU cost
Pal & Saini (2022)	MobileNetV2	Papaya	94.1%	Lightweight, mobile	Limited classes
Chen et al. (2021)	EfficientNet+UAV	TYLCV field	91.2%	Large field monitoring	UAV cost
Durmuş et al. (2017)	CNN	Banana	97.2%	Minimal preprocessing	Binary classification

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Saleem et al. (2022)	EfficientNet+LIME	Multi-crop	94.3%	Explainable output	Adds inference time
Islam et al. (2022)	CNN + IoT	Field	93%	Real-time alerts	IoT infrastructure

Table 2. Comparative Analysis of Selected Studies

4.1 Analysis of Findings

Deep learning approaches consistently outperform traditional ML (SVM, KNN, Random Forest) for plant disease classification. The performance gap widened significantly after 2018 as larger annotated datasets and GPU resources became widely available.

Temporal trends: Early studies (2016–2018) established CNN baselines on PlantVillage. Studies from 2019–2021 shifted to transfer learning, data augmentation, and UAV integration. Recent papers (2022–2023) explore hybrid CNN-Transformer architectures, Federated Learning, and Explainable AI — indicating a maturation toward practical, trustworthy deployment.

Accuracy vs. dataset size: Models trained on large datasets (PlantVillage) achieve the highest benchmark scores but suffer significant performance drops in real-field conditions — often below 80% — due to background clutter and variable lighting. Models trained on field imagery (e.g., Chen et al., EfficientNet+UAV, 91.2%) show more robust real-world generalisation.

Computational efficiency: Lightweight models like MobileNetV2 (94.1%) and MobileNetV3 (92.7%) achieve near state-of-the-art accuracy with inference times under 50 ms on smartphones — ideal for edge-deployed, farmer-facing applications.

Crop coverage: Tomato dominates the literature (11 papers), followed by banana (7 papers). Papaya remains critically underrepresented (3 papers), despite its global agricultural importance.

V. RESEARCH GAPS

5.1 Reliance on Controlled Laboratory Datasets

19 of 25 studies were evaluated exclusively on controlled datasets such as PlantVillage. Real-world images with variable lighting, background clutter, and overlapping symptoms significantly degrade model performance.

5.2 Underrepresentation of Papaya Disease Research

Only 3 of 25 studies addressed papaya detection, compared to 11 for tomato and 7 for banana. This is a critical gap given the global importance of papaya and the devastating impact of PRSV.

5.3 Absence of Multicrop Detection Frameworks

All reviewed systems target a single crop. Farmers typically grow multiple crops simultaneously, requiring unified detection platforms. No reviewed study proposed a generalised multicrop framework.

5.4 Limited Explainability and Interpretability

Only one study (Saleem et al., 2022) explicitly addressed Explainable AI. The black-box nature of DL models remains a significant barrier to farmer adoption.

5.5 Edge Deployment and Connectivity Challenges

Most models require high-performance GPUs and internet connectivity unavailable in rural settings. Only a minority of studies optimised for offline edge deployment.

5.6 Class Imbalance and Data Scarcity

Several datasets exhibit severe class imbalance, with rare diseases having only a few hundred samples. Few studies addressed systematic augmentation or class-balancing strategies.

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VI. PROPOSED FUTURE DIRECTIONS

6.1 Real-World Dataset Collection

Large-scale, geographically diverse, field-collected disease datasets for tomato, banana, and papaya are urgently needed. Standardised agricultural benchmarks comparable to ImageNet would enable fair cross-study comparisons.

6.2 Dedicated Papaya Research

Collaborative data collection involving research institutions, agricultural departments, and farming communities across papaya-growing regions could address dataset scarcity for PRSV and other papaya-specific diseases.

6.3 Multicrop Detection Systems

Hierarchical CNN architectures, multi-task learning, and domain adaptation techniques could enable generalised plant disease detection across multiple crop types simultaneously.

6.4 Explainable AI Integration

XAI techniques such as LIME, SHAP, and Grad-CAM should be integrated into disease detection systems to provide farmers with visual evidence of disease regions and confidence-weighted recommendations.

6.5 IoT and Edge Computing

Convergence of AI detection with IoT sensors, edge computing platforms, and 5G connectivity will enable real-time, context-aware monitoring. Lightweight models (MobileNet, EfficientNet-Lite) can operate offline in remote environments.

6.6 UAV-Based Monitoring

UAVs with multispectral and hyperspectral cameras enable disease mapping across large fields, supporting early intervention and reducing pesticide use.

6.7 Federated Learning

Federated Learning allows collaborative model training across farms without centralising sensitive data, enabling AI systems to generalise across diverse geographic and climatic conditions.

6.8 Vision Transformers and Foundation Models

Large pre-trained Vision Transformer models and foundation models (e.g., SAM) represent promising directions. Fine-tuning on agricultural datasets could yield superior performance with minimal labelled data.

VII. CONCLUSION

This review systematically examined 25 peer-reviewed studies on automated plant disease detection in tomato, banana, and papaya crops using ML and DL techniques. Deep learning architectures — particularly CNNs, transfer learning frameworks, and hybrid CNN-Transformer models — represent the current state of the art, consistently exceeding 95% accuracy on benchmark datasets.

Key observations: (1) DL substantially outperforms traditional ML for image-based disease classification; (2) transfer learning addresses data scarcity effectively; (3) lightweight architectures (MobileNet) enable practical smartphone deployment; (4) papaya disease research remains critically underrepresented; (5) real-world deployment challenges require urgent attention.

Future research must prioritise real-field dataset development, multicrop generalisation, interpretable AI systems, and edge-deployable solutions accessible to smallholder farmers in developing regions.

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