Crop Disease and Pest Detection Using Deep Learning and Transformer Models

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Abstract

Recently, advanced works in agricultural intelligence have emerged, focusing on deep learning algorithms for pest and crop diseases identification. The article presents an analysis of Vision Transformer models, Convolutional Neural Networks, and hybrid models incorporating global contexts with local attribute retrievals. A total of ten articles published within the time span of 2016 to 2025 have been surveyed based on model architectures, preprocessing algorithms, application of datasets, and feasibility of implementation. The article exemplifies how image classification algorithms based on CNN have evolved to become attention-driven, efficient, and optimized models fit for edge or mobile implementation. Major challenges have been noted, including interpretability, class imbalance, generality over different crops, explainability over geographics, and resource-optimization.

Keywords

Crop disease detection; Pest detection; Deep learning; Convolutional Neural Networks; Vision Transformers; Edge deployment

1. Introduction

The global production in agriculture is hampered by crop diseases and pests. To improve food security and facilitate crop production, early and accurate identification is necessary. Traditional approaches in this regard include manual identification and lab analysis, which are not always feasible in a large-scale setup or in resource-poor environments.

The identification of diseases and pests using photos captured with smartphone cameras, cameras, and drones has become feasible with technology advancement in computer vision and deep learning AI. While state-of-the-art models in image-driven identification were achieved with CNN models, focus is currently placed on improving robustness and efficiency of methodologies.

A brief survey of ten important works in this area, highlighting accuracy, efficiency, and practicality in their application in the field, is presented in this paper.

2. Crop Disease and Pest Detection — Methods

2.1 Mohanty et al. [1] (2016)

A seminal work by Mohanty et al. used over 50,000 leaf image samples, which belonged to 26 diseases in 14 species, to show the efficacy of deep learning methods for plant disease identification over conventional machine learning systems. While both studies and experiments were lab-based, this work formed a basis for establishing a need for deep learning in plant disease analysis.

2.2 Ahmed et al. [2] (2022)

The authors proposed AgroPath with an Image Quality Assessment (IQA) stage before the classification step by Ahmed et al. The idea of filtering out poor-quality images before making predictions enhanced robustness in real-world image acquisition. Their research bridged the gap in the application of lab-grade datasets in real-world settings.

2.3 Yuan et al. [3] (2024)

Yuan et al. proposed an improved deep learning model based on lightweight attention mechanisms and efficient architecture components with a small number of parameters. They focused on providing a balance between accuracy and complexity for edge devices.

2.4 Foysal et al. [4] (2024)

Foysal et al. constructed a CNN-based multi-class leaf disease identification model into a mobile application. The application allowed leaf diseases to be detected offline without an internet connection, emphasizing the need for an application-centric model with usability and real-time support.

2.5 Lebrini and Gotor [5] (2024)

This research focused on the gap between research-oriented plant disease identification models and practical solutions. The importance of fidelity in datasets, common evaluation standards, and a focus on end-user requirements were highlighted in this research.

2.6 Ashurov et al. [6] (2024)

Ashurov et al. offered a depthwise SE-CNN model which incorporated both squeeze-excitation blocks, depthwise separable convolutions, and residual connections. The network achieved better efficiency in the computation of features but saw an impact on accuracy due to increased crop datasets.

2.7 Upadhyay et al. [7] (2025)

A complete literature review has been conducted by Upadhyay et al. on various aspects like CNN, Vision Transformer, combination of architectures, datasets, and latest trends in the field of precision agriculture. The article highlighted the issues in datasets being biased, a lack of capability to generalize, and a lack of uniformity in evaluation.

2.8 Thanjaivadivel et al. [8] (2025)

Thanjaivadivel et al. introduced an improved CNN model named 'EnConv', which focused on class imbalance and intra-class variability issues using depthwise convolutions and class-balanced loss functions. Their work enhanced the model's generalization capabilities in heterogeneous datasets on less common diseases.

2.9 Baiju et al. [9] (2025)

Baiju et al. introduced a compact deep learning pipeline optimized for edge deployment, focusing on Corn, Rice, and Wheat crops. The model achieved high classification accuracy while maintaining low computational requirements, making it suitable for mobile and embedded systems.

Table 1. Comparative Summary of Crop Disease and Pest Detection Approaches

Paper (Year)	**Approach**	**Dataset/Crops**	**Key Strength**	**Limitations**
Mohanty et al. [1] (2016)	CNN-based	Multiple crops	Baseline DL model	Controlled dataset
Ahmed et al. [2] (2022)	IQA + CNN	Foliar diseases	Robust to poor images	Extra preprocessing
Yuan et al. [3] (2024)	Lightweight attention CNN	Leaf images	Efficient & compact	Accuracy trade-off
Foysal et al. [4] (2024)	CNN + Mobile app	Leaf datasets	Field-ready deployment	Limited diversity

Paper (Year)	Approach	Dataset/Crops	Key Strength	Limitations
Lebrini & Gotor [5] (2024)	Review	Multiple crops	Deployment insights	No experiments
Ashurov et al. [6] (2024)	Depthwise SE-CNN	Diverse crops	High accuracy	Dataset dependent
Upadhyay et al. [7] (2025)	Review	Multiple datasets	Trends & taxonomy	No evaluation
Thanjaivadivel et al. [8] (2025)	EnConv	Leaf datasets	Handles imbalance	Needs augmentation
Baiju et al. [9] (2025)	Edge CNN	CRW crops	Mobile-friendly	Domain-specific

3. Evolution of Techniques and Taxonomy

The literature reviewed can be classified into four paradigms:

(1) Early CNN-based architectures for setting a baseline performance;

(2) Quality-conscious and data-driven paradigms with a focus

'(3) Parameter efficient and attention augmented CNN architectures

(4) Mobile and edge-optimized deployment-oriented

Taken together, these categories represent a progression from lab research to a workable agricultural AI system.

4. Merits and Demerits

Merits

- High accuracy achieved on filtered datasets
- Parameter efficient designs for edge implementation
- Increased robustness via quality-conscious preprocessing
- Effective guidance for deployment in the field and scalability

Demerits

- Very limited cross-dataset and cross-regional validation

- Latency with Multi-Stage Pipelined Processors
- Absence of Common Benchmarks in Energy and Latency
- Generalization under Harsh Conditions

5. Conclusion and Future Directions

This literature review conducted an assessment of the most important breakthroughs in crop diseases and pests using deep learning algorithms. The evolution of baseline CNN models to optimized mobile-compatible models shows an increasing interest in implementation.

Future work must focus on trustable AI with farmer-centric interfaces, bench-marking based on accuracy, latency, and energy usage, federated learning for collaborative work with privacy preservation, and sensing based on RGB and spectral imaging.

References

1. Mohanty, Sharada P., David P. Hughes, and Marcel Salathé. "Using deep learning for image-based plant disease detection." Frontiers in plant science 7 [1](2016): 215232.

2. Ahmed, Nisar, et al. "Image quality assessment for foliar disease identification (AgroPath)." arXiv preprint arXiv:2209.12443 [2](2022).

3. Yuan, Yongqi, Jinhua Sun, and Qian Zhang. "An Enhanced Deep Learning Model for Effective Crop Pest and Disease Detection." Journal of Imaging 10.11 [3](2024): 279.

4. Foysal , Md Aziz Hosen, Foyez Ahmed, and Md Zahurul Haque. "Multi-Class Plant Leaf Disease Detection: A CNN-based Approach with Mobile App Integration." arXiv preprint arXiv:2408.15289 [4](2024).

5. Lebrini, Youssef, and Alicia Ayerdi Gotor. "Crops Disease Detection, from Leaves to Field: What We Can Expect from Artificial Intelligence." Agronomy 14.11 [5](2024): 2719.

6. Ashurov, A. Y., Al-Gaashani, M. S. A. M., Samee, N. A., Alkanhel, R., Atteia, G., Abdallah, H. A., & Muthanna, M. S. A. [6](2024). Enhancing plant disease detection through deep learning: A depthwise CNN with squeeze-and-excitation integration and residual skip connections. Applied Intelligence, 54 , 9832–9845.

7. Upadhyay, Abhishek, et al. "Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture." Artificial Intelligence Review 58.3 [7](2025): 92.

8. Thanjaivadivel, M., et al. "EnConv: enhanced CNN for leaf disease classification." Journal of Plant Diseases and Protection 132.1 [8](2025): 32.

9. Baiju, B. V., et al. "Robust CRW crops leaf disease detection and classification in agriculture using hybrid deep learning models." Plant Methods 21.1 (2025): 18.