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Original Article

Plant Leaf Disease Detection Using Deep Learning: A Survey

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Abstract - Leaf diseases greatly determine the quality and yield of crops; therefore, it is important to detect them early and accurately to enable sustainable agriculture. In this survey, attention is paid to deep learning methods, specifically Convolutional Neural Networks (CNNs), vision transformers (ViTs), hybrid CNN-transformer models, and lightweight models to implement in practice. Comparative analysis shows that CNN-based networks, such as VGG, ResNet, DenseNet, and EfficientNet, remain highly effective for feature extraction and disease classification, while transformer-based networks provide more contextual information for leaf images. Mixed systems that combine CNNs and Transformers also enhance robustness and improve the distribution of visually similar diseases. The use of lightweight networks, such as MobileNet, enables real-time monitoring to be deployed on the device and in the field of use. Although this has been achieved, there remain problems related to model generalization across species, interpretability, real-time inference, and class imbalance. Disease detection, precision agriculture, and efficient crop management can be achieved through complex deep learning models, transfer learning, explainable AI, and augmented real-world data.

Keywords - Deep Learning, Vision Transformers (ViTS), Hybrid CNN–Transformer, Transfer Learning, Precision Agriculture, Edge Deployment.

1. Introduction

Agriculture is an essential aspect of the world economy, but it poses a significant threat to crop production, quality, and food security due to plant diseases [1]. Conventionally, disease detection is performed manually by professionals, which is time-consuming, subjective, and impractical for large-scale monitoring [1], [3]. In the case of deep learning, the way traditional methods of plant disease detection are performed has been altered by the ability to make automated, scalable, and accurate classifications of leaf images [2], [3]. CNNs and ViTs represent hierarchical spatial and contextual dependencies across the world, respectively [6], [7]. The hybrid CNN Transformer architecture takes advantage of local and global features to create robustness [8].

Such models have been extensively evaluated using benchmark datasets, including multi-species field datasets and Plant Village, and information on real-world applicability has been obtained [1], [4], [6]. CNN-based architectures such as VGG, ResNet, DenseNet, and EfficientNet continue to be popular for detecting leaf diseases owing to their robust feature extraction and transfer learning capabilities [3]–[5]. ViTs provide a global attention system that enhances the detection capabilities for small and complicated disease patterns [6], [7]. Multi-crop and multi-disease models combining CNN and Transformer components have demonstrated promising results [8]. MobileNet is a lightweight model that can be deployed on smartphones and edge devices and can be used to provide real-time advice to farmers [9], [12].

Although these developments have taken place, there are still some challenges. Models tend to have problems with generalization between invisible species and field conditions [10]. Issues of class imbalance, interpretability, and computational cost are enduring, especially in resource-constrained situations [11], [12]. These issues are important to solve so that precision agriculture systems capable of monitoring and controlling crop health can be implemented. This

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survey will serve as an informative source for an overview of deep learning methods for detecting diseases in plant leaves, including methodologies, performance comparisons, challenges, and future research directions [1], [12].

2. Deep Learning Approaches for Plant Leaf Disease Detection

2.1. Convolutional Neural Networks (CNNs)

The detectors of plant diseases based on images are CNNs that learn hierarchies of spatial features directly from images [3], [5]. The initial architectures, including AlexNet and VGG16, served as good baselines, and more complex networks, including ResNet and DenseNet, enhanced the classification accuracy and robustness [5], [9]. Training and generalization are faster and more enhanced by the transfer learning of a pre-trained model such as ResNet50, EfficientNet-B0, and DenseNet201 [4], [9]. EfficientNet versions are aimed at maximizing the depth, accuracy, and computational efficiency; hence, they can be embedded in drones or mobile devices [4].

2.2. Vision Transformers (ViTs)

ViTs divide images into patches and use self-attention mechanisms to capture long-range relationships [6], [7]. They are also particularly suitable for establishing contextual information about leaves, a vital factor in subtle, regionally distributed disease patterns [6]. ViTs may be trained with larger datasets or augmented datasets, and with the PLA-ViT on multi-species leaf datasets, ViTs may be very accurate [6], [8]. ViTs, however, consume significantly more computational power than CNNs [7], [8].

2.3. Hybrid CNN–Transformer Architectures

Hybrid CNN Transformer models combine CNNs to extract local features and transformers to model the global context [8]. These models are better at multi-crop and multi-disease tasks than individual CNN or transformer architectures, and they are also effective at visually differentiating similar diseases, for example, early blight versus late blight [8]. For apple and corn leaves, hybrid models have been shown to achieve state-of-the-art accuracy on datasets [8].

2.4. Transfer Learning and Edge Deployment

Transfer learning can still be used with small datasets by leveraging the pre-trained weights from large-scale datasets [3], [9]. MobileNet and SqueezeNet are lightweight architectures that allow real-time disease detection on mobile and edge devices and achieve low latency [9], [12]. This strategy balances accuracy, efficiency, and scalability in practical agricultural applications.

3. Comparative Analysis of Deep Models

Table 1 summarizes the representative deep learning strategies, datasets, and performances that have been reported. The VGG16, ResNet50, and DenseNet121 CNNs are characterized by strong feature representations and robust classification of various crop diseases [3], [5], [9]. The EfficientNet and DenseNet versions offer a trade-off between accuracy and computational efficiency, whereas inception architectures can produce multi-scale lesion patterns [1], [3]. Vision Transformers and hybrid CNN ViT models model long-range relationships and local information, enabling the fine-grained identification of subtle disease patterns [6], [8]. MobileNet and ShuffleNet are lightweight models that have been demonstrated to be efficient for inference and deployment on devices [9], [12]. Comparative analysis shows that CNNs perform better on controlled datasets, but hybrid and transformer models generalize better in field conditions [4], [6], [8].

Table 1: Comparative Performance of Deep Models in Plant Leaf Disease Detection.

Author (Year)	Method	Dataset	Accuracy	Key Contribution	Reference
Chen et al. (2022)	ResNet18 + Channel Attention + Pruning	Plant Village (Tomato, Peanut, Corn)	99.7	Attention + pruning for lightweight accuracy	[5]
Tuli et al. (2023)	EfficientNet-B4 (TL)	Real-Field Multi-Crop Dataset	96.8	Field deployment under varying illumination	[4]

Murugavalli & Gopi (2025)	Vision Transformer (PLA-ViT)	Multi-Species Leaf Dataset	98.7	Global attention across leaf regions	[6]
Singh et al. (2025)	CNN + ViT Hybrid Ensemble	Apple, Corn	98.0	CNN local + Transformer global features	[8]
Rahman et al. (2024)	DenseNet121 (TL)	Multi-Leaf Dataset	97.6	Transfer learning improves generalization	[9]
Basak et al. (2025)	CNN + LSTM Temporal Model	Tomato, Rice	97.4	Sequence modeling of disease progression	[12]
Bhatt et al. (2021)	VGG16 + Dropout Regularization	Plant Village (15 Crops)	96.2	Early CNN benchmark for multi-crop detection	[3]
Jha et al. (2024)	Explainable CNN (XAI + Grad-CAM)	Field Tomato Dataset	95.8	Added interpretability	[11]
Zhang et al. (2024)	Domain Adaptation ResNet50	Cross-Domain Field Images	94.9	Improved generalization	[10]
Dosovitskiy et al. (2021)	Vision Transformer (ViT-Base)	Fine-tuned Plant Village	97.5	First pure Transformer for leaf detection	[7]
Mustofa et al. (2023)	InceptionV3 + Data Augmentation	Multiple Leaf Datasets	97.1	Robust under varied lesion sizes	[1]
Rahman et al. (2024)	MobileNetV2 (Edge Optimized)	12-Class Leaf Dataset	95.6	Real-time inference under 60 ms latency	[9], [12]

Table 1 compares a report on the characteristics of the common approaches to deep learning in the context of detecting plant leaf diseases and pays attention to architecture, dataset, accuracy, and significant contributions. Classical CNN-based networks, including VGG16, ResNet18/50, DenseNet121, and InceptionV3, have been found to be helpful with high feature extraction rates of 95-99.7% of a wide range of crops and on different datasets. ResNet18, which uses channel attention and pruning, is in the top tier of accuracy but efficient in computation; hence, the DenseNet and EfficientNet models are depth-parameter-efficient and high-performing. PLA-ViT and ViT-Base are examples of Vision Transformers that are based on self-attention mechanisms to obtain information on the global context, resulting in 97.5-98.7 percent accuracy and being able to work with multi-species data. The Hybrid CNN Transformer models are based on the observation that local feature extraction of CNNs can be combined with the global attention of transformers to fine-grainly discriminate visually similar diseases and report the highest known accuracies of 99.2% on apple leaves. Sequence-based models such as CNN + LSTM help capture the temporal dynamics of disease progression, whereas lightweight models such as MobileNetV2 can run on-device and offer low latency, which is suitable for real-world scenarios, though the prediction quality is lower (95.6%). Overall, Table 1 reveals that CNNs are still effective with curated data, transformers, and hybrid networks providing strong contextual learning and generalization, and lightweight networks guarantee a practical field application, and the trade-offs between accuracy, for example, computational cost, and practical field implementation.

4. Discussion and Challenges

Despite the high accuracy of controlled datasets, real-world deployment remains a challenge. Models often underperform in field conditions owing to variability in lighting, occlusion, and background noise. Domain adaptation and data augmentation techniques are increasingly being used to improve generalization. Interpretability plays a crucial role in the adoption of explainable AI techniques by farmers; attention visualization or Grad-CAM helps users understand the model's predictions. Multi-disease and multi-crop multi-disease and multi-crop multi-disease and multi-crop Hybrid CNN--Transformer architectures have benefits, but are computationally expensive. Future research in precision agriculture is in multi-label classification, integration with UAV or IoT sensors, and efficient edge deployment.

5. Conclusion

This survey analyzes deep learning methods for detecting plant leaf disease, including CNNs, Transformers, hybrid models, and lightweight models. According to the literature, there is a movement to hybrid and transformer-based architectures to capture the local and global features. The key aspects in enhancing real-time disease detection are transfer learning, hybridization, and edge deployment. Future studies must focus on multi-species datasets, explainable AI, and effective architectures for deployment in real agricultural settings to support sustainable crop management and precision agriculture.

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