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Deep Learning Approaches for Apple Leaf Disease Detection and Classification: A Comprehensive Review

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***Abstract*—foliar diseases pose a major threat to apple cultivation, severely affecting crop yield and quality. Conventional disease detection relies on manual expert examination—a slow, subjective, and error-prone process. Recent advances in deep learning, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable capability to automate plant disease detection with high precision. This review comprehensively surveys state-of-the-art deep learning models for apple leaf disease detection, covering research published between 2021 and 2025. We compare architectures such as Dense Net, Efficient Net, Mobile Net, Inception-V3, and Vision Transformers with respect to performance metrics, limitations, and real-world applicability. Current models achieve 90–98.32% classification accuracy, yet significant challenges remain in dataset diversity, field generalization, early-stage detection, and edge deployment. The review provides actionable directions for future research in precision agriculture.**

***Keywords*—Apple disease detection, CNN models, Deep neural networks, Smart agriculture, Transfer learning, Model generalization, Mobile deployment.**

I. Introduction

Apple trees (Malus domestica) represent one of the most vital agricultural fruit trees which produce more than 86 million metric tons of apples each year. Fungal and bacterial and viral pathogens continually threaten apple orchards which cause up to 50 percent loss of their harvest [1]. The principal leaf diseases of apple trees consist of apple scab (Venturia inaequalis), cedar apple rust (Gymnosporangium juniperi-virginianae), black rot (Diplodia seriata), Alternaria leaf spot, and powdery mildew [2].

The traditional diagnostic method depends on agronomists conducting visual assessments which require significant effort and produce results that lack reliability and consistency. Deep learning especially CNNs [8] has brought a revolution to plant disease detection through its ability to extract hierarchical features from visual data [3][4]. High-accuracy detection systems become possible through three factors which include PlantVillage and the growth of computational power and the development of new architectural designs [5][6].

A. Research Objectives

This review: (1) surveys state-of-the-art deep learning methods for apple leaf disease detection (2021–2025); (2) compares architectures including Dense Net, Efficient Net, Mobile Net, ResNet, and Vision Transformers; (3) identifies key datasets and limitations; (4) highlights research gaps; and (5) discusses emerging trends in explainable AI and knowledge distillation.

B. Paper Organisation

Sections II–III cover disease characteristics and datasets. Section IV analyses architectures. Section V evaluates performance. Section VI identifies research gaps. Section VII proposes future directions.

II. Apple Leaf Diseases

Table I summarises the primary diseases studied .Apple Scab. Caused by Venturia inaequalis, it produces dark olive-green to black velvety spots during cool wet weather; yield losses reach 100% without management. Cedar Apple Rust. Gymnosporangium juniperi-virginianae causes bright orange circular lesions with black aecia on leaves in late spring, causing premature defoliation. Black Rot. Diplodia seriata causes dark necrotic “frogeye” concentric-ring spots on leaves, fruits, and branches under warm, humid conditions [7].

Alternaria Leaf Spot. Alternaria mali produces brown spots with dark margins and grey centres, common in warm climates. Powdery Mildew. Podosphaera leucotricha causes a white powdery coating on leaves and shoots without requiring free water to infect.

TABLE I. CHARACTERISTICS OF MAJOR APPLE LEAF DISEASES

Disease	Visual Symptoms	Conditions	Impact
Apple Scab	Dark spots	Cool, wet	High
Cedar Rust	Orange lesions	Circular Spring	Moderate
Black Rot	Frog-eye necrotic spots	Warm, humid	Mod–High
Alternaria	Brown concentric rings	Warm, humid	Moderate
Powdery Mildew	White powdery coating	Dry, moder-Ate	Moderate

TABLE II. COMPARISON OF DATASETS FOR APPLE LEAF DISEASE DETECTION

Dataset	Images Classes	Setting	Key Limitation	
PlantVillage	3,000+	3–4	Controlled Low	field
PlantDoc	2,500+2	Field	Ility Small,	few
ADID	29,000	6	Mixed	ClassesLimited
Multispectral	Variable	1–4	NIR / lab	documentation Needs

With near-infrared spectral data captured, multispectral datasets allow the prediction of disease before initial symptoms appear, but this requires special hardware [4].

III. DEEP LEARNING ARCHITECTURES

A. Baseline CNNs

CNNs learn hierarchical features through their use of convolution and activation and pooling and fully-connected layers. The custom three-layer CNN reached 98% accuracy on PlantVillage for apple scab and black rot and cedar rust detection

B. DenseNet

Dense Net provides every layer access to all previous layers which supports gradient propagation and enables feature reuse [8]. Focal loss method used in DenseNet121 achieved accuracy of 93.71%. The 33 million parameter Deep DenseNet-264 showed its best performance with 98.32% accuracy while achieving 97.83% precision and 98.21% recall and 98.02% F1 score.

C. Efficient Net

EfficientNet uses compound scaling to adjust depth and width and resolution [9]. EfficientNet-B3 achieved 73.31% on PlantDoc and 80.19% with combined web-sourced data. The combination of Ensemble methods with DenseNet produced improved accuracy results in classification tasks.

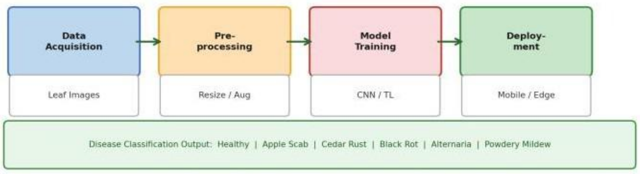

Fig. 1. General pipeline for deep learning-based apple leaf disease detection

data acquisition, pre-processing, model training, and deployment

D. Inception-V3 and ResNet

Mobile Net uses depth wise-separable convolutions for inimal parameters, targeting edge deployment [10].MobileNetV3-Large provides competitive accuracy for real-time orchard applications

E. MobileNet

Vision Transformers (ViT) use self-attention mechanisms to process image patches. The method shows potential for detecting apple diseases but its extensive training data needs prevent widespread implementation.

F. Attention Mechanisms and ECA-KDNet

The Efficient Channel Attention system when combined with knowledge distillation creates ECA-KDNet which achieves 98.28% accuracy while using only 3.38 million parameters to demonstrate that attention mechanisms can deliver better accuracy and efficiency results.

G. Ensemble Methods and Transfer Learning

The ensemble combination of DenseNet-121 and EfficientNet-B7 and EfficientNet-B0 achieved a 96.25% accuracy for single disease detection and a 90% accuracy for all other cases. (Multidisease). With a standard move that has shown to boost convergence speed and final accuracies when applying transfer learning from ImageNet.

IV. PERFORMANCE METRICS AND EVALUATION

A. StandardMetrics

According to standard evaluation metrics Accuracy, precision, recall, F1-score and ROC-AUC serve as fundamental measurement tools. The presence of class imbalance makes Accuracy misleading while F1-score serves as the better metric for testing unbalanced data sets.

B. Architecture Comparison

Table III presents essential data about the architectures. Also, Fig. 2 illustrates the accuracy–parameter trade-off.

C. Cross-Dataset Generalisation

The Plant Village models achieve an accuracy range of 73 to 77 percent when tested on Planetdom and field images which results in a 20 to 25 percent accuracy decrease. The training process requires authentic training data which must include various types of real-world scenarios.

TABLE III. PERFORMANCE COMPARISON OF DEEP LEARNING ARCHITECTURES

Model	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Params (M)
Custom CNN	98.00	—	—	—	2–5

DenseNet121	93.71	—	—	—	7.0
DenseNet264	98.32	97.83	98.21	98.02	33.0
EffNet-B3	80.19	—	—	—	12.0
MobileNet V3	94.0†	—	—	—	5.4
Inception-V3	≈97.5	High	High	—	23.8
ECA-KDNet	98.28	—	—	96.64	3.38
Ensemble	96.25	—	—	—	40+

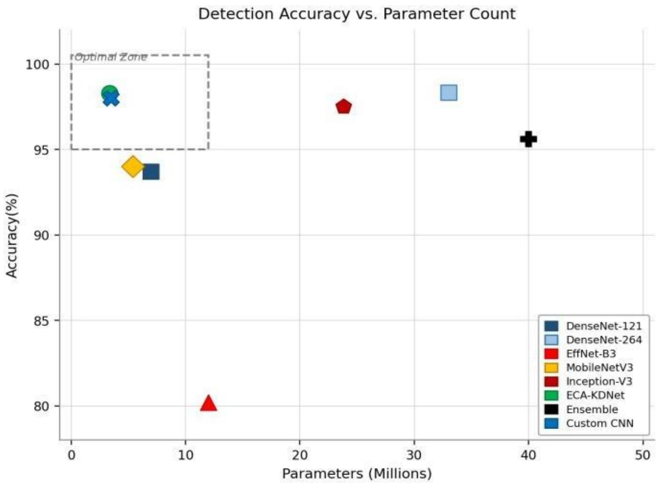

Fig. 2. Accuracy vs. parameter count. Models in the optimal zone (topleft) achieve high accuracy with few parameters—ideal for mobile and edge deployment.

Statistical models are useful for fashioning synthetic data, thereby augmenting deficient real-life collections.

D. *Early Detection Performance*

Early-stage detection studies report 85 through 90 percent accuracy which falls short of their later-stage testing results. NIR multispectral imaging technology identifies bodily changes which occur before any outward physical signs of those changes become detectable.

E. *Computational Efficiency*

ECA-KDNet requires 3.38 million parameters to achieve 98.28% accuracy while MobileNetV3Large performs better for mobile applications. The cloud environment or high-performance infrastructure is necessary to operate DenseNet-264 which requires 33 million parameters and delivers 98.32% accuracy.

V. RESEARCH GAPS AND LIMITATIONS

A. *Dataset Limitations*

The available datasets to researchers show coverage of specific geographic areas with particular cultivars under controlled research conditions which results in poor cross-orchard application of their findings. The existence of class imbalance results in decreased performance of the model system.

B. *Field Generalisation*

When lab-trained models are deployed in real orchards with different lighting, background clutter, and occlusion, their accuracy goes down by 20-25%.

C. *Early-Stage Detection*

Early infections present subtle changes that are challenging to identify as distinct from healthy tissue. The availability of annotated early-stage training images is limited and the system demonstrates high false-positive rates which decrease its accuracy.

D. *Multi-Disease Recognition*

Current models achieve approximately 90% for multidecade classification yet they achieve 96 to 98 percentage points for single-disease classification because actual orchards display multiple diseases at the same time.

E. *Model Interpretability*

Deep CNNs function as "black boxes" which prevent farmers and agronomists from using this technology according to research. XAI tools which include GradCAM do not achieve common usage in operational systems.

F. *Deployment Constraints*

The orchard edge devices cannot support the computation needs of high-performing models according to reference. The orchard management process needs real-time feedback for its effective execution.

VI. FUTURE RESEARCH DIRECTIONS

A. *Enhanced Dataset Development*

Future datasets should include data from different cultivars and different geographical areas and all growth stages and different environmental conditions [9]. The combination of GANs and diffusion models enables the creation of synthetic data which helps to compensate for insufficient real-world data.

B. *Domain Adaptation*

Models can adapt to new orchards using adversarial domain adaptation and self-supervised learning and few-shot learning techniques which require only minimal additional labelled data [10].

C. *Explainable AI*

Building user trust and adoption into the deployed systems require an integration of attention visualization, saliency maps, as well as concept-based explanations [11].

D. *Multispectral Imaging*

The extension of NIR beyond the scope of RGB to multispectral imaging paves way for the monitoring of diseases at an early stage of development. Widespread proliferation will call for considerable efforts in bringing down costs.

E. *Edge Optimisation*

The combination of quantisation and pruning together with neural architecture search and knowledge distillation will make it possible to achieve real-time inference on mobile phones and embedded systems.

F. *Continuous Learning*

Dynamic and continually changing environments demand learning systems that are able to update existing models with new realities as and whenever they happen, retaining significant prior knowledge.

TABLE IV. RESEARCH GAPS AND PROPOSED SOLUTIONS

Gap	Current Limitation	Proposed Solution	Expected Impact
Dataset	Limited geographic	Limited geographic	+15–25% data; gener-
Generalisation	20–25% drop in field	accuracy Domain adaptation	90% field accuracy
Early Detection	85–90% accuracy	Multispectral, temporal models	7–14 days earlier de-tection
Multi-Disease	90% vs. 96–98%	Multi-label architectures	Gap <3%
Interpretability	Black-box models	GradCAM; XAI in-tegration	Increased user trust
Deployment	Edge-incompatible params	KD, NAS models	<5M parametrs;>95% accuracy
Standardisation	Inconsistent benchm	Community compar-ison	Fair protocols

VII. CONCLUSION

This review examined deep learning for apple leaf disease detection, synthesising research from 2021 to 2025. State-ofthe-art models achieve 90–98.32% classification accuracy on The study demonstrates two optimal accuracy-efficiency trade-offs and transfer learning leads to faster convergence and multispectral NIR imaging shows earlier disease detection than RGB and ensemble methods provide better system resilience through their substantial processing requirements. The research faces major challenges because it needs numerous different datasets, orchard conditions cause a 20 to 25 percent drop in accuracy, the system cannot detect multiple diseases at an early stage, it produces black-box results, and it cannot operate in edge computing environments. The solution needs computer scientists to work together with plant pathologists and agronomists and farmers for successful outcomes.

The process of automated disease detection will change precision agriculture because it will decrease crop losses and pesticide misuse while creating sustainable farming methods that can be implemented across large areas.

VIII. ACKNOWLEDGMENT

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