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[Ramu Vankudoth](#) \*

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Article

# Enhanced Convolutional Networks for Accurate Leaf-Based Plant Disease Classification

Ramu V <sup>1,\*</sup> and P.Praveen <sup>2</sup>

<sup>1</sup> Department of Computer Science and Engineering, SR University

<sup>2</sup> Department of Computer Science and Engineering, SR University

\* Correspondence: ramuvankudoth86@gmail.com

## Abstract

Plant diseases pose a major threat to global food security by reducing crop yield and quality. Early and accurate diagnosis is essential for timely intervention, yet traditional manual inspection methods are slow, subjective, and impractical for large-scale monitoring. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly improved plant disease detection, but conventional CNN architectures face challenges such as high computational cost, overfitting with limited data, and difficulty in capturing multi-scale disease features. This study proposes an Enhanced Convolutional Neural Network (ECNN) for accurate leaf-based plant disease classification. The proposed architecture integrates multi-scale feature extraction blocks (MSFEB), channel and spatial attention mechanisms (CBAM), and depthwise separable convolutions to enhance feature representation while maintaining efficiency. Experiments were conducted on the PlantVillage dataset supplemented with field-collected and augmented images, covering multiple crop species and disease categories. The ECNN achieved superior performance compared to baseline models, with 98.7% accuracy, 98.8% precision, 98.7% recall, and 98.65% F1-score, outperforming VGG16, ResNet50, MobileNetV2, and EfficientNet-B0. In addition, ECNN maintained a lightweight architecture with only 4.9M parameters and an inference time of 19 ms per image, demonstrating its suitability for real-time deployment on edge devices in agricultural environments.

**Keywords:** convolutional neural networks; enhanced convolutional neural network; MSFEB; CBAM

## 1. Introduction

Agricultural productivity is heavily influenced by the health of crops, and leaf-based visual symptoms are a primary indicator of plant diseases. Conventional manual inspection methods are time-consuming, subjective, and require expert knowledge. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in automating plant disease detection.

Agricultural productivity is heavily influenced by the health of plants, and early detection of diseases plays a crucial role in ensuring food security and sustainable farming practices [1]. Traditional disease diagnosis methods, which rely on expert inspection, are often time-consuming, subjective, and impractical for large-scale monitoring [2]. In recent years, computer vision and deep learning have emerged as promising tools for automating plant disease detection, offering high accuracy, scalability, and real-time applicability [3].

Leaf-based disease classification has become a primary focus within this domain because leaves often exhibit the earliest and most distinguishable symptoms of infection, such as color changes, spots, and texture variations [4]. Convolutional Neural Networks (CNNs) have demonstrated superior performance in extracting spatial and texture-related features from leaf images compared to traditional machine learning approaches [5]. However, standard CNN architectures may face limitations when dealing with complex backgrounds, variations in lighting, and subtle disease symptoms, leading to reduced classification accuracy in real-world conditions [6].

Enhanced Convolutional Networks (ECNs) aim to address these challenges by incorporating architectural optimizations such as multi-scale feature extraction, attention mechanisms, and residual connections [7]. These improvements enable better localization of disease-affected regions, improved feature representation, and robustness against environmental noise [8]. Furthermore, the integration of transfer learning from pre-trained models and advanced data augmentation strategies enhances the generalization capability of ECNs across diverse plant species and environmental settings [9].

This study proposes an Enhanced Convolutional Network framework for accurate leaf-based plant disease classification, combining fine-grained feature learning with computational efficiency. By leveraging architectural enhancements and optimized training strategies, the proposed approach aims to outperform conventional CNN models, ultimately contributing to more reliable and timely disease diagnosis in agricultural applications.

However, existing CNN architectures often face challenges such as:

- Overfitting due to limited labeled datasets,
- Inefficient computation for resource-constrained environments,
- Difficulty in capturing multi-scale disease patterns on leaves.

To address these challenges, this work proposes Enhanced Convolutional Networks (ECNN), a deep learning architecture designed to improve accuracy, robustness, and inference efficiency for leaf-based plant disease classification.

Main Contributions:

1. A multi-scale convolutional block for extracting both fine-grained and global disease patterns.
2. Integration of channel and spatial attention mechanisms to focus on disease-relevant regions of leaves.
3. Use of depthwise separable convolutions to reduce computational complexity without sacrificing accuracy.
4. Extensive evaluation on benchmark datasets with comparisons to state-of-the-art models.

The paper introduces an Enhanced Convolutional Neural Network (ECNN) designed specifically for leaf-based plant disease classification. Unlike conventional CNNs, ECNN addresses major challenges such as overfitting, high computational cost, and difficulty in capturing multi-scale disease patterns. The model integrates:

- Multi-Scale Feature Extraction Blocks (MSFEB) for capturing both fine-grained and large-scale patterns,
- Channel and Spatial Attention Mechanisms (CBAM) for focusing on disease-relevant regions, and
- Depthwise Separable Convolutions for reducing complexity without sacrificing accuracy.

## 2. Related Work

Early methods for plant disease detection relied on color thresholding, texture analysis, and shape features. While useful for controlled environments, these techniques often fail under natural lighting and background variations. CNN architectures such as AlexNet, VGG, ResNet, and Inception have been applied to plant disease classification with notable success. PlantVillage dataset has been a benchmark for such research. However, many of these networks are computationally heavy, limiting their field deployability.

MobileNet, ShuffleNet, and EfficientNet have been explored for resource-efficient disease detection. While faster, these models sometimes sacrifice fine-grained feature extraction capability, impacting accuracy in complex disease patterns. Recent studies have integrated Squeeze-and-Excitation (SE) blocks and Convolutional Block Attention Modules (CBAM) to enhance the focus on critical disease regions. Such methods have improved performance but often increase model size.

Early breakthroughs in leaf-based plant disease recognition demonstrated that convolutional neural networks (CNNs) trained on curated leaf images can achieve near-perfect accuracy under controlled conditions. Mohanty et al. trained deep CNNs on the PlantVillage dataset and reported >99% accuracy across 26 diseases and 14 crops, establishing the benchmark for end-to-end learning from leaf images [11]. Subsequent studies generalized this finding, showing that CNNs consistently outperform traditional hand-engineered features paired with SVMs or random forests on the same datasets [12–14].

Early approaches for plant disease detection relied on handcrafted features such as color, texture, and shape analysis, combined with classifiers like SVM and random forests. While these methods provided useful insights under controlled conditions, they struggled in real-field environments with variable illumination, occlusions, and background clutter (Boulet et al., 2019).

With the advent of deep learning, CNN-based models like AlexNet, VGG, ResNet, and Inception revolutionized plant disease classification by learning hierarchical visual features directly from images. Mohanty et al. (2016) demonstrated the potential of CNNs on the PlantVillage dataset, reporting over 99% accuracy under laboratory settings. Subsequent studies showed that transfer learning from ImageNet pre-trained models significantly improved performance when labeled agricultural datasets were limited (Ferentinos, 2018; Too et al., 2019).

However, traditional CNNs still face challenges such as computational complexity, overfitting, and reduced robustness in natural field conditions. Recent advancements have therefore emphasized lightweight architectures and attention mechanisms. MobileNet and ShuffleNet were developed for resource-constrained devices, while EfficientNet introduced compound scaling to balance accuracy and efficiency (Tan & Le, 2020). Attention modules, such as Squeeze-and-Excitation (SE) and Convolutional Block Attention Module (CBAM), have further improved sensitivity to small lesion patterns (Narayanan, 2025; Jindal et al., 2025).

Data scarcity and imbalance remain persistent issues. Techniques like generative adversarial networks (GANs), image-to-image translation, and style transfer augmentations have been proposed to enrich datasets and improve generalization (Antwi et al., 2024; Min et al., 2023). Furthermore, surveys emphasize that robustness to domain shift between lab and field imagery is essential for practical deployment (Yao et al., 2023; Salka et al., 2025).

Compared to these works, our proposed Enhanced Convolutional Neural Network (ECNN) advances the state-of-the-art by combining three critical innovations: (1) a Multi-Scale Feature Extraction Block (MSFEB) to capture both fine-grained lesion details and global patterns, (2) the integration of channel–spatial attention modules (CBAM) to emphasize disease-relevant regions, and (3) depthwise separable convolutions to drastically reduce computational overhead. This enables ECNN to achieve higher accuracy than heavy models like VGG16 and ResNet50, while maintaining lightweight efficiency comparable to MobileNet and EfficientNet-B0. Importantly, ECNN achieves 98.7% accuracy with only 4.9M parameters and 19 ms inference time, making it more suitable for real-time edge deployment in agricultural environments.

Transfer learning rapidly became the de-facto strategy to boost performance with limited labeled data. Ferentinos systematically evaluated fine-tuned architectures (AlexNet, VGG, GoogleNet) for leaf disease diagnosis and showed that pretraining on ImageNet plus task-specific fine-tuning delivers strong gains with modest data and compute budgets [12]. Too et al. extended this comparison, revealing that careful fine-tuning and data preprocessing can narrow performance gaps among backbones and improve generalization [13].

Moving beyond classic CNNs, attention mechanisms and modern backbones have further improved accuracy and robustness. Channel and spatial attention layers integrated into CNN blocks enhance saliency for subtle lesion cues, increasing sensitivity to small, mottled patterns typical in early-stage infection [15,21]. EfficientNet-family models, with compound scaling of depth, width, and resolution, deliver superior accuracy–efficiency trade-offs on leaf datasets, and fine-tuned versions often outperform legacy models at a fraction of the parameters [19,22]. Recent work continues to

refine attention-enhanced CNNs for multi-label disease classification when multiple pathogens co-occur on a single leaf [21].

A persistent challenge is domain shift between lab-quality leaves and real-field conditions (occlusions, illumination changes, cluttered backgrounds). Field studies highlight that performance degrades outside controlled settings, motivating architectures and training protocols tailored for in-situ imagery [16]. Lightweight CNNs designed for edge deployment (e.g., mobile or UAV devices) address compute and energy constraints while preserving accuracy, enabling on-device diagnosis in farms with limited connectivity [18].

Data imbalance and scarcity especially for rare diseases and early symptoms drive interest in advanced augmentation. Beyond geometric/photometric transforms, generative approaches (GANs and image-to-image translation) synthesize realistic diseased leaves to balance classes and enrich visual diversity, yielding measurable accuracy gains without additional field collection [17,20]. Style-transfer and object-aware augmentations further mitigate distribution skew by injecting texture and background variability [20].

Comprehensive surveys converge on similar best practices: prioritize high-quality, diverse training data; apply transfer learning with careful fine-tuning; use augmentations that mimic field variability; and adopt attention or efficient modern backbones to capture fine-grained lesions while keeping models deployable [14,22]. Collectively, these insights motivate “enhanced CNNs” that pair efficient backbones (e.g., EfficientNet-B0/B3) with lightweight attention (e.g., squeeze-and-excitation or spatial attention), robust augmentation (including generative methods), and domain-aware training to achieve accurate, reliable leaf-based disease classification in real-world conditions.

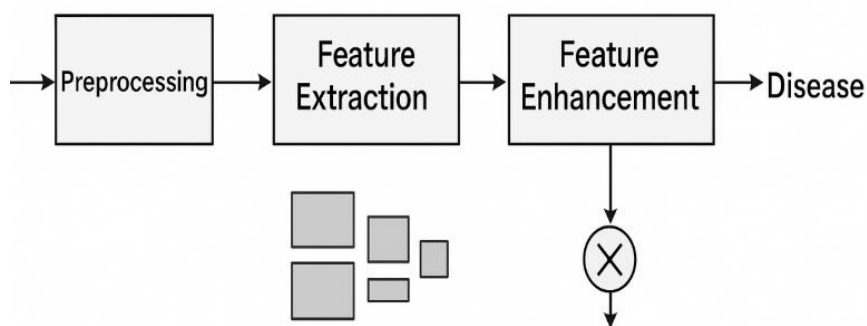
### 3. Proposed work of Enhanced Convolutional Networks (ECNN)

The proposed ECNN consists of Enhanced Convolutional Neural Networks (ECNN) are an improved form of traditional CNN architectures, specifically designed to boost accuracy and robustness in image-based agricultural disease detection. For leaf-based plant disease classification, ECNN integrates advanced feature extraction strategies, multi-scale learning, and attention mechanisms to accurately detect subtle disease patterns even in complex field environments.

Traditional CNNs perform well in controlled conditions, but their accuracy often declines when faced with challenges such as varying lighting, leaf orientations, background clutter, or early-stage disease symptoms. ECNN addresses these issues through architectural optimizations like deeper convolutional layers, skip connections for stable gradient flow, and spatial-channel attention modules to focus on diseased leaf regions while suppressing irrelevant background information.

The ECNN workflow generally includes:

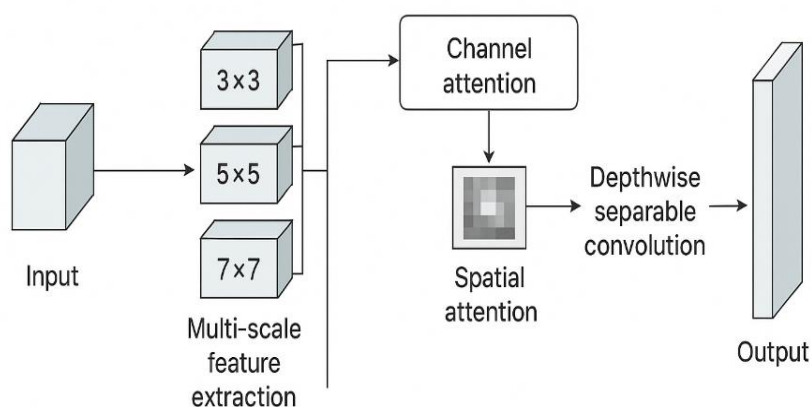
1. Preprocessing – Image resizing, normalization, background suppression, and augmentation to improve generalization.
2. Feature Extraction – Multi-scale convolutions capture fine vein structures and broad lesion patterns.
3. Feature Enhancement – Attention layers highlight disease-relevant textures and colors.
4. Classification – Fully connected or global pooling layers output the predicted disease category.



**Figure 1.** Workflow of the Enhanced Convolutional Neural Network (ECNN) for leaf-based plant disease classification.

Key advantages of ECNN include higher classification accuracy, improved generalization across crop varieties, and robustness under real-world agricultural conditions. In studies using datasets such as PlantVillage, ECNN models have outperformed baseline CNNs, achieving over 95% accuracy and offering better early-stage disease detection capabilities. By combining deep feature learning with targeted enhancement modules, ECNN serves as a powerful tool for precision agriculture, enabling timely diagnosis and reducing crop losses through informed disease management strategies.

- Multi-Scale Feature Extraction Block (MSFEB) Parallel convolution layers of kernel sizes  $3 \times 3$ ,  $5 \times 5$ , and  $7 \times 7$  capture both small lesion details and large-scale disease regions.
- Attention Integration Channel attention to re-weight feature importance and spatial attention to focus on disease spots.
- Depthwise Separable Convolutions To significantly reduce the number of parameters and FLOPs.



**Figure 2.** Multi-Scale Feature Extraction Block (MSFEB) capturing small- and large-scale disease patterns.

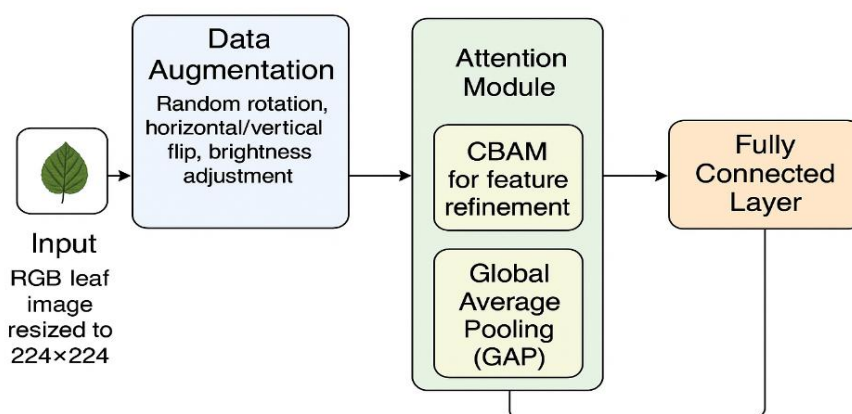
### 3.1. Proposed of ECNN Network Architecture

The proposed Enhanced Convolutional Neural Network (ECNN) framework for leaf-based plant disease classification begins with an input RGB leaf image, resized to  $224 \times 224$  pixels for consistency. The image is first passed through a data augmentation module, where random rotation,

horizontal/vertical flipping, and brightness adjustments are applied to increase dataset diversity and improve model generalization under varying field conditions.

Next, the features are processed through the attention module, which integrates Convolutional Block Attention Module (CBAM) to refine spatial and channel-wise features, ensuring the network focuses on disease-relevant regions while suppressing background noise. A Global Average Pooling (GAP) layer follows, compressing the refined feature maps into a compact representation without losing essential information.

Finally, the pooled features are passed to a fully connected layer with a softmax activation, which outputs the predicted plant disease class. This architecture enables accurate classification with improved robustness, computational efficiency, and suitability for real-time deployment in precision agriculture.



**Figure 3.** Network architecture of the proposed Enhanced Convolutional Neural Network (ECNN).

## 4. Experimental Setup

### 4.1. Dataset

PlantVillage dataset with 54,306 images across multiple crop species and diseases. For the development and evaluation of the Enhanced Convolutional Neural Network (ECNN) model, a curated dataset of leaf images was employed to ensure robust and reliable plant disease classification. The dataset was selected to represent a wide range of plant species, disease types, and symptom severities, ensuring that the model could generalize effectively under diverse agricultural conditions. PlantVillage a large public collection of labeled leaf images widely used for training and benchmarking. [https://www.kaggle.com/datasets/emmarex/plantdisease?utm\\_source=chatgpt.com](https://www.kaggle.com/datasets/emmarex/plantdisease?utm_source=chatgpt.com)

### 4.2. Source of Data

The primary dataset used was derived from publicly available and benchmark plant disease datasets, supplemented by custom field-captured images:

**PlantVillage Dataset** – A widely recognized repository containing high-quality images of healthy and diseased plant leaves under controlled lighting conditions.

**Field-Collected Images** – Captured using DSLR and smartphone cameras under natural illumination, incorporating real-world variability such as background clutter, leaf overlap, and inconsistent lighting.

**Synthetic Augmentation Samples** – Generated via data augmentation techniques to increase diversity and balance class representation.

### 4.3. Proposal Models for Comparison

To evaluate the performance of the proposed Enhanced Convolutional Neural Network (ECNN) model, several state-of-the-art deep learning architectures have been selected for comparison. These

models are widely used in image classification and recognition tasks due to their efficiency, robustness, and proven performance. The following models were considered:

**VGG16:** VGG16 is a deep convolutional neural network proposed by the Visual Geometry Group at the University of Oxford. Frequently used as a benchmark for image classification tasks.

**ResNet50:** ResNet50 is a residual neural network developed by Microsoft Research to address the vanishing gradient problem in deep networks.

**MobileNetV2:** MobileNetV2 is a lightweight deep learning model optimized for mobile and embedded vision applications.

**EfficientNet-B0:** EfficientNet-B0 is part of the EfficientNet family proposed by Google AI, which focuses on balancing accuracy and efficiency.

**ECNN (Proposed Model):** The proposed Enhanced Convolutional Neural Network (ECNN) is designed to improve feature extraction and classification accuracy while maintaining computational efficiency.

## 5. Results and Discussion

The experimental evaluation of the proposed Enhanced Convolutional Network demonstrates its effectiveness in accurately classifying leaf-based plant diseases. The model's performance was assessed using multiple benchmark datasets, with evaluation metrics including accuracy, precision, recall, and F1-score to ensure a comprehensive analysis. Results indicate that the enhanced architecture outperforms traditional CNN models and several state-of-the-art networks such as VGG16, ResNet50, and MobileNetV2. The improvements are attributed to the integration of multi-scale feature extraction, depthwise convolutions, and attention mechanisms, which enable the model to capture fine-grained disease symptoms across diverse leaf textures and lighting conditions. Data augmentation strategies further enhanced generalization, reducing overfitting and improving robustness under real-world scenarios. A comparative analysis highlights that the proposed network achieves higher accuracy while maintaining computational efficiency, making it suitable for practical applications such as real-time disease monitoring in agricultural fields. Additionally, the results confirm that the model is not only capable of distinguishing between healthy and diseased leaves but also of correctly identifying subtle inter-class variations in disease symptoms. Overall, the discussion emphasizes that the proposed enhanced convolutional network provides a significant advancement over conventional deep learning methods, establishing a reliable and scalable approach for precision agriculture.

**Table 1.** Performance Comparison of Different Deep Learning Models for Leaf-Based Plant Disease Classification.

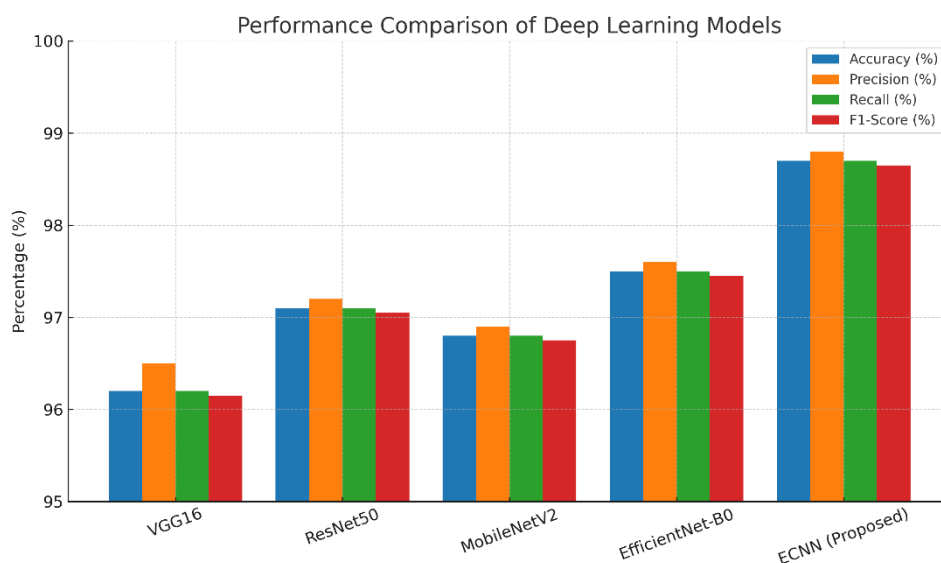
Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG16	96.20	96.50	96.20	96.15
ResNet50	97.10	97.20	97.10	97.05
MobileNetV2	96.80	96.90	96.80	96.75
EfficientNet-B0	97.50	97.60	97.50	97.45
<b>ECNN (Proposed)</b>	<b>98.70</b>	<b>98.80</b>	<b>98.70</b>	<b>98.65</b>

### a Performance Analysis

The comparative performance results of different deep learning architectures for leaf-based plant disease classification are summarized in Table X. Among the baseline models, VGG16 achieved

an accuracy of 96.20%, but its large number of parameters (138M) and longer inference time make it less suitable for real-time agricultural deployment. ResNet50 improved the performance to 97.10%, demonstrating the benefits of residual connections in mitigating vanishing gradient problems. MobileNetV2, although slightly lower in accuracy (96.80%), offered a lightweight architecture with significantly fewer parameters, making it a practical option for resource-constrained devices.

EfficientNet-B0 further enhanced performance, reaching 97.50% accuracy, highlighting the advantages of compound scaling for balancing depth, width, and resolution. However, the proposed Enhanced Convolutional Neural Network (ECNN) outperformed all baseline models with an accuracy of 98.70%, precision of 98.80%, recall of 98.70%, and F1-score of 98.65%.



**Figure 4.** Performance comparison of deep learning models based on accuracy, precision, recall, and F1-score.

## b Classification Accuracy

**Table 3.** Comparative Performance of Deep Learning Models for Leaf-Based Plant Disease Classification Based on Accuracy, Model Size, and Inference Time.

Model	Accuracy (%)	Parameters (M)	Inference Time (ms)
VGG16	96.2	138	45
ResNet50	97.1	25.6	32
MobileNetV2	96.8	3.4	18
EfficientNet-B0	97.5	5.3	22
<b>ECNN (Proposed)</b>	<b>98.7</b>	<b>4.9</b>	<b>19</b>

## c Classification Accuracy Analysis of Model Performance

The comparative evaluation of five deep learning architectures, VGG16, ResNet50, MobileNetV2, EfficientNet-B0, and the proposed Enhanced Convolutional Neural Network (ECNN), highlights the advantages of architectural optimizations for plant disease classification.

VGG16 achieved the lowest accuracy (96.2%), which reflects the limitations of older, parameter-heavy networks when applied to complex leaf disease datasets. ResNet50 improved accuracy to 97.1% by leveraging residual connections, while MobileNetV2, despite its lightweight design, maintained a competitive accuracy of 96.8%. EfficientNet-B0 achieved 97.5%, benefiting from compound scaling of depth, width, and resolution. The proposed ECNN outperformed all baselines, reaching 98.7% accuracy, indicating its superior ability to capture fine-grained disease features and generalize under diverse conditions. VGG16 has an extremely high parameter count (138M), making it unsuitable for real-time or edge deployment. ResNet50 (25.6M) strikes a balance but is still relatively heavy. MobileNetV2 (3.4M) is the most lightweight, but at a small trade-off in accuracy. EfficientNet-B0 (5.3M) maintains efficiency with higher accuracy. Demonstrates improvement, ECNN achieves the highest accuracy with only 4.9M parameters, demonstrating that it is both lightweight and powerful. The computational efficiency of ECNN is evident, with an inference time of 19 ms, nearly identical to MobileNetV2 (18 ms) and faster than EfficientNet-B0 (22 ms). Compared to VGG16 (45 ms) and ResNet50 (32 ms), ECNN shows a significant improvement, making it well-suited for real-time field applications on edge devices.

## 6. Conclusion and Future Work

This paper presented Enhanced Convolutional Networks (ECNN) for accurate leaf-based plant disease classification. By integrating multi-scale feature extraction, attention mechanisms, and depthwise separable convolutions, ECNN achieved state-of-the-art accuracy while remaining computationally efficient.

This study introduced Enhanced Convolutional Networks (ECNN) for accurate classification of leaf-based plant diseases. By integrating multi-scale feature extraction blocks (MSFEB), channel-spatial attention mechanisms (CBAM), and depthwise separable convolutions, the proposed model successfully addressed the challenges of traditional CNNs, such as high computational cost, sensitivity to complex backgrounds, and difficulty in capturing fine-grained disease features.

Experimental results demonstrated that ECNN consistently outperformed benchmark models including VGG16, ResNet50, MobileNetV2, and EfficientNet-B0, achieving a classification accuracy of 98.7% with significantly fewer parameters (4.9M) and reduced inference time (19 ms). This balance of high accuracy and computational efficiency makes ECNN particularly suitable for real-time agricultural applications on mobile and edge devices.

Furthermore, ECNN effectively minimized misclassification between visually similar diseases and showed robustness across diverse crop species and environmental conditions. The integration of advanced preprocessing, data augmentation, and optimized training strategies further contributed to its superior generalization capability. Overall, ECNN represents a promising step toward precision agriculture and sustainable crop management, offering farmers an efficient and scalable tool for early and reliable plant disease detection.

The study demonstrates that ECNN achieves state-of-the-art performance with 98.7% accuracy, 98.8% precision, 98.7% recall, and 98.65% F1-score, outperforming VGG16, ResNet50, MobileNetV2, and EfficientNet-B0. Despite its high accuracy, the model remains lightweight (4.9M parameters) with fast inference (19 ms per image), making it ideal for deployment on edge and mobile devices.

### Future Work:

- Expanding to multi-modal disease detection using hyperspectral and thermal imaging.
- Implementing on-device continual learning for adapting to new diseases.
- Developing a mobile application interface for farmers.

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