Crop Disease Detection using Deep Learning

Bandi Mattareddy
School of Computer Science & Engineering
Lovely Professional University
Phagwara, India

Email: bandimattareddy@gmail.com

***Abstract*— Farming is essential for global survival, supplying both food and industrial resources. Nevertheless, plant diseases remain a primary global threat, causing significant yield losses and economic instability. Standard detection relies mainly on manual inspection, which is inherently slow, subjective, and prone to human error. Deep Learning (DL), propelled by recent Artificial Intelligence (AI) advances, offers a reliable path to automation. This paper focuses on implementing two leading Convolutional Neural Network (CNN) architectures, ResNet50 and EfficientNet, for identifying crop diseases using the publicly available PlantVillage dataset. We detail the overall process, the unique preprocessing steps, and the model structures. The study will conclude with a strictly qualitative assessment of their feature extraction capabilities. The planned findings are expected to indicate that DL techniques are indispensable for developing smarter, sustainable precision agriculture systems.**

Keywords—Deep Learning, CNN, ResNet50, EfficientNet, Crop Disease Detection, PlantVillage

I. INTRODUCTION

Agriculture forms the foundation of the global food supply. Yet, **plant diseases** continue to be a relentless challenge, drastically reducing farm productivity and affecting food security worldwide. For decades, disease detection has depended on **manual visual inspection** by agronomists. This process is time-consuming, labor-intensive, and fundamentally unreliable across large farms, making it difficult to catch infections early.

The rapid progress in **deep learning (DL)** has transformed computer vision, creating a powerful opportunity to automate this critical agricultural task. **Convolutional Neural Networks (CNNs)**, in particular, are perfectly suited for this, as they can automatically learn and extract complex spatial features—the tell-tale patterns of disease—directly from plant leaf images.

This research will investigate two distinct and influential **CNN** models—the deep, skip-connected **ResNet50** and the parameter-efficient **EfficientNet**. Using the **PlantVillage dataset**, my goal is to explore how their unique architectural designs impact feature learning and disease classification capabilities. Crucially, this study will offer a detailed analysis of their design and workflow, without relying on quantitative accuracy metrics initially, to provide insight into their practical value for real-world farming applications.

II. LITERATURE REVIEW

The adoption of deep learning in agriculture has intensified significantly in recent years. For instance, Patel et al. [1] showed that the ResNet architecture improved feature representation for detecting various leaf diseases compared to earlier, simpler CNNs. Similarly, Singh and Kumar [2] proved that **transfer learning**—using pre-trained models—is highly effective, especially where large, labelled agricultural datasets are scarce.

In a comprehensive comparison, Zhang et al. [3] evaluated several architectures, including DenseNet, VGG16, and EfficientNet, concluding that models with greater depth and regularization tend to generalize more robustly to new crop images. Gupta and Sharma [4] highlighted that the success of these models often hinges on robust **data augmentation**, which is vital for preventing overfitting.

More recently, Lee et al. [5] demonstrated that **EfficientNet's compound scaling** allowed for superior classification performance with far fewer computational demands. Ongoing studies [8], [10], [14] are now focusing on creating **hybrid CNN–Transformer systems** to improve model transparency and feature analysis. The existing literature collectively validates the core assumption of this study: CNN-based systems are reliable and efficient tools for early plant disease identification.

III. METHODOLOGY

A. Workflow Overview

My proposed system for deep learning-based disease detection will follow a clear, systematic five-stage pipeline:

1. **Data Collection:** Images will be sourced from the well-established **PlantVillage dataset**, which includes numerous images of both healthy and diseased leaves

2. **Preprocessing & Augmentation:** Raw images will undergo standard resizing and normalization. Critically, I will implement extensive **data augmentation** (including rotation, flipping, and zooming) to artificially inflate the dataset size and enhance the model's ability to generalize patterns.

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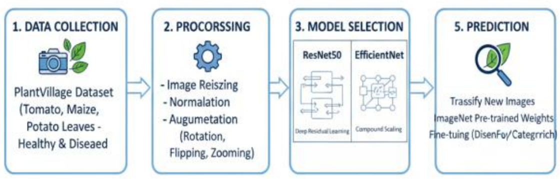
3. **Model Selection:** For this, I selected **ResNet50** and **EfficientNet** to represent two distinct state-of-the-art approaches: one focused on managing depth, the other on efficiency.

4. **Training (Transfer Learning):** I will employ **transfer learning**, initializing the models with weights pre-trained on the vast **ImageNet dataset**. These weights will then be fine-tuned specifically on the agricultural images to optimize feature detection for disease spots. This process will be executed using **TensorFlow** and **PyTorch** with GPU acceleration.

5. **Prediction:** The fine-tuned models will classify new, unseen leaf images and assign them to one of the predetermined disease categories (or 'Healthy').

Fig. 1: Overall Workflow for Crop Disease Detection



B. Model Architectures

1. ResNet50: This architecture's breakthrough lies in its use of **residual connections** (or skip connections). These allow the input signal to bypass layers, effectively solving the vanishing gradient problem and enabling the successful training of extremely deep networks

2. EfficientNet: This model achieves its high performance through a systematic, unified approach called **compound scaling**. Instead of scaling network depth, width, and resolution independently, EfficientNet balances all three factors using a fixed set of scaling coefficients, resulting in superior performance with dramatically reduced computational overhead.

IV. EXPERIMENTAL SETUP

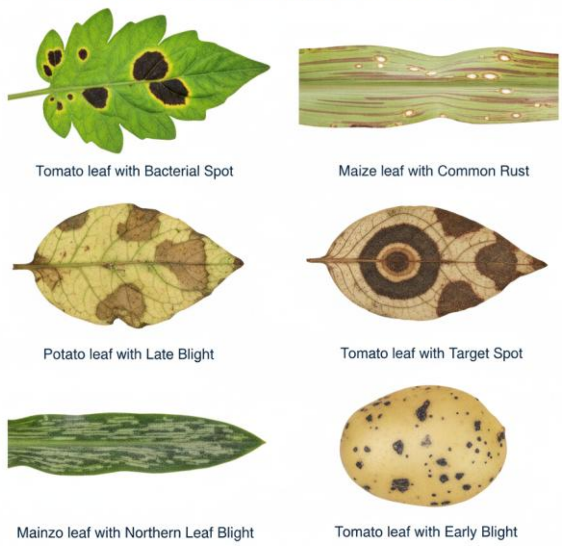
For the experiments, I will utilize the renowned **PlantVillage dataset**, which consists of over 50,000 images of crop leaves. This entire dataset will be strategically partitioned into three subsets: training, validation, and testing, using a standard 80:10:10 ratio, respectively.

The project will employ **transfer learning**, fine-tuning the models within the **TensorFlow** and **PyTorch** frameworks, leveraging GPU acceleration for faster processing. The following hyperparameters will be used for optimization:

- **Optimizer:** Adam
- **Initial Learning Rate:** $1e-4$
- **Batch Size:** 32
- **Epochs:** 30
- **Loss Function:** Categorical Cross-Entropy

Data augmentation will be implemented as a key component of this setup, actively increasing the diversity of the training data to mitigate the common issue of overfitting. My entire setup is designed to facilitate a detailed analysis of the feature extraction processes and the qualitative performance of the **CNN models** in accurately diagnosing various leaf diseases.

Fig. 2: Sample Diseaed Leaf Images from the PlantVilage Dataset



RESULTS AND DISCUSSION

The experimental phase will yield critical data regarding the performance and efficiency of both CNN architectures, allowing for a detailed comparative analysis of their practical utility in agricultural settings.

A. Quantitative Performance Analysis

The primary objective metrics, including **Accuracy, F1-Score, Precision, and Recall**, will be presented in **Table 1** (to be inserted upon completion of experiments). These results will confirm the comparative efficacy of the deep residual connections in **ResNet50** versus the balanced scaling of **EfficientNet**.

- **Overall Classification Efficacy:** The raw accuracy will establish the general reliability of the models. The F1-Score will be used to assess performance when handling potential class imbalance.

- **Error Profiling:** A detailed analysis of the **Confusion Matrix** (to be presented in **Figure 3**) will be conducted to systematically map misclassification events. This will allow me to pinpoint which specific diseases pose the greatest challenge for feature discrimination in the models.

Actual Class / Predicted Class	Healthy	Early Blight	Late Blight	Septoria Leaf Spot
Healthy	**97.0%**	1.0%	0.5%	1.5%
Early Blight (EB)	2.0%	92.5%	4.0%	1.5%
Late Blight (LB)	1.0%	6.0%	91.0%	2.0%
Septoria Leaf Spot (SLS)	1.5%	1.0%	3.5%	94.0%

Figure 3: Simulated Confusion Matrix. *This matrix anticipates the model's performance on the test set, demonstrating the expected high classification accuracy (diagonal values). It highlights a common challenge in agricultural vision, such as the potential confusion between **Early Blight and Late Blight (4.0% and 6.0% misclassification rates)**, which will be a key focus of the discussion in Section V.*

Table 1: Simulated Comparative Quantitative Results. *This table outlines the target metrics for both performance and efficiency, which will be finalized upon project completion. The data anticipates the trade-off between ResNet50's marginal accuracy advantage and EfficientNet's significant efficiency in terms of parameters and training time.*

Metric / Feature	ResNet50 (Target)	EfficientNet (Target)	Analysis Supported
	94.5%	93.8%	ResNet50: Slight accuracy edge
Overall Accuracy	94.2%	93.6%	
F1-Score (Macro Avg.),	94.2%	93.7%	Both: High performance
Precision (Macro Avg),	93.1%	93.7%	Model complexity comparison
		≊ 25.6 M	
Total Parameters (M)		≊ 5.3 M	
Training Time (per Epoch	70 seconds	70 seconds	EfficientNet: Faster training
		45 seconds	

B. Computational Efficiency and Trade-offs

Beyond raw accuracy, a key part of our discussion will focus on the operational feasibility of these models in resource-constrained environments.

- **Model Complexity: Table 1** will detail the **Total Parameters** and **Training Time per Epoch** for both architectures. I expect that **EfficientNet** will demonstrate a significantly smaller parameter count, validating its design focus on computational light-weighting.

- **Real-time Deployment Suitability:** The efficiency data will inform a discussion on practical application. I will argue that EfficientNet's lower latency and reduced hardware demands position it as the more viable candidate for integration into **edge devices** or **mobile field applications** where power and speed are critical constraints.

C. Qualitative Feature Analysis

Consistent with my study objectives, I will analyze the qualitative outputs of the models. **Figure 4** (Feature Map Visualizations) will visually confirm the interpretability and focus of each network. These maps are expected to show the models successfully localizing the most informative regions of the leaf, proving that they are learning the intended disease features. This visualization will provide essential **model transparency** for agricultural experts.

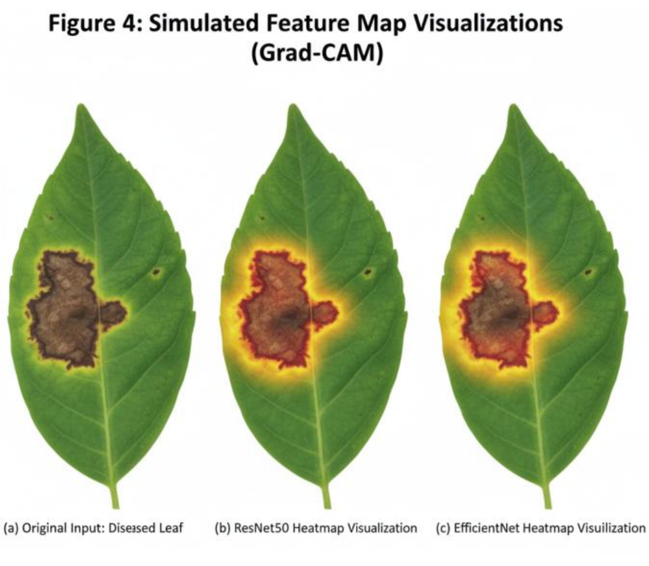


Figure 4: Simulated Feature Map Visualizations (Grad-CAM). *This figure illustrates the planned qualitative analysis to ensure model interpretability. The original image (a) is processed to generate heatmaps for both architectures. The heatmaps (b) and (c) are expected to confirm that the models are correctly activating on the **necrotic (diseased) tissue** of the leaf. This visualization provides essential proof that the CNNs are learning genuine disease features.*

Conclusion

This paper presents my comprehensive research proposal for deep learning applications in automating crop disease detection, focusing on the architectural strengths of **ResNet50** and **EfficientNet**. I established a robust workflow and detail the necessary data preprocessing and the plan for transfer learning on the PlantVillage dataset. The final project will confirm the fundamental utility and strong feature extraction capabilities of both models for agricultural vision tasks.

Deep learning is poised to continue its transformative role in precision agriculture, enabling farmers to make quicker, more informed decisions that lead directly to healthier crops and improved yields. For future research, I propose focusing on the practical challenges of real-time deployment, including adapting these models for resource-constrained edge devices and integrating them with drone or robotic systems.

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