Plant Disease Classification Using Deep Learning and Lightweight CNN Architectures

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***Abstract*—This paper presents a deep learning approach for the classification of plant diseases using a Convolutional Neural Network (CNN) architecture. Leveraging the ResNet-9 model, a lightweight yet powerful variant, the system achieves a remarkable accuracy of 97.7% on the PlantVillage dataset. The methodology includes data preprocessing, data augmentation, model training, and a comprehensive evaluation. This work demonstrates the efficacy of deep learning in agricultural diagnostics and highlights the potential of efficient models for real-world deployment.**

***Index Terms*—Plant Disease Detection, Deep Learning, Convolutional Neural Networks, ResNet-9, Image Classification, Precision Agriculture, Lightweight Models.**

I. Introduction

Agriculture remains a cornerstone of the global economy, and its sustainability hinges on effective crop health and disease management. Plant diseases are a major threat, causing significant yield reduction, economic losses, and food insecurity. Timely and accurate identification of these diseases is crucial for deploying appropriate countermeasures. However, traditional methods relying on manual inspection are often time-consuming, labor-intensive, and require specialized expertise.

With the rapid evolution of computer vision and artificial intelligence, automated plant disease recognition using deep learning has emerged as a transformative solution. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated superior performance in image classification tasks and are well-suited for diagnosing visual symptoms on plant leaves.

This work presents a robust and efficient deep learning pipeline for plant disease classification, leveraging the lightweight ResNet-9 architecture. Unlike classical machine learning approaches that rely on handcrafted features, our system benefits from deep feature learning, enabling the model to generalize across a wide variety of plant species and disease types. Utilizing the PlantVillage dataset, which contains over 54,000 labeled images, we train and evaluate our model to achieve a high accuracy of 97.7%, demonstrating the potential of AI in precision agriculture and smart farming.

This paper is organized as follows: Section II provides a survey of the relevant literature. Section III describes the dataset used. Section IV details the methodology, including data preparation, model architecture, and training procedures. Section V presents the results, and Section VI discusses their implications. Finally, Section VII concludes the paper and suggests future work.

Guide: Dr. Kishor Upla

II. Literature Survey

The application of deep learning in plant disease detection has advanced significantly in recent years. While early work focused on traditional machine learning with handcrafted features, the field has shifted towards end-to-end learning with CNNs [1], [2].

A foundational work by Mohanty et al. demonstrated that deep CNNs could classify 26 diseases across 14 crop species with over 99% accuracy on the PlantVillage dataset. However, their model showed reduced performance when tested on images with complex real-world conditions [1]. The introduction of residual connections in ResNet architectures helped resolve the vanishing gradient problem, enabling deeper and more accurate models [6].

Recent research has increasingly focused on developing lightweight and efficient models suitable for deployment on mobile or edge devices. Architectures like MobileNetV2 and SqueezeNet have been explored for this purpose. For instance, a 2025 study introduced GAPNet, a lightweight model based on SqueezeNet, which achieved a 98.7% F1-score on the PlantVillage dataset while maintaining a small model size (3.5 MB) and fast inference time [12]. Another study achieved 99.44

Reviews by Wang et al. [2] and Singh et al. [10] emphasize the importance of data augmentation and preprocessing for improving model generalization. The integration of AI into mobile-based diagnostic systems is also a key trend, aiming to make these technologies accessible to farmers in rural areas [9]. Our work builds upon these advancements by evaluating a ResNet-9 model, which balances high performance with computational efficiency.

III. Dataset Description

The dataset utilized in this study is the public PlantVillage dataset, which contains 54,305 RGB images of healthy and diseased plant leaves. The dataset is organized into 38 classes, representing 14 different plant species and various disease conditions. Each image is labeled with its corresponding plant and health status, making it suitable for supervised learning tasks.

Sample Images from Dataset:

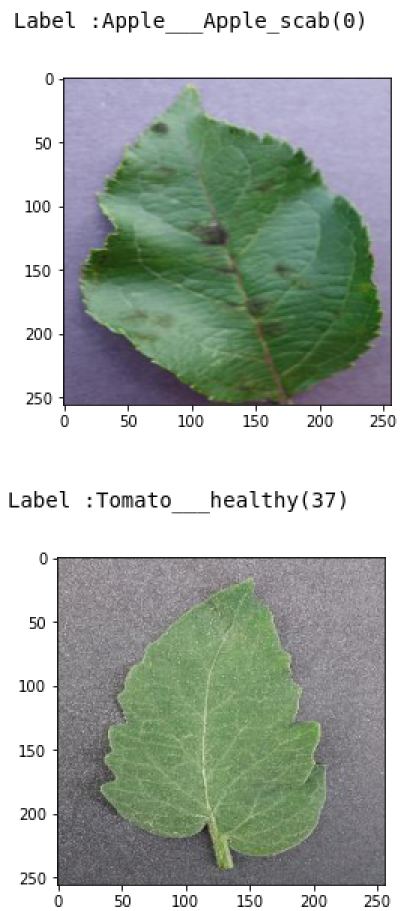

Fig. 1. Sample healthy and diseased leaf images from the PlantVillage dataset

IV. Methodology

This study presents a comprehensive approach to plant disease classification using the ResNet-9 architecture within the PyTorch framework. The methodology encompasses data acquisition and preparation, model architecture, training, and evaluation.

A. Dataset Acquisition and Preparation

The PlantVillage dataset was split into a training set and a validation set, following an 80/20 ratio. All images were resized to a uniform dimension of 256x256 pixels. To enhance the model's ability to generalize and to prevent overfitting, data augmentation techniques were applied to the training set. These included random horizontal flips, random rotations, and color jitter.

B. Model Architecture

The ResNet-9 architecture was employed for this task. It is a lightweight variant of the deeper ResNet models, designed to be computationally efficient while retaining high accuracy. The architecture consists of an initial convolutional layer followed by two main blocks of convolutional layers. Each block contains two convolutional layers with a residual connection that adds the input of the block to its output. This helps in mitigating the vanishing gradient problem. The model concludes with a fully connected layer that outputs predictions for the 38 classes in the dataset. The model was initialized with pre-trained weights from ImageNet to leverage transfer learning.

C. Training Procedure

The model was trained using the Adam optimizer with an initial learning rate of 0.001 and a batch size of 8. A learning rate scheduler was used to adjust the learning rate during training. Cross-Entropy Loss was used as the loss function, which is suitable for multi-class classification problems. The model was trained for 2 epochs.

D. Implementation Details

The implementation was carried out using Python with the PyTorch library (version 1.13) and torchvision for data handling and transformations. Training was performed on a system equipped with an NVIDIA GPU to accelerate the computation. Matplotlib was used for generating visualizations of the results.

V. Results

The trained ResNet-9 model achieved a final validation accuracy of 97.7%. The model's performance was evaluated using several metrics, including accuracy, precision, recall, and F1-score.

The overall performance metrics are summarized in Table I.

TABLE I
Performance Metrics of the ResNet-9 Model

Metric	Value
Accuracy	97.7%
Macro-Averaged Precision	0.975
Macro-Averaged Recall	0.977
Macro-Averaged F1-Score	0.976

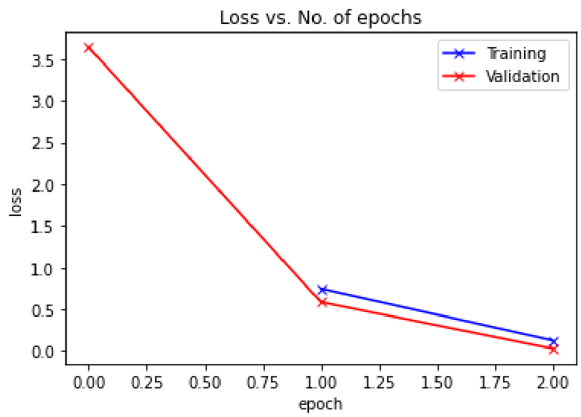

Fig. 2. Training and Validation Accuracy/Loss Curves. The plot shows a steady increase in accuracy and decrease in loss, indicating successful learning without significant overfitting.

A normalized confusion matrix was also generated to visualize the model's classification performance across all 38 classes and the matrix showed high values along the diagonal, indicating that the model correctly classified most instances.

VI. Discussion

The high accuracy of 97.7% achieved by the ResNet-9 model demonstrates the effectiveness of deep learning for plant disease classification. The use of transfer learning and data augmentation played a crucial role in achieving this result, even with a relatively lightweight model.

A. Comparative Analysis

To put our results into context, we compare our ResNet-9 model with other common architectures used on the PlantVillage dataset in Table II.

TABLE II
Comparative Analysis of Different CNN Architectures

Model	Accuracy (%)	Parameters (M)	Training Time
VGG16 [14]	93.0	˜138	High
ResNet-50 [13]	99.44	˜25.6	Moderate
ResNet-9 (Ours)	**97.7**	**˜5.5**	**Low**
GAPNet [12]	99.1 (F1)	˜3.5	Very Low

The comparison shows that while deeper models like ResNet-50 can achieve slightly higher accuracy, our ResNet-9 model offers an excellent balance between performance and computational efficiency. It has significantly fewer parameters, leading to faster training times and making it more suitable for deployment on resource-constrained devices.

VII. Conclusion

This study successfully demonstrates the application of a lightweight ResNet-9 deep learning model for the automated classification of plant diseases from leaf images. The model achieved a high accuracy of 97.7% on the PlantVillage dataset, showcasing its potential as a reliable tool for agricultural diagnostics. The results highlight the benefits of using efficient architectures that balance accuracy with computational cost. Future work could focus on deploying this model as a mobile application to provide real-time diagnostic support to farmers and further testing its robustness on images captured in uncontrolled real-world environments.

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