Deep Learning for Plant Disease Detection

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Abstract

Plant diseases represent a major threat to agricultural productivity worldwide, causing substantial yield and economic losses. Traditional detection methods rely on manual expert inspection, which is labor-intensive, error-prone, and unscalable. This thesis presents a deep learning-based approach for automated plant disease classification using leaf images. Leveraging the PlantVillage dataset and the EfficientNetB3 convolutional neural network architecture, the model achieved a state-of-the-art test accuracy of 99.56% across 38 plant disease and healthy classes. Advanced training techniques including transfer learning, data augmentation, and class balancing were applied to ensure robustness and generalization. The results demonstrate the potential for deploying this system in real-world agricultural settings to support precision farming, early disease detection, and improved crop management.

Chapter 1

Introduction

Agriculture underpins global food security, yet crop yields are constantly threatened by plant diseases. Early and accurate detection of plant diseases is vital for intervention and prevention of large-scale losses. Existing IoT and sensor-based approaches, while promising, suffer from cost, data scarcity, and implementation constraints. Consequently, this research focuses exclusively on image-based plant disease detection using deep learning. Leaf images provide clear visual indicators of plant health, and when paired with modern deep learning architectures, they enable scalable, efficient, and highly accurate disease diagnosis.

1.1 Problem Statement

Traditional approaches to disease detection in agriculture require significant manual labor, expertise, and time. IoT sensor-based systems require hardware, controlled environments, and reliable connectivity, which limit their adoption in resource-constrained regions. A scalable, cost-effective, and accurate method is required to empower farmers and agricultural experts alike. This research proposes the use of a deep learning-based classifier trained on large plant leaf image datasets to provide such a solution.

1.2 Objectives

The primary objectives of this research are:

- To design and implement a deep learning model for multi-class plant disease classification using leaf images.
- To evaluate the performance of EfficientNetB3 on the PlantVillage dataset, comparing with traditional CNN baselines.
- To optimize the model using data augmentation, transfer learning, and class balancing for robustness.
- To discuss deployment strategies for mobile and field-based real-time disease monitoring.

Chapter 2

Literature Review

Plant disease monitoring has traditionally relied on manual inspection and laboratory tests. IoT-based systems have been explored, involving sensors that monitor soil conditions, temperature, and humidity. However, such systems face challenges of scalability and data limitations (Pantazi et al., 2019).

Recent advances in deep learning have enabled the automation of disease identification using convolutional neural networks (CNNs). Studies have applied VGG16, ResNet, and Inception networks to the PlantVillage dataset, achieving classification accuracies between 90–96% (Mohanty et al., 2016; Ferentinos, 2018). EfficientNet, introduced by Tan and Le (2019), introduced compound scaling to balance network depth, width, and resolution, leading to higher accuracy with fewer parameters. Early applications of EfficientNet in agriculture have reported improved performance over traditional CNNs (Too et al., 2019).

Chapter 3

Dataset and Preprocessing

3.1 Dataset Description

This research uses the PlantVillage dataset (Hughes and Salathé, 2015), which contains over 54,000 images of plant leaves from 14 crop species across 38 disease and healthy classes. Examples include "Tomato Late Blight", "Potato Early Blight", and "Apple Scab".

- Total Images: 54,310.
- Classes: 38 (26 diseases, 12 healthy states).
- Split: 80% training, 10% validation, 10% testing.

3.2 Preprocessing and Augmentation

Images were resized to 224x224 pixels. Data augmentation was applied to simulate real-world variability:

- Rotation up to 20 degrees.
- Horizontal flipping.
- Width and height shifts up to 20%.

- Zoom up to 15%.
- Shear up to 15%.

This preprocessing pipeline ensured robustness against variations in field conditions.

Chapter 4

Methodology

4.1 Model Architecture

The model employed EfficientNetB3 pre-trained on ImageNet. The base model was frozen, and a custom classification head was added with batch normalization, dropout, and fully connected layers.

4.2 Training Pipeline

- Optimizer: Adamax, learning rate 0.001.
- Loss: Categorical cross-entropy.
- Metrics: Accuracy, Precision, Recall, F1-score.
- Epochs: 10 (with early stopping).
- Callbacks: ReduceLROnPlateau, EarlyStopping, ModelCheckpoint.

4.3 Implementation

Training was performed on a GPU-enabled environment using TensorFlow/Keras, with modular code for reproducibility.

Chapter 5

Results

5.1 Performance Metrics

The model achieved the following results on the PlantVillage test set:

- Test Accuracy: 99.56%.
- Precision (Weighted): 1.00.
- Recall (Weighted): 1.00.
- F1-score (Weighted): 1.00.

5.2 Confusion Matrix

Minimal misclassifications were observed, particularly between visually similar diseases such as early and late blight.

5.3 Comparison with Prior Work

Prior CNN models such as ResNet and VGG16 achieved 95% accuracy. The proposed EfficientNetB3 model surpasses these benchmarks by a significant margin.

Chapter 6

Discussion

The superior performance of EfficientNetB3 demonstrates the advantage of compound scaling and transfer learning in agricultural image classification tasks. While the model excels on the PlantVillage dataset, real-world conditions such as variable lighting and occlusions present challenges. Future work should validate the model on field-collected datasets and explore lightweight architectures for mobile deployment.

Chapter 7

Conclusion

This thesis presents a highly accurate deep learning model for plant disease classification based on leaf images. By leveraging EfficientNetB3 and applying rigorous preprocessing, augmentation, and transfer learning, the model achieved 99.56% accuracy, surpassing prior benchmarks. Unlike earlier proposals that included IoT sensor monitoring, this thesis focuses exclusively on image-based detection, ensuring feasibility, scalability, and practicality. Future work includes adaptation to field images, integration into mobile platforms, and extension to real-world agricultural systems.

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