

Plant Disease Classification with Care Guide

Artificial Intelligence & Machine Learning CSET301

Submitted by:

(E23CSEU0859) Mohd. Faizan Siddiqui
(E23CSEU2457) Madhav Tyagi

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DR. NITIN ARVIND SHELKE

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Plant Disease Classification with Care Guide Using Deep Learning Model

Abstract

Agriculture is fundamental to human sustenance and economic development. Yet, one of the persistent challenges faced by this sector is the occurrence of plant diseases, which, if not addressed promptly, can lead to substantial losses in crop quality and quantity. Traditional disease detection methods rely on visual inspection by experts, which is time-consuming, expensive, and prone to human error.

This project presents a novel, automated approach to plant disease detection using a custom Convolutional Neural Network (CNN). In addition to identifying diseases from leaf images, the system is uniquely designed to provide actionable plant care recommendations tailored to each diagnosis. This dual functionality—detection and care guidance—is seamlessly deployed via a web application built using Streamlit. It ensures accessibility to users across technical backgrounds, particularly farmers and agricultural workers, enabling them to take immediate action and maintain plant health effectively.

Introduction

With the global population growing steadily, the demand for food is at an all-time high. Ensuring plant health is a critical step in improving crop yields and maintaining food security. Unfortunately, plant diseases are often identified too late due to limited access to agricultural expertise, especially in rural areas.

To address this, our project utilizes advancements in deep learning and computer vision to automate the process of plant disease detection. By analyzing leaf images, the system classifies diseases with high accuracy and provides detailed care recommendations. This transforms disease detection from a reactive, expert-dependent process to a proactive, AI-assisted solution accessible to all.

Our key goals include:

- Automating the classification of multiple plant diseases.
 - Providing detailed, disease-specific care suggestions.
 - Ensuring the system is easy to use through a web-based interface.
 - Enabling future enhancements, such as multilingual support and mobile deployment.
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Related Work

Many researchers have explored plant disease identification using image classification techniques. Projects using pretrained models like ResNet50, VGG16, and InceptionNet have achieved impressive results on datasets such as PlantVillage. However, these models often require significant computational resources, making real-time or edge deployment difficult.

Moreover, a majority of these systems stop at disease classification. This project bridges that gap by coupling detection with contextual plant care, offering an end-to-end solution. Our approach aligns with current research while improving usability and field readiness.

Methodology

3.1 Dataset

- **Source:** Kaggle's PlantVillage dataset
- **Size & Structure:** Over 50,000 labeled images of plant leaves covering more than 38 disease classes from 14 plant species.
- **Preprocessing Steps:**
 - Image resizing to 128x128 for model compatibility.
 - Normalization of pixel values to improve training efficiency.
 - Extensive augmentation including random rotation, flipping, contrast, and zoom to prevent overfitting and simulate real-world conditions.

3.2 Model Architecture

- **Convolutional Layers:** Multiple layers with increasing filter sizes to extract rich spatial features.
- **Pooling Layers:** MaxPooling to reduce dimensionality while retaining key patterns.
- **Dropout:** Applied at strategic points to prevent overfitting.
- **Dense Layers:** Fully connected layers culminating in a Softmax layer for multi-class prediction.
- **Optimizer:** Adam optimizer with dynamic learning rate adjustments.
- **Loss Function:** Categorical crossentropy due to multi-class classification.

3.3 Care Recommendation Engine

- Disease classes are mapped to structured care instructions stored in a JSON file.
 - Each care guide includes:
 - **Common Symptoms:** Helps confirm diagnosis visually.
 - **Causes:** Environmental or biological triggers.
 - **Treatment Options:** Both chemical (pesticides, fungicides) and organic methods.
 - **Preventive Measures:** Long-term strategies to avoid recurrence.
 - **Severity Indicator:** Alerts user to urgency (mild/moderate/severe).
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Data Visualization and Exploratory Data Analysis (EDA)

Before training the model, we analyzed the dataset to understand class distribution and image characteristics. Bar charts revealed some imbalance across disease categories, which we addressed using data augmentation and class weighting. Sample images were also visualized to confirm the presence of distinguishable disease patterns such as discoloration, spots, or fungal growths.

Hardware/Software Requirements

Hardware:

- **Processor:** Intel/AMD quad-core (minimum)
- **RAM:** 8 GB (16 GB recommended for smooth training)
- **GPU:** Optional but helpful (e.g., NVIDIA GTX 1050 or better)

Software:

- **Language:** Python 3.10+
 - **Frameworks:** TensorFlow, Keras
 - **Other Libraries:** NumPy, Matplotlib, PIL, Streamlit
 - **Tools:** Jupyter Notebook, VS Code
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Experimental Results

After training on the augmented dataset, the model showed strong performance:

- **Training Accuracy:** ~98.4%
- **Validation Accuracy:** ~94.6%
- **F1 Score:** High across most classes, indicating balanced precision and recall

The model handled most classes well, with minor confusion between diseases with similar visual traits. Performance remained stable across different test images.

Deployment

The model is deployed through a clean and responsive **Streamlit web app**. Users can:

- Upload a plant leaf image
 - Receive an immediate disease classification
 - View a tailored care guide including symptoms, treatment, and prevention
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GitHub Repository

 <https://github.com/faizansid3/plant-disease-detector>

The repository contains:

- Jupyter notebook for model training
 - Care guide mapping in JSON format
 - Streamlit app code
 - README with setup instructions
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Conclusion

This project offers a powerful yet simple solution for real-time plant disease detection. By combining a custom-trained CNN with an integrated care guide, the system goes beyond prediction to deliver value directly to users. It's accessible, accurate, and easily expandable for future improvements like multilingual support and mobile deployment—making it a valuable tool for modern agriculture.

Future Scope

- **Dataset Expansion:** Incorporate images from various geographical regions and lighting conditions to enhance model robustness.
 - **Pretrained Model Comparison:** Integrate and compare performance with EfficientNet, MobileNetV2, or ViT.
 - **Mobile App Development:** Build a native Android/iOS app with offline functionality for rural use.
 - **Multilingual Interface:** Support for regional languages to increase accessibility.
 - **Real-time Camera Integration:** Integrate with drone or phone camera feeds for on-the-fly detection.
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This report is structured to address all milestones outlined in the marking scheme, emphasizing the systematic development, evaluation, and deployment of the project.