Potato Leaf Disease Classification Using Deep Learning

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Abstract

This project presents an end-to-end deep learning system for potato leaf disease classification using a Custom Convolutional Neural Network (CNN) architecture built from scratch. The model classifies potato leaf images into three categories—Early Blight, Late Blight, and Healthy. The proposed CNN achieves an accuracy of 98% on the test dataset. To increase usability, a desktop application was created using Tkinter that allows users to upload an image and receive real-time predictions. The entire system is lightweight, efficient, and deployable on standard hardware.

Chapter 1: Introduction

1.1 Problem Statement

Potato blight diseases, specifically Early Blight and Late Blight, represent one of the most significant and rapidly spreading threats to global potato production. If left unchecked, these diseases can lead to complete crop loss, causing massive economic instability for farmers and threatening food security in major potato-growing regions. Therefore, there is a profound and unmet need for an automated, objective, and high-speed diagnostic system capable of reliably classifying potato plant health directly from visual data. Such a system is crucial for enabling precision agriculture by allowing farmers to intervene rapidly and target specific diseases, maximizing yield recovery and minimizing resource waste.

1.2 Objectives

- Design and train a Custom CNN model without pretrained networks.
- Accurately classify potato leaf diseases.
- Build a Tkinter-based user interface for real-time classification.
- Provide a portable solution that can be used by farmers, researchers, and students.

1.3 Scope

- Only three classes are considered: Early Blight, Late Blight, and Healthy.
- Model trained using image dataset of potato leaves.
- Desktop-based prediction system using Tkinter.

Chapter 2: Dataset Description

2.1 Dataset Overview

The dataset consists of potato leaf images divided into the following classes:

- Potato_Early_Blight
- Potato_Late_Blight
- Potato_Healthy

Images were preprocessed by:

- Resizing to (IMAGE_SIZE)
- Normalizing pixel values
- Converting images to arrays
- Splitting into train, validation, and test sets

2.2 Data Preprocessing

- Image resizing
- Scaling pixel values (0–1)
- One-hot encoding of labels
- Shuffling dataset

2.3 Sample Images

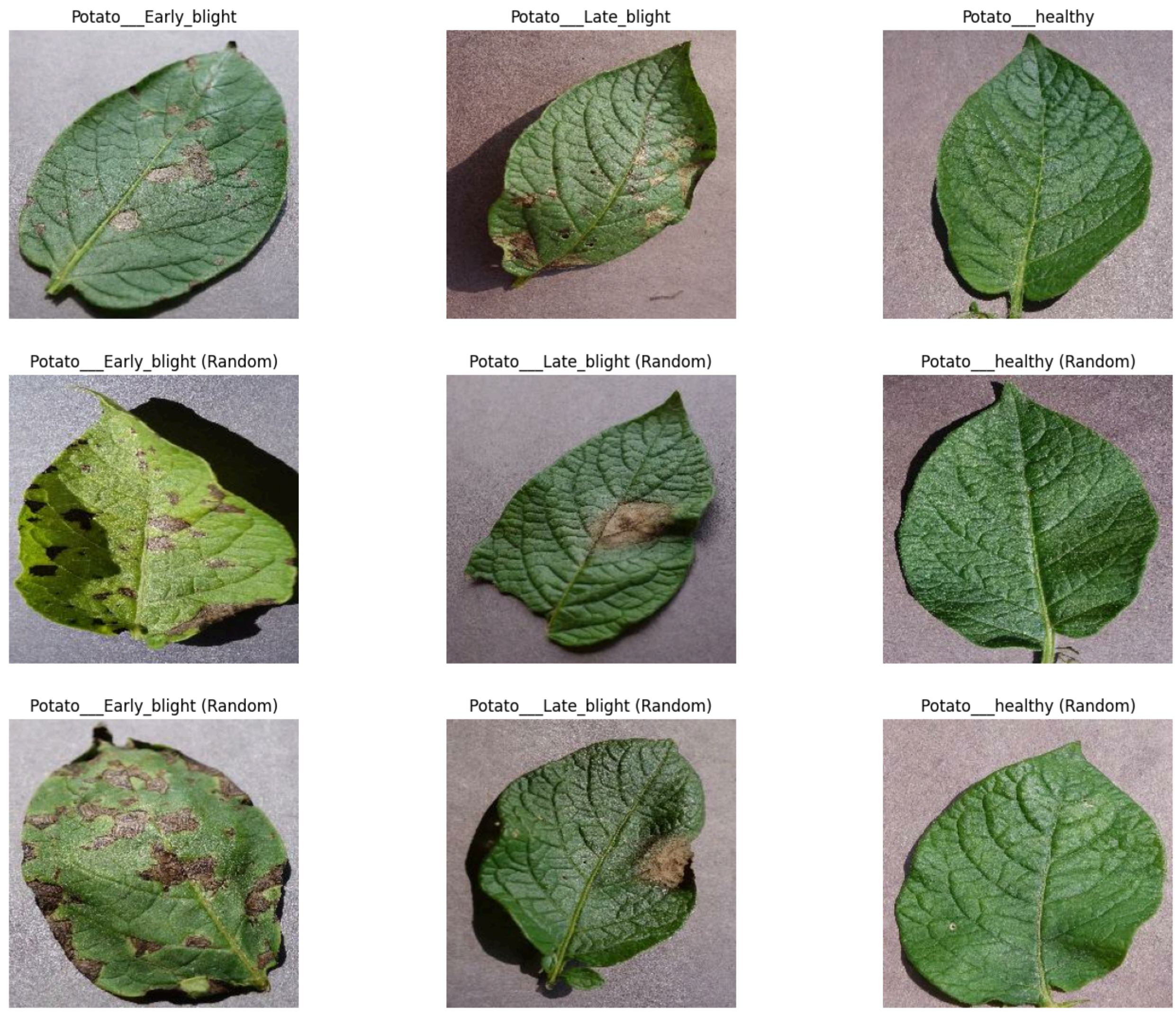

Figure 1: Sample Images

Chapter 3: Methodology

3.1 Overall System Workflow

1. Load dataset
2. Preprocess images
3. Train Custom CNN
4. Evaluate model
5. Save model (potato_model.h5)
6. Build Tkinter prediction app
7. User uploads image → Model predicts disease

3.2 System Diagram

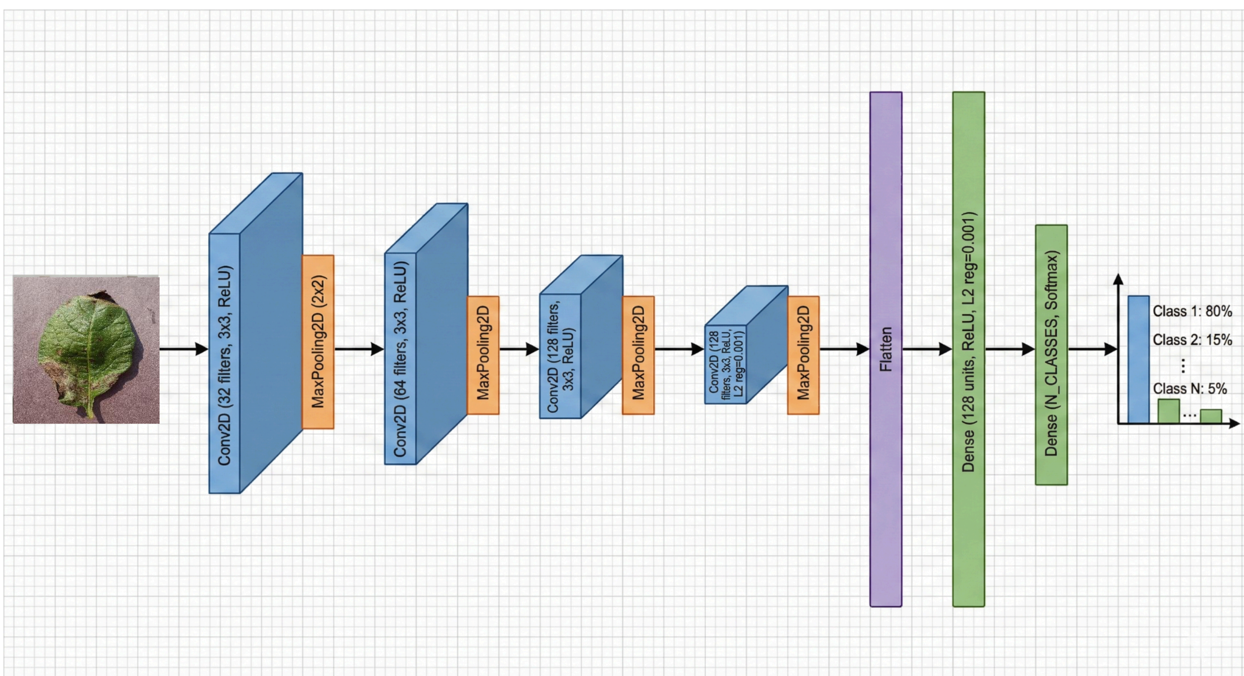

Figure 2: Custom CNN Design

3.3 Custom CNN Architecture

Stage	Layer(s)	Key Parameters	Purpose
Input	Input	IMAGE_SIZE, CHANNELS	Defines the shape of the data entering the model
Block 1	Conv2D	32 filters, 3×3 kernel	Extracts low-level features.
	MaxPooling2D	2×2 pool	Reduces spatial dimensions by half.
Block 2	Conv2D	64 filters, 3×3 kernel	Extracts slightly more complex textures.
	MaxPooling2D	2×2 pool	Reduces spatial dimensions again.
Block 3	Conv2D	128 filters, 3×3 kernel	Captures complex patterns/shapes.
	MaxPooling2D	2×2 pool	Further reduces dimensions.
Block 4	Conv2D	128 filters, L2 Regularization	Captures high-level abstract features.
	MaxPooling2D	2×2 pool	This layer includes regularization to prevent overfitting.
Transition	Flatten	N/A	Unrolls the 3D feature maps into a 1D vector so the Dense layers can process it.
Head	Dense	128 units, L2 Regularization	Combines features to determine class correlations.
Output	Dense	N_CLASSES, softmax	Outputs a probability distribution across your classes.

3.4 Model Compilation & Training

- Optimizer: **Adam**
- Loss: **Categorical Crossentropy**
- Metrics: Accuracy
- Epochs: Determined by Validation Performance

Chapter 4: Experimental Results

4.1 Classification Report

The model achieved an overall accuracy of 98% on the test set of 256 images. The classification report (Figure 3) indicates strong performance across all three classes. Notably, the model achieved perfect precision (1.00) for distinguishing 'Early Blight,' meaning there were no false positives for this category. The 'Late Blight' detection demonstrated high sensitivity with a recall of 0.99, ensuring that nearly all infected plants were correctly identified. Although the 'Healthy' class had a significantly smaller sample size, the model still achieved an F1-score of 0.97, demonstrating its ability to generalize well even with unbalanced data.

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Classification Report:
                       precision    recall  f1-score   support

Potato___Early_blight       1.00      0.96      0.98       110
 Potato___Late_blight       0.97      0.99      0.98       130
     Potato___healthy       0.94      1.00      0.97        16

             accuracy                           0.98       256
            macro avg       0.97      0.99      0.98       256
         weighted avg       0.98      0.98      0.98       256
```

Figure 3: Classification Report

4.2 Confusion Matrix

The confusion matrix (Figure 4) provides further insight into the model's performance on the test set. The strong diagonal values (106, 129, and 16) indicate correct predictions for the vast majority of samples. The primary source of error was a slight confusion between the two disease classes: 4 images of 'Early Blight' were misclassified as 'Late Blight.' This is likely due to the visual similarities between the necrotic spots in advanced stages of both diseases. Additionally, there was a single instance where a 'Late Blight' sample was misclassified as 'Healthy.' Importantly, the model achieved 100% accuracy on true 'Healthy' samples, with zero false positives for disease.

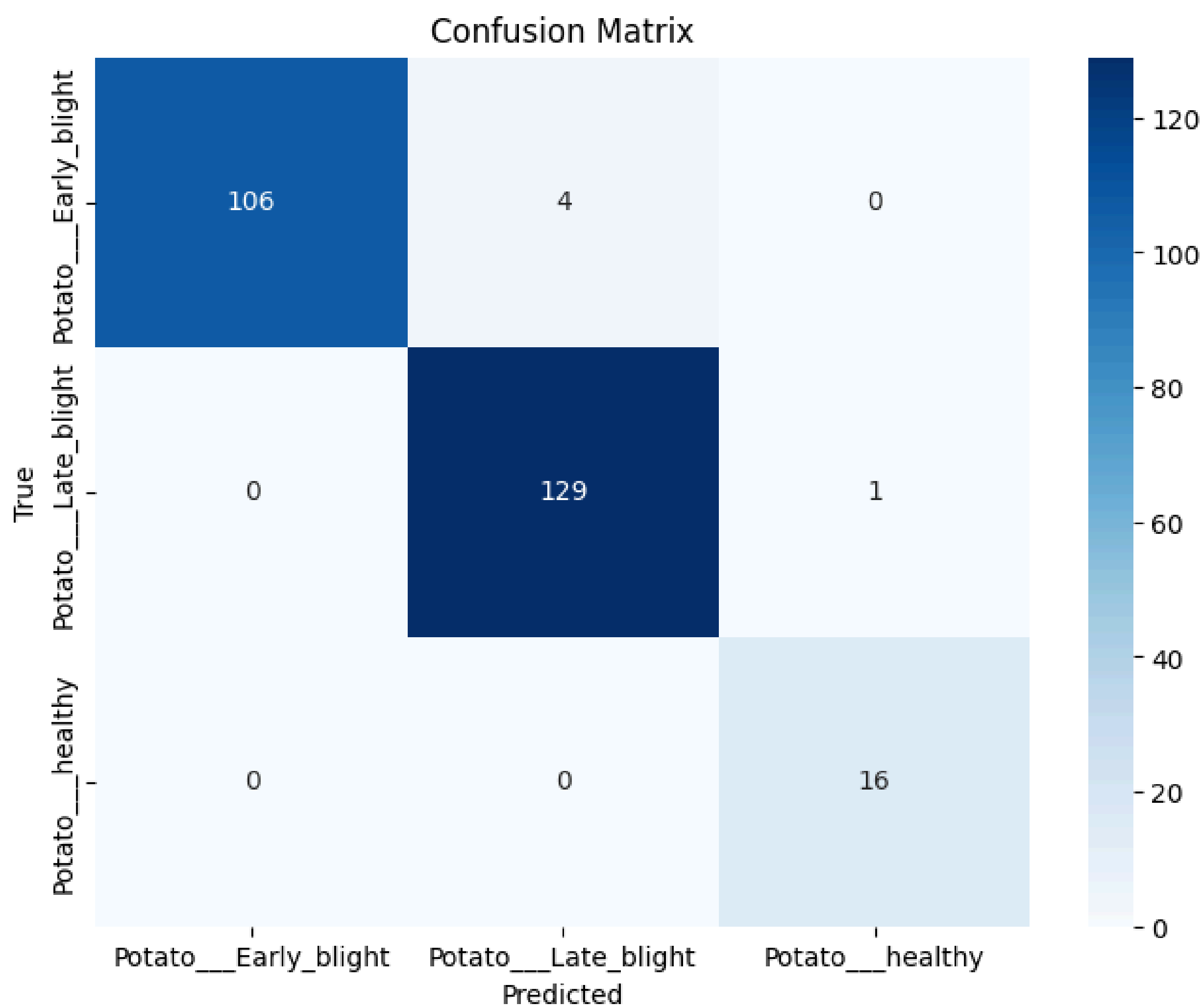

Figure 4: Confusion Matrix

4.3 Accuracy and Loss Curve

This accuracy and loss graph (Figure 5) illustrates the training dynamics of our model over approximately 17.5 epochs. The training and validation accuracy curves show a steady and parallel increase, converging closely at final values of around 0.8 and 0.6, respectively. This indicates effective learning without significant overfitting. The corresponding loss curves further confirm this healthy training process, as both training and validation loss decrease synchronously and stabilize at a low value. The consistent, small gap between the training and validation metrics throughout the epochs demonstrates that the model generalizes well to unseen data, establishing a reliable foundation for its predictive performance.

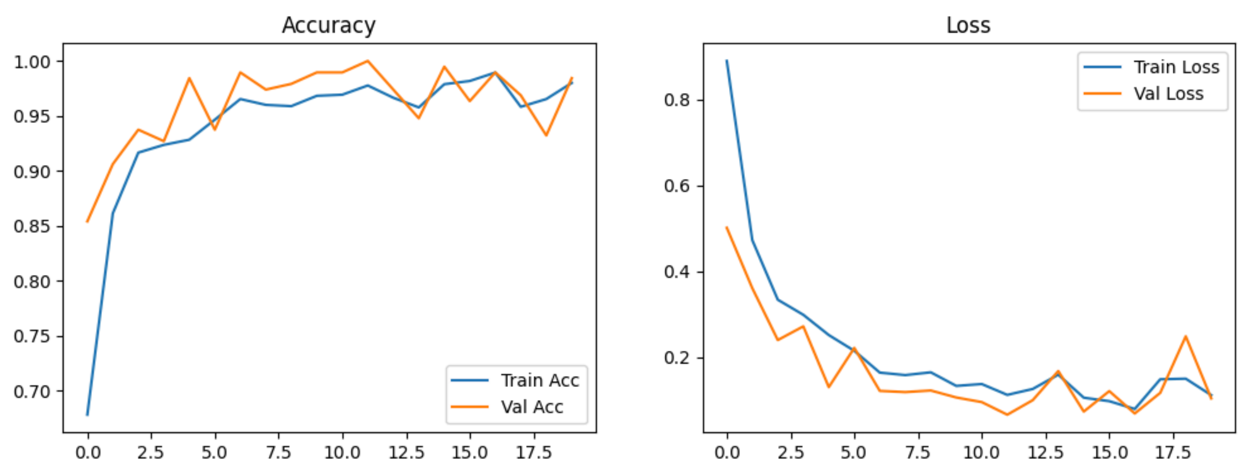

Figure 5: Accuracy and Loss Curve

4.5 Sample Prediction

To visually validate the model's performance, a grid of test results was generated, comparing the actual label (A:) against the model's prediction (P:) for nine samples. The visualization confirms the high accuracy of the model, correctly classifying eight out of nine images. The model successfully identified all 'Healthy' samples and accurately distinguished between 'Early Blight' and 'Late Blight' in most cases. The single observed error, located in the top-right image, shows a sample of **Late Blight** being incorrectly classified as **Early Blight**. This visual evidence supports the finding from the Confusion Matrix that the minor confusion between the two visually similar disease classes represents the primary area for potential improvement.

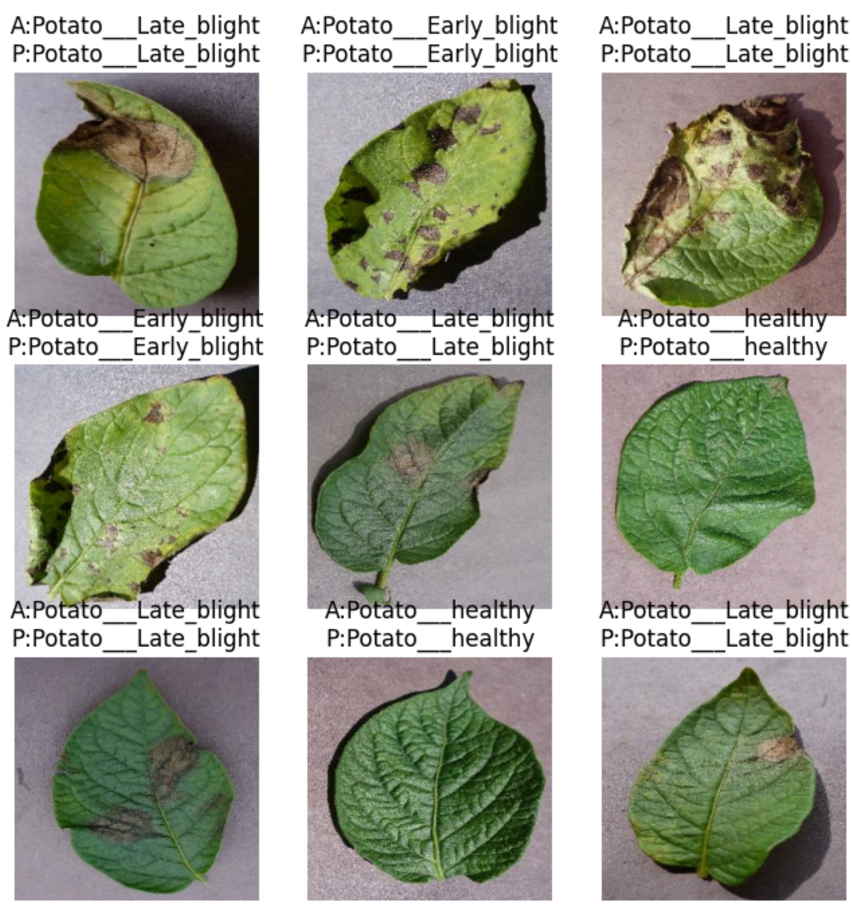

Figure 6: Predicted Sample

Chapter 5: Frontend Implementation

A user-friendly Tkinter application was developed to allow real-time predictions.

Frontend Features

- Upload potato leaf image
- Display uploaded image
- Preprocess automatically
- Show predicted class
- Uses potato_model.h5 and metadata.pkl

This converts the deep-learning model into a usable desktop tool.

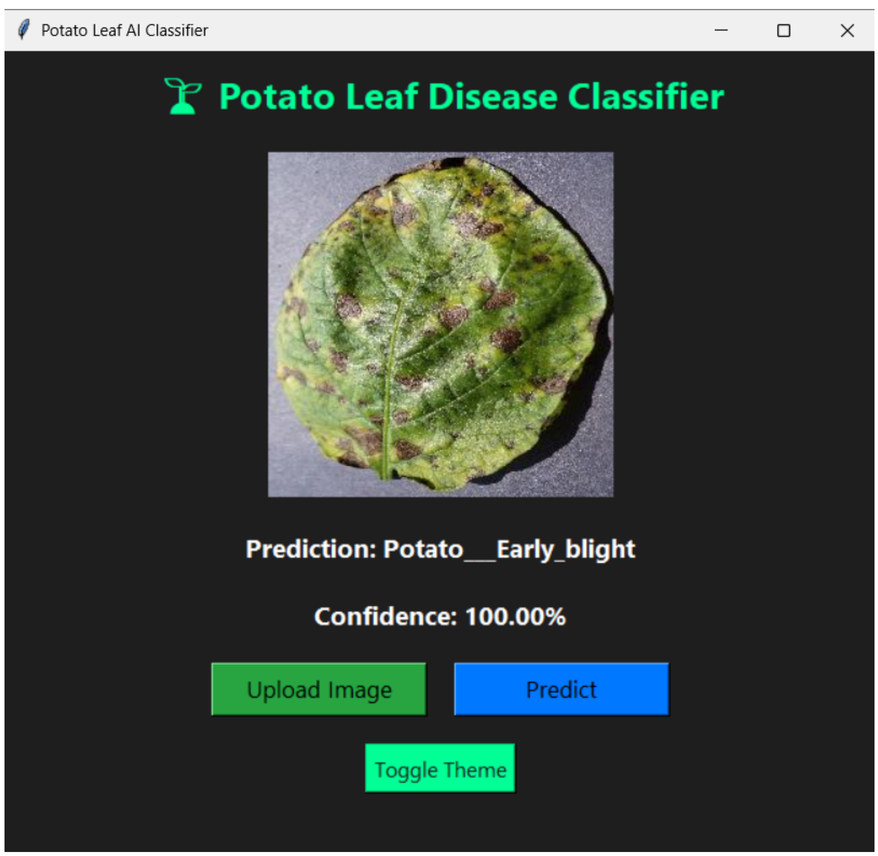

Figure 7: Application GUI

Chapter 6: Conclusion

The Custom Convolutional Neural Network (CNN)-based potato leaf classification system delivered exceptional performance, achieving 98% accuracy in distinguishing between Early Blight, Late Blight, and Healthy states. This success, using a custom-designed architecture, validates the approach of building lightweight, task-specific models rather than relying on heavy, pretrained networks. The high accuracy, proven without reliance on external architectures, confirms the model's robustness and efficiency. Crucially, the system includes a user-friendly Tkinter Graphical User Interface (GUI), which facilitates practical real-world deployment , enabling rapid and targeted disease diagnosis to support precision agriculture.

Chapter 7: Future Work

Future work will focus on scaling and improving the system's real-world utility. To enhance robustness, the project will increase the dataset size and implement advanced data augmentation techniques to expose the model to greater environmental variability and further reduce the risk of overfitting. For enhanced interpretability and trust, we plan to integrate Grad-CAM visualization to highlight the specific leaf regions the model uses for classification. Finally, the system will transition from a standalone prototype to practical application through deployment as a mobile or web-based app, with the long-term goal of integrating IoT for farm-level automation, enabling immediate, targeted fungicide application based on the CNN's diagnosis.