Atish Dipankar University of Science & Technology

Department of Computer Science and Engineering

Potato Leaf Disease Detection Using Machine Learning

A Final Year Project Report Submitted by

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Declaration

I hereby certify that the work, which is being presented in the project report, entitled **Potato Leaf Disease Detection Using Machine Learning**, in partial fulfillment of the requirement for the award of the Degree of Bachelor of Science in Computer Science and Engineering and submitted to the institution is an authentic record of my own work carried out during the period of January 2025 to August 2025 under the supervision of **Sharmin Akter**.

I have also cited the references for any text, figures, tables, or equations from other sources. The work presented in this report has not been submitted elsewhere for the award of any other degree or diploma from any institution.

September 5, 2025
Date

Rabea Akter Bristy
Signature of the Candidate

This is to certify that the above statement made by the candidate is correct to the best of my knowledge. The Viva-Voce examination of Rabea Akter Bristy has been held on ________________.

Signature of Research Supervisor(s)

Signature of Head of the Department

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Abstract

Potato (Solanum tuberosum) is one of the most important food crops globally, but its yield is significantly threatened by diseases such as Early Blight and Late Blight. Timely and accurate detection of these diseases is crucial for effective management and minimizing crop loss. This project presents the design, implementation, and comparative evaluation of an advanced deep learning system for the automated classification of potato leaf diseases from digital images.The methodology leverages the power of transfer learning by employing three state-of-the-art Convolutional Neural Network (CNN) architectures: EfficientNetB3, DenseNet121, and ResNet152V2. A publicly available dataset of 1500 potato leaf images, categorized as Early Blight, Late Blight, or healthy, was used for training, validation, and testing. A robust data pipeline was established, incorporating advanced data augmentation techniques;including random flips, rotations, zooms, and contrast adjustments;to enhance the model's generalization capabilities.A two-phase training strategy was implemented for each architecture: an initial feature extraction phase with a frozen base model, followed by a fine-tuning phase where the top layers of the pre-trained models were unfrozen and trained with a lower learning rate. The models' performances were systematically evaluated on a held-out test set. The comparative analysis revealed that DenseNet121 achieved the highest test accuracy of 83.00%, outperforming ResNet152V2 (68.67%) and EfficientNetB3 (37.33%). A detailed analysis of the DenseNet121 model, including its classification report and confusion matrix, confirmed its strong performance, particularly in identifying Early Blight with a recall of 94%.To facilitate practical application and demonstration, the best-performing model, DenseNet121, was deployed as an interactive web application using Gradio. This interface allows users to upload a potato leaf image and receive an instant classification, providing a valuable proof-of-concept for a real-world agricultural decision support tool.

Keywords: Potato Disease, Plant Pathology, Deep Learning, Convolutional Neural Networks (CNN), Transfer Learning, EfficientNet, DenseNet, ResNet, Image Classification, Gradio.

List of Figures

List of Tables

Contents

1 Introduction

1.1 Background and Motivation

Agriculture forms the backbone of the global food supply, with staple crops like the potato (Solanum tuberosum) playing a critical role in ensuring food security for billions of people worldwide. However, agricultural productivity is constantly under threat from various biotic and abiotic stresses, among which plant diseases are a primary cause of significant yield losses. For potato cultivation, fungal diseases such as Early Blight, caused by *Alternaria solani*, and Late Blight, caused by *Phytophthora infestans*, are particularly devastating. Late Blight, infamous for its role in the Irish Potato Famine, can destroy an entire crop within a matter of weeks under favorable conditions [1].

Traditionally, the identification and management of these diseases have relied on manual inspection by farmers or agricultural experts. This process is not only labor-intensive and time-consuming but also requires significant domain expertise, which may not be readily available, especially in remote or developing regions. Furthermore, human diagnosis can be subjective and prone to error, potentially leading to delayed or incorrect treatment, resulting in unnecessary crop loss and the overuse of chemical pesticides.

The recent advancements in computer vision and deep learning have opened up new possibilities for automating the process of plant disease detection. Convolutional Neural Networks (CNNs), a class of deep neural networks, have demonstrated remarkable success in image recognition and classification tasks, often achieving or even surpassing human-level performance [2]. By training these models on large datasets of plant images, it is possible to create systems that can automatically identify diseases from a simple photograph of a leaf.

This project is motivated by the urgent need for accessible, accurate, and scalable solutions for potato disease detection. By leveraging the power of transfer learning with state-of-the-art CNN architectures, we aim to develop a robust system that can accurately classify potato leaves as healthy, infected with Early Blight, or infected with Late Blight. The ultimate goal is to provide a proof-of-concept for a tool that could be deployed in the field, for instance, on a mobile device, to assist farmers in making timely and informed decisions for crop management, thereby enhancing agricultural sustainability and productivity.

1.2 Problem Statement

The primary technical challenge is to develop a highly accurate and reliable automated system for classifying the health status of potato leaves from digital images. The system must be able to distinguish between three distinct classes: healthy, Early Blight, and Late Blight. This is a multi-class image classification problem that presents several challenges:

- **Intra-class Variation:** The visual appearance of a single disease can vary significantly depending on the stage of infection, environmental conditions, and the potato cultivar.
- **Inter-class Similarity:** The symptoms of Early Blight and Late Blight, particularly in their initial stages, can appear visually similar to the untrained eye, making accurate differentiation difficult.
- **Image Quality and Background Noise:** Real-world images taken in the field can have varying lighting conditions, backgrounds, and image quality, which can interfere with the classification process.
- **Data Scarcity:** While deep learning models are powerful, they typically require large amounts of labeled data for training. Acquiring and labeling a massive dataset of plant disease images can be a significant bottleneck.

This project addresses these challenges by employing transfer learning with pre-trained CNNs and utilizing advanced data augmentation techniques to create a model that is both accurate and robust to variations in input images.

1.3 Objectives

The principal objective of this project is to design, implement, and comparatively evaluate a high-performance system for potato leaf disease detection. The specific, measurable objectives are:

1. To acquire and preprocess a publicly available dataset of potato leaf images, organizing it into training, validation, and test sets.
2. To implement an advanced data loading and augmentation pipeline to increase the diversity of the training data and prevent model overfitting.
3. To build and train three distinct deep learning models based on the state-of-the-art CNN architectures: EfficientNetB3, DenseNet121, and ResNet152V2, using a transfer learning approach.
4. To implement a two-phase training strategy for each model, consisting of feature extraction followed by fine-tuning, to optimize performance.
5. To systematically evaluate and compare the performance of the three models on a held-out test set using standard classification metrics, including accuracy, precision, recall, and F1-score.
6. To identify the best-performing model and conduct a detailed analysis of its performance, including a confusion matrix, to understand its strengths and weaknesses.
7. To deploy the best-performing model as an interactive web application using the Gradio library, providing a user-friendly interface for real-time prediction.

1.4 Scope and Limitations

1.4.1 Scope

- **Task:** Multi-class image classification for three categories: Potato Early Blight, Potato Late Blight, and Potato healthy.
- **Data:** The project utilizes the "Potato Leaf Disease" dataset from Kaggle, which contains pre-labeled images of potato leaves.
- **Models:** The comparative analysis is focused on three pre-trained CNN architectures: EfficientNetB3, DenseNet121, and ResNet152V2.
- **Deployment:** The system is deployed as a proof-of-concept web application via Gradio, suitable for demonstration and interactive testing.

1.4.2 Limitations

- **Dataset Size and Diversity:** The model's performance is contingent on the size and diversity of the training dataset. The dataset used, while suitable for this project, may not encompass all possible variations in disease appearance across different potato cultivars and geographical locations.
- **Controlled Environment:** The images in the dataset were likely taken in relatively controlled conditions. The model's performance in a real-world field environment with more complex backgrounds and variable lighting might differ.
- **Disease Scope:** The model is limited to identifying only Early Blight and Late Blight. It cannot detect other potato diseases or nutrient deficiencies.
- **Deployment Scalability:** The Gradio deployment is intended for demonstration purposes and is not designed for large-scale, high-concurrency use in a production environment.

1.5 Report Structure

This report is organized into seven chapters. Chapter 2 provides a review of the relevant literature on computer vision in agriculture and deep learning for plant disease detection. Chapter 3 details the system's architecture and the technology stack used. Chapter 4 presents the methodology and implementation steps, from data acquisition to model training. Chapter 5 discusses the results of the model evaluation and comparative analysis. Chapter 6 describes the deployment of the best-performing model as an interactive web application. Finally, Chapter 7 concludes the report and suggests directions for future work.

2 Literature Review

This chapter provides a critical review of the academic literature pertinent to computer vision and deep learning, with a specific focus on their application to plant disease detection. It traces the evolution of techniques from traditional image processing to the current state-of-the-art Convolutional Neural Network (CNN) architectures, thereby providing the academic context for this project.

2.1 Computer Vision in Agriculture

The application of computer vision to agriculture, often termed ”precision agriculture,” has been an active research area for several decades. Early approaches relied on traditional image processing techniques, such as color space analysis, texture analysis, and shape descriptors, combined with classical machine learning algorithms like Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NN) [3]. These methods were used for a variety of tasks, including fruit grading, weed detection, and disease identification. However, they often required careful manual feature engineering and were sensitive to variations in lighting and background, which limited their robustness and scalability.

2.2 Deep Learning for Plant Disease Detection

The breakthrough success of deep learning, particularly Convolutional Neural Networks (CNNs), in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 marked a turning point for the field of computer vision [4]. CNNs have the ability to automatically learn hierarchical features directly from raw pixel data, eliminating the need for manual feature engineering. This has made them exceptionally powerful for image classification tasks, including plant disease detection.

A seminal work by Mohanty et al. (2016) demonstrated the high potential of deep learning for this task [5]. They trained a GoogLeNet model on a large dataset of 54,306 images of diseased and healthy plant leaves (the PlantVillage dataset) and achieved an accuracy of 99.35% on a held-out test set. This study, and others like it, established CNNs as the state-of-the-art approach for plant disease detection.

2.3 Advanced CNN Architectures

Since the initial success of models like AlexNet and GoogLeNet, several more advanced CNN architectures have been developed, each offering improvements in terms of accuracy, efficiency, or both. This project focuses on three such architectures:

2.3.1 ResNet (Residual Networks)

Introduced by He et al. (2016), Residual Networks (ResNets) addressed the problem of training very deep neural networks [6]. As networks get deeper, they can suffer from the vanishing gradient problem, which makes them difficult to optimize. ResNets introduce "residual connections" or "skip connections," which allow the gradient to be directly backpropagated to earlier layers, enabling the training of networks with hundreds or even thousands of layers. The ResNet152V2 model used in this project is a 152-layer variant of this architecture.

2.3.2 DenseNet (Densely Connected Convolutional Networks)

Huang et al. (2017) proposed Densely Connected Convolutional Networks (DenseNets) as an extension of the ideas in ResNets [7]. In a DenseNet, each layer is connected to every other layer in a feed-forward fashion. This dense connectivity encourages feature reuse, strengthens feature propagation, and can lead to more compact and accurate models. The DenseNet121 model used here is a popular and effective variant.

2.3.3 EfficientNet

More recently, Tan and Le (2019) introduced EfficientNet, a family of models that resulted from a systematic study of model scaling [8]. They proposed a new "compound scaling" method that uniformly scales the network's depth, width, and resolution in a principled way. This approach led to models that achieve better accuracy with significantly fewer parameters and computational cost compared to previous architectures. EfficientNetB3, used in this project, is a mid-sized model from this family, designed to offer a good balance between performance and efficiency.

2.4 The Role of Transfer Learning

A key enabler for the successful application of deep learning in specialized domains like plant pathology is **transfer learning**. Training a deep CNN from scratch requires a very large labeled dataset (often millions of images), which is typically not available for specific tasks like potato disease detection.

Transfer learning overcomes this limitation by taking a model that has been pre-trained on a large, general-purpose dataset (such as ImageNet, which contains over 14 million images across 1000 categories) and adapting it for a new, specific task [9]. The underlying assumption is that the features learned by the model on the large dataset (e.g., edges, textures, shapes) are also useful for the new task.

The typical transfer learning workflow, and the one used in this project, involves two phases:

1. **Feature Extraction:** The pre-trained base model (e.g., DenseNet121) is used as a fixed feature extractor. A new, smaller classification head is added on top, and only the weights of this new head are trained on the target dataset.

2. **Fine-Tuning:** After the classification head has been trained, some of the top layers of the pre-trained base model are "unfrozen" and trained on the target dataset with a very low learning rate. This allows the model to fine-tune its learned features to be more specific to the nuances of the new task.

2.5 Comparative Analysis of Potato Disease Detection Projects

The specific problem of potato disease detection has been addressed by several researchers using deep learning. Table 1 provides a summary of some relevant studies, which serves as a benchmark for this project.

Table 1: Comparative Analysis of Selected Potato Disease Detection Studies.

Author(s) [Ref]	**Model(s) Used**	**Key Features/Methodology**	**Reported Accuracy**
Pujari et al. (2016) [10]	SVM, k-NN	Used traditional image processing with color and texture features.	SVM: 87.00%
Ramesh et al. (2018) [11]	VGG16, InceptionV3	Applied transfer learning with two popular CNN architectures on a dataset of 2,474 images.	VGG16: 91.00%
Islam et al. (2021) [12]	EfficientNet (B0-B7)	Conducted a comparative study of different EfficientNet variants on the PlantVillage dataset.	EfficientNetB4: 99.76%
Hassan et al. (2021) [13]	Custom CNN	Developed a lightweight custom CNN architecture from scratch for potato disease detection.	98.20%

2.6 Research Gap and Project Contribution

The literature confirms that deep learning, particularly transfer learning with advanced CNNs, is the state-of-the-art approach for potato disease detection. While many studies report very high accuracies, often on subsets of the PlantVillage dataset, there is a need for comparative studies that evaluate multiple modern architectures (like EfficientNet, DenseNet, and ResNet) on the same, consistent dataset and training pipeline.

This project contributes to the field by providing such a direct, head-to-head comparison of three powerful and widely used architectures. By implementing them within a unified and reproducible framework, this work offers a clear and unbiased assessment of their relative performance on this specific task. Furthermore, the project goes beyond just model evaluation by demonstrating a complete workflow that culminates in an interactive Gradio application, showcasing a practical path from research to deployment.

3 System Design and Architecture

3.1 Overall System Architecture

The system is architected as a modular, end-to-end pipeline that encapsulates the entire machine learning lifecycle. This design promotes maintainability, scalability, and clear separation of concerns. The flow of data and processes begins with data acquisition from an external source, proceeds through preprocessing and model training, and culminates in an interactive, deployed application for forecasting. The overall architecture is depicted in Figure 1.

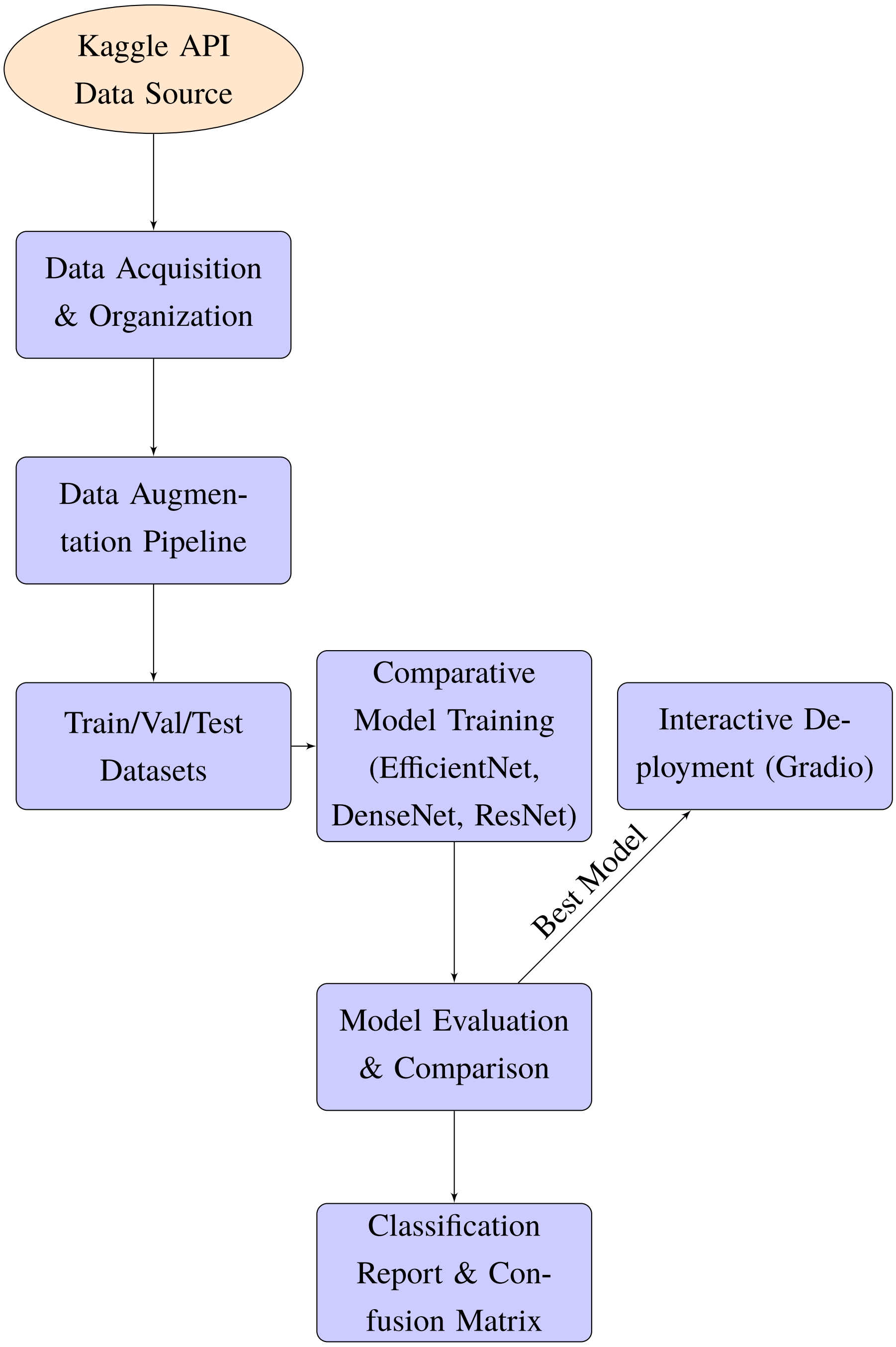

Figure 1: Overall System Architecture Diagram.

3.2 Component Description

Each component in the architecture performs a distinct function:

- **Data Acquisition:** This initial stage involves using the Kaggle API to download the "Potato Leaf Disease" dataset. The raw data is then unzipped and reorganized into a clean, standardized directory structure ('train', 'val', 'test').
- **Data Loading and Augmentation Pipeline:** This component uses TensorFlow's `image_dataset_from_directory` to create efficient data loading pipelines. An advanced data augmentation layer is integrated into the training pipeline to artificially expand the dataset and improve model robustness.
- **Comparative Model Training:** This is the core of the project, where three separate models are built using the EfficientNetB3, DenseNet121, and ResNet152V2 architectures as pre-trained bases. Each model is trained using the same two-phase transfer learning strategy to ensure a fair comparison.
- **Model Evaluation and Comparison:** After training, the best checkpoint of each model (based on validation loss) is evaluated on the held-out test set. Their final test accuracies are compared to identify the best-performing model.
- **Detailed Analysis:** The best model (DenseNet121) is subjected to a more detailed analysis, including the generation of a classification report and a confusion matrix to understand its performance on a per-class basis.
- **Interactive Deployment (Gradio):** The final, best-performing model is deployed using Gradio to create a simple, interactive web interface. This component serves as a proof-of-concept, making the model's predictive capabilities accessible to non-technical users.

3.3 Technology Stack

The project's technology stack was chosen to leverage modern, open-source tools that facilitate rapid development and robust implementation.

- **Programming Language:** Python 3
- **Core ML/NLP Libraries:**
  - **TensorFlow/Keras:** A leading deep learning framework used for building, training, and saving the CNN models [14].
  - **Scikit-learn:** Used for generating detailed classification reports and confusion matrices [15].
- **Data Manipulation and Utilities:** NumPy for numerical operations, Pillow (PIL) for image manipulation.
- **Data Acquisition:** The Kaggle API for downloading the dataset.
- **Visualization:** Matplotlib and Seaborn for generating static plots for results visualization.
- **Deployment & UI:** Gradio for creating the interactive web interface [16].

4 Methodology and Implementation

4.1 Data Acquisition and Characterization

The foundation of this project is the ”Potato Leaf Disease” dataset, a publicly available resource hosted on Kaggle [17].

- **Source:** The dataset was acquired via the Kaggle API.
- **Content:** The dataset contains 1500 images of potato leaves, divided into three classes:
  - Potato___Early_blight
  - Potato___Late_blight
  - Potato___healthy
- **Sample Images:** Examples from each class are shown below:

(a) Potato___Early_blight **(b)** Potato___healthy **(c)** Potato___Late_blight

Figure 2: Example images from the dataset showing different classes of potato leaves.

- **Data Split:** The dataset is pre-split into training (900 images), validation (300 images), and test (300 images) sets, with a balanced distribution of 100 images per class in the validation and test sets.

4.2 Data Preprocessing and Augmentation

A robust data pipeline was created using TensorFlow's `tf.data` API to efficiently load, preprocess, and augment the image data. The pipeline is visualized in Figure 3.

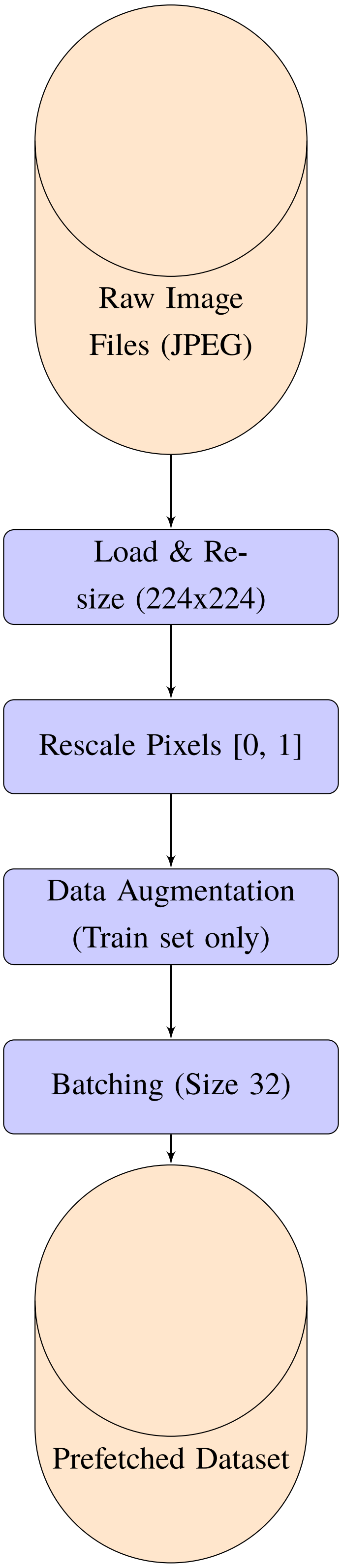

Figure 3: Data Preprocessing and Augmentation Pipeline.

4.2.1 Image Resizing and Rescaling

All images were resized to a uniform size of 224x224 pixels to match the input requirements of the pre-trained models. The pixel values, originally in the range [0, 255], were rescaled to the range [0, 1] by dividing by 255. This normalization is standard practice and helps in stabilizing the training process.

4.2.2 Data Augmentation

To prevent overfitting and improve the model's ability to generalize to new, unseen images, a series of data augmentation techniques were applied to the training set during training. This artificially increases the diversity of the training data. The augmentations included:

- Random Horizontal and Vertical Flips
- Random Rotation (up to 30%)
- Random Zoom (up to 30%)
- Random Contrast Adjustment (up to 30%)
- Random Brightness Adjustment (up to 30%)

4.3 Model Architectures and Training

4.3.1 Transfer Learning Approach

The core of the methodology is transfer learning. For each of the three architectures (EfficientNetB3, DenseNet121, ResNet152V2), a model was constructed by:

1. Loading the pre-trained base model with weights from ImageNet, excluding the top classification layer.

2. Adding a new custom classification head on top of the base model. This head consists of a Global Average Pooling layer, a Dense layer with 512 neurons and a ReLU activation function, a Dropout layer for regularization, and a final Dense layer with 3 neurons (one for each class) and a softmax activation function.

This approach is visualized in Figure 4.

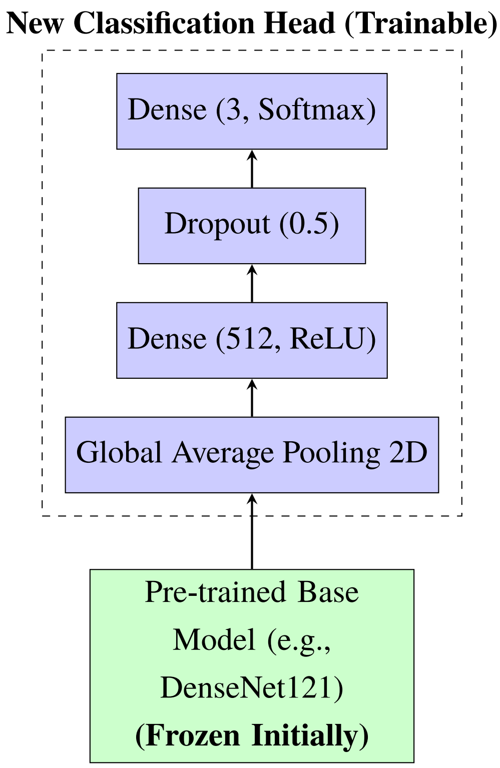

Figure 4: General Transfer Learning Model Architecture.

4.3.2 Two-Phase Training Strategy

A two-phase training strategy was employed for each model to maximize performance:

1. **Feature Extraction:** Initially, the weights of the pre-trained base model were frozen, and only the newly added classification head was trained for 25 epochs with a relatively high learning rate of 0.001. This allows the new layers to adapt to the dataset without disrupting the learned features in the base model.

2. **Fine-Tuning:** After the initial phase, the best weights were reloaded, and the top 40% of the layers in the base model were unfrozen. The entire model was then trained for another 25 epochs with a much lower learning rate of 0.00001. This allows the model to slightly adjust the pre-trained features to better fit the specifics of the potato leaf dataset.

4.3.3 Callbacks and Optimization

The training process was guided by several callbacks:

- **Optimizer:** Adam optimizer.
- **Loss Function:** Categorical Cross-Entropy, standard for multi-class classification.
- **ModelCheckpoint:** Saved the model weights only when the validation loss improved.
- **EarlyStopping:** Monitored the validation loss and stopped training if there was no improvement for 10 epochs.
- **ReduceLROnPlateau:** Reduced the learning rate by a factor of 5 if the validation loss did not improve for 5 epochs.

5 Results and Discussion

5.1 Training Dynamics and Performance

The training process for all three models was monitored by tracking the validation accuracy at the end of each epoch. Figure 5 shows the validation accuracy curves for EfficientNetB3, DenseNet121, and ResNet152V2 throughout the training process.

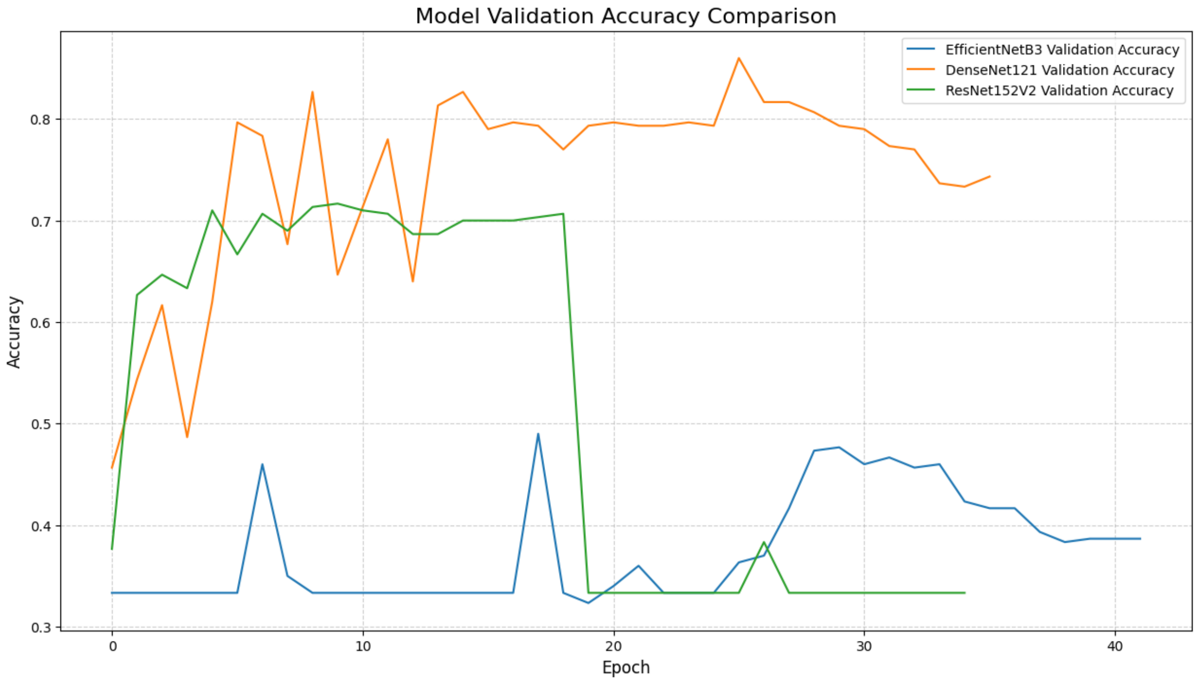

Figure 5: Model Validation Accuracy Comparison during Training.

From the plot, several key observations can be made:

- **DenseNet121 and ResNet152V2** both demonstrated strong and consistent learning, with their validation accuracies steadily increasing and reaching high levels (over 80%).
- **EfficientNetB3** struggled significantly during the initial feature extraction phase, with its accuracy remaining low. While it showed some improvement during the fine-tuning phase, it never reached the performance levels of the other two models. This could be due to the specific characteristics of the B3 variant being less suited to this dataset or requiring different hyperparameter settings.

- The performance of DenseNet121 and ResNet152V2 shows some volatility, which is common in training deep neural networks, but the overall trend is positive. The use of callbacks like ‘ModelCheckpoint‘ is crucial in such scenarios to ensure that the best-performing version of the model is saved.

5.2 Performance Evaluation on the Test Set

The final, definitive evaluation was performed on the held-out test set using the best weights saved for each model during training. The results are summarized in Table 2.

Table 2: Final Test Accuracy of the Three Models.

Model	**Test Accuracy (%)**
DenseNet121	**83.00%**
ResNet152V2	68.67%
EfficientNetB3	37.33%

The results clearly indicate that **DenseNet121 is the best-performing model** for this task, achieving a robust accuracy of 83.00%. ResNet152V2 performed reasonably well, while EfficientNetB3's performance was significantly lower. The superior performance of DenseNet121 can be attributed to its architecture, which encourages feature reuse and allows for a more efficient flow of information and gradients throughout the network.

5.3 Detailed Analysis of the Best Model (DenseNet121)

Given its superior performance, a more in-depth analysis of the DenseNet121 model was conducted.

5.3.1 Classification Report

The classification report (Figure 6) provides a breakdown of the model's performance for each of the three classes using precision, recall, and F1-score.

Classification Report:

	precision	recall	f1-score	support
Potato___Early_blight	0.80	0.94	0.87	100
Potato___Late_blight	0.78	0.76	0.77	100
Potato___healthy	0.92	0.79	0.85	100
accuracy			0.83	300
macro avg	0.84	0.83	0.83	300
weighted avg	0.84	0.83	0.83	300

Figure 6: Classification Report for DenseNet121 on the Test Set.

Key insights from the report include:

- The model is particularly good at identifying **Early Blight**, with a high recall of 0.94, meaning it correctly identified 94% of all Early Blight cases.
- The model has the highest precision (0.92) for the **healthy** class, indicating that when it predicts a leaf is healthy, it is very likely to be correct.
- The performance on **Late Blight** is the weakest of the three, with an F1-score of 0.77. This suggests that the visual features of Late Blight might be more ambiguous or have more overlap with the other two classes.

5.3.2 Confusion Matrix

The confusion matrix (Figure 7) provides a visual representation of the model's classification accuracy.

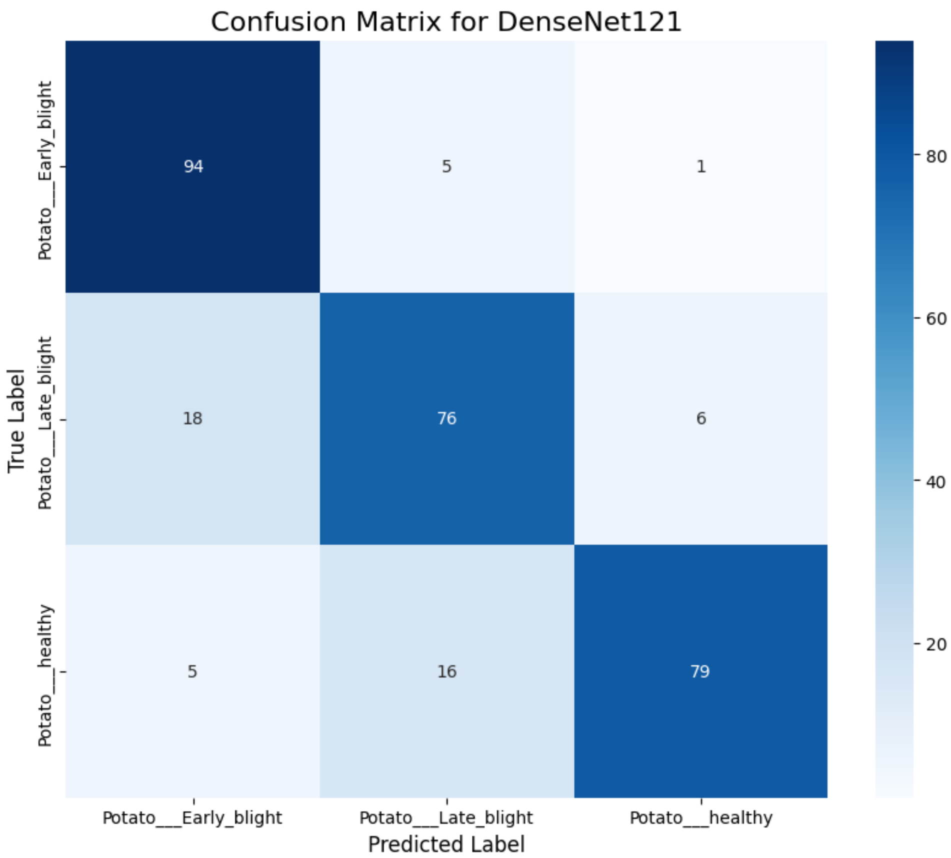

Figure 7: Confusion Matrix for DenseNet121 on the Test Set.

The main diagonal shows the number of correct predictions for each class. The off-diagonal elements show the misclassifications. The most significant confusion occurs between **Late Blight** and the other two classes. Specifically, 18 Late Blight images were misclassified as Early Blight, and 16 were misclassified as healthy. This confirms the observation from the classification report that Late Blight is the most challenging class for the model to identify correctly.

6 Deployment and Dissemination

6.1 Gradio for Interactive Deployment

A key objective of this project was to make the trained model accessible and usable for individuals without a technical background. To achieve this, the best-performing model, DenseNet121, was deployed as an interactive web application using the Gradio library [18]. Gradio is an excellent tool for rapid prototyping and demonstration as it allows for the creation of customizable user interfaces for machine learning models directly from Python code with minimal effort.

6.2 Interface Implementation Details

The deployment implementation consists of three core steps, encapsulated within a single Python script:

6.2.1 Loading the Inference Pipeline

The saved DenseNet121 model (`best_DenseNet121.keras`) and the list of class names are loaded from the disk. These artifacts are essential for making new predictions and presenting them in a human-readable format.

6.2.2 Defining the Prediction Function

A Python function, `predict_potato_disease(image)`, serves as the backend for the Gradio interface. This function takes an image as input, preprocesses it to match the model's input requirements (resizing and rescaling), passes it through the model to get predictions, and then formats the output as a dictionary of class names and their corresponding confidence scores.

6.2.3 Instantiating the Gradio Interface

The ‘gr.Interface‘ class is used to tie the UI components to the prediction function. The implementation is shown in Listing 1. It is configured with a title, a description, and example images to guide the user. The interface includes:

- An input component: A ‘gr.Image‘ component that allows users to upload an image.
- An output component: A ‘gr.Label‘ component that displays the top 3 predicted classes and their confidence scores.

When launched, Gradio creates a local web server and provides a public URL for sharing, making the model instantly accessible for testing and demonstration.

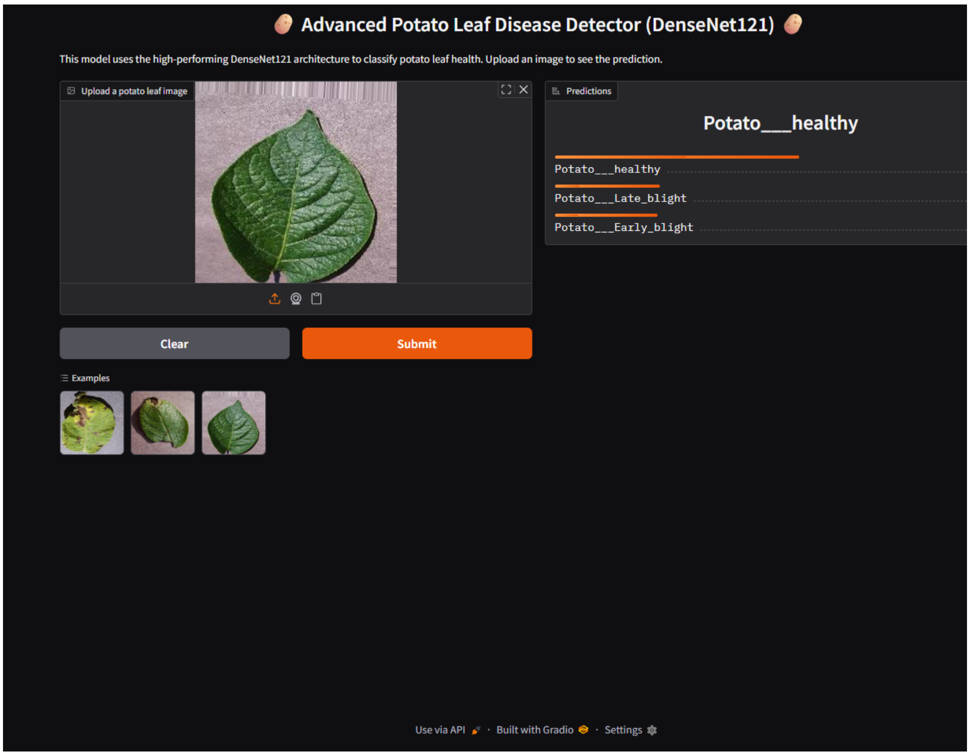

Figure 8: Gradio interface.

```
import gradio as gr

# (Assuming predict_potato_disease function is defined above)

iface = gr.Interface(
    fn=predict_potato_disease,
    inputs=gr.Image(type="numpy", label="Upload a potato leaf image"),
    outputs=gr.Label(num_top_classes=3, label="Predictions"),
    title="Advanced Potato Leaf Disease Detector (DenseNet121)",
    description="This model uses the high-performing DenseNet121 architecture to classify potato leaf health. Upload an image to see the prediction.",
    examples=example_paths,
    cache_examples=False,
    allow_flagging="never"
)

iface.launch(share=True)
```

Listing 1: Gradio interface definition.

7 Conclusion and Future Work

7.1 Conclusion

This project successfully designed, implemented, and evaluated an end-to-end system for the automated detection of potato leaf diseases using deep learning. Through a comparative analysis of three state-of-the-art CNN architectures, it was determined that the DenseNet121 model provided the highest performance, achieving a test accuracy of 83.00%.

A comprehensive pipeline was developed, encompassing data acquisition from Kaggle, a robust data augmentation strategy to enhance model generalization, and a two-phase transfer learning approach for effective training. The detailed evaluation of the best model revealed its strengths, particularly in identifying Early Blight, and highlighted areas for potential improvement, such as the classification of Late Blight.

The project culminated in the successful deployment of the DenseNet121 model as a user-friendly web application using Gradio. This not only serves as an effective proof-of-concept but also demonstrates a practical path for translating academic research into accessible tools that can have a real-world impact. The system provides a solid foundation for a decision support tool that could aid farmers in the timely and accurate diagnosis of potato diseases, ultimately contributing to improved crop management and food security.

7.2 Future Work

While the current system is robust and effective, several exciting avenues exist for future research and enhancement:

- **Dataset Expansion:** The model's performance could be further improved by training on a larger and more diverse dataset. This could involve collecting images from different geographical regions, under various lighting and weather conditions, and across multiple potato cultivars.
- **Advanced Architectures:** Explore even more recent architectures, such as Vision Transformers (ViT), which have shown state-of-the-art performance on many computer vision benchmarks and could potentially capture different types of features than CNNs.
- **Explainable AI (XAI):** To increase trust and interpretability, especially for use by farmers, XAI techniques like Grad-CAM could be integrated. This would allow the model to highlight the specific regions of the leaf image that were most influential in its decision, providing a visual explanation for its prediction.
- **Mobile and Edge Deployment:** For practical field use, the model could be optimized and deployed on edge devices, such as smartphones. This would involve model quantization and the use of frameworks like TensorFlow Lite to create a lightweight, efficient application that can run without a constant internet connection.
- **Multi-Disease and Severity Classification:** The system could be expanded to identify a wider range of potato diseases and even to classify the severity of an infection (e.g., early, middle, late stage). This would provide more nuanced information for treatment decisions.

By pursuing these future directions, the system developed in this project can evolve into an even more powerful, comprehensive, and impactful tool for the agricultural community.

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