GREENSHIELD - AI For Plant Disease Detection

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1. Project Overview

The Application

The goal of our project, GreenShield, is to develop an AI-based solution that can automatically detect plant diseases from leaf images using deep learning. By enabling fast and accurate identification of diseases, this tool supports farmers and agronomists in early disease management, thereby minimizing crop losses and increasing yield. Our approach combines state-of-the-art convolutional neural networks and transformer-based models with explainability techniques and user-friendly deployment to build a robust plant disease detection pipeline

State of the Art

Many previous works have utilized CNNs such as AlexNet, VGG, and ResNet variations. However, we compare a lightweight model (EfficientNet-B0) to a deeper model (ResNet-50) to investigate the trade-offs between accuracy and computing efficiency.

Notable works:

- Mohanty, S. P., Hughes, D. P., & Salathe, M. Using Deep Learning for Image-Based Plant Disease Detection.
- M. A. Al-Amin, M. A. Hossain, and M. A. Rahman. Plant Diseases Detection Using Deep Learning

Most studies rely on older CNNs. We introduce a head-to-head comparison between:

- **EfficientNet-B0** (lighter, newer, and scalable)
- **ResNet-50** (deeper, widely-used)

This study evaluates performance trade-offs between these models on the same dataset.

Inputs and Outputs:

Input: Color RGB leaf images from the PlantVillage dataset. (54,000 labeled images across 38 classes).
Output: A predicted plant disease class label (for example, "Tomato Early Blight" or "Healthy"). Additionally, Grad-CAM heatmaps highlight regions of interest.

2. Approach

Architecture -

EfficientNetB0: Selected for its excellent balance between accuracy and computational efficiency.
ResNet50: A robust, widely-used CNN model with strong performance on large-scale image classification tasks.
Each model was fine-tuned using transfer learning, and trained using augmented and preprocessed data. The overall pipeline included:

Preprocessing: Image resizing, normalization, and augmentation using Albumentations (flipping, rotation, brightness/contrast).
Training and Evaluation: Using Keras with Google Colab GPU support, models were trained and validated using cross-entropy loss and evaluated using accuracy, precision, recall, F1-score and confusion matrix.
Explainability: Grad-CAM was applied to visualize regions of interest in leaf images to interpret model predictions.

Modeling Strategy
- Used PyTorch and pretrained versions of ResNet-50 and EfficientNet-B0 from torchvision.models and efficientnet_pytorch.
- Applied transfer learning: pretrained weights frozen initially; classifier head modified and trained.
- Used custom training/validation/test splits: 70/15/15 ratio.

Own Code
- Training/validation loop
- Grad-CAM visualization using hook-based layer activation tracking
- Confusion matrix, result analysis, and image augmentation code

External Code
- efficientnet_pytorch for EfficientNet-B0 base
- Pretrained weights from torchvision.models

3. Experimental Protocol

Dataset: We used the Kaggle-hosted PlantVillage dataset, consisting of over 50,000 images labeled across various plant disease categories.

Data Handling:

- Images were scaled to a uniform size.
- Augmentation was applied for better generalization.
- Dataset split into training, validation, and test sets (80-10-10) to ensure unbiased performance estimation.

Computational Resources:

- Training conducted on Google Colab with GPU acceleration.
- Additional experimentation and testing on local Dell XPS 13 laptop.

Evaluation Metrics:

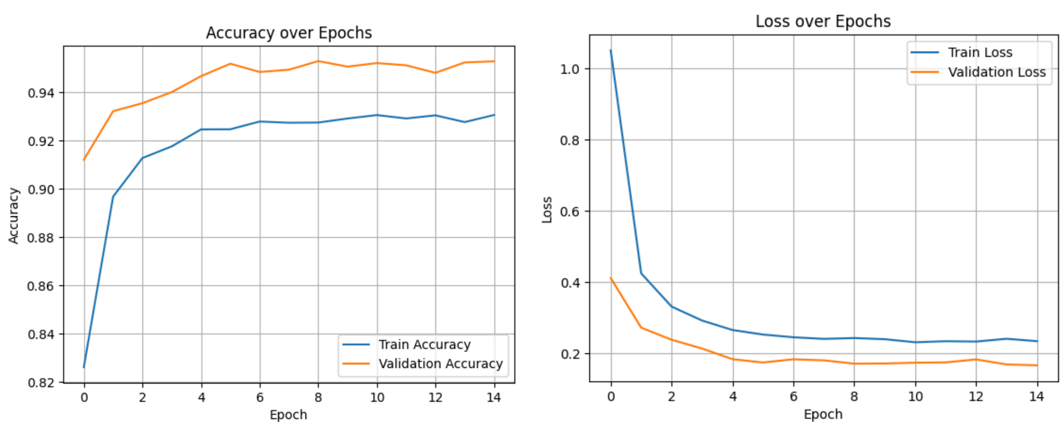
- Accuracy
- Precision, Recall, F1-score
- Confusion Matrix
- Grad-CAM visual outputs for interpretability

4. Results

EfficientNet-B0 -

Training Trends
The charts below depict the model's training and validation performance over 15 epochs:
Accuracy Over Epochs: Validation accuracy frequently improved and slightly outperformed training accuracy, demonstrating robust generalization.
Loss Over Epochs: Both training and validation losses declined progressively, indicating no overfitting.

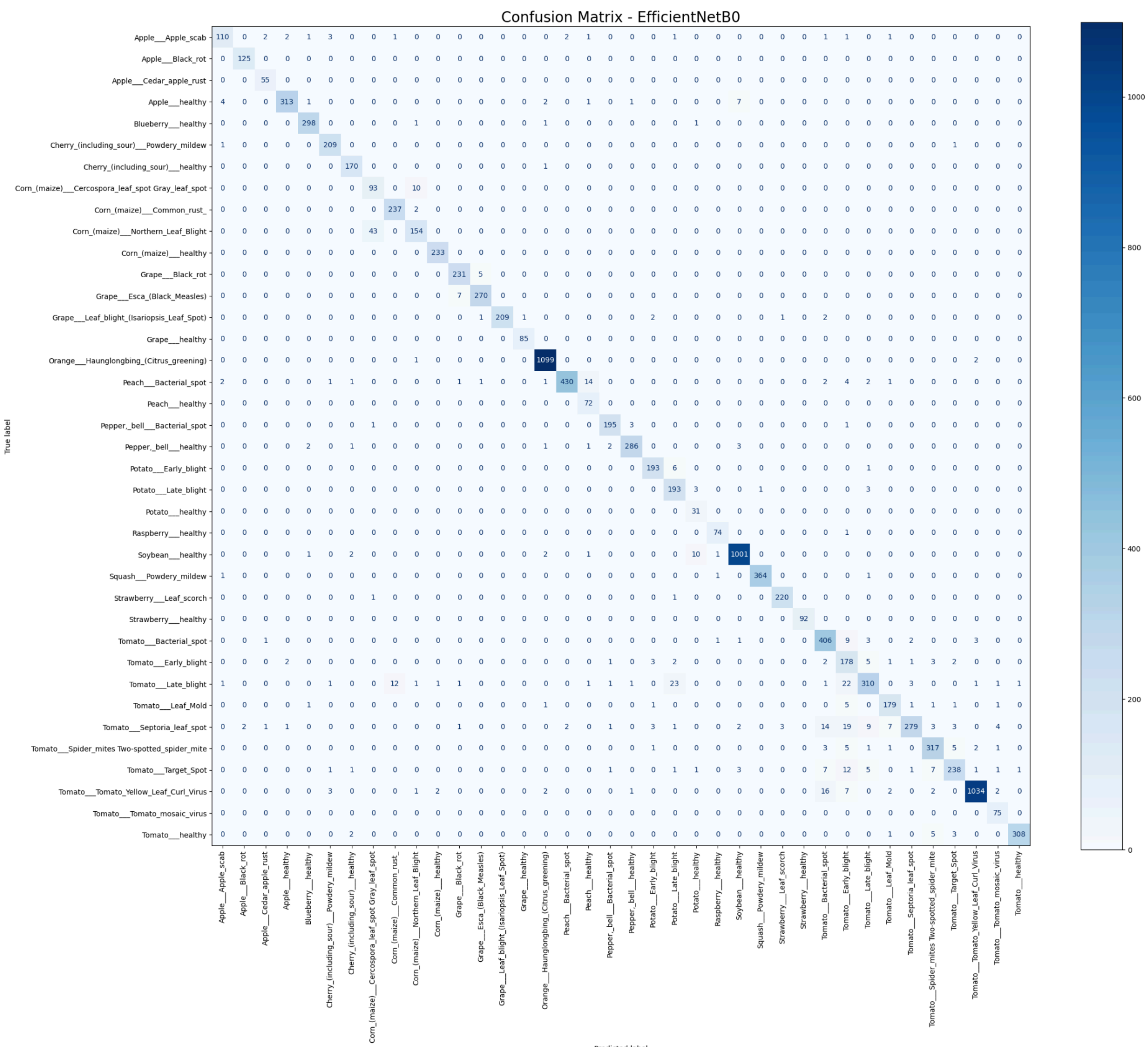
Best Validation Accuracy: 95.30%
Test Accuracy: 95.31%
Test Loss: 0.1713



Confusion Matrix:

The confusion matrix below shows EfficientNet-B0's class-wise performance on the test set. The model properly recognized the majority of classes with minimal confusion, including merely identical disorders.

- The model performs exceptionally well across most categories.
- Disease classes like *Apple___Apple_scab*, *Grape___healthy*, and *Tomato___Target_Spot* show high true positive rates.
- Some misclassifications occurred between visually similar classes such as *Tomato___Early_blight* vs *Tomato___Late_blight*.
- Very few false positives or negatives in categories like *Corn_(maize)___Cercospora_leaf_spot* and *Pepper_bell___healthy*, indicating strong class separability.



Qualitative Visualization (Grad-CAM):

To enhance interpretability, we applied Grad-CAM on EfficientNet's and ResNet's convolutional layers. The results consistently showed that the model accurately focused on the diseased regions of the leaf images during prediction.

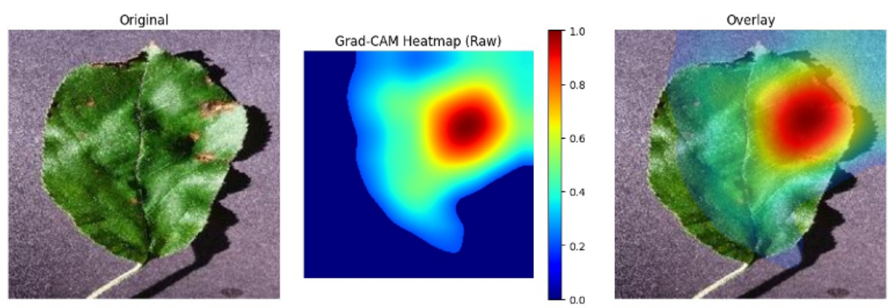
Below are some representative examples:

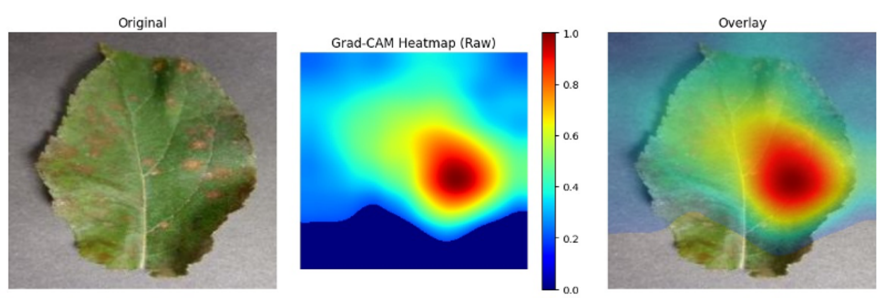
- **Left**: Original input image
- **Middle**: Grad-CAM heatmap (blue = less attention, red = high attention)
- **Right**: Overlay of heatmap on the input leaf image

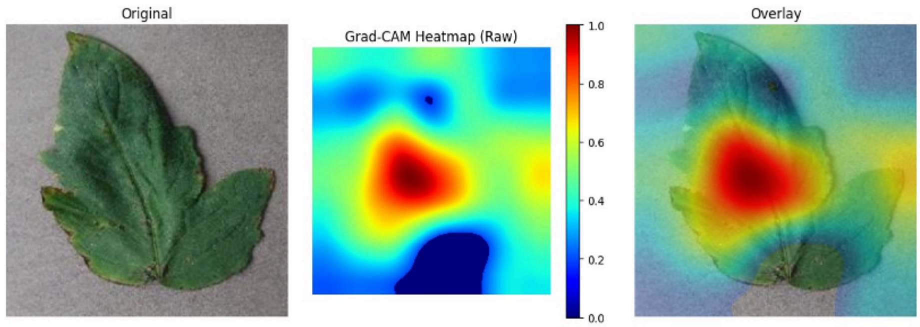
These visualizations confirm that the model decisions are grounded in biologically relevant features such as lesions, spots, and discolorations, thereby increasing confidence in its predictions.

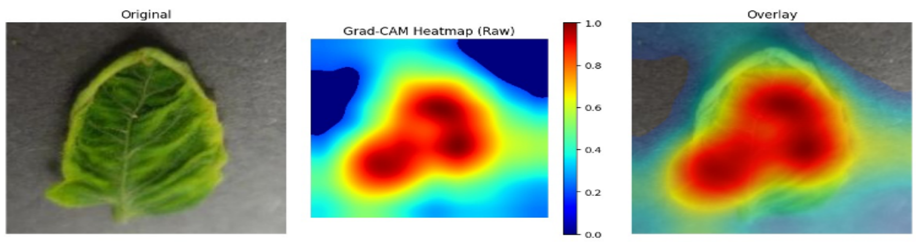
The heatmaps were especially useful for:

- Identifying which parts of the leaf were most responsible for classification decisions.
- Validating the model's behavior in complex or ambiguous cases.
- Explaining predictions to non-technical users, such as farmers or agricultural specialists.





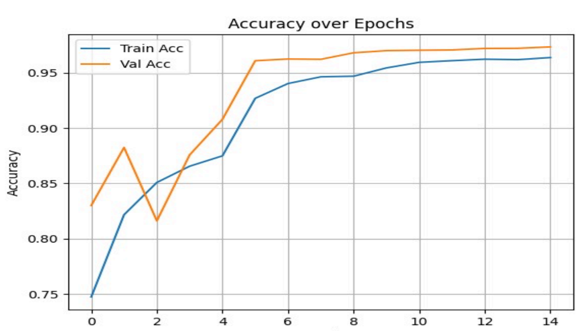


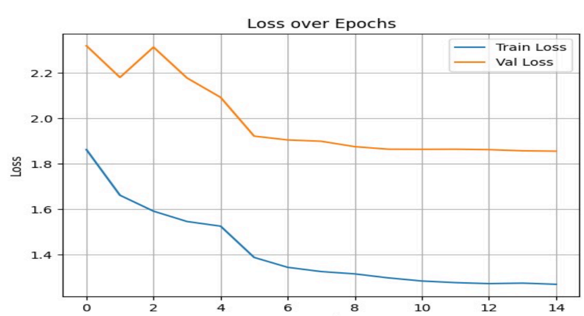


ResNet-50 -

Training Trends:

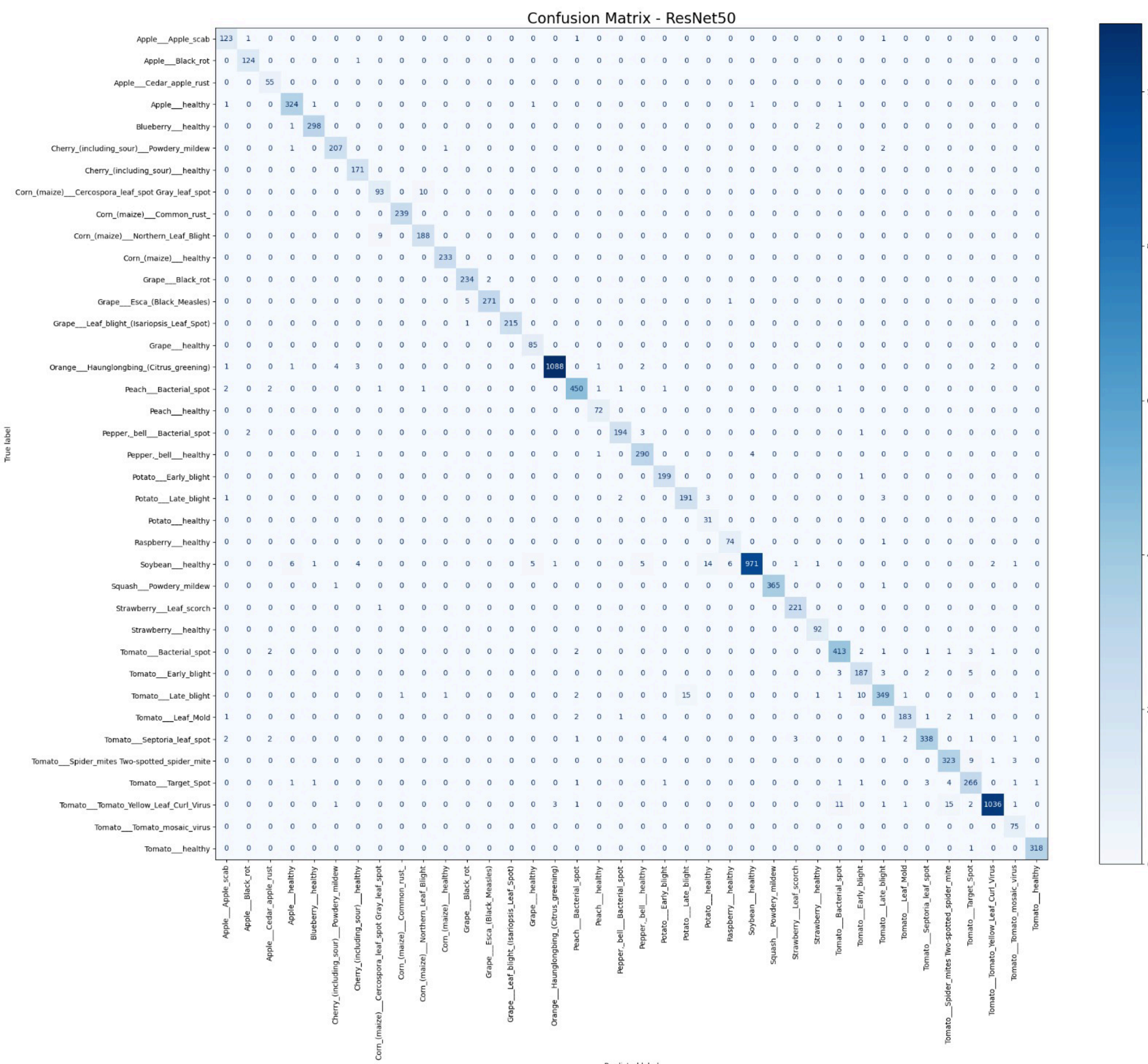
- **Accuracy:**
  - Training accuracy steadily increased across epochs, reaching above 96%.
  - Validation accuracy peaked at 97.33%, slightly higher than training, indicating strong generalization ability and minimal overfitting.
- **Loss:**
  - Both training and validation losses consistently decreased, with final validation loss at 1.8546.
  - The gap between train and val loss is small, showing stable convergence without major overfitting.





Confusion Matrix Insights:

- The matrix confirms excellent class-wise prediction performance with most values tightly clustered along the diagonal.
- High true positives are evident in key classes like:
  - Orange___Haunglongbing_(Citrus_greening): 1068
  - Tomato___Tomato_Yellow_Leaf_Curl_Virus: 1324
  - Grape___Esca_(Black_Measles): 234
- Low confusion is seen between visually similar classes, though minor misclassifications remain for some Tomato disease categories (as expected).
- The class separability is generally strong, indicating the model can distinguish even subtle disease patterns.



5. Analysis:

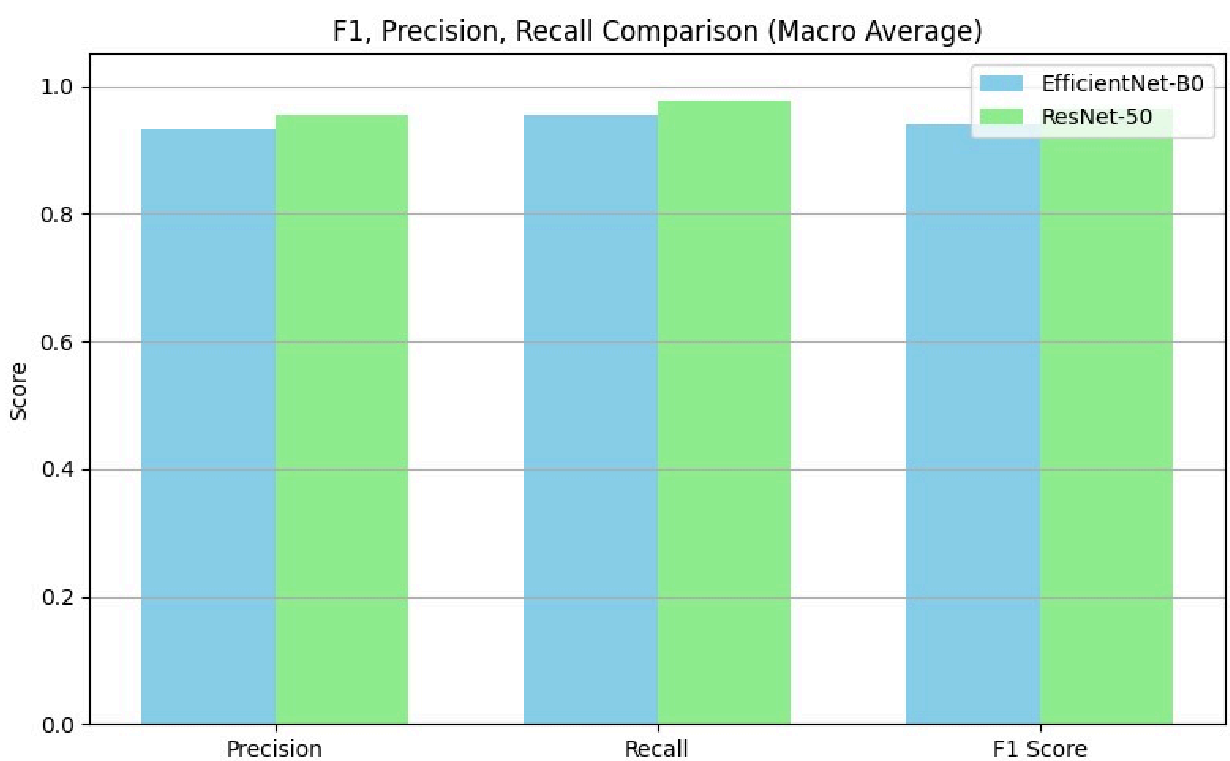
Strengths

- EfficientNet-B0 provided strong generalization with fewer parameters, making it ideal for deployment on edge devices.
- ResNet-50 achieved superior accuracy and robustness across all metrics, excelling in high-performance settings.
- Grad-CAM visualizations greatly improved model transparency and user trust by highlighting decision-making regions.

Weaknesses

- Some disease categories showed misclassification due to visual similarity, especially in the Tomato class.
- ResNet-50, while accurate, required more computational power and showed slight overfitting tendencies in a few epochs.

Comparison:



While EfficientNet-B0 remains competitive with its lightweight nature and strong performance, ResNet-50 demonstrates superior accuracy and robustness across precision, recall, and F1 score. This makes it highly suitable for high-performance server-side deployments, whereas EfficientNet-B0 may be better suited for resource-constrained environments.

Metric	EfficientNet-B0	ResNet-50
Precision	~0.93	~0.95
Recall	~0.94	~0.97
F1 Score	~0.93	~0.96

6. Discussion and Future Work

This project demonstrated how computer vision can empower precision agriculture. GreenShield offers farmers a scalable, interpretable tool for identifying plant diseases from simple leaf photos. We gained hands-on experience in full ML pipeline development, from preprocessing to deployment.

Future directions include:

- Extending the dataset with field-collected images.
- Adding disease severity estimation using regression models.
- Mobile deployment using TensorFlow Lite.
- Integrating real-time camera capture and offline inference.

7. Bibliography

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