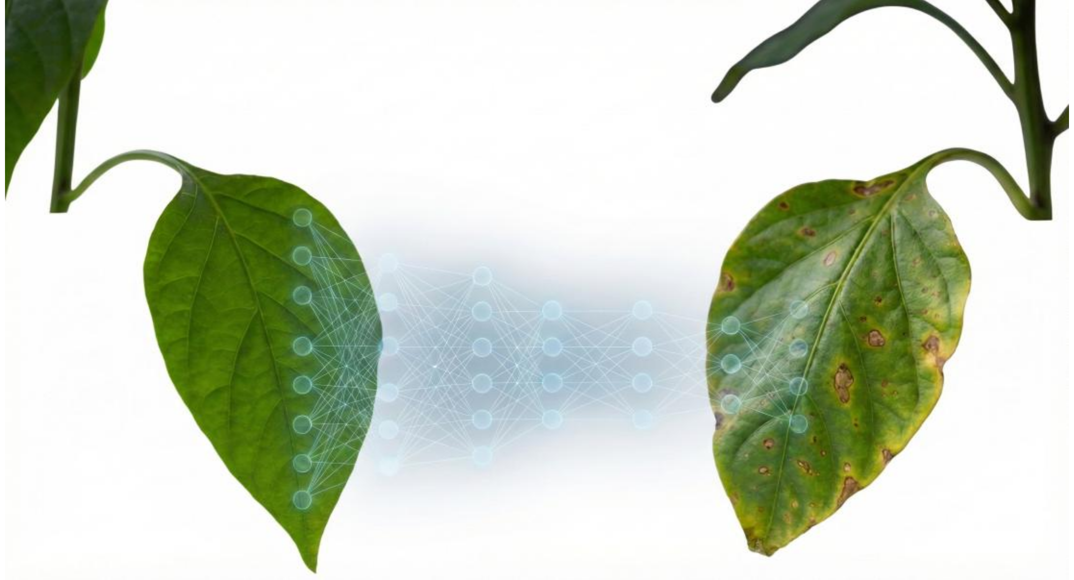
WELCOME



LIGHTWEIGHT CNN FOR PLANT DISEASE DETECTION: TRANSFER LEARNING AND XAI

February 05, 2026

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Introduction

Overview of Plant Disease?

A plant disease is a physiological disorder or abnormality that alters the normal structure and function of a plant. It stops the plant from performing to its maximum potential, leading to:

- **Reduced Yield:** Lower production of fruits, vegetables, or grains.
- **Poor Quality:** Aesthetic damage (spots, wilting) making produce unmarketable.
- **Economic Loss:** Significant financial loss for farmers and threats to global food security.

Introduction

These diseases are primarily caused by **pathogens** such as:

- **Fungi:** (e.g., Late Blight, Black Rot)
- **Bacteria:** (e.g., Bacterial Spot)
- **Viruses:** (e.g., Yellow Leaf Curl Virus)

Problem Statement

Manual Diagnosis Limitations:

- Time-consuming, subjective, and prone to human error.
- Scarcity of experts in remote agricultural areas.

Computational Constraints:

- High accuracy models (e.g., ResNet50) are too heavy for mobile devices.
- High memory usage and slow inference speed.

Problem Statement

The "Black Box" Issue:

- Lack of transparency in Deep Learning models.
- Farmers distrust "unexplained" predictions.

Accuracy vs. Efficiency Gap:

- Existing lightweight models often sacrifice accuracy for speed.

Literature Review

Existing Approaches:

- **Mohanty et al. (2016):** Used AlexNet/GoogLeNet. High accuracy (**99.35%**) but struggled with generalization [1].
- **Ferentinos (2018):** Used VGG16. Best accuracy (**99.53%**) but computationally very expensive (**138M params**) [2].
- **MobileNet Studies:** Focused on speed but often sacrificed accuracy on fine-grained diseases [3].

Literature Review

Limitations in Literature:

- Heavy models (ResNet/VGG) are unsuitable for mobile apps.
- Lack of **Explainability (XAI)** – most works are "Black Boxes."

How Our Work is Different (Novelty):

- **Optimal Balance:** Proposed **Custom CNN** matches ResNet accuracy but is **12x smaller**.
- **Transparency:** Integrated **Grad-CAM** to visually validate the model's focus (lesions vs. background).
- **Efficiency:** Surpassed MobileNetV2 in accuracy while remaining lightweight (**7.6 MB**).

Research Objectives

- To develop a **Custom Lightweight CNN** optimized for leaf disease classification.
- To implement Transfer Learning using **ResNet50** and **MobileNetV2** for comparative analysis.
- To validate model transparency using **Explainable AI (Grad-CAM)**.
- To deploy the best model via a user-friendly Web Application.

Dataset

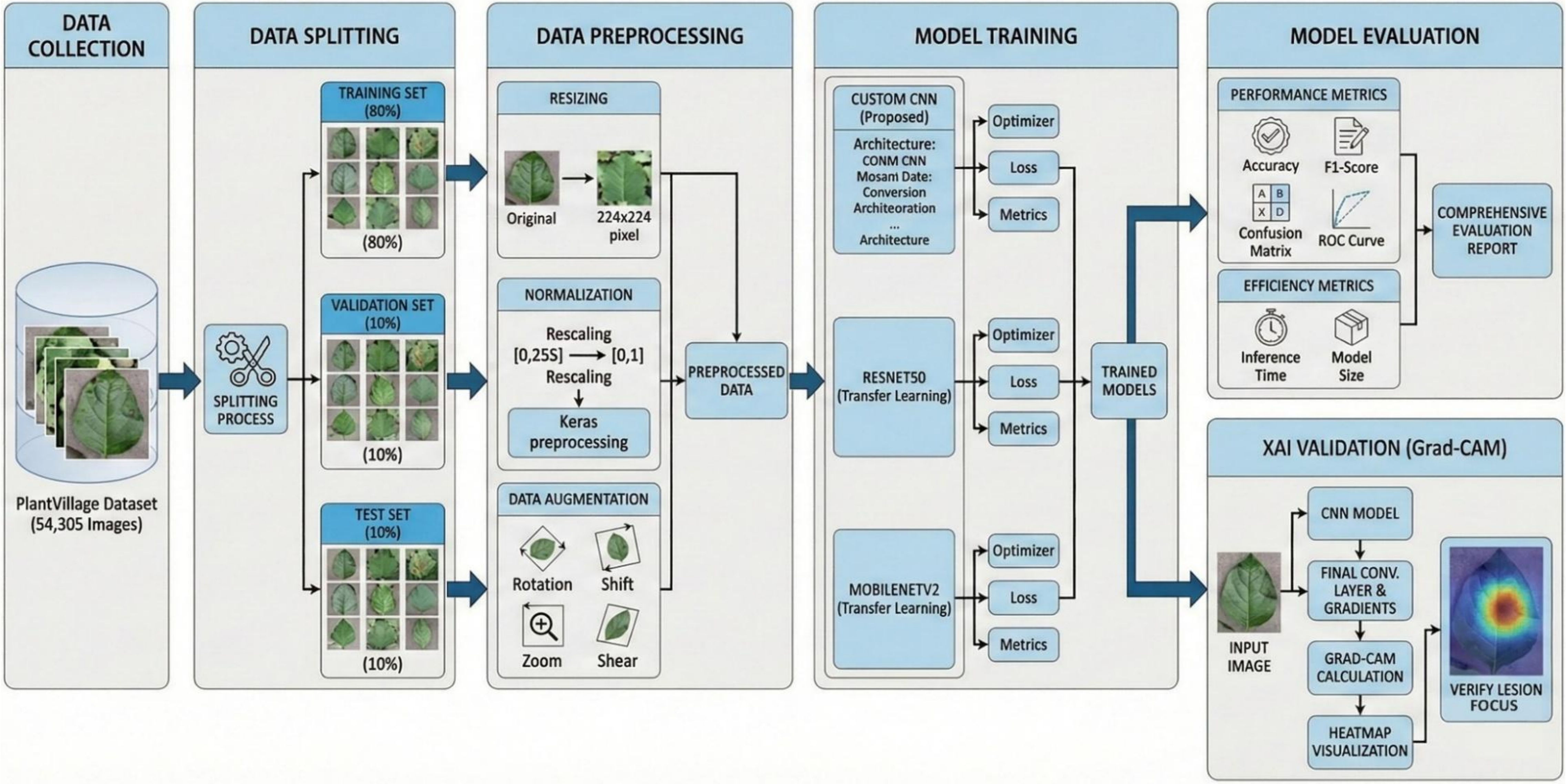
- **Source:** PlantVillage Dataset (Open Access).
- **Total Images:** 54,305 images.
- **Classes:** 38 distinct classes (Disease + Healthy).
- **Crop Species:** 14 different plants.
- **Environment:** Controlled laboratory settings (Uniform background).

Dataset

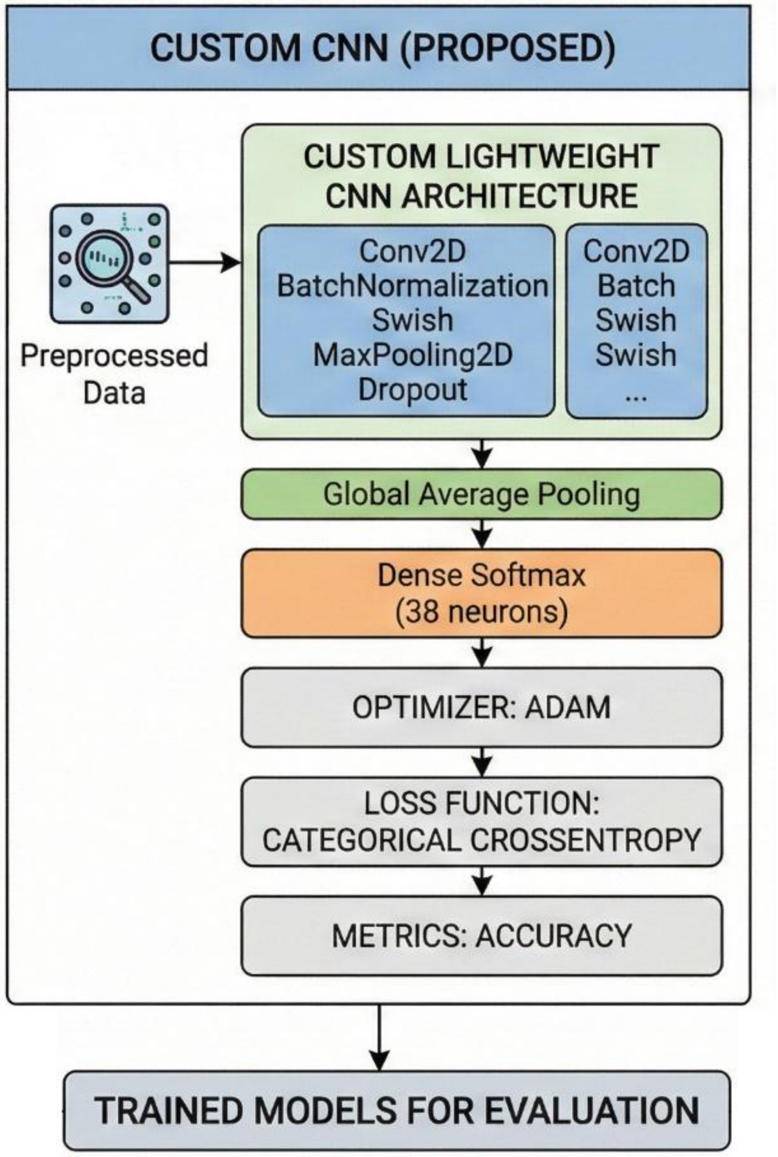
List of 14 Crop Species:

Apple	Blueberry
Cherry	Corn (Maize)
Tomato	Grape
Orange	Peach
Pepper (Bell)	Potato
Raspberry	Soybean
Squash	Strawberry

Methodology



Proposed CNN Architecture



Proposed CNN Architecture

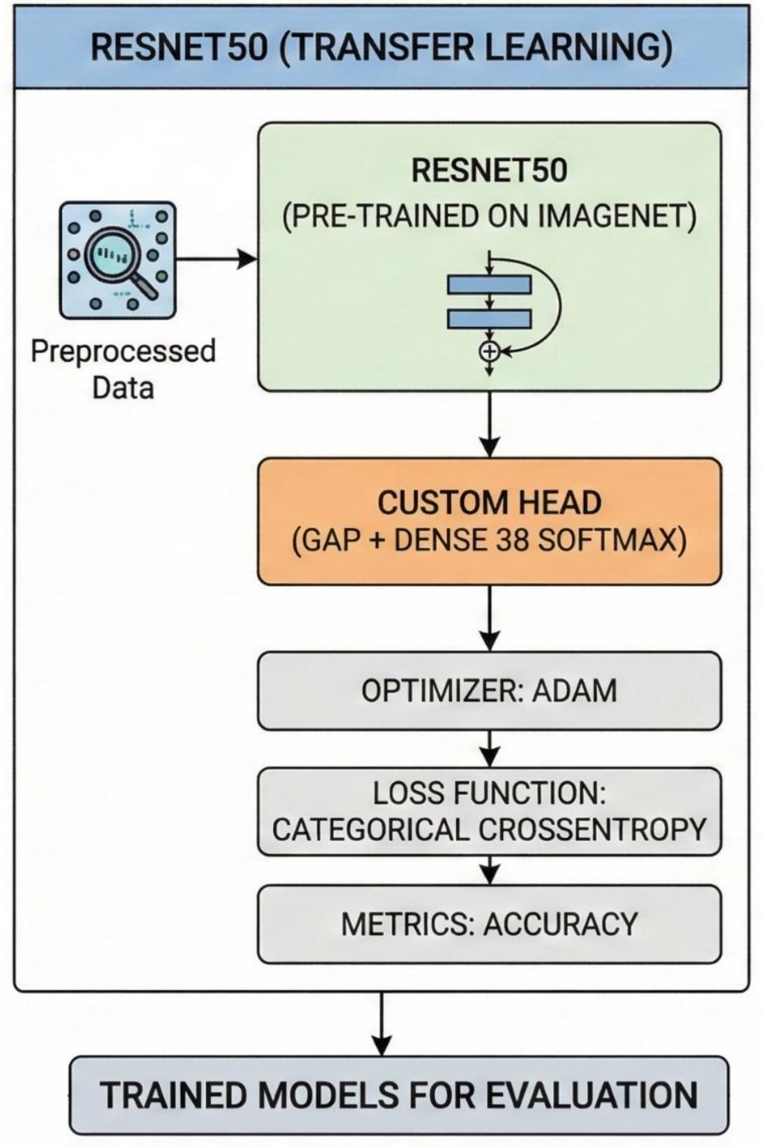
Key Specifications:

- **Input Shape:** 224 * 224 * 3 (RGB Images)
- **Total Parameters: 652,198 (approx. 0.65 Million)**
- **Structure:** 3 Convolutional Blocks + Classification Head
- **Regularization:** Batch Normalization & Dropout (0.25 - 0.5)

CNN Layer Configuration Summary:

Block	**Layer Type**	**Filters / Units**	**Output Shape**	**Function**
Input	Input Layer	-	(224, 224, 3)	Image Entry
Block 1	2x Conv2D + MaxPool	32 → 64	(112, 112, 64)	Low-level Features (Edges)
Block 2	2x Conv2D + MaxPool	64 → 128	(56, 56, 128)	Mid-level Features (Textures)
Block 3	2x Conv2D + MaxPool	128 → 256	(28, 28, 256)	High-level Features (Patterns)
Head	Global Avg Pooling	-	(256)	Dimensionality Reduction
Output	Dense (Softmax)	38	(38)	**38-Class Classification**

Transfer Learning with ResNet50



Transfer Learning with ResNet50

Model Strategy:

- **Base Model:** ResNet50 pre-trained on ImageNet (Weights Frozen).
- **Custom Classification Head:** Added to fit our 38 classes.

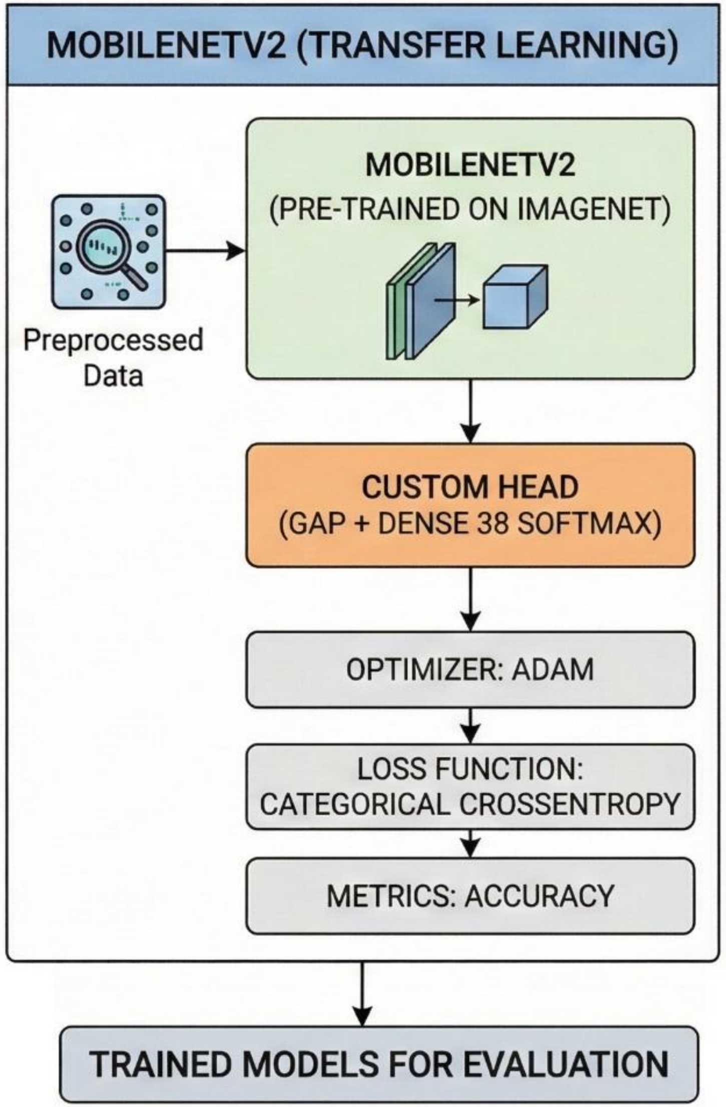
Custom Head Configuration:

- **Global Average Pooling:** Vectorizes feature maps.
- **Dense Layer (256):** With **Swish** activation & Batch Normalization.
- **Dropout (0.5):** To prevent overfitting.
- **Output Layer:** 38 Neurons (Softmax).

Parameter Summary:

Parameter Type	Count	Implication
Total Parameters	**24,123,046**	Deep feature extraction capability.
Non-Trainable	23,588,224	Frozen ImageNet weights (Base).
Trainable	**534,822**	**Only the Custom Head is trained.**

MobileNetV2 Architecture



MobileNetV2 Architecture

Model Strategy:

- **Pipeline:** Standard Transfer Learning.
- **Base:** MobileNetV2 (Pre-trained on ImageNet, Frozen).
- **Head:** Custom Classification Head (GAP → Dense → Dropout → Softmax).

Parameter Efficiency (The Advantage):

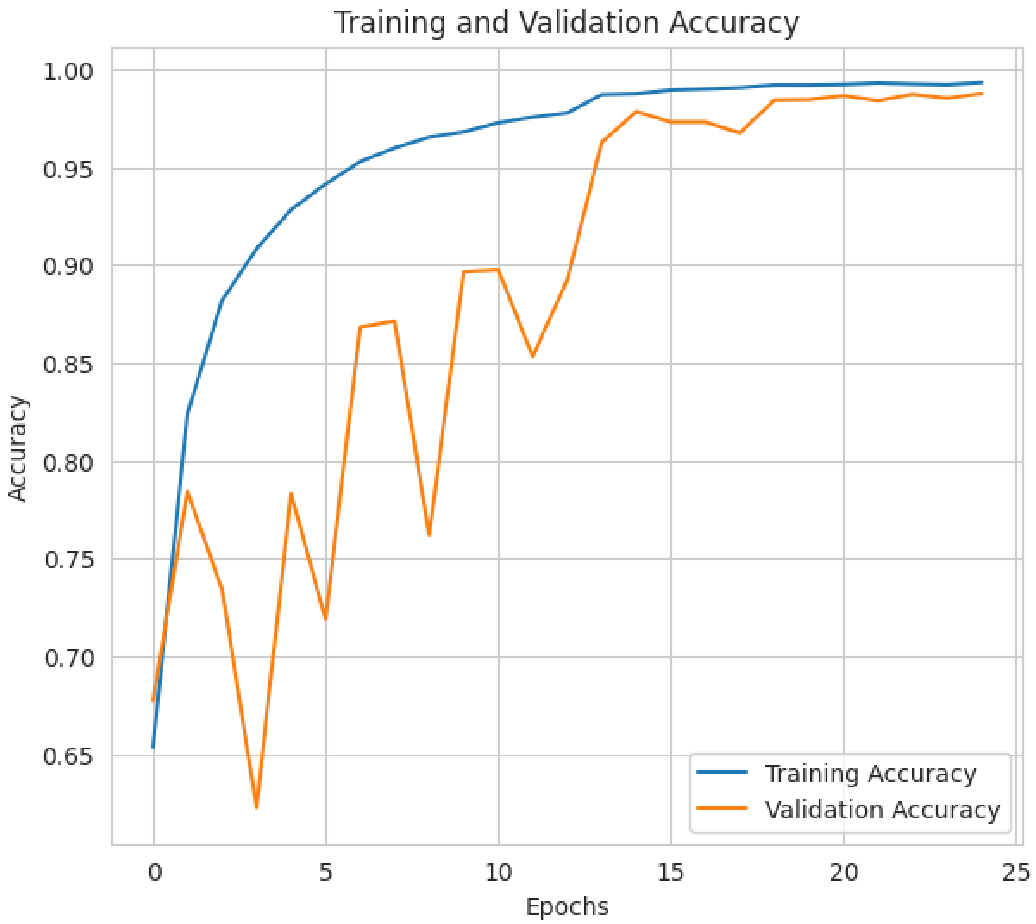
- **Total Parameters: ~2.6 Million** (10x smaller than ResNet50).
- **Target Use Case:** Highly suitable for **Smartphones & Edge Devices**.

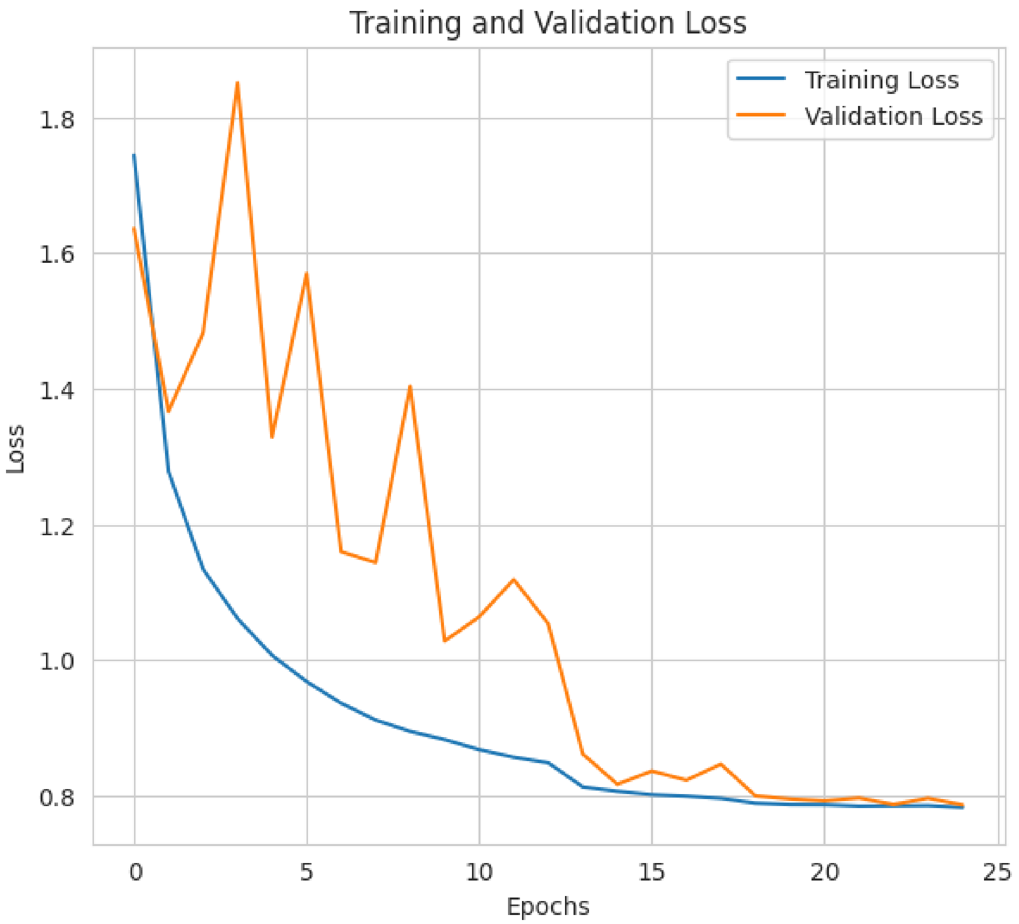
MobileNetV2 Architecture

Configuration Summary:

Component	Specification / Count
Input Shape	(224, 224, 3)
Custom Head	GAP → Dense(256) → Dropout(0.5) → Output(38)
Total Params	**2,596,710 (~2.6 M)**
Trainable	**338,214** (Head Only)
Non-Trainable	2,258,496 (Frozen Base)

Result(Custom CNN)





Result(Custom CNN)

Performance:

- **Test Accuracy: 98.71%** (Highest among all).
- **Loss:** 0.7809

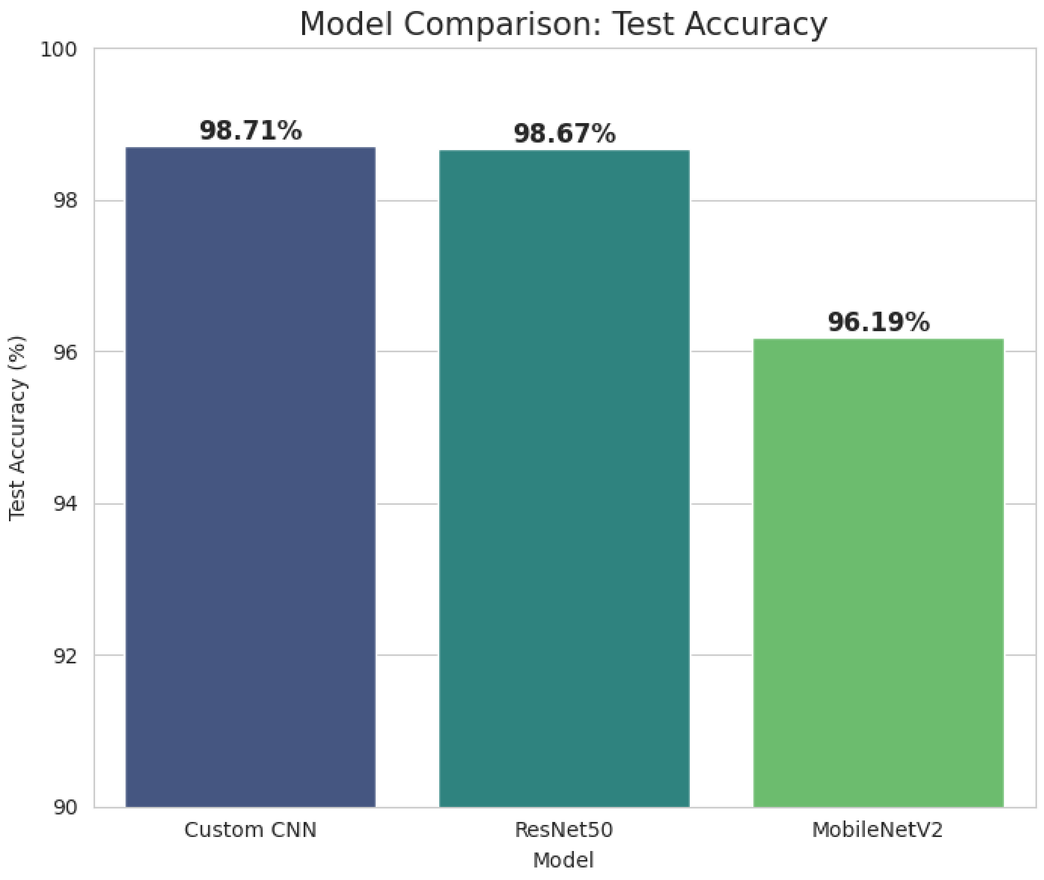
Observation

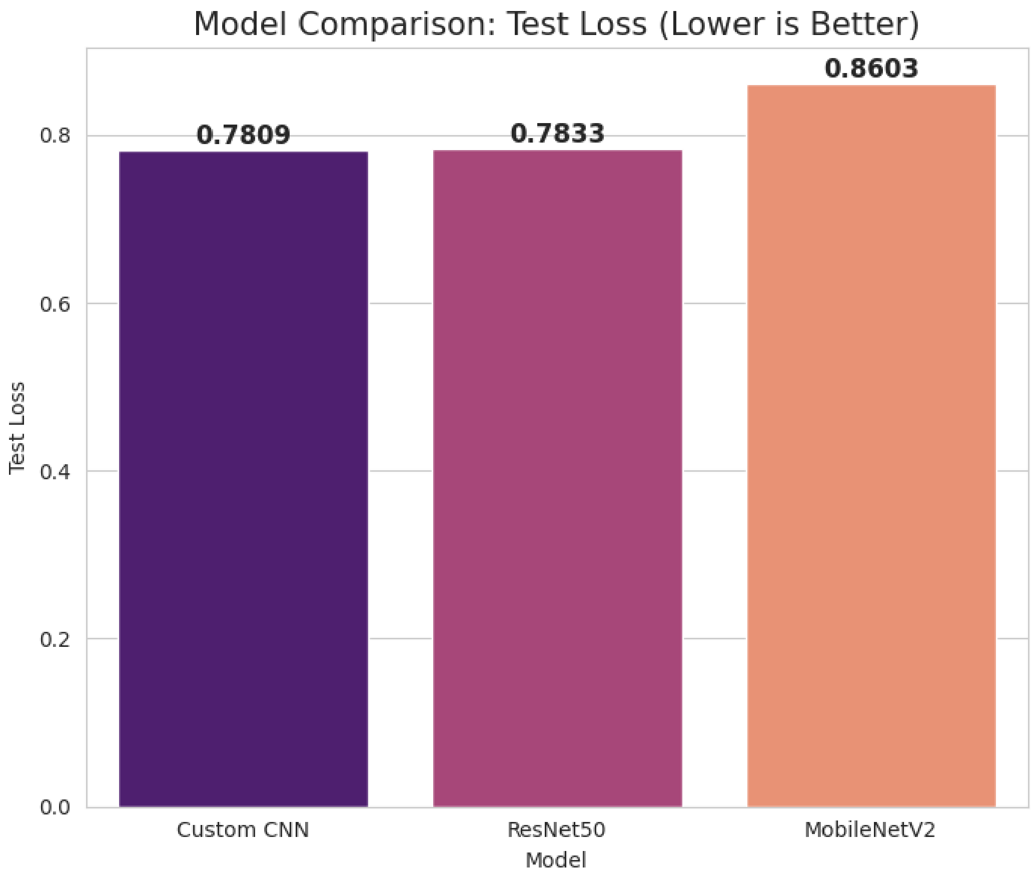
- Rapid convergence.
- Minimal gap between Training and Validation accuracy (No overfitting).

Classification Report(Test Set)

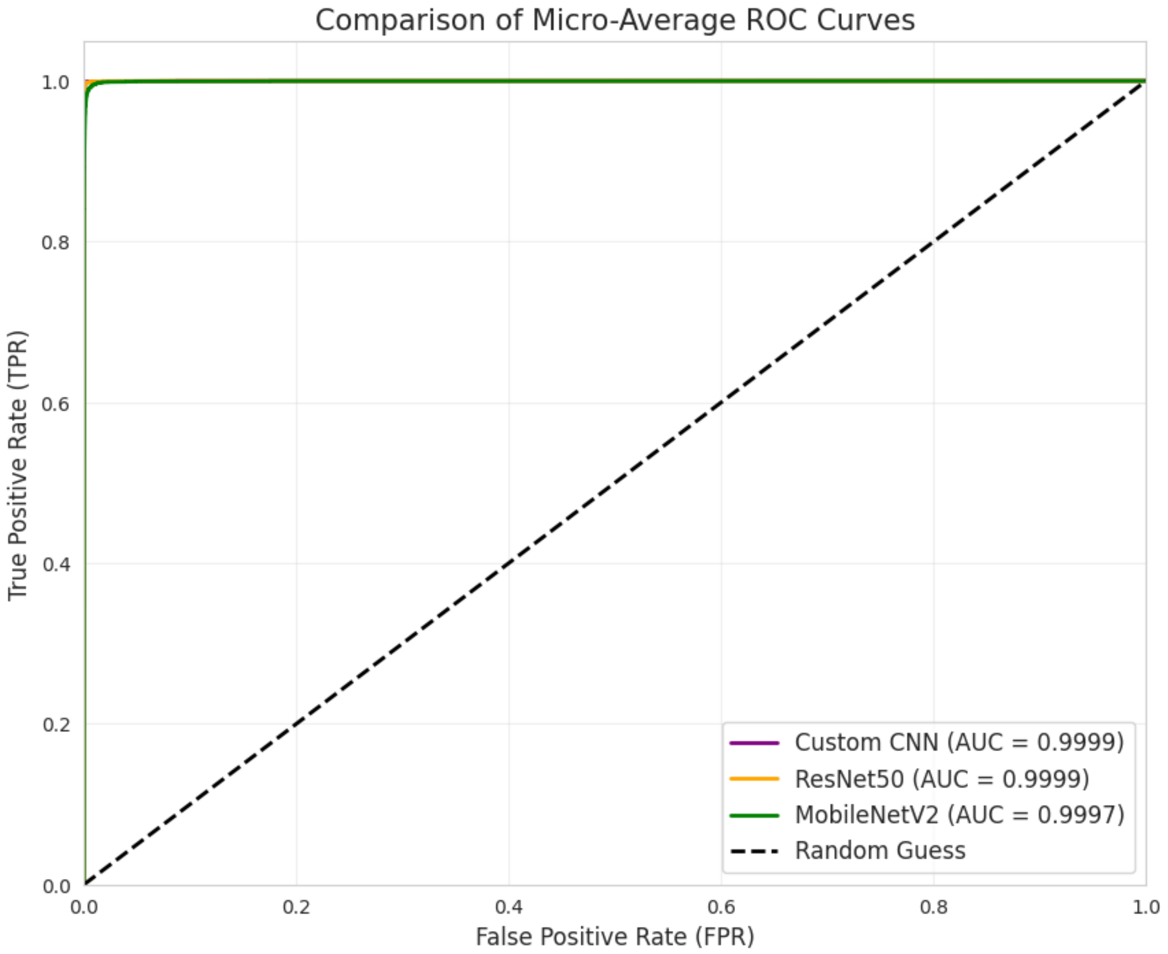
Metric	Score
Accuracy	99%
Macro Average (Precision)	99%
Macro Average (Recall)	99%
Macro Average (F1-Score)	99%
Weighted Average F1-Score	0.99

Model Comparison

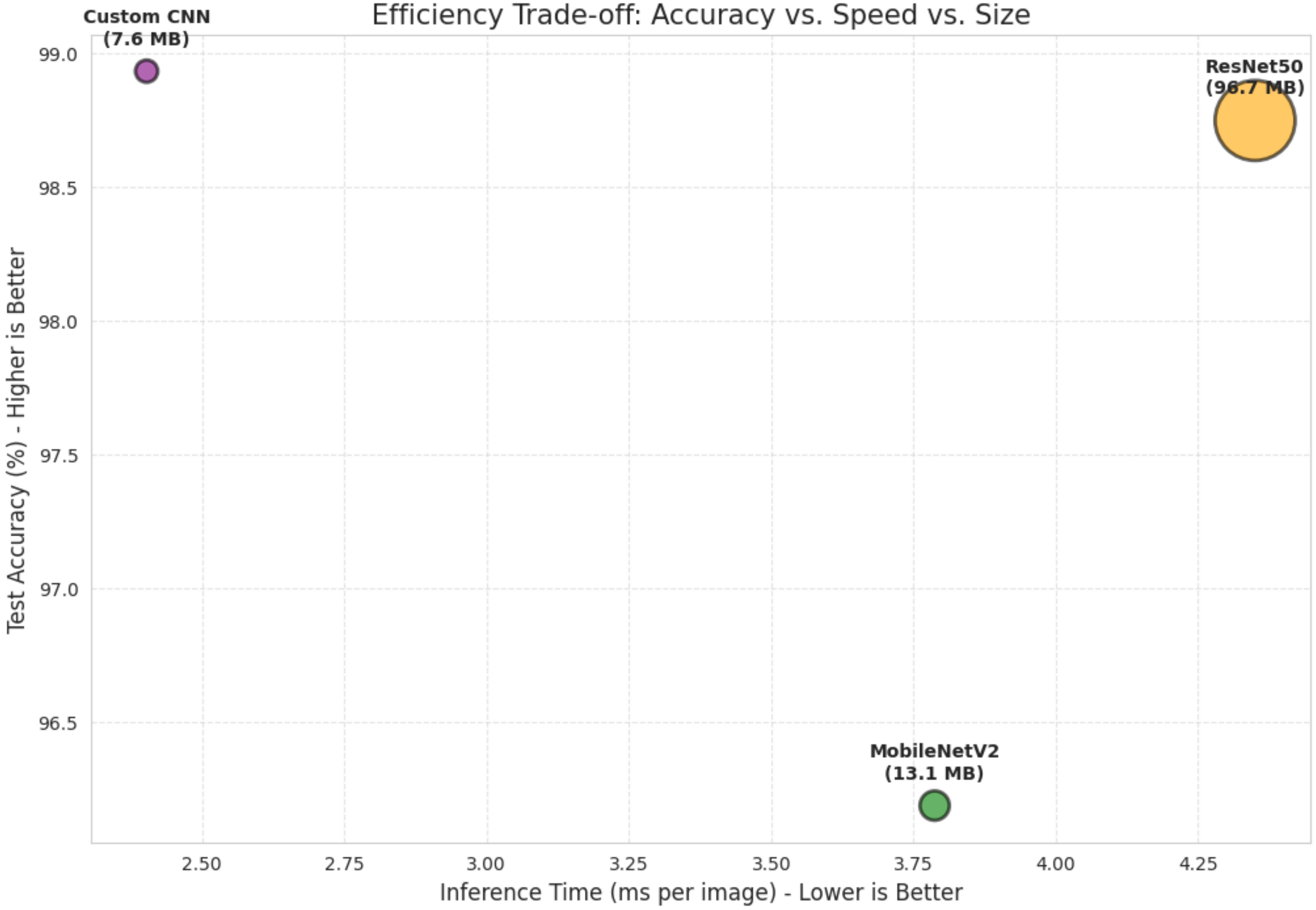




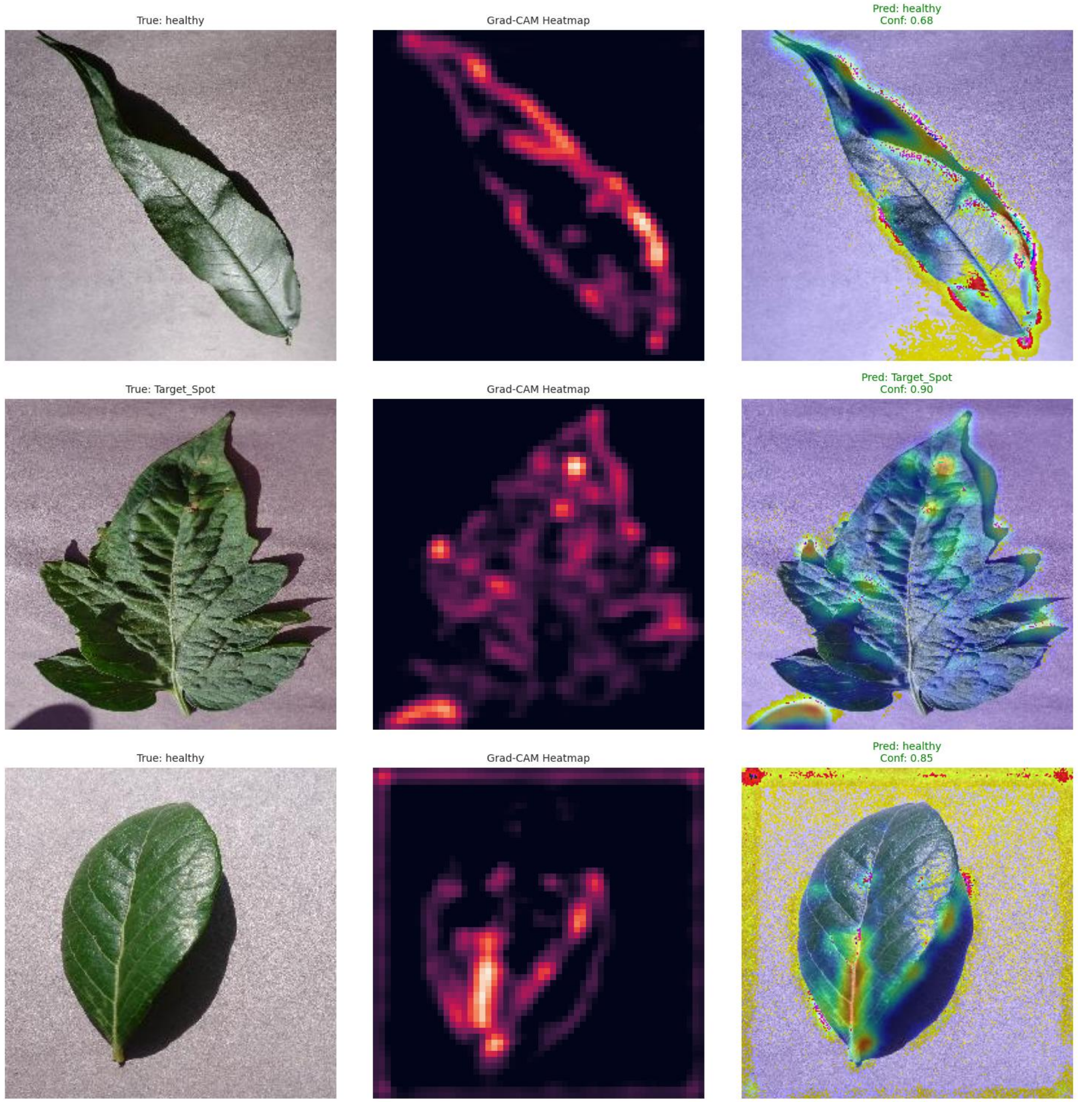
Model Comparison



Model Comparison



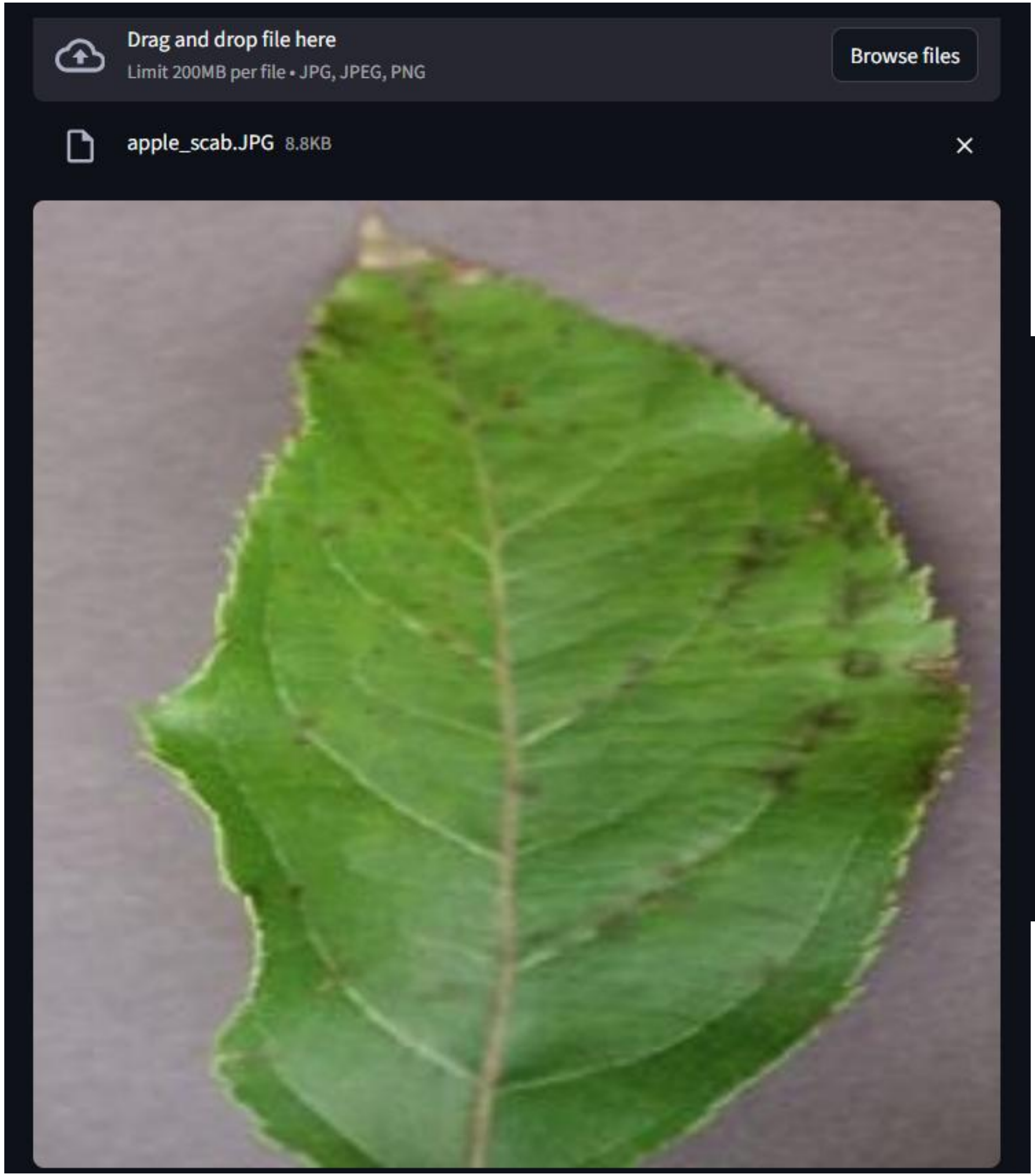
Explainable AI (Grad-CAM Validation)



Implementation (Web App Demo)

Streamlit APP

- **Tools:** Python, Streamlit, TensorFlow.
- **Features:**
    - Real-time Image Upload.
    - Instant Prediction with Confidence Score.
    - "Healthy" vs "Disease" visual alerts.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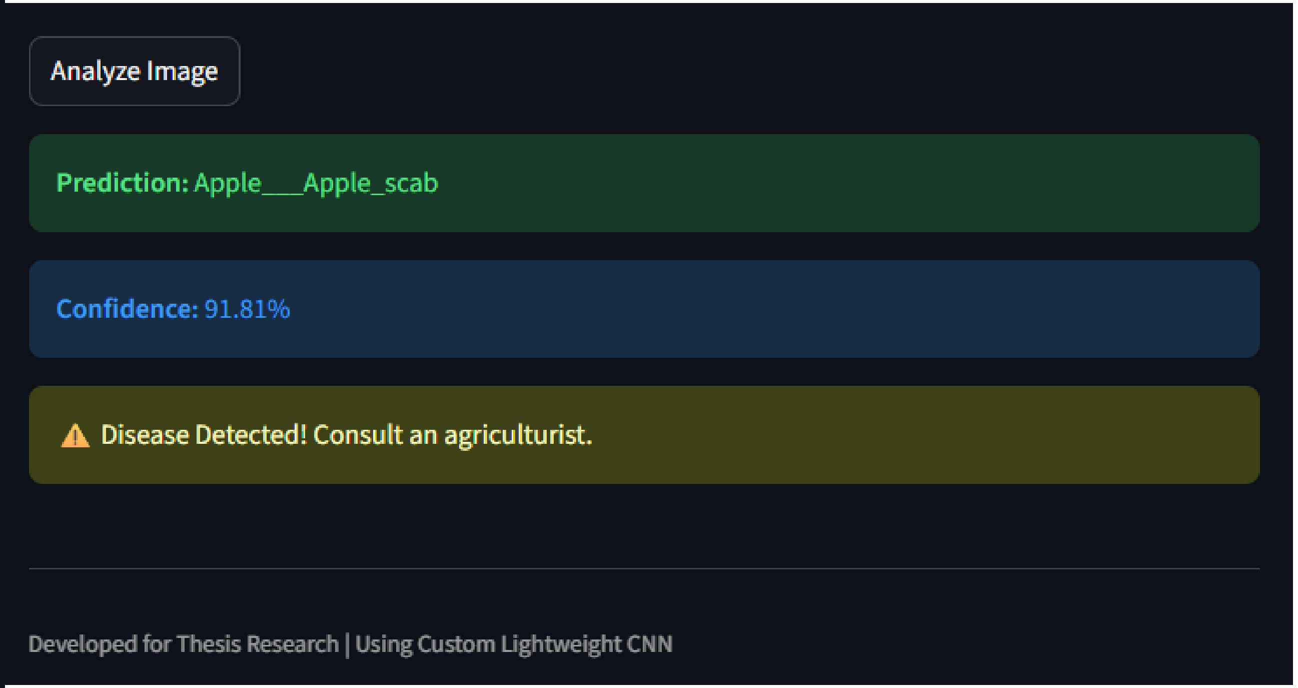
Limit 200MB per file • JPG, JPEG, PNG
Browse files
apple_scab.JPG 8.8KB


Analyze Image
Prediction: Apple___Apple_scab
Confidence: 91.81%
Disease Detected! Consult an agriculturist.
Developed for Thesis Research | Using Custom Lightweight CNN

Conclusion

- Developed a highly efficient CNN model (**98.71% Accuracy**).
- Outperformed MobileNetV2 and matched ResNet50 while being significantly lighter (**7.6 MB**).
- Validated reliability using **Grad-CAM**.
- Ready for deployment on edge devices/smartphones for farmers.

Future Work

Mobile App: Convert to TFLite for offline Android App.

Real-field Data: Collect images from local Bangladeshi fields to handle complex backgrounds.

Recommendation System: Suggest fertilizers/medicines based on detection.

References

- **[1]** D. P. Hughes and M. Salathé, "An open access repository of images on plant health," *arXiv preprint*, 2015.
- **[2]** S. P. Mohanty et al., "Using deep learning for image-based plant disease detection," *Frontiers in Plant Science*, 2016.
- **[3]** K. He et al., "Deep residual learning for image recognition (ResNet)," *IEEE CVPR*, 2016.
- **[4]** M. Sandler et al., "MobileNetV2: Inverted residuals and linear bottlenecks," *IEEE CVPR*, 2018.
- **[5]** K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, 2018.
- **[6]** R. R. Selvaraju et al., "Grad-CAM: Visual explanations from deep networks," *IEEE ICCV*, 2017.

For your attention

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