



Plant Village Diseases Image Classification by Transfer learn- ing

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Contents

1. Introduction	4
2. About dataset	4
Key characteristics of Dataset	4
3. Data preprocessing	5
3.1. Decreasing Approach (Class Reduction)	5
3.2. Image Resizing	5
3.3. Normalization / Rescaling	6
3.4. Train - Validation – Test Split	6
4. Handling Data imbalance	6
4.1. The problem	6
4.2. Solution : Class-Balanced Sampling	7
4.3. Data Augmentation	7
4.4. Data Loader setup	7
5. Model Architectures	8
5.1. VGG19	8
5.2. ResNet50	9
5.3. Inception V1	11
5.4. MobileNet V2	12
6. Experimental Setup	13
6.1. VGG19	13
6.1.1. Environment Setup	13
6.1.2. Training Method	14
6.2. ResNet	14
6.2.1. Environment Setup	14
6.2.2. Training Method	15
6.3. Inception V1	15
6.3.1. Environment Setup	15
6.3.2. Training Method	16
6.4. MobileNet	16

6.4.1. Environment Setup.....	16
6.4.2. Training Method	17
7. Results & Comparative Analysis	18
7.1. Performance Metrics.....	18
7.1.1. VGG 19	18
7.1.2. ResNet 50.....	21
7.1.3. Inception V1.....	24
7.1.4. MobileNet.....	27
7.2. Comparison Table	30
7.3. Analysis.....	30
7.3.1. VGG 19	30
7.3.2. ResNet.....	31
7.3.3. Inception v1	32
7.3.4. MobileNet.....	33
8. Conclusion	34

1. Introduction

Plant diseases reduce crop quality and yield, creating major challenges for farmers. Early detection is important, but traditional diagnosis requires experts and takes time. Deep learning provides an automated and accurate way to identify diseases from leaf images.

In this project, we use the **Plant Village dataset** to build a plant disease classification system. Four pretrained CNN architectures are evaluated: **VGG19 (Scartch Model)**, **ResNet**, **MobileNet**, and **Inception v1**. The images are resized, augmented, and balanced to improve model performance. The dataset is also split into training, validation, and testing sets.

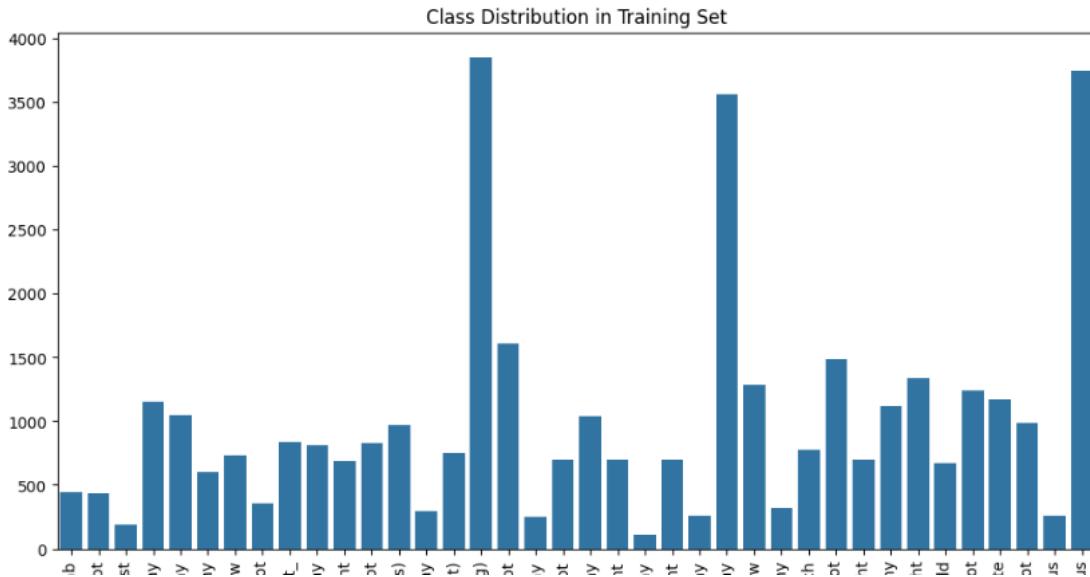
The goal of the project is to compare these architectures and determine which one provides the highest accuracy and best performance for detecting plant diseases. This system can help support modern agriculture by offering fast and reliable disease diagnosis.

2. About dataset

The dataset represents the diseases happened in plant that appeared in leaf images

Key characteristics of Dataset

1. Total number of images : ~ 54,300 images
2. Number of Classes : 38 Classes (Healthy / Not Healthy) of crop species
3. Crop species :14 different species(Apples, Blueberries, Cherries, Corn, Grape, Orange, Peach, Pepper, Potato, Raspberry, Soybean, Strawberry and Tomato)
4. Image type : RGB photos ; All photographed in same background but different lightening and leaf shape
5. Distribution : The Data is not perfectly balanced; some classes are representative (with max count images 3854) and some of them has few images



3. Data preprocessing

3.1. Decreasing Approach (Class Reduction)

To handle severe class imbalance in the PlantVillage dataset, a **decreasing approach** was applied.

Minor crops and under-represented disease categories were removed to prevent extremely skewed class distributions.

After removal, the dataset was reduced from **38 classes to 25–26 classes**, ensuring:

- Better class balance
- More meaningful representation
- Improved model performance and stability

This pruning step helps the models learn consistently without being dominated by rare classes that have only a few samples.

3.2. Image Resizing

All images were resized to **224 × 224 × 3**, which is the standard input size required by the CNN architectures used in this project (VGG19, ResNet, MobileNet, Inception v1). This ensures:

- Uniformity across all inputs
- Compatibility with pretrained ImageNet-based models
- Reduced computational cost

3.3. Normalization / Rescaling

Pixel values were normalized using ImageNet statistics:

$$\text{mean} = [0.485, 0.456, 0.406], \text{std} = [0.229, 0.224, 0.225]$$

Normalization benefits include:

- Faster and more stable training
- Compatibility with pretrained weights
- Improved numerical performance

3.4. Train - Validation – Test Split

The dataset was split as follows:

- 70% Training
- 15% Validation
- 15% Testing

This split ensures:

- Sufficient data for training
- Reliable model evaluation during training
- Unbiased final testing performance

4. Handling Data imbalance

4.1. The problem

Even after removing under-represented classes, the dataset still contains **unequal samples per class**.

Some disease categories naturally have more images, which can bias the model toward majority classes.

4.2. Solution : Class-Balanced Sampling

a. Compute Class weights.

Which obtained from training labels and Classes with fewer samples receive **higher weights**, ensuring they appear more frequently during training.

b. Weighted Random Sampler

The sampler uses these weights to draw samples so that **all classes appear with similar frequency** in each epoch, without duplicating images.

This approach ensures:

- Balanced batches
- Better minority class learning
- Improved overall accuracy

4.3. Data Augmentation

Used to increase dataset variability and help the model generalize better:

- **RandomHorizontalFlip**: Randomly flips the image left-right to simulate natural variations in leaf orientation.
- **RandomRotation(10°)**: Rotates images slightly to make the model robust against positional differences.
- **ToTensor()**: Converts the image into a PyTorch tensor and scales pixel values from 0–255 to 0–1.

Outcome : A more balanced and diverse training set that prevents model bias toward majority classes and enhances overall performance.

4.4. Data Loader setup

The dataloaders were configured as follows:

Training Data loader:

- Uses **WeightedRandomSampler**
- Balanced batches
- No shuffle needed

Validation & Test Data Loaders:

- No Sampler

- Shuffle = False
- Reflect real distribution for proper evaluation

5. Model Architectures

5.1. VGG19

i. Architecture:

The custom VGG19 model implemented from scratch follows the core design principles of the original VGG19 paper—using **deep stacks of small 3×3 convolution filters**, increasing the number of channels gradually, and applying **max pooling** to reduce spatial dimensions.

This implementation includes:

1. Feature Extraction Blocks (Block 1 → Block 5)

Each block consists of:

- **3×3 convolution layers** with padding=1
- **Batch Normalization** (an improvement over the original VGG19, which stabilizes training)
- **ReLU activation**
- A **MaxPool2d** layer to downsample by a factor of 2

The number of filters grows as follows:

- Block 1 → 64 channels
- Block 2 → 128 channels
- Block 3 → 256 channels
- Block 4 → 512 channels
- Block 5 → 512 channels

Each block deepens the network and increases its capacity to learn complex features.

2. Adaptive Average Pooling

After the 5 convolutional blocks, an **AdaptiveAvgPool2d(7×7)** layer ensures the output is always the same size, regardless of input resolution.

3. Fully Connected Classifier

The classifier is a simplified version of VGG19's original FC layers:

- Flatten
- Linear → 1024
- ReLU + Dropout
- Linear → 512

- ReLU + Dropout
- Linear \rightarrow num_classes (26)

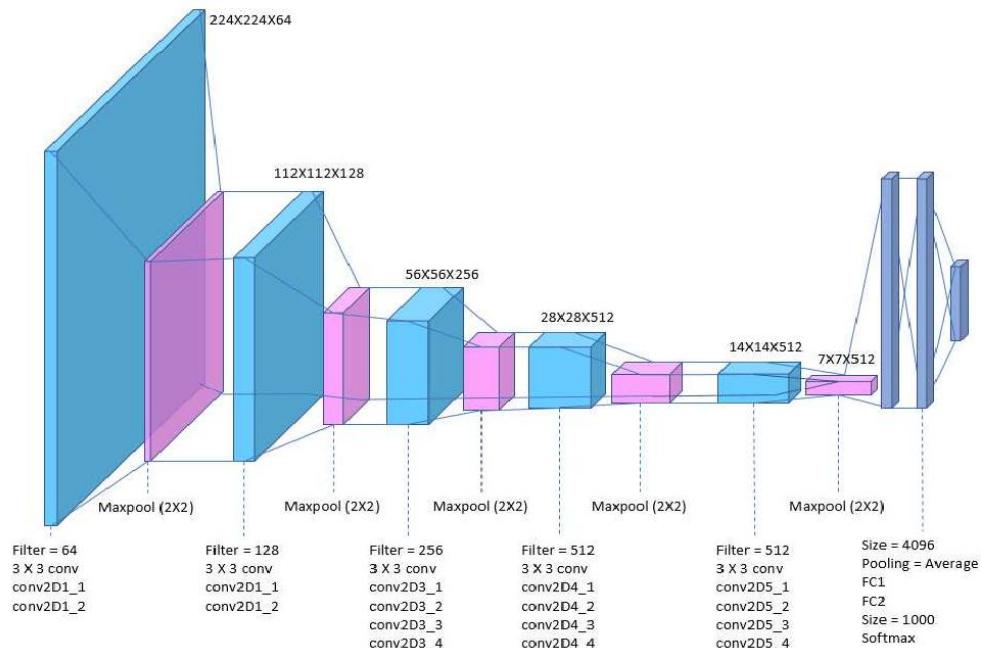
This reduces overfitting and improves generalization.

4. Forward Pass

The input passes through:

Block 1 \rightarrow Block 2 \rightarrow Block 3 \rightarrow Block 4 \rightarrow Block 5 \rightarrow AvgPool \rightarrow Classifier

ii. Diagram:



iii. Proper Referencing of the Original Papers:

Simonyan, K., & Zisserman, A. (2014).

“Very Deep Convolutional Networks for Large-Scale Image Recognition.”

<https://arxiv.org/abs/1409.1556>

5.2. ResNet50

i. Architecture:

ResNet-50 is a 50-layer deep convolutional network built using **bottleneck residual blocks**.

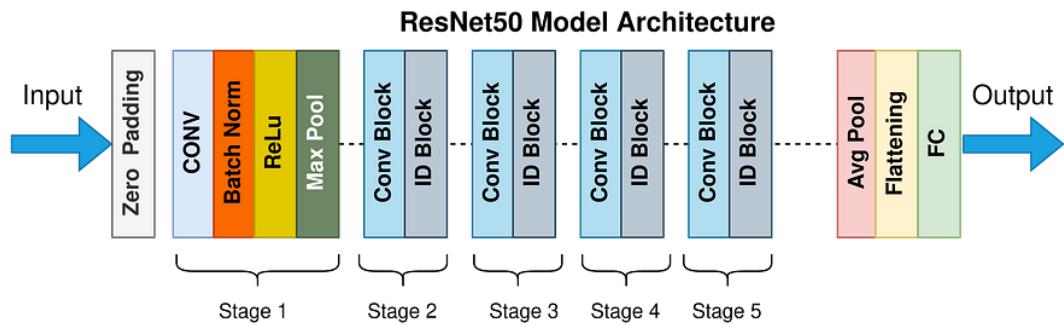
The main feature of ResNet is the use of **skip connections** (identity shortcuts) that

allow the gradient to flow easily through very deep networks, solving the vanishing gradient problem.

Key components:

1. Initial 7×7 Conv layer \rightarrow BatchNorm \rightarrow ReLU \rightarrow 3×3 MaxPool
2. **4 stages** of bottleneck residual blocks:
 - Conv2_x \rightarrow 3 blocks
 - Conv3_x \rightarrow 4 blocks
 - Conv4_x \rightarrow 6 blocks
 - Conv5_x \rightarrow 3 blocks
3. Each bottleneck block contains:
 - 1×1 Conv (reduce channels)
 - 3×3 Conv
 - 1×1 Conv (expand channels)
 - Skip connection
4. Global Average Pooling
5. Fully connected (FC) classification layer

ii. Diagram:



iii. Proper Referencing of the Original Papers:

He, K., Zhang, X., Ren, S., & Sun, J. (2015).

"Deep Residual Learning for Image Recognition."

In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778.

<https://arxiv.org/abs/1512.03385>

5.3. Inception V1

i. Architecture:

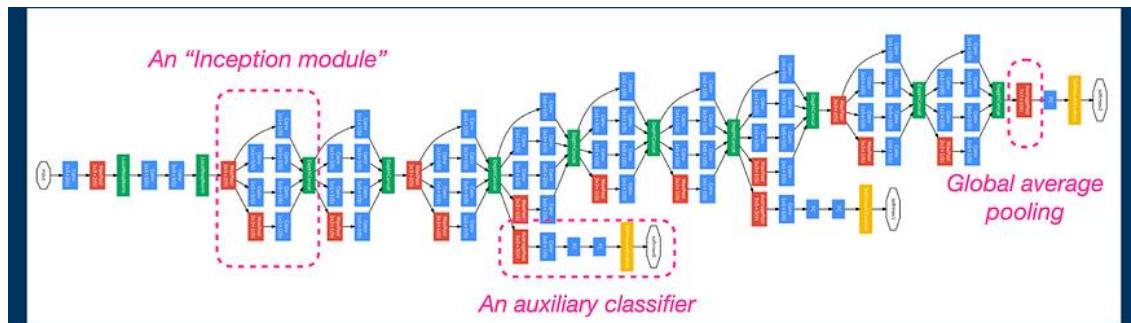
Inception v1 is a 22-layer deep CNN designed to improve both accuracy and computational efficiency.

Its main feature is the **Inception module**, which processes the input at multiple filter sizes simultaneously.

Key Components:

1. Parallel convolutions inside each module:
 - 1×1
 - 3×3
 - 5×5
 - MaxPool $\rightarrow 1 \times 1$
2. Dimensionality reduction using 1×1 Conv
3. Stacking multiple Inception modules
4. Auxiliary classifiers at intermediate layers (for training)
5. Global Average Pooling
6. Fully connected classifier

ii. Diagram:



iii. Proper Referencing of the Original Papers:

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., et al. (2014).

"Going Deeper with Convolutions."

In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). <https://arxiv.org/abs/1409.4842>

5.4. MobileNet V2

i. Architecture:

MobileNet is built for mobile and real-time applications.

The key idea in **MobileNetV2** is the **Inverted Residual Block with Linear Bottleneck**, which improves feature representation while keeping computation low.

Each block is built from three main steps:

1. **Expansion Layer (1×1 convolution)** → increases the number of channels
2. **Depthwise convolution (3×3)** → applies one filter per channel
3. **Projection Layer (1×1 convolution, linear)** → reduces the channels back to a compact form

MobileNetV2 also uses **shortcut (skip) connections** between blocks when the input and output dimensions match.

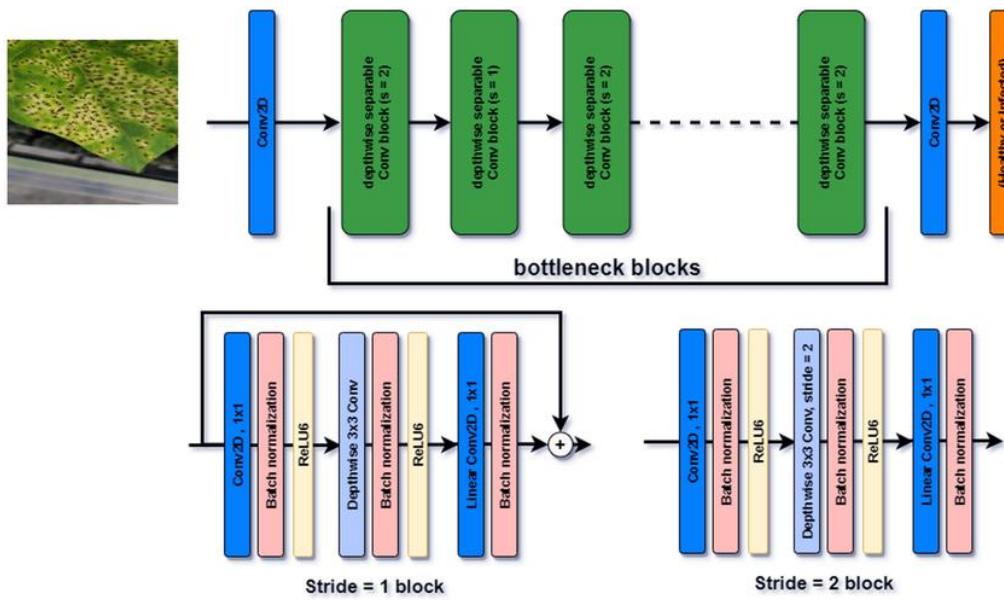
This results in:

- ~30–40% fewer parameters than standard CNNs
- Much faster inference on mobile and embedded devices
- Improved accuracy compared to MobileNetV1

Architecture Flow:

1. **Initial 3×3 convolution**
2. **Repeated inverted residual blocks:**
 - 1×1 Expansion Conv
 - 3×3 Depthwise Conv
 - 1×1 Linear Projection Conv
3. **Global Average Pooling**
4. **Fully connected classifier**

ii. Diagram:



iii. Proper Referencing of the Original Papers:

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., et al. (2017).

“MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications.”

<https://arxiv.org/abs/1704.04861>

6. Experimental Setup

6.1. VGG19

6.1.1. Environment Setup

i. GPU:

CUDA GPU

ii. Library:

PyTorch (torch, torch.nn, torch.optim, tqdm)

iii. Training Epochs: **15 Epochs**

iv. Batch Size: **16**

v. Optimizer:

Adam optimizer

vi. Loss Function:

CrossEntropyLoss

vii. Learning Rate: **0.0001 (1e-4)**

6.1.2. Training Method

i. Method:

Training from scratch using custom VGG19 architecture with supervised learning and mini-batch gradient descent.

ii. Frozen layers: **None (all layers are trainable)**

iii. Fine Tuning process:

No fine-tuning applied (model trained entirely from scratch).

Early stopping implemented with:

- Patience = 10
- Min delta = 0.001

6.2. ResNet

6.2.1. Environment Setup

i. GPU:

CUDA GPU

ii. Library:

PyTorch, Torchvision

iii. Training Epochs:

- Initial training: **10 epochs**
- Fine-tuning phase: **5 epochs**

Total: 15 epochs

iv. Batch Size: **32**

v. Optimizer:

Adam optimizer

vi. Loss Function:

CrossEntropyLoss with:

- Class weights (to handle class imbalance)

vii. Learning Rate:

- initial training: **1e-4 (0.0001)**
- Fine-tuning phase: **1e-5 (0.00001)**

6.2.2. Training Method

i. Method:

Transfer learning using **pretrained ResNet50** backbone with custom fully connected classifier.

ii. Frozen layers:

- Initially: **all backbone layers frozen**
- During fine-tuning: **All layers unfrozen (full network trainable)**

iii. Fine Tuning process:

- Train only the new fully connected head with the pretrained backbone frozen.
- Unfreeze all network layers.
- Continue training with a lower learning rate (1e-5).
- Save the best model based on validation accuracy.

6.3. Inception V1

6.3.1. Environment Setup

i. GPU:

CUDA GPU

ii. Library:

PyTorch, Torchvision

iii. Training Epochs:

- Initial training: **6 epochs**
 - Fine-tuning phase: **12 epochs**
- Total: 18 epochs**

iv. Batch Size: **32**

v. Optimizer:

- Initial training: **AdamW**
- Fine-tuning phase: **SGD with momentum**

vi. Loss Function:

CrossEntropyLoss with:

- Class weights (to handle class imbalance)

vii. Learning Rate:

- initial training: 1e-3 (0.001)
- Fine-tuning phase: 1e-4 (0.0001)

6.3.2. Training Method

i. Method:

Transfer learning using **pretrained GoogLeNet (Inception-V1)** with auxiliary classifiers and two-stage training strategy.

ii. Frozen layers:

- Initially: **all backbone layers frozen**, only :
 - Final fully connected layer (fc)
 - Auxiliary classifiers (aux1, aux2) were trainable
- During fine-tuning: all layers unfrozen

iii. Fine Tuning process:

- Train only the classification head and auxiliary classifiers for 6 epochs (AdamW, LR = 1e-3).
- Load best head weights.
- Unfreeze the entire network.
- Fine-tune all layers for 12 epochs using SGD with momentum and LR = 1e-4.
- Best models saved based on validation accuracy.

6.4. MobileNet

6.4.1. Environment Setup

i. GPU:

CUDA GPU

ii. Library:

PyTorch, Torchvision

iii. Training Epochs:

- Initial training: **10 epochs**
 - Fine-tuning phase: **5 epochs**
- Total: 15 epochs**

iv. Batch Size: 32

v. Optimizer:

Adam optimizer

vi. Loss Function:

CrossEntropyLoss with:

- Class weights (to handle class imbalance)
- Label smoothing (0.1)

vii. Learning Rate:

- initial training: 1e-4 (0.0001)
- Fine-tuning phase: 1e-5 (0.00001)

6.4.2. Training Method

i. Method:

Transfer learning using **pretrained MobileNetV2** with:

- Frozen backbone
- Custom classifier head
- Data augmentation
- CosineAnnealingLR learning rate scheduler

ii. Frozen layers:

- Initially: **all backbone layers frozen**
- During fine-tuning: all layers frozen **except blocks “17” and “18”** in model.features

iii. Fine Tuning process:

- Train only the custom classifier with frozen backbone.
- Unfreeze last convolutional blocks (layers 17 and 18).
- Retrain full model using a smaller learning rate (1e-5).
- Save best model based on validation accuracy.

7. Results & Comparative Analysis

7.1. Performance Metrics

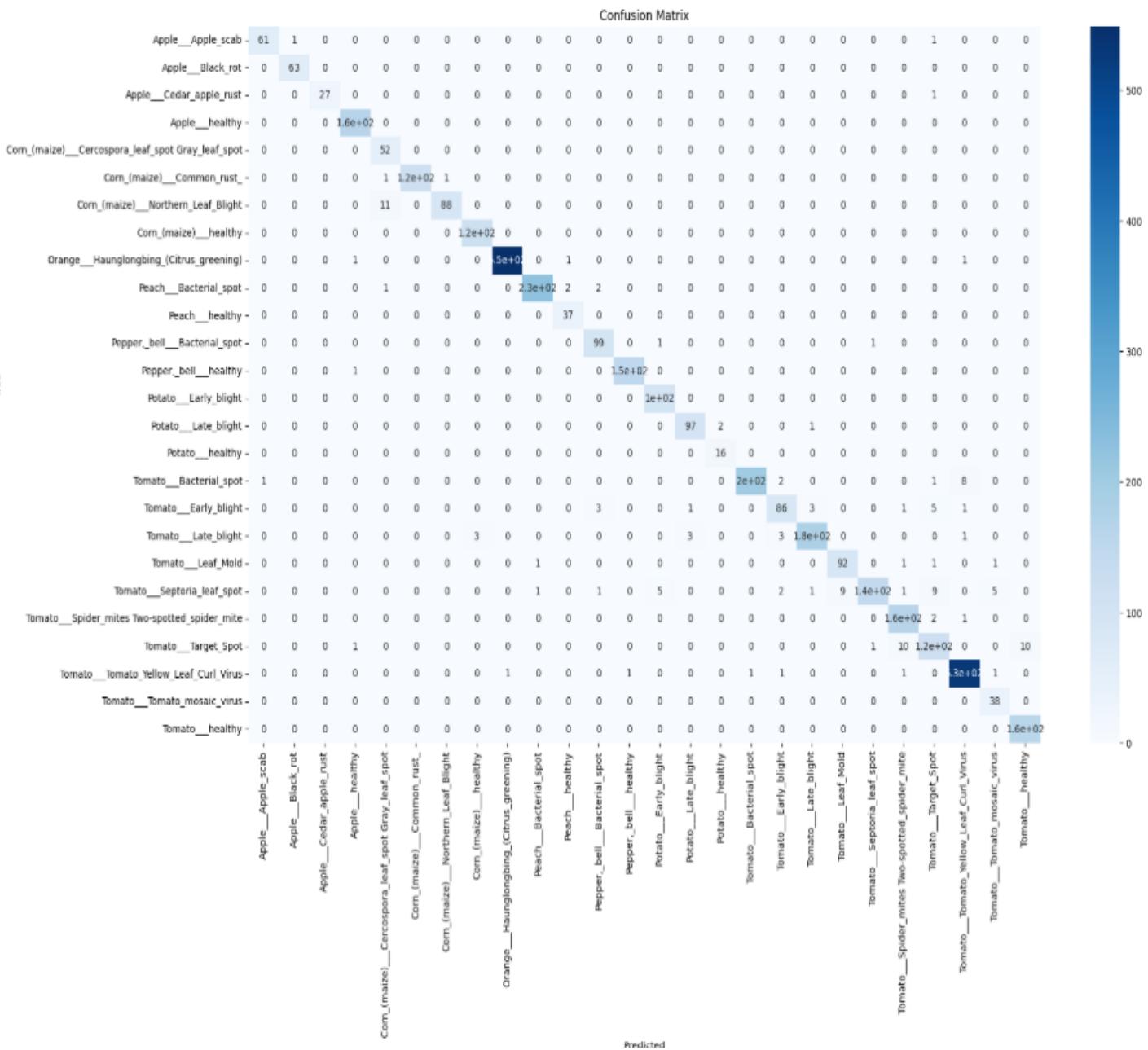
7.1.1. VGG 19

i. Accuracy: 0.964641173389209

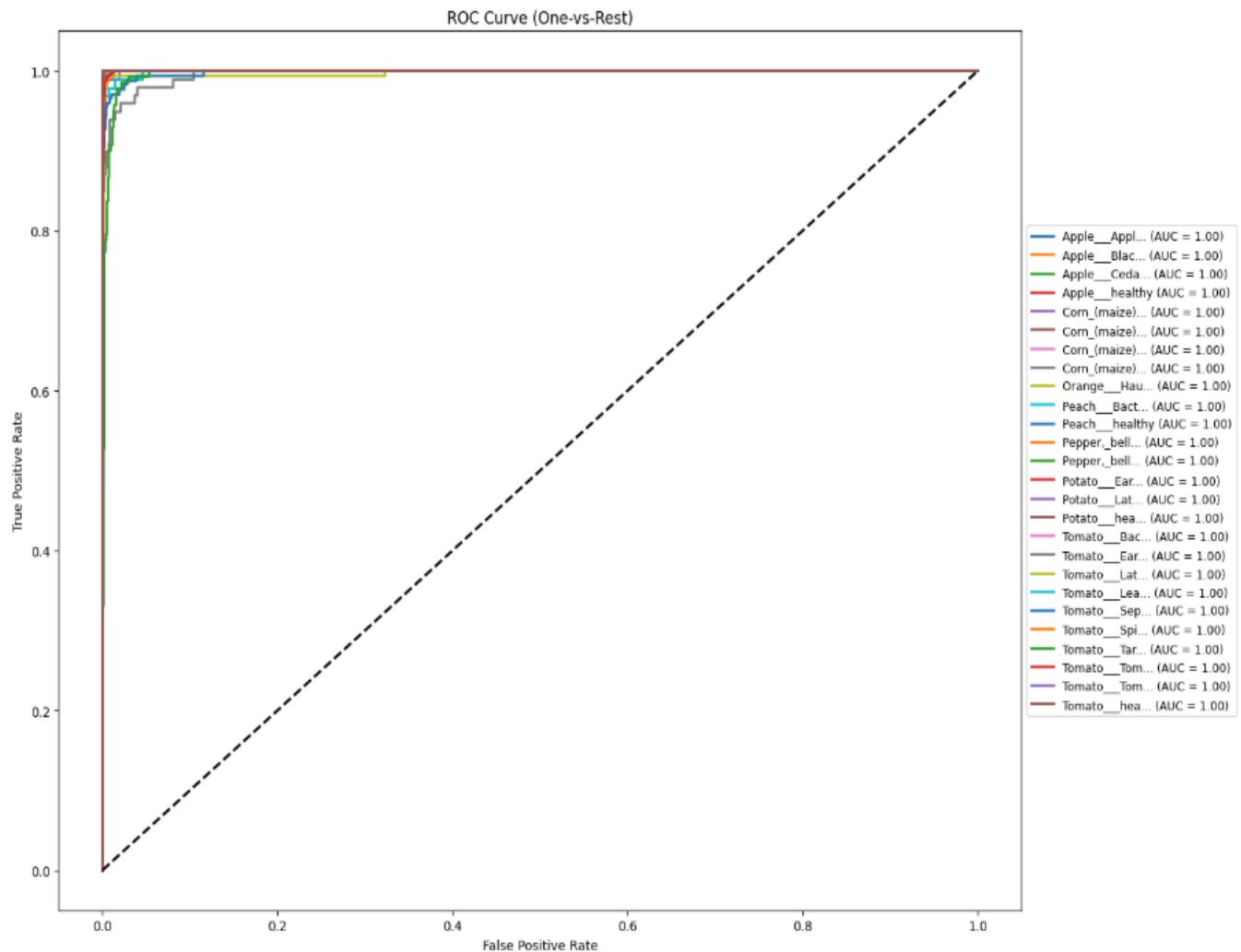
ii. Classification report:

	precision	recall	f1-score	support
Apple__Apple_scab	0.98	0.97	0.98	63
Apple__Black_rot	0.98	1.00	0.99	63
Apple__Cedar_apple_rust	1.00	0.96	0.98	28
Apple__healthy	0.98	1.00	0.99	165
Corn_(maize)___Cercospora_leaf_spot_Gray_leaf_spot	0.80	1.00	0.89	52
Corn_(maize)___Common_rust_	1.00	0.98	0.99	120
Corn_(maize)___Northern_Leaf_Blight	0.99	0.89	0.94	99
Corn_(maize)___healthy	0.97	1.00	0.99	117
Orange__Haunglongbing_(Citrus_greening)	1.00	0.99	1.00	552
Peach__Bacterial_spot	0.99	0.98	0.98	231
Peach__healthy	0.93	1.00	0.96	37
Pepper,_bell__Bacterial_spot	0.94	0.98	0.96	101
Pepper,_bell__healthy	0.99	0.99	0.99	149
Potato__Early_blight	0.94	1.00	0.97	100
Potato__Late_blight	0.96	0.97	0.97	100
Potato__healthy	0.89	1.00	0.94	16
Tomato__Bacterial_spot	1.00	0.94	0.97	214
Tomato__Early_blight	0.91	0.86	0.89	100
Tomato__Late_blight	0.97	0.95	0.96	192
Tomato__Leaf_Mold	0.91	0.96	0.93	96
Tomato__Septoria_leaf_spot	0.99	0.81	0.89	178
Tomato__Spider_mites_Two-spotted_spider_mite	0.92	0.98	0.95	168
Tomato__Target_Spot	0.86	0.85	0.85	142
Tomato__Tomato_Yellow_Leaf_Curl_Virus	0.98	0.99	0.98	537
Tomato__Tomato_mosaic_virus	0.84	1.00	0.92	38
Tomato__healthy	0.94	1.00	0.97	160
accuracy			0.96	3818
macro avg	0.95	0.96	0.95	3818
weighted avg	0.97	0.96	0.96	3818

iii. Confusion Matrix:



iv. ROC Curve:



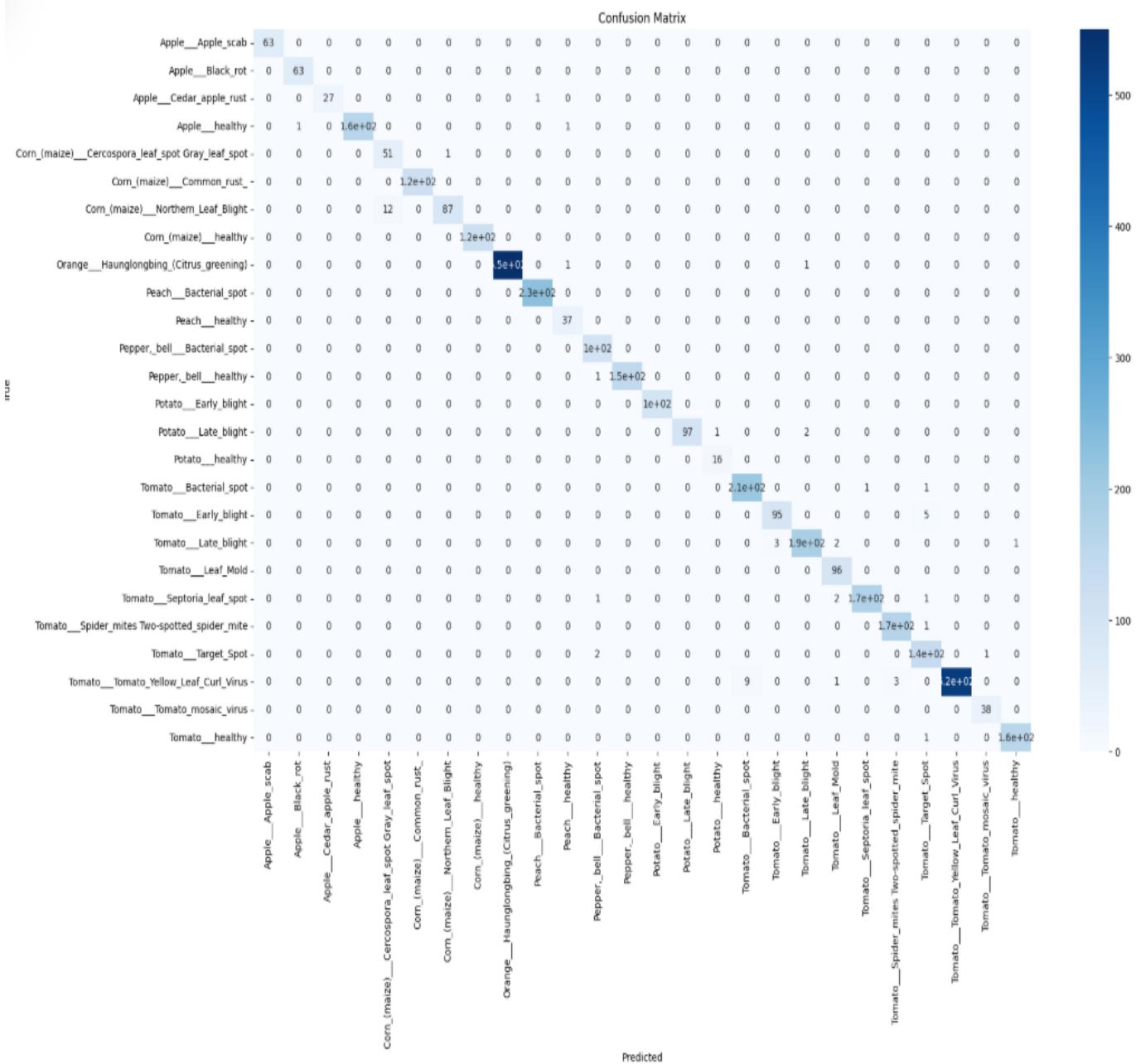
7.1.2. ResNet 50

i. Accuracy: 0.9850707176532216

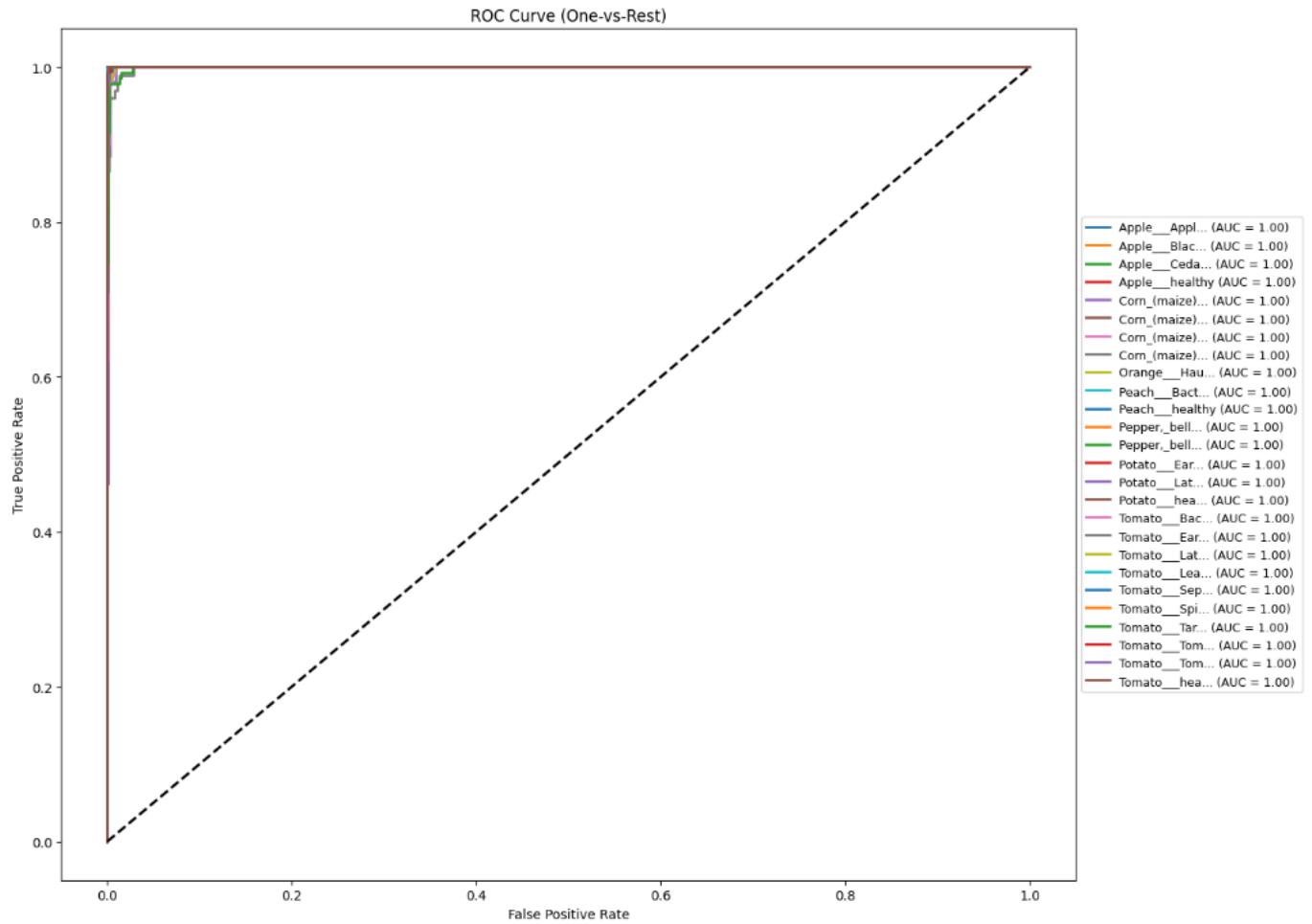
ii. Classification report:

		precision	recall	f1-score	support
	Apple__Apple_scab	1.00	1.00	1.00	63
	Apple__Black_rot	0.98	1.00	0.99	63
	Apple__Cedar_apple_rust	1.00	0.96	0.98	28
	Apple__healthy	1.00	0.99	0.99	165
Corn_(maize)___Cercospora_leaf_spot_Gray_leaf_spot		0.81	0.98	0.89	52
	Corn_(maize)___Common_rust_	1.00	1.00	1.00	120
	Corn_(maize)___Northern_Leaf_Blight	0.99	0.88	0.93	99
	Corn_(maize)___healthy	1.00	1.00	1.00	117
Orange___Haunglongbing_(Citrus_greening)		1.00	1.00	1.00	552
	Peach__Bacterial_spot	1.00	1.00	1.00	231
	Peach__healthy	0.95	1.00	0.97	37
Pepper,_bell__Bacterial_spot		0.96	1.00	0.98	101
	Pepper,_bell__healthy	1.00	0.99	1.00	149
Potato__Early_blight		1.00	1.00	1.00	100
	Potato__Late_blight	1.00	0.97	0.98	100
	Potato__healthy	0.94	1.00	0.97	16
Tomato__Bacterial_spot		0.96	0.99	0.97	214
	Tomato__Early_blight	0.97	0.95	0.96	100
	Tomato__Late_blight	0.98	0.97	0.98	192
	Tomato__Leaf_Mold	0.95	1.00	0.97	96
Tomato__Septoria_leaf_spot		0.99	0.98	0.99	178
Tomato__Spider_mites_Two-spotted_spider_mite		0.98	0.99	0.99	168
	Tomato__Target_Spot	0.94	0.98	0.96	142
Tomato__Tomato_Yellow_Leaf_Curl_Virus		1.00	0.98	0.99	537
	Tomato__Tomato_mosaic_virus	0.97	1.00	0.99	38
	Tomato__healthy	0.99	0.99	0.99	160
	accuracy			0.99	3818
	macro avg	0.98	0.98	0.98	3818
	weighted avg	0.99	0.99	0.99	3818

iii. Confusion Matrix:



iv. ROC Curve:



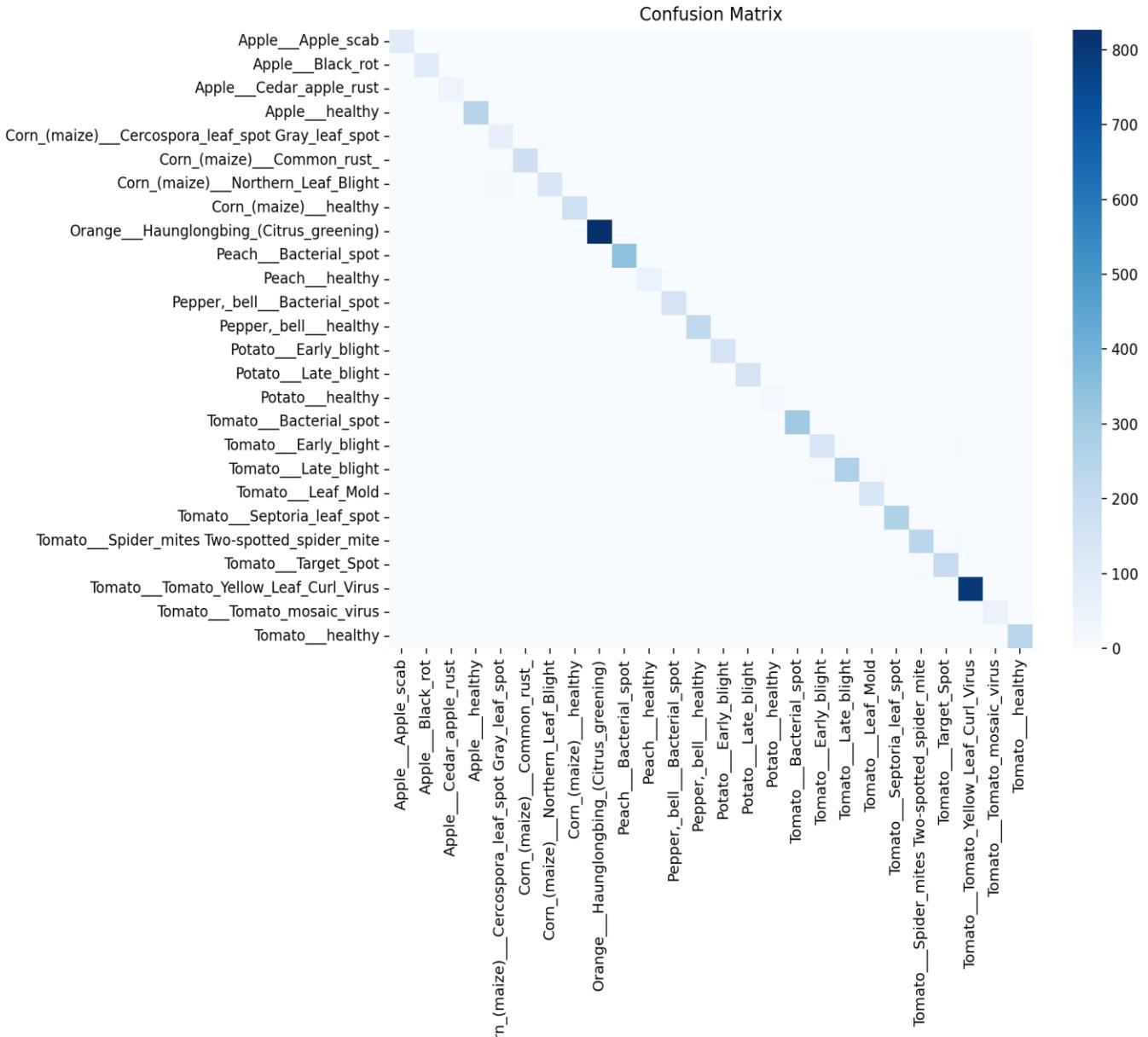
7.1.3. Inception V1

i. Accuracy: 0.9794952681388013

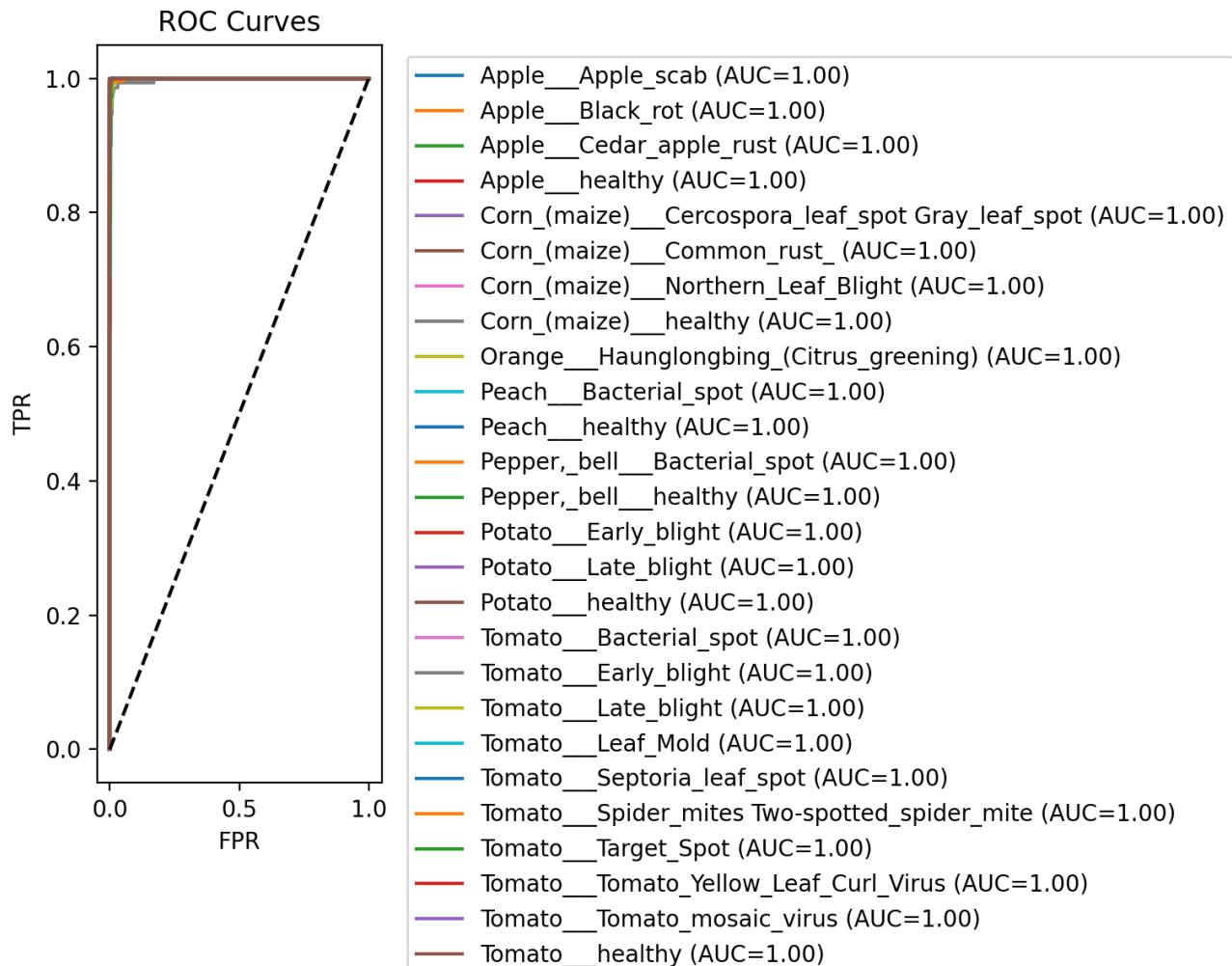
ii. Classification report:

	precision	recall	f1-score	support
Apple__Apple_scab	0.99	0.99	0.99	95
Apple__Black_rot	0.98	1.00	0.99	94
Apple__Cedar_apple_rust	0.98	1.00	0.99	42
Apple__healthy	0.98	1.00	0.99	247
Corn_(maize)___Cercospora_leaf_spot_Gray_leaf_spot	0.80	0.91	0.85	77
Corn_(maize)___Common_rust_	1.00	1.00	1.00	179
Corn_(maize)___Northern_Leaf_Blight	0.95	0.89	0.92	148
Corn_(maize)___healthy	0.99	0.99	0.99	175
Orange___Haunglongbing_(Citrus_greening)	1.00	1.00	1.00	827
Peach__Bacterial_spot	1.00	1.00	1.00	345
Peach__healthy	1.00	0.98	0.99	54
Pepper,_bell__Bacterial_spot	0.99	0.99	0.99	150
Pepper,_bell__healthy	1.00	1.00	1.00	222
Potato__Early_blight	1.00	0.99	0.99	150
Potato__Late_blight	0.97	0.98	0.98	150
Potato__healthy	0.96	0.96	0.96	23
Tomato__Bacterial_spot	0.98	0.97	0.97	320
Tomato__Early_blight	0.94	0.87	0.90	150
Tomato__Late_blight	0.96	0.94	0.95	287
Tomato__Leaf_Mold	0.96	0.94	0.95	143
Tomato__Septoria_leaf_spot	0.96	0.99	0.98	266
Tomato__Spider_mites_Two-spotted_spider_mite	0.96	0.96	0.96	252
Tomato__Target_Spot	0.92	0.97	0.94	211
Tomato__Tomato_Yellow_Leaf_Curl_Virus	1.00	1.00	1.00	804
Tomato__Tomato_mosaic_virus	0.97	1.00	0.98	56
Tomato__healthy	0.98	1.00	0.99	239
accuracy			0.98	5706
macro avg	0.97	0.97	0.97	5706
weighted avg	0.98	0.98	0.98	5706

iii. Confusion Matrix:



iv. ROC Curve:



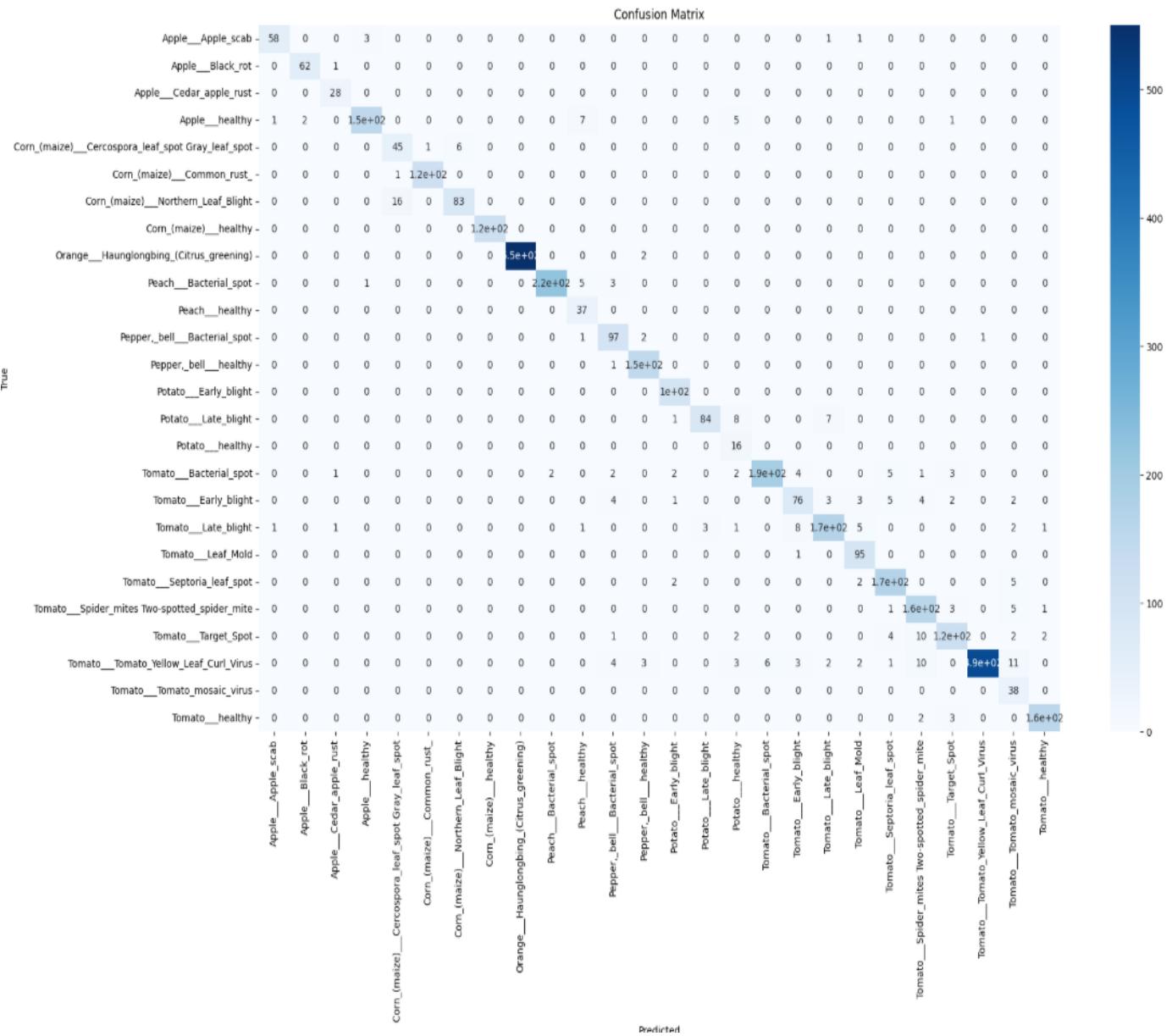
7.1.4. MobileNet

i. Accuracy: 0.9376636982713462

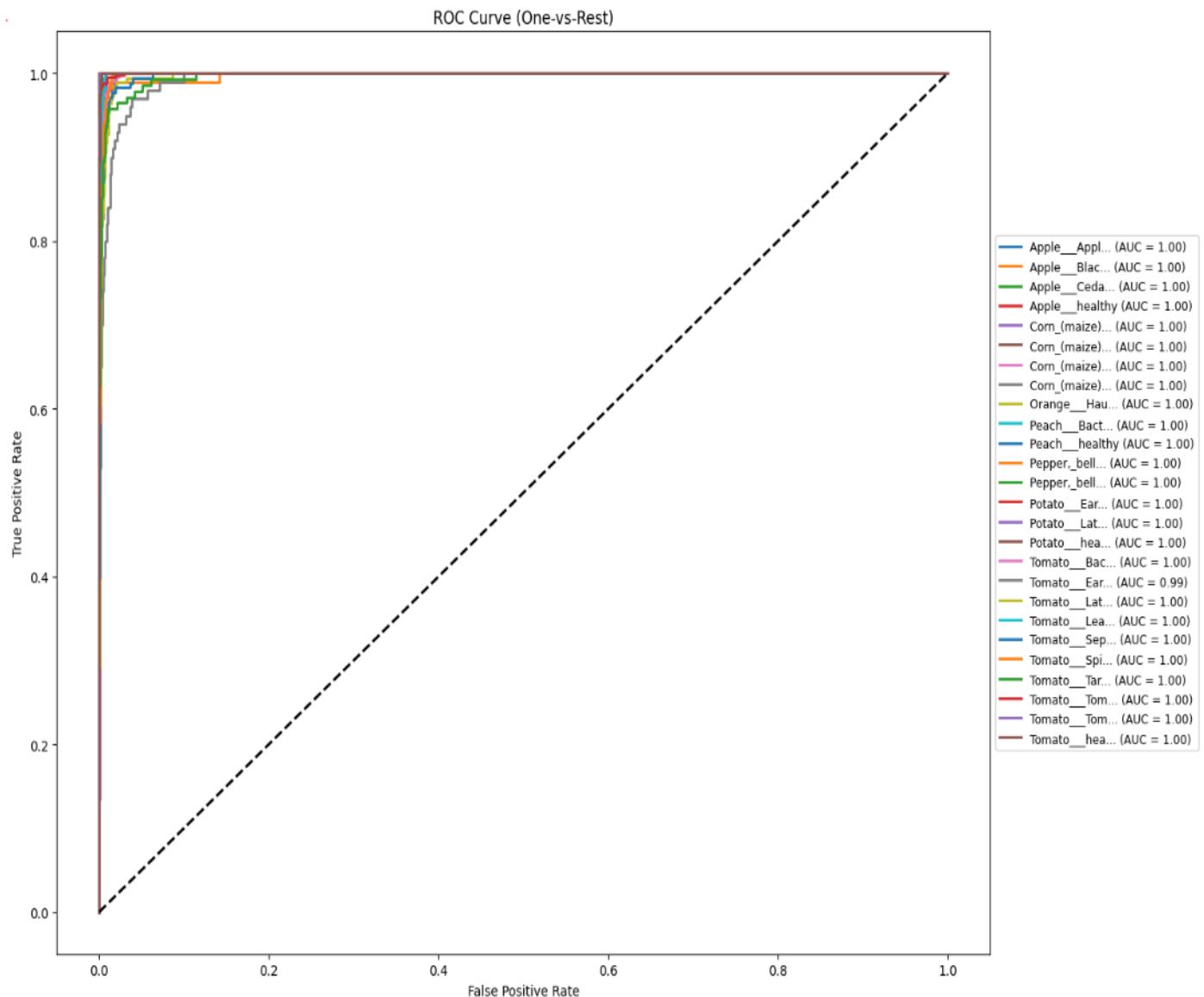
ii. Classification report:

	precision	recall	f1-score	support
Apple__Apple_scab	0.97	0.92	0.94	63
Apple__Black_rot	0.97	0.98	0.98	63
Apple__Cedar_apple_rust	0.90	1.00	0.95	28
Apple__healthy	0.97	0.90	0.94	165
Corn_(maize)__Cercospora_leaf_spot_Gray_leaf_spot	0.73	0.87	0.79	52
Corn_(maize)__Common_rust_	0.99	0.99	0.99	120
Corn_(maize)__Northern_Leaf_Blight	0.93	0.84	0.88	99
Corn_(maize)__healthy	1.00	1.00	1.00	117
Orange__Haunglongbing_(Citrus_greening)	1.00	1.00	1.00	552
Peach__Bacterial_spot	0.99	0.96	0.98	231
Peach__healthy	0.73	1.00	0.84	37
Pepper,_bell__Bacterial_spot	0.87	0.96	0.91	101
Pepper,_bell__healthy	0.95	0.99	0.97	149
Potato__Early_blight	0.94	1.00	0.97	100
Potato__Late_blight	0.97	0.84	0.90	100
Potato__healthy	0.43	1.00	0.60	16
Tomato__Bacterial_spot	0.97	0.90	0.93	214
Tomato__Early_blight	0.83	0.76	0.79	100
Tomato__Late_blight	0.93	0.88	0.90	192
Tomato__Leaf_Mold	0.88	0.99	0.93	96
Tomato__Septoria_leaf_spot	0.91	0.95	0.93	178
Tomato__Spider_mites_Two-spotted_spider_mite	0.85	0.94	0.90	168
Tomato__Target_Spot	0.91	0.85	0.88	142
Tomato__Tomato_Yellow_Leaf_Curl_Virus	1.00	0.92	0.96	537
Tomato__Tomato_mosaic_virus	0.58	1.00	0.74	38
Tomato__healthy	0.97	0.97	0.97	160
accuracy			0.94	3818
macro avg	0.89	0.94	0.91	3818
weighted avg	0.95	0.94	0.94	3818

iii. Confusion Matrix:



iv. ROC Curve:



7.2. Comparison Table

Model	Train Acc	Val Acc	Test Acc	Parameters (Approx.)	Inference Speed
VGG19	0.9512	0.96	0.9646	~144 million	Slow
ResNet50	0.9766	0.9829	0.985	~25 million	Medium
Inception v1	0.98	0.9794	0.9794	~6.8 million	Medium
MobileNetV2	0.9205	0.9370	0.9377	~3.4 million	Fast

7.3. Analysis

7.3.1. VGG 19

i. Performance

- Train Accuracy: 0.9512
- Validation Accuracy: 0.9600
- Test Accuracy: 0.9646

VGG19 performed reasonably well but was surpassed by ResNet50 and Inception v1 in overall generalization.

ii. Why it performed this way

- VGG19 uses very deep sequential convolutional layers (19 layers) without shortcut connections.
- It extracts strong spatial features but suffers from:
 - Large parameter count
 - Higher risk of overfitting
 - Slower optimization and poorer gradient flow

iii. Model Size & Speed

- ~144M parameters → the largest model in the comparison.
- Inference speed: Slow, making it less suitable for real-time systems.

iv. Overfitting / Underfitting Behavior

- Slight overfitting: Train acc (0.9512) < Val/Test acc
This means augmentation helped VGG19 generalize better, but the heavy architecture still tends to memorize training examples.

v. Impact of Augmentation

- Data augmentation helped reduce overfitting.
- Improved validation accuracy by increasing data diversity, which is crucial for such a heavy model.

7.3.2. ResNet

i. Performance

- Train Accuracy: 0.9766
- Validation Accuracy: 0.9829
- Test Accuracy: 0.9850

ResNet50 achieved the **highest performance** across all models.

- ii. Why it performed this way
 - Its residual connections solve the vanishing gradient problem, allowing deeper and more effective training.
 - Better feature reuse → stronger generalization
 - Balanced capacity makes it ideal for medium-sized image datasets..
- iii. Model Size & Speed
 - **~25M parameters** → significantly smaller than VGG19 but larger than MobileNet/Inception.
 - **Inference speed: Medium** — good for both training and deployment.
- iv. Overfitting / Underfitting Behavior
 - **Minimal overfitting**: train/validation/test accuracies are very close.
 - **The model generalizes extremely well due to:**
 - Residual blocks
 - Batch normalization
 - Strong pretraining weights
- v. Impact of Augmentation
 - Augmentation slightly improved generalization, but ResNet50 performs strongly even without heavy augmentation thanks to its architecture.

7.3.3. Inception v1

- i. Performance
 - Train Accuracy: 0.98
 - Validation Accuracy: 0.9794
 - Test Accuracy: 0.9794
- Inception v1 performed very close to ResNet50, showing excellent generalization

ii. Why it performed this way

- Uses multi-scale convolutions (1×1 , 3×3 , 5×5) inside each Inception module.
- Extracts fine- and coarse-level features simultaneously.
- Efficient architecture for complex pattern variation

iii. Model Size & Speed

- **~6.8M parameters** — smaller than ResNet, much smaller than VGG19.
- **Inference speed: Medium**, faster than ResNet but not as fast as MobileNet.

iv. Overfitting / Underfitting Behavior

- No significant overfitting: train \approx val \approx test.
- Auxiliary classifiers improve gradient propagation and stabilize training.

v. Impact of Augmentation

- Augmentation boosted robustness to rotation/scale changes, which aligns well with Inception's multi-scale processing..

7.3.4. MobileNet

i. Performance

- Train Accuracy: 0.9205
- Validation Accuracy: 0. 9370
- Test Accuracy: 0. 0.9377

MobileNetV2 showed good performance but noticeably lower than the heavier models — expected for a mobile-optimized architecture.

ii. Why it performed this way

- Uses **depthwise separable convolutions and inverted residual blocks**, focusing on efficiency rather than maximum accuracy.
- Lightweight design trades representational power for speed.

iii. Model Size & Speed

- **~3.4M parameters** \rightarrow the **smallest** model.
- **Inference speed: Fast** — ideal for mobile and real-time use.

vi. Overfitting / Underfitting Behavior

- Slight **underfitting**: train accuracy significantly lower than val/test.
- Model capacity is lower, so it can't learn very complex spatial patterns as deeply as ResNet or Inception.

vii. Impact of Augmentation

- **Augmentation helped significantly, especially:**
 - Random rotation
 - Random resized cropping
 - Color jitter
- These strengthen MobileNet's generalization due to its limited representational power.

8. Conclusion

Among the four models tested, **ResNet50** achieved the best overall performance with the highest validation and test accuracy, thanks to its residual connections that enable deeper learning without overfitting. **Inception v1** offered a good balance between accuracy and size, while **VGG19** was accurate but very large and slow. **MobileNetV2** was the fastest and smallest but had lower accuracy.

Data augmentation improved generalization across all models. For accuracy-critical tasks, **ResNet50** is preferred, while for speed or resource-constrained environments, **MobileNetV2** is the best choice.