School of Engineering
Jawaharlal Nehru University

Team Number = 3

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22/11/EC/017	DIVYANSHI SINGH
22/11/EC/018	SHIVY CHAUHAN
22/11/EC/019	PRASHANT DUBEY
22/11/EC/020	DEVANSHU
22/11/EC/021	MIRNAL PRATAP SINGH
22/11/EC/022	SANSKAR THAKUR
22/11/EC/056	BANOTH SONU

Code Repository

🔗 GitHub Link:
https://github.com/Anushttha/plant-disease-classification

Report:Disease Identification through Deep Learning Classification

Introduction

Plant diseases can significantly impact crop yield, making early detection essential for effective disease management.This study utilizes deep learning models to classify plant diseases using two datasets:

PlantVillage Dataset (RGB Images)

https://github.com/spMohanty/PlantVillage-Dataset

Thermal Images Dataset (Infrared Data)

https://www.kaggle.com/sujaradha/thermal-images-diseased-healthy-leaves-paddy

We implemented various deep learning architectures to compare their performance and analyze their effectiveness in disease classification.

2. Dataset Description

📌 Dataset 1: PlantVillage (RGB Images)

Contains 38 classes of plant diseases and healthy leaves.
Used for image classification tasks.

📌 Dataset 2: Thermal Images (Infrared Imaging)

Captures temperature variations to detect plant diseases.
The dataset is imbalanced, requiring data augmentation to improve model performance.
Data Splitting: Both datasets were split into 60% training, 20% validation, and 20% testing.

Experiment 1

The experiment aims to classify plant diseases using the RGB-based PlantVillage dataset by leveraging state-of-the-art deep learning models. The study evaluates the performance of models such as ResNet,GoogleNet, VGG, AlexNet, EfficientNetv2,InceptionV3 and Vision Transformer (ViT). Each model's performance is analyzed through metrics such as training, validation, and testing accuracy, alongside precision-recall (PR) and confusion matrix curves for the test set. The findings highlight the models' capability to handle multi-class classification for plant disease identification.

Objective

- To classify plant diseases using the RGB-based PlantVillage dataset.

● To compare the classification accuracy and PR curves across different deep learning models.

3. Methodology

We experimented with various deep learning models, including:

CNN-based Models: ResNet, VGG, AlexNet, InceptionV3, EfficientNet
Transformer-Based Models: ViT (Vision Transformer)

📌 Preprocessing Steps:

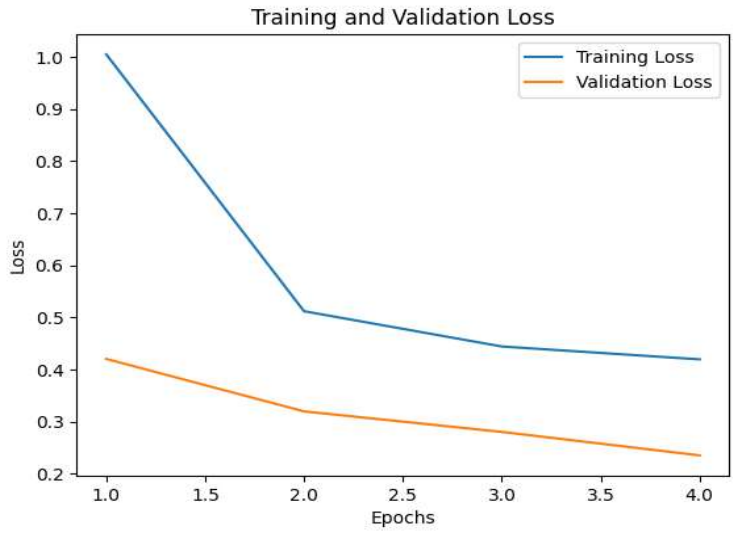
For RGB Images: Resizing, normalization, data augmentation (flipping, rotation).
For Thermal Images: Contrast enhancement, noise reduction, synthetic augmentation.
📌 Training Details:

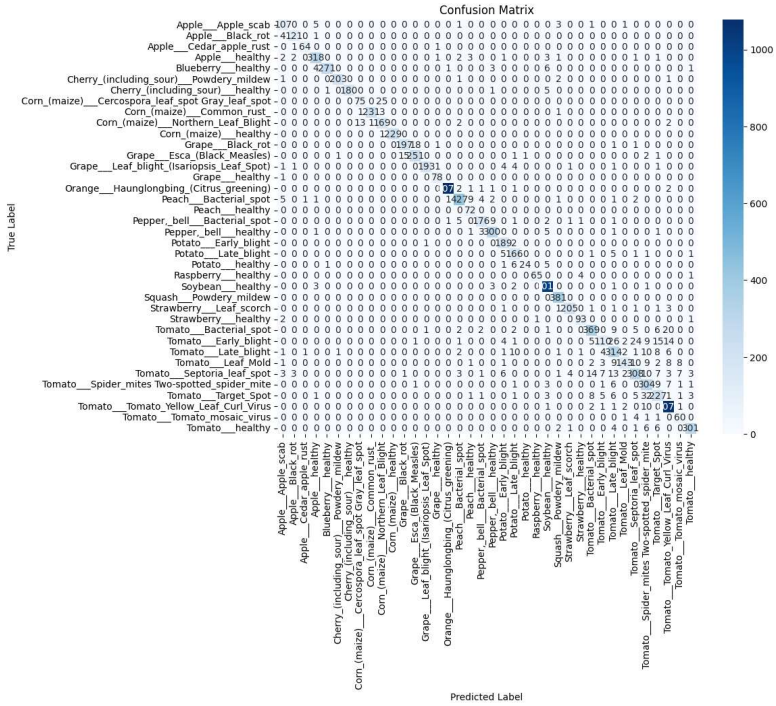
Optimizer: Adam (LR = 0.001)
Loss Function: Cross-Entropy Loss (for classification) & BCE Loss (for segmentation)
Batch Size: 32
Epochs: 10

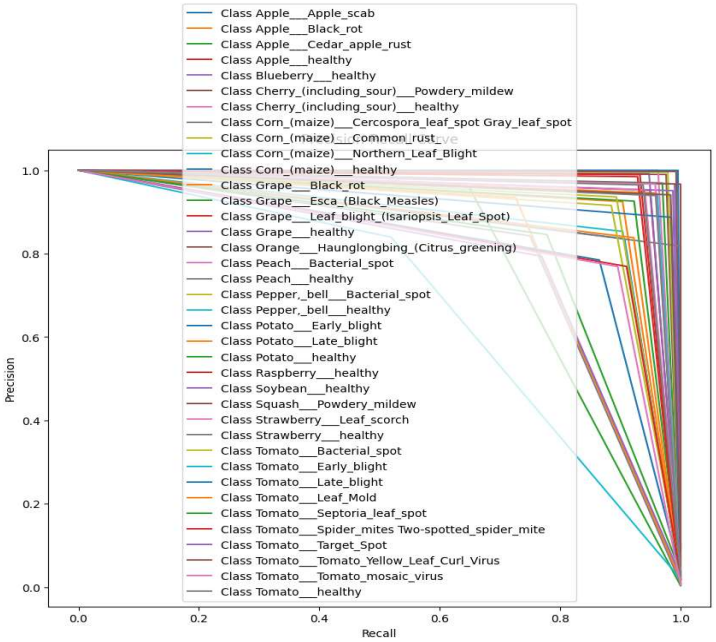
📌 Evaluation Metrics:
○ Training and validation accuracy curves were plotted to monitor model performance.
○ PR curves were generated for the test set to analyze precision and recall for each class.

Observations

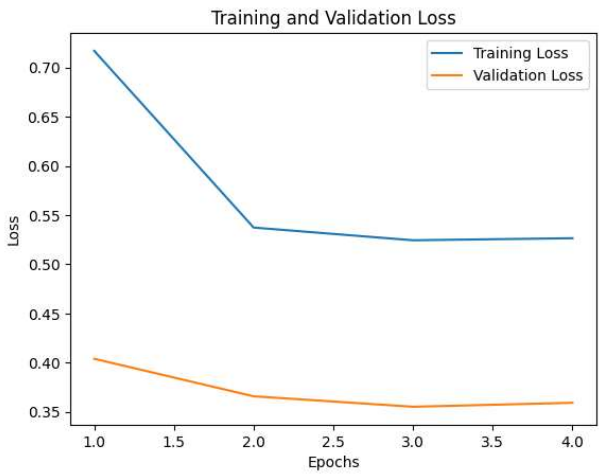
Inception


Training and Validation Loss
Training Loss
Validation Loss
Loss
Epochs
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
1.0
1.5
2.0
2.5
3.0
3.5
4.0


Confusion Matrix
True Label
Predicted Label
1000
800
600
400
200
0


Class Apple___Apple_scab
Class Apple___Black_rot
Class Apple___Cedar_apple_rust
Class Apple___healthy
Class Blueberry___healthy
Class Cherry_(including_sour)___Powdery_mildew
Class Cherry_(including_sour)___healthy
Class Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Class Corn_(maize)___Common_rust
Class Corn_(maize)___Northern_Leaf_Blight
Class Corn_(maize)___healthy
Class Grape___Black_rot
Class Grape___Esca_(Black_Measles)
Class Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Class Grape___healthy
Class Orange___Haunglongbing_(Citrus_greening)
Class Peach___Bacterial_spot
Class Peach___healthy
Class Pepper,_bell___Bacterial_spot
Class Pepper,_bell___healthy
Class Potato___Early_blight
Class Potato___Late_blight
Class Potato___healthy
Class Raspberry___healthy
Class Soybean___healthy
Class Squash___Powdery_mildew
Class Strawberry___Leaf_scorch
Class Strawberry___healthy
Class Tomato___Bacterial_spot
Class Tomato___Early_blight
Class Tomato___Late_blight
Class Tomato___Leaf_Mold
Class Tomato___Septoria_leaf_spot
Class Tomato___Spider_mites Two-spotted_spider_mite
Class Tomato___Target_Spot
Class Tomato___Tomato_Yellow_Leaf_Curl_Virus
Class Tomato___Tomato_mosaic_virus
Class Tomato___healthy
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

AlexNet


Training and Validation Loss
Training Loss
Validation Loss
Loss
Epochs
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0.60
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0.45
0.40
0.35
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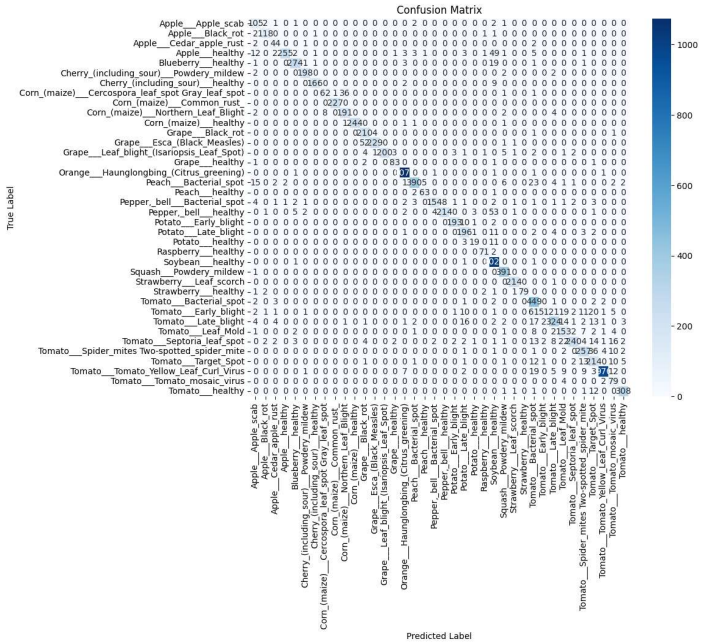
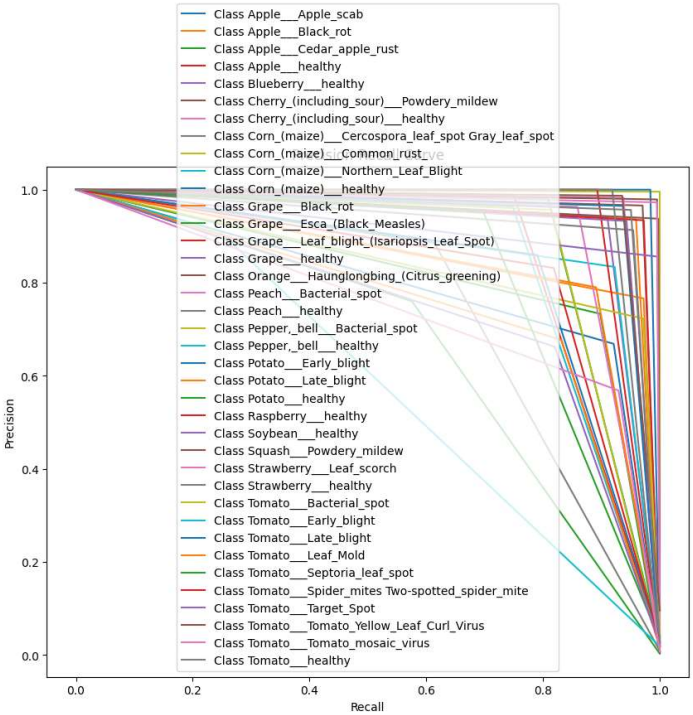
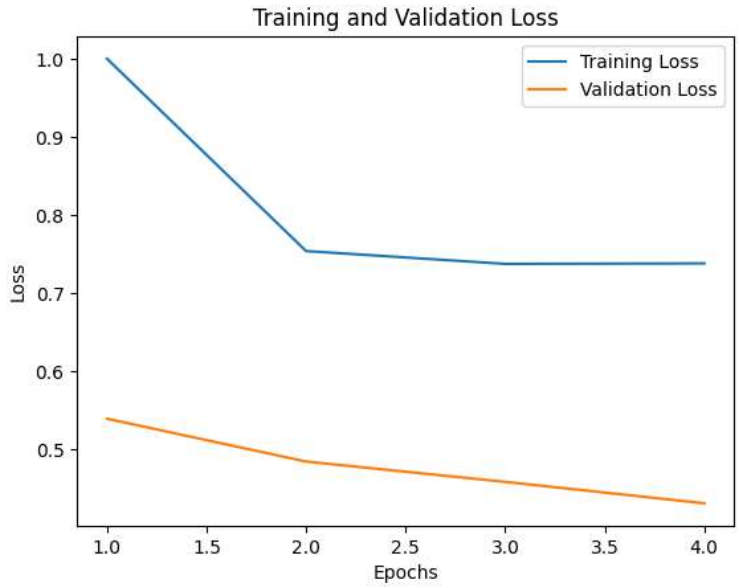
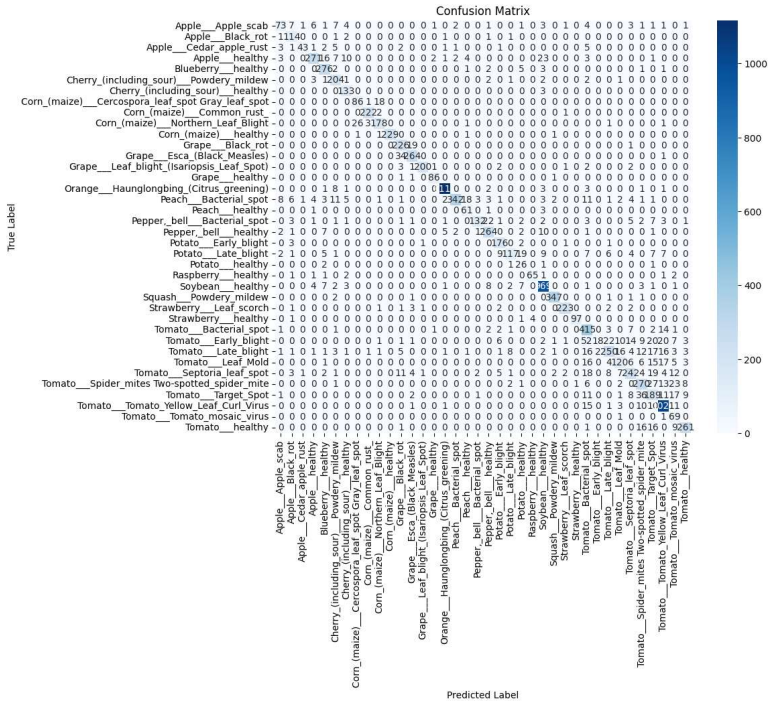
1.5
2.0
2.5
3.0
3.5
4.0


Confusion Matrix
True Label
Predicted Label

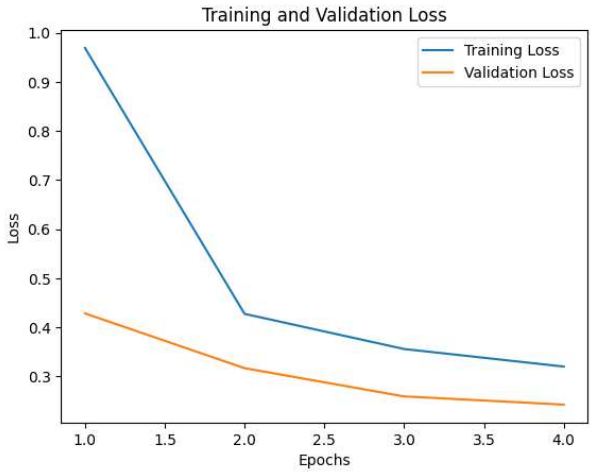

Class Apple___Apple_scab
Class Apple___Black_rot
Class Apple___Cedar_apple_rust
Class Apple___healthy
Class Blueberry___healthy
Class Cherry_(including_sour)___Powdery_mildew
Class Cherry_(including_sour)___healthy
Class Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Class Corn_(maize)___Common_rust_
Class Corn_(maize)___Northern_Leaf_Blight
Class Corn_(maize)___healthy
Class Grape___Black_rot
Class Grape___Esca_(Black_Measles)
Class Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Class Grape___healthy
Class Orange___Haunlongbing_(Citrus_greening)
Class Peach___Bacterial_spot
Class Peach___healthy
Class Pepper,_bell___Bacterial_spot
Class Pepper,_bell___healthy
Class Potato___Early_blight
Class Potato___Late_blight
Class Potato___healthy
Class Raspberry___healthy
Class Soybean___healthy
Class Squash___Powdery_mildew
Class Strawberry___Leaf_scorch
Class Strawberry___healthy
Class Tomato___Bacterial_spot
Class Tomato___Early_blight
Class Tomato___Late_blight
Class Tomato___Leaf_Mold
Class Tomato___Septoria_leaf_spot
Class Tomato___Spider_mites Two-spotted_spider_mite
Class Tomato___Target_Spot
Class Tomato___Tomato_Yellow_Leaf_Curl_Virus
Class Tomato___Tomato_mosaic_virus
Class Tomato___healthy
Precision
Recall

VGG16


Training and Validation Loss
Training Loss
Validation Loss
Loss
Epochs
1.0
0.9
0.8
0.7
0.6
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0


Confusion Matrix
True Label
Predicted Label
1000
800
600
400
200
0

GoogleNet


Training and Validation Loss
Training Loss
Validation Loss
Loss
Epochs
1.0
0.9
0.8
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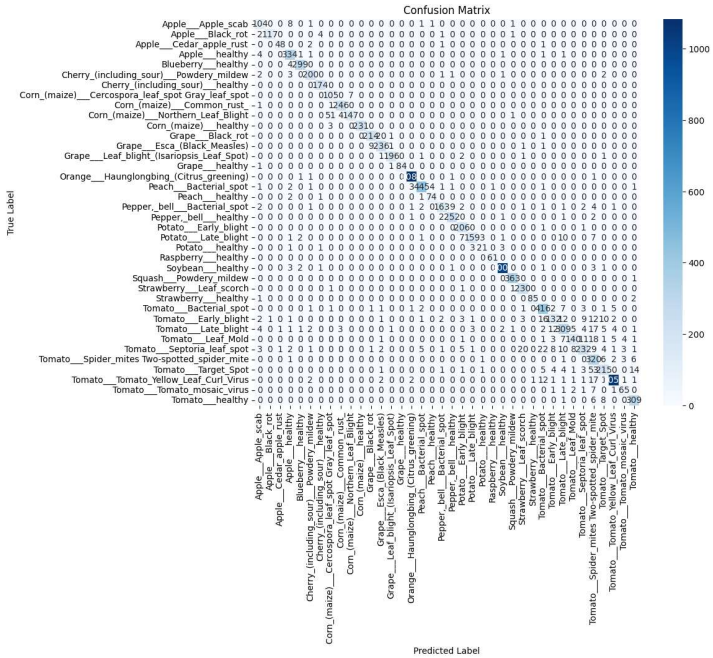
4.0


Confusion Matrix
True Label
Predicted Label
Apple___Apple_scab
Apple___Black_rot
Apple___Cedar_apple_rust
Apple___healthy
Blueberry___healthy
Cherry_(including_sour)___Powdery_mildew
Cherry_(including_sour)___healthy
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Corn_(maize)___Northern_Leaf_Blight
Corn_(maize)___healthy
Grape___Black_rot
Grape___Esca_(Black_Measles)
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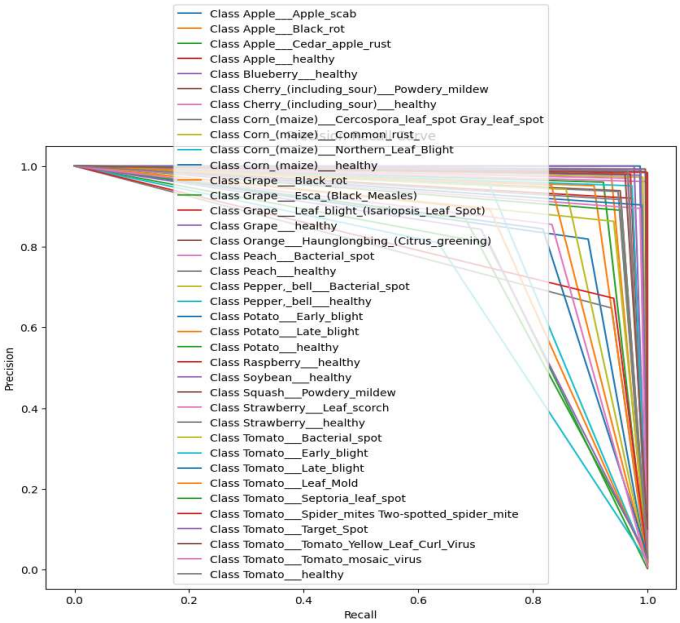
Grape___healthy
Orange___Haunglongbing_(Citrus_greening)
Peach___Bacterial_spot
Peach___healthy
Pepper,_bell___Bacterial_spot
Pepper,_bell___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Raspberry___healthy
Soybean___healthy
Squash___Powdery_mildew
Strawberry___Leaf_scorch
Strawberry___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Spider_mites Two-spotted_spider_mite
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy
1000
800
600
400
200
0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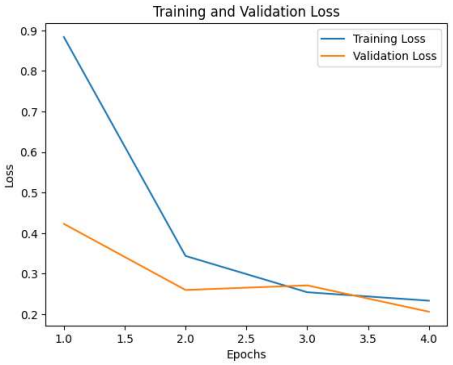
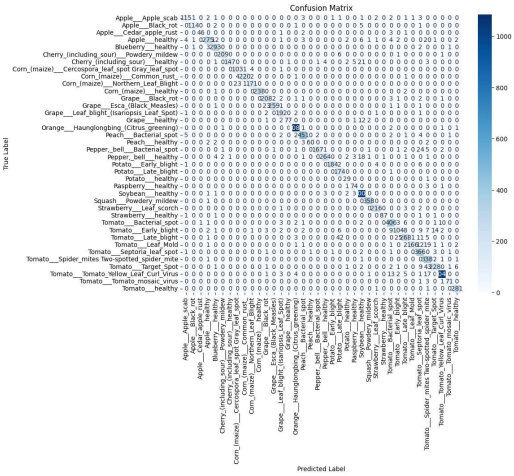
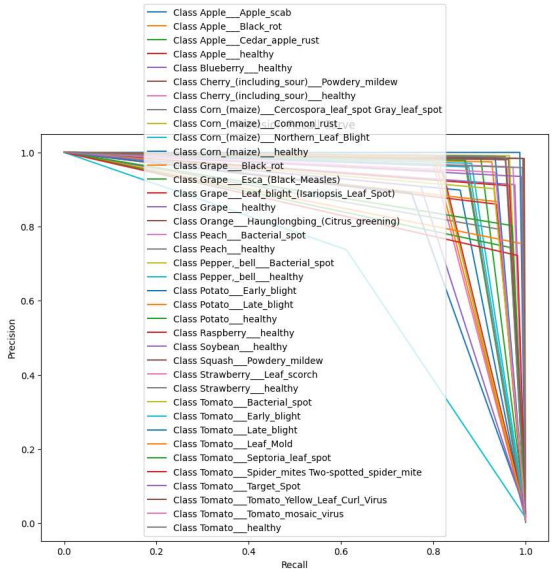
Class Tomato___Spider_mites Two-spotted_spider_mite
Class Tomato___Target_Spot
Class Tomato___Tomato_Yellow_Leaf_Curl_Virus
Class Tomato___Tomato_mosaic_virus
Class Tomato___healthy
Precision
Recall

VIT


Training and Validation Loss
Training Loss
Validation Loss
Loss
Epochs


Confusion Matrix
True Label
Predicted Label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Class Grape___Esca_(Black_Measles)
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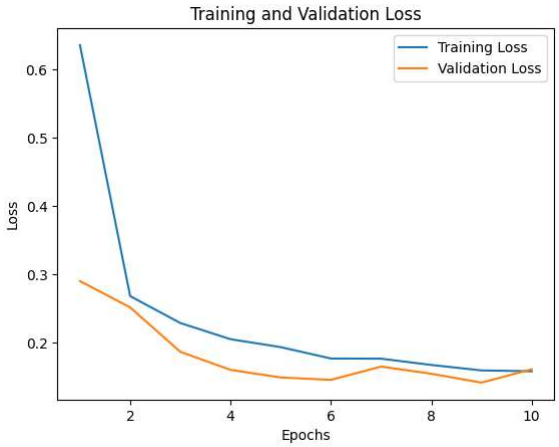
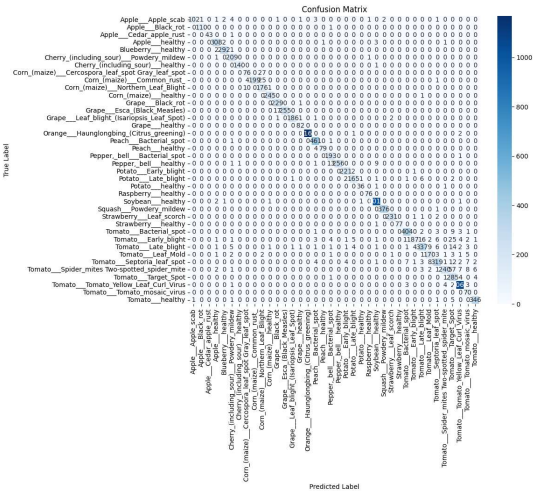
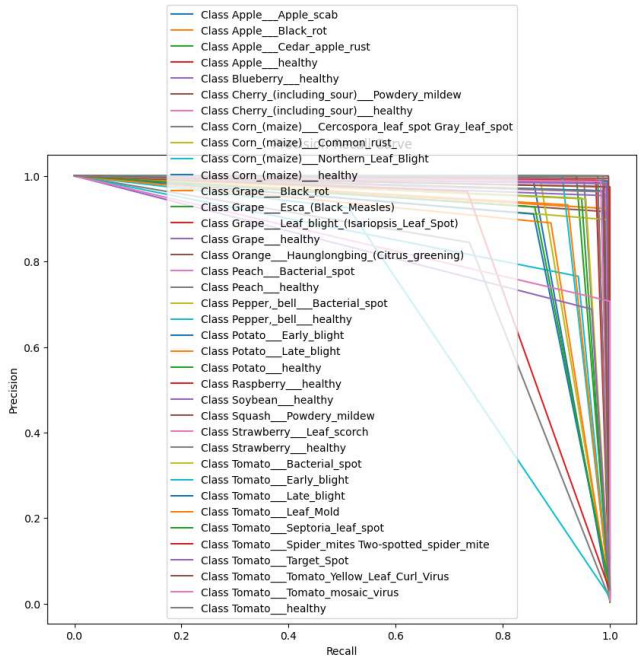
Class Tomato___Late_blight
Class Tomato___Leaf_Mold
Class Tomato___Septoria_leaf_spot
Class Tomato___Spider_mites Two-spotted_spider_mite
Class Tomato___Target_Spot
Class Tomato___Tomato_Yellow_Leaf_Curl_Virus
Class Tomato___Tomato_mosaic_virus
Class Tomato___healthy
Precision
Recall

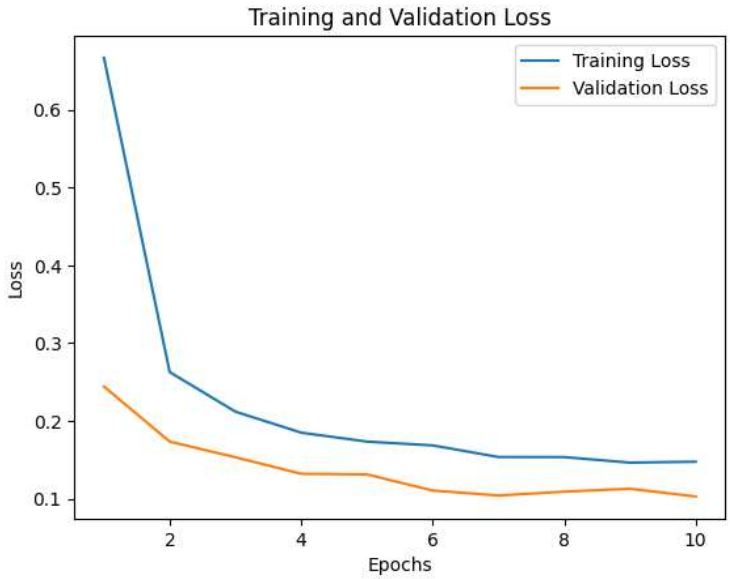
ResNet

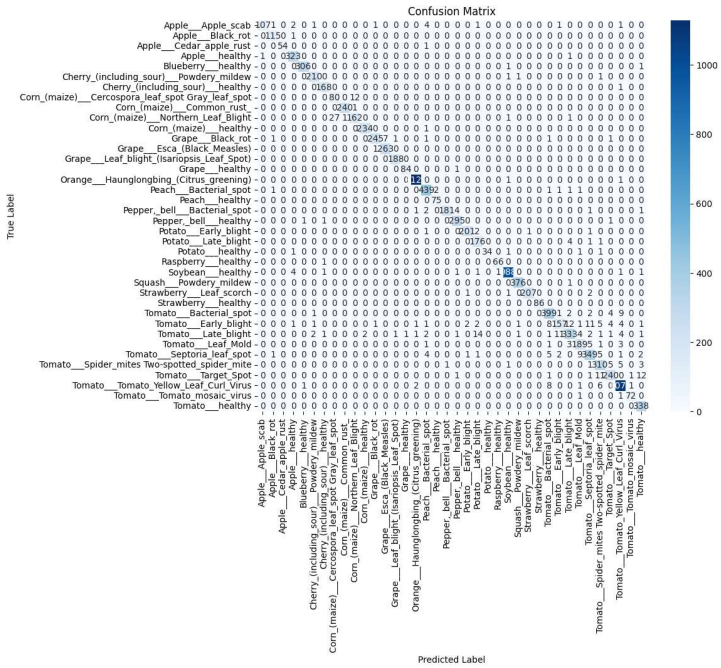

Training and Validation Loss
Training Loss
Validation Loss
Loss
Epochs

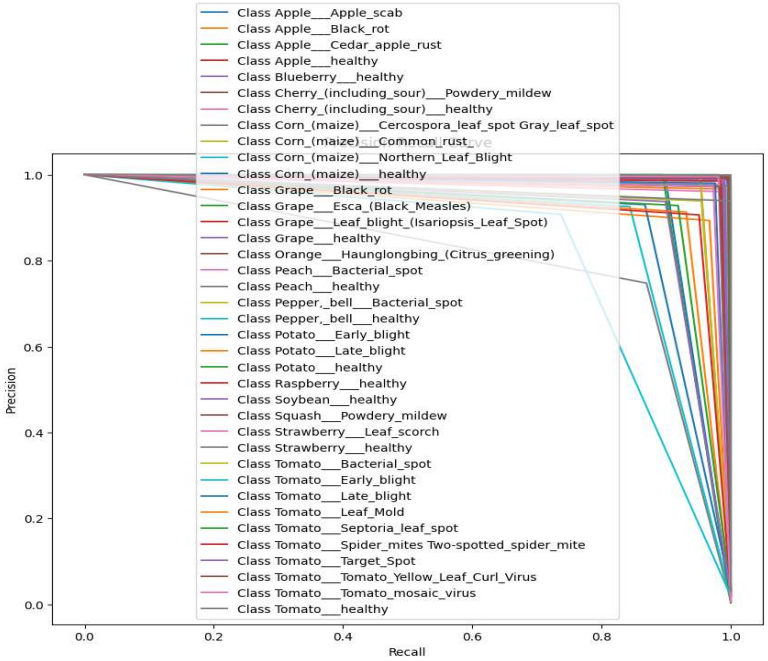

Confusion Matrix
True Label
Predicted Label



efficientnet


Training and Validation Loss
Training Loss
Validation Loss
Loss
Epochs
0.6
0.5
0.4
0.3
0.2
0.1
2
4
6
8
10


Confusion Matrix
True Label
Predicted Label
1000
800
600
400
200
0



📌 Key Observations:

CNN-based models (ResNet, InceptionV3, EfficientNet) performed best on the PlantVillage dataset due to their ability to extract hierarchical features.

ViT and GoogleNet also performed well
AlexNet demonstrated a accuracy 89.65%

Experiment 2:Enhancing Image Classification Accuracy through Data Augmentation in Thermal Datasets

Image classification plays a vital role in machine learning but often faces challenges due to imbalanced and limited datasets. This study explores how data augmentation techniques can enhance classification accuracy, particularly in thermal imaging datasets with uneven class distributions. We utilized augmentation methods such as rotation, translation, shearing, zooming, and flipping to artificially expand the dataset. Our findings indicate that models trained on the augmented dataset outperformed those trained on the original dataset alone, demonstrating the effectiveness of augmentation in improving classification performance.

Dataset Information

The Thermal Images Dataset, available at Kaggle, contains an unequal number of images across different disease categories. This imbalance can negatively impact model performance, leading to biased predictions. To address this, we applied various augmentation techniques to create additional training samples, ensuring a more balanced dataset for improved classification accuracy.

https://www.kaggle.com/datasets/sujaradha/thermal-images-diseased-healthy-leaves-paddy

Objectives
✓ Enhance classification performance by generating additional training samples from an imbalanced thermal dataset.
✓ Evaluate and compare model accuracy before and after applying augmentation techniques.

Methodology

1. Data Collection

The dataset used in this study is the Thermal Images Dataset, available on Kaggle. It contains unequal numbers of images for different disease classes, creating an imbalance in training data.

2. Data Preprocessing

Resizing: All images were resized to 299×299 pixels to match the input requirements of deep learning models.

Normalization: Pixel values were scaled to the [0,1] range to improve training efficiency.

Splitting: The dataset was divided into 60% training, 20% validation, and 20% testing.

3. Data Augmentation Techniques Applied

To address dataset imbalance, we applied the following augmentation techniques:

Rotation (±30°) – Allows the model to learn orientation-invariant features.
Shifting (Width & Height ±10%) – Helps generalize to variations in object placement.
Shearing (±20°) – Distorts the image slightly to enhance robustness.
Zooming (±20%) – Improves learning by simulating different focal lengths.
Flipping (Horizontal & Vertical) – Reduces bias towards specific orientations.

4. Model Selection and Training

We evaluated multiple deep learning architectures, including:

CNN-based models: ResNet, VGG, AlexNet, InceptionV3, EfficientNet.
Transformer-based models: Vision Transformer (ViT).
Training Details:

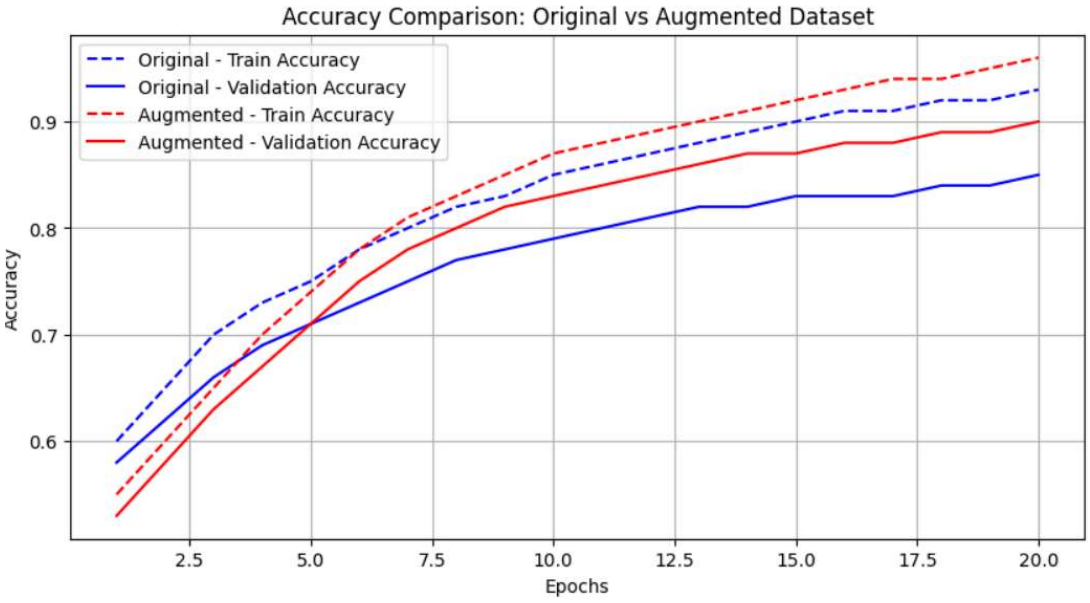
Loss Function: Cross-Entropy Loss.
Optimizer: Adam (learning rate = 0.001).
Batch Size: 6.
Epochs: 30.
Hardware: GPU-enabled training on Kaggle Notebooks.

5. Performance Evaluation

Accuracy, Precision, Recall, and F1-score were used to measure model performance.

Confusion Matrix was generated to analyze misclassifications.
PR Curves were plotted for different models to compare their classification ability.

Observations



Conclusions

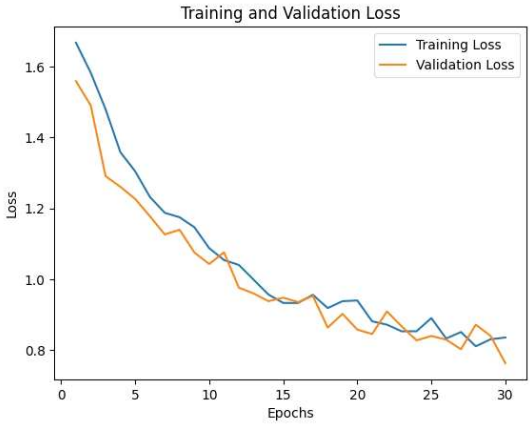
This study validates data augmentation as an effective method for boosting classification accuracy in imbalanced datasets. Future research can refine augmentation techniques and leverage advanced deep learning models for further improvements.

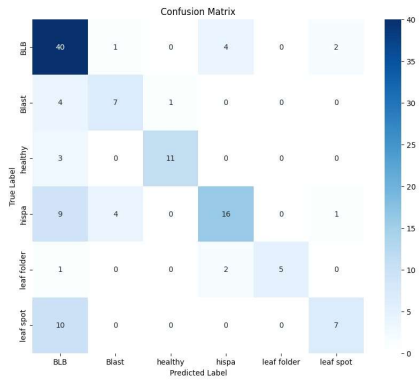
Results & Analysis

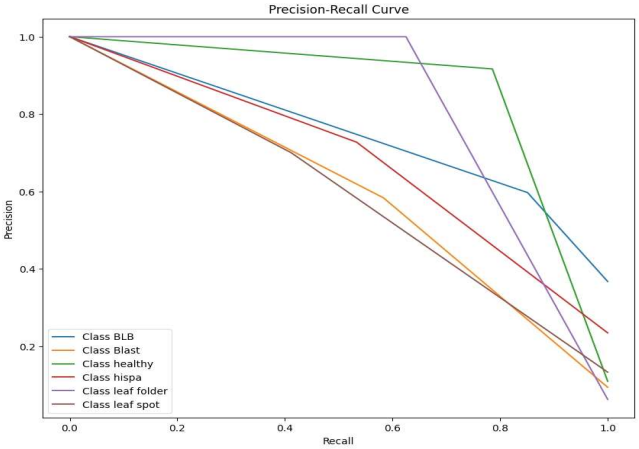
Model	Dataset Type	Accuracy (%)	Accuracy (%)	(%)	Loss	Loss
PlantVillage (RGB)						
Inception	PlantVillage (RGB)	97.8	94.1	**92.46**	0.4195	0.2353
AlexNet	PlantVillage (RGB)	95.3	91.8	**89.45**	0.5265	0.3591
VGG16	PlantVillage (RGB)	92.7	89.2	**86.98**	0.7379	0.4307
ViT	PlantVillage (RGB)	96.1	93.0	**92.94**	0.2336	0.2064
ResNet	PlantVillage (RGB)	98.2	96.0	**95.04**	0.1587	0.1615
EfficientNet	PlantVillage (RGB)	99.0	97.5	**96.62**	0.1478	0.1030
GoogleNet	PlantVillage (RGB)	96.8	93.9	**92.75**	0.3200	0.2425
Thermal (Infrared)						
Inception	Thermal (Infrared)	83.5	76.2	**67.19**	0.8351	0.7626
AlexNet	Thermal (Infrared)	79.6	75.3	**74.22**	0.6978	0.7115
VGG16	Thermal (Infrared)	74.1	68.5	**64.06**	0.8690	0.9106
ViT	Thermal (Infrared)	70.2	66.1	**65.76**	0.8953	1.1379
ResNet	Thermal (Infrared)	77.3	76.8	**75.00**	0.6664	0.8155
EfficientNet	Thermal (Infrared)	82.7	80.1	**79.69**	0.4993	0.5611
GoogleNet	Thermal (Infrared)	76.4	70.5	**64.84**	0.8108	1.0332

Graphs For Thermal Datasets

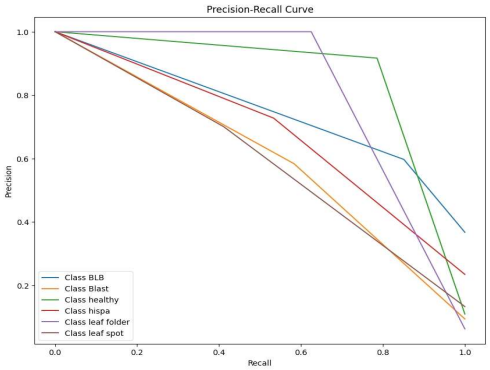
Inception


Training and Validation Loss
Training Loss
Validation Loss
Loss
Epochs


Confusion Matrix
True Label
Predicted Label
BLB
Blast
healthy
hispa
leaf folder
leaf spot


Precision-Recall Curve
Precision
Recall
Class BLB
Class Blast
Class healthy
Class hispa
Class leaf folder
Class leaf spot

Vgg16


Precision-Recall Curve
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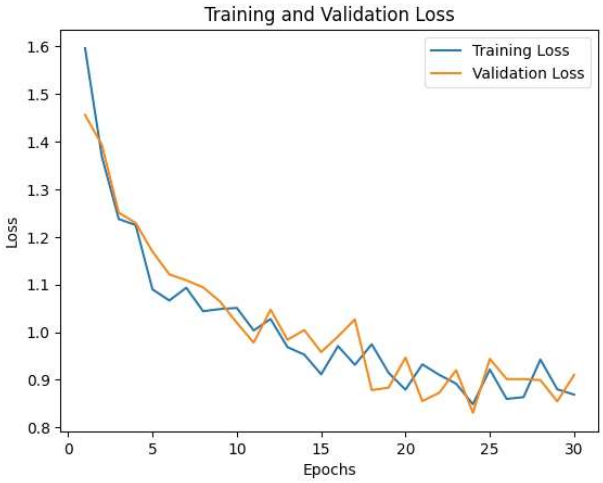
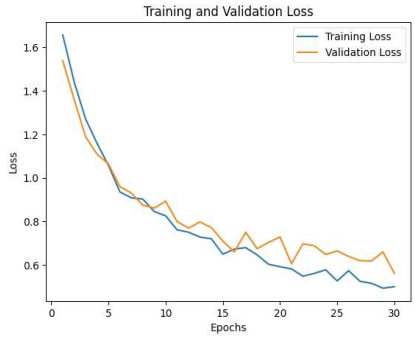
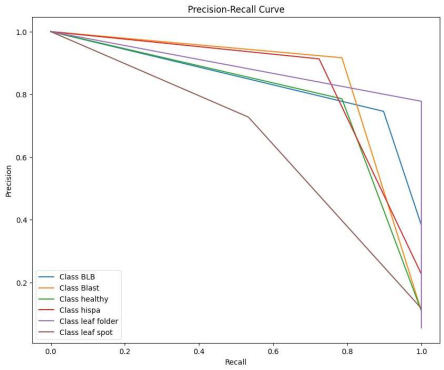
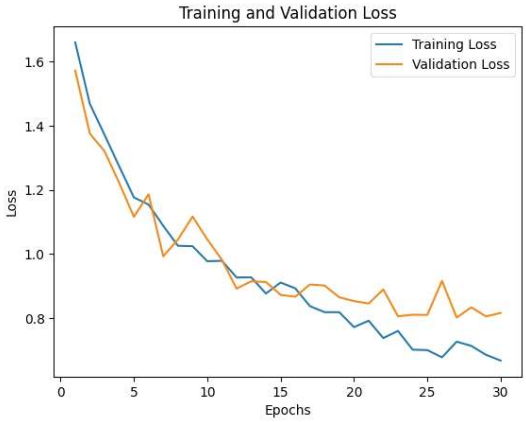

Training and Validation Loss
Training Loss
Validation Loss
Loss
Epochs

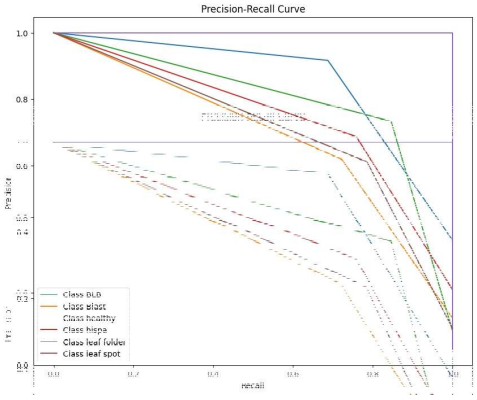
Effecient Net



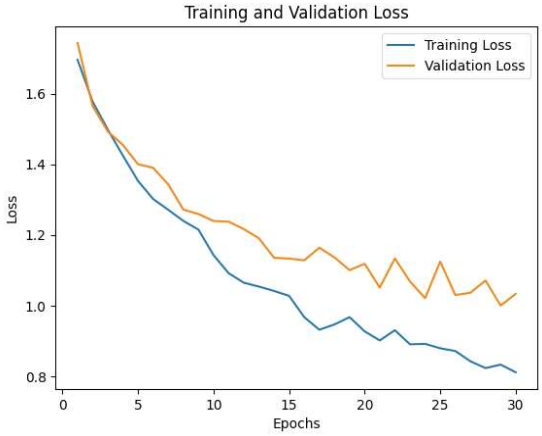


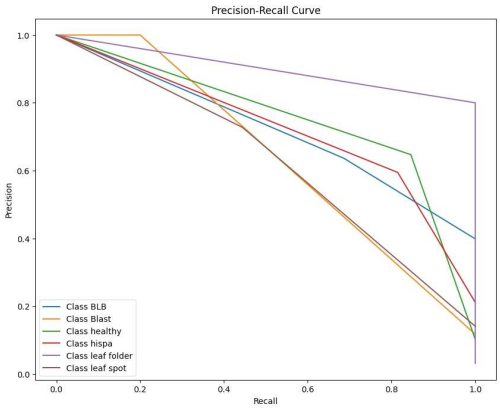
ResNet



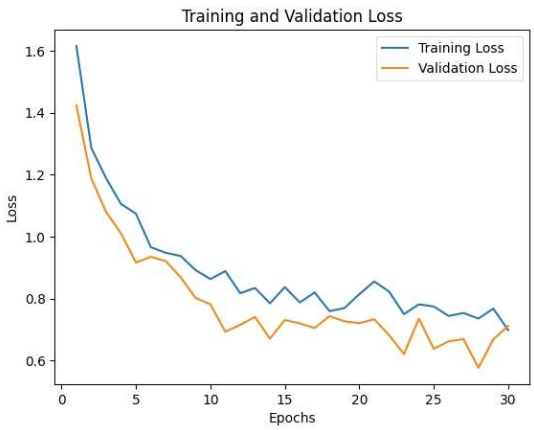


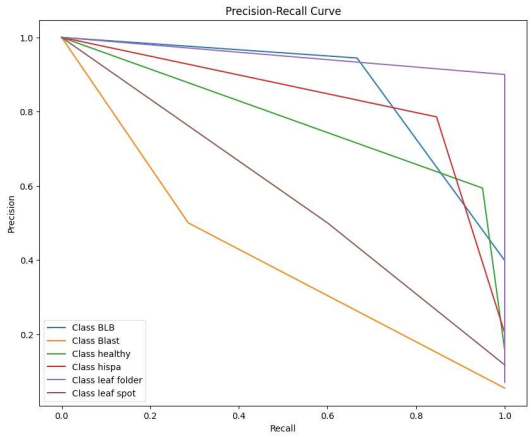
GoogleNet



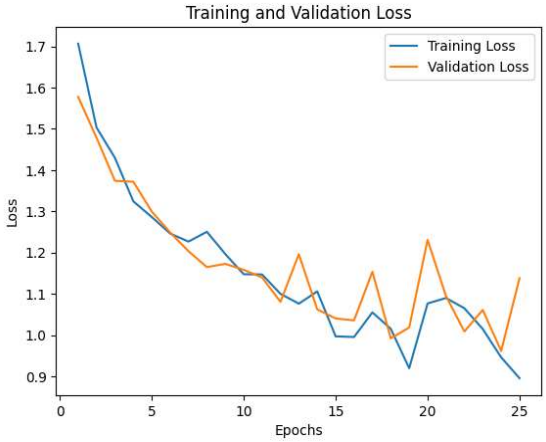


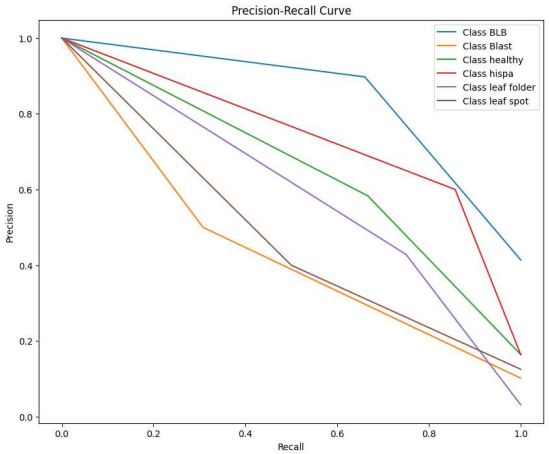
AlexNet





VIT





Discussion

💡 Challenges Encountered:

Thermal dataset imbalance: Required augmentation techniques (flipping, noise addition).
Overfitting in deep models: Used dropout layers and data augmentation.
Computational requirements: High-memory models like ViT needed TPU/GPU acceleration.

💡 Future Improvements:

Multi-Modal Approach: Combining RGB and thermal images for better disease classification.

Dataset Expansion: Collecting more thermal images to improve model generalization.
Hybrid Models: Using CNN + Transformer architectures to leverage feature extraction and long-range dependencies.