Enhancing Plant Disease Detection: A Deep Learning Approach and Comparative Analysis of Pretrained Models with Explainable AI Visualization.

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Dear Fahim,

I am happy to recommend your work to present at the Thesis Defense board.

Good luck and please let me know if there is anything else I can do to support you.

Regards,
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INTRODUCTION

- **Significant Crop Losses**
  - Annually, 20% to 40% of global crop production is lost to pests.
  - Resulting in 220 billion dollars in economic losses [nifa.usda.gov].
- **AI in Agriculture**
  - Artificial Intelligence (AI) is increasingly being adopted in agriculture.
  - Machine Learning (ML) and Deep Learning (DL) models are used to detect and diagnose plant diseases.

Figure 0: Plant Leaf Disease Scenario

- **Advantages of AI**
  - AI, particularly deep learning through convolutional neural networks (CNNs), offers the ability to analyze complex data like images, enabling early and accurate detection of plant diseases.
- **Challenges and Collaboration**
  - The adoption of AI in agriculture faces challenges that require interdisciplinary collaboration and efforts to ensure access to AI tools in less wealthy regions.

Problem Statement

- Need for Accurate and Efficient Plant Disease Detection. However, there are limitations of Traditional Methods.
- There are so many potentials of Deep Learning Models but Issues such as class imbalance and the need to achieve high-performance metrics (accuracy, precision, recall) remain challenges in deploying CNN models effectively.

Figure 0.1: Disease Identification Problem Scenario

LITERATURE REVIEW

Title	Findings	Date
Deep Learning for Plant Disease Detection Munaf Mudheher Khalid, Oguz Karan Altinbas University, 34217 İstanbul, Turkiye malmoudher97@gmail.com; oguz.karan@altinbas.edu.tr	CNN model achieved an accuracy of 89%, with precision and recall of 96% and an F1-score of 96%. The MobileNet model demonstrated an accuracy of 96%, with slightly lower precision, recall, and F1-score values of 90%, 89%, and 89% respectively.	Vol. 2024
Plant leaf disease detection using computer vision and machine learning algorithms Sunil S. Harakannanavar a , ∗ , Jayashri M. Rudagi b , Veena I Puranikmath b , Ayesha Siddiqua a , R Pramodhini a	The main finding of the paper is that the proposed model for plant leaf disease detection using computer vision and machine learning algorithms achieves high accuracy in classifying tomato leaf diseases, with an accuracy of 99.5% on a dataset of 600 samples	2022
End-to-End Deep Learning Model for Corn Leaf Disease Classification	The results of the paper show that the proposed end-to-end deep learning model for classifying corn leaf diseases achieved high accuracy, with a classification accuracy of 98.56%.	March 14, 2022

Continue

Title	Findings	Date
Detection of COVID-19 Using Transfer Learning and Grad-CAMVisualization on Indigenously Collected X-ray Dataset	The paper presents a successful application of transfer learning for COVID-19 detection using chest X-ray images, with DenseNet-121 achieving the highest accuracy of 96.49%. The study also highlights the effectiveness of Grad-CAM visualization and identifies 'RMSprop' as the optimal optimizer for training.	29 August 2021
Grad-CAM: Visual Explanations from Deep Networks via Gradient based Localization	The paper presents Grad-CAM, a versatile technique for producing visual explanations in CNN-based models, enhancing their transparency and interpretability across various tasks. Its effectiveness is demonstrated through improved localization, robustness to adversarial perturbations, and enhanced user trust in deep network predictions.	2022

Table 1: Literature Review

Motivation

- Enhancing Agricultural Productivity.
- Ensuring Food Security.
- Overcoming Limitations of Traditional Disease Detection Methods.

Goal

- Our goal is to create a reliable deep-learning model that accurately detects and classifies crop diseases. This addresses the need for better agricultural productivity and sustainability through technology.

Objective

The primary objective of our research is to develop an advanced deep-learning model to enhance the classification of plant leaf diseases using images from the Plant Village dataset. Additionally, We applied explainable AI visualization for enhanced interpretability.

Proposed Methodology

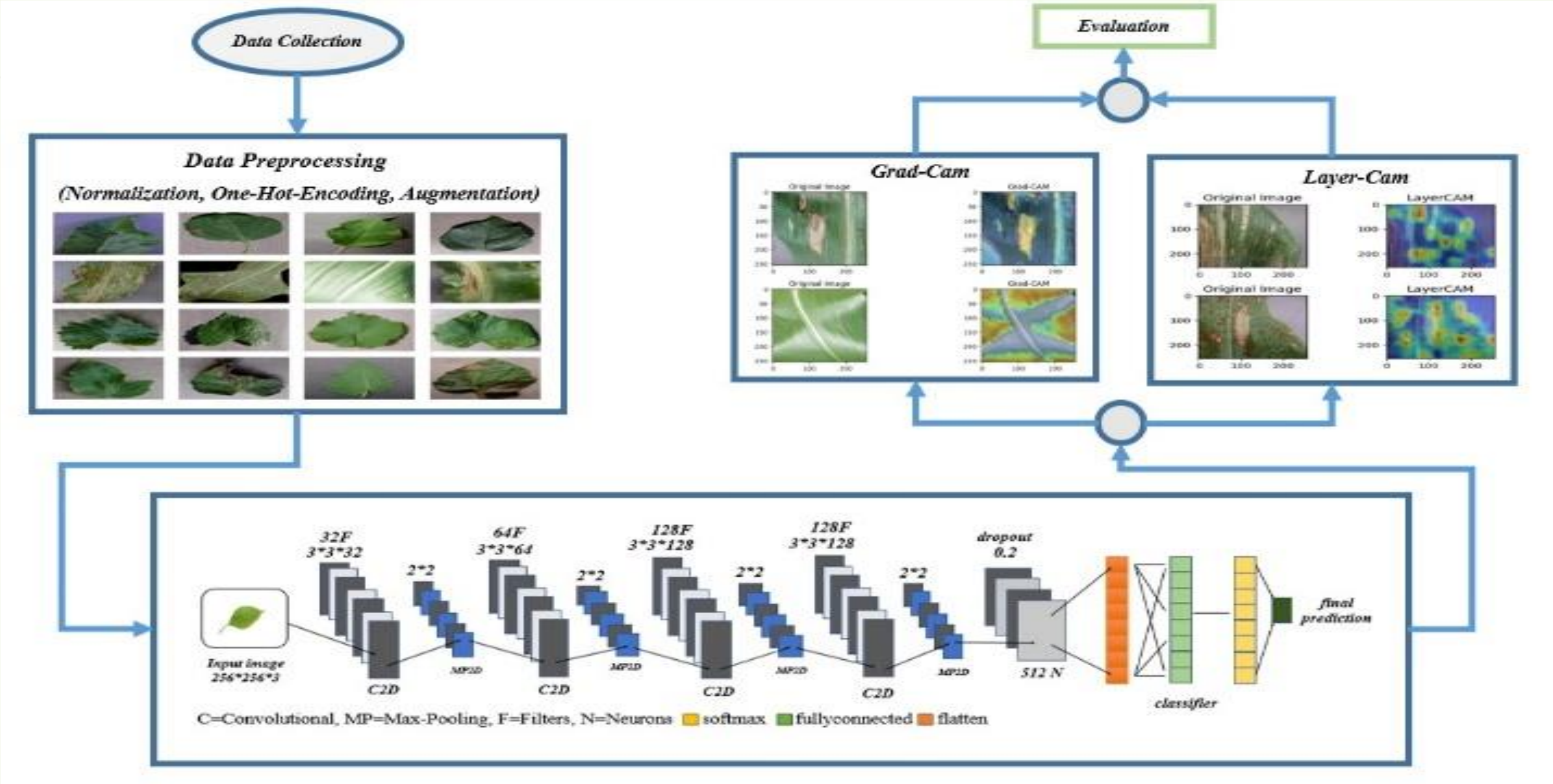

Figure 2: Proposed Methodology

Data Set Description

- **Data Collection**
  - For this research we have collected an image dataset of various plant diseases with healthy images.
  - This dataset is publicly available on GitHub, Kaggale, and other sites as the name of Plant Village Dataset.
  - This dataset contains 54,707 images along with 38 distinct classes.
- **Dataset Re-formation**
  - For our research we have selected 16 classes from the full dataset.
  - We selected the 16 classes based on the availability of images in the main dataset.

Classes Names			
Apple Black rot	Corn Gray leaf spot	Grape Black rot	Tomato Bacterial spot
Apple Cedar apple rust	Corn Common rust	Grape Esca	Tomato Early blight
Apple scab	Corn Leaf Blight	Grape Leaf blight	Tomato Late blight
Apple healthy	Corn healthy	Grape healthy	Tomato healthy

Table 2: Class names of the dataset

Crop-Disease Images

- To prepare the dataset for the Deep Learning model we split the dataset into three different parts.
- We allocate 70% of the image for training the model 20% of the image for the validation of the model and rest 10% for testing the Model.
- Total Number of train images is 22,488 RGB images and for validation, 6,425 images were used and for testing the model we used 3,214 images.
- For each class there are 1400 images for the train along with 400 and 200 images for Validation and Testing the model.

Fig 1: Crop-Disease Image

partition	number of images
train	22,488
validation	6,425
test	3,214

Table 3: partition of data sets

Data Pre-Processing & Augmentation

- Pre-processing
  - **Resizing**: All images were resized to a consistent shape of 256*256 to ensure compatibility with the CNN model.
  - **Normalization**: Image pixel values were normalized to a range of 0 to 1, improving the model's ability to learn efficiently.

- Data Augmentation
  - Helps prevent overfitting
  - Increasing the diversity of training data.
  - Enhances the model's ability to generalize to unseen images.

Applied Techniques	
Rotation	40
Shear Transformation	0.2
Zoom	0.2
Flipping	True
Brightness Adjustment	(0.5, 1.5)

Table 4: Techniques parameter

Model Architecture

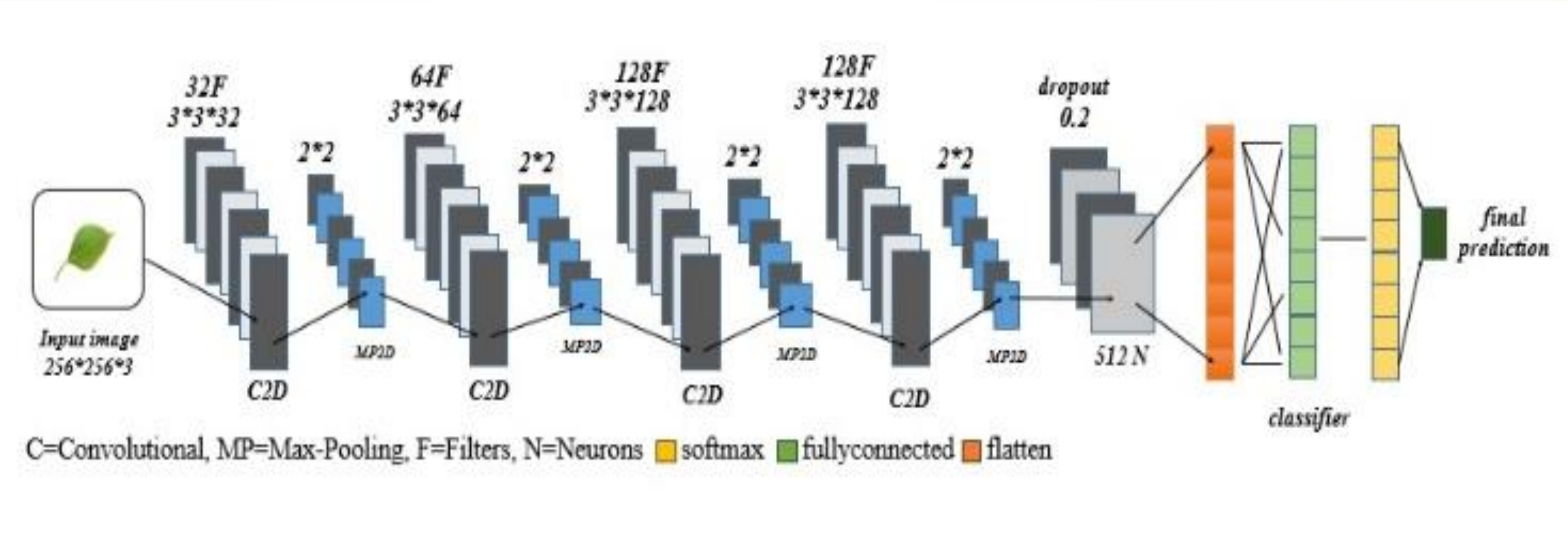

Fig 3: Model Architecture

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- Input Layer
  - Input shape 256*256*3 representing 256*256 pixels and 3 represents RGB channel.
- Convolutional Layers

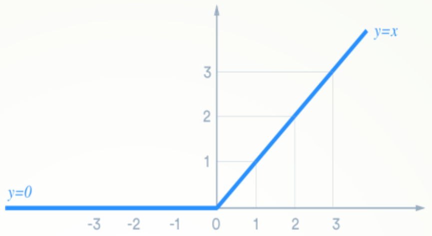
Layer No	Filter	Karnel	Act. Fn	Function
1st	32	3*3	ReLU	extracts basic features.
2nd	64	3*3	ReLU	captures more complex.
3rd	128	3*3	ReLU	focusing on high-level features.
4th	128	3*3	ReLU	focusing on high-level features.

Table 5: layer wise explanation

- Pooling Layers
- Flattening Layer
- Dense Layers
  - 1st and 2nd sense layers with 512 and 16 filters and a dropout layer.

Continue

- **ReLU**
  - ReLU is an activation function defined as $f(x) = max(0, x)$. It outputs the input directly if it is positive; otherwise, it outputs zero. We use it for Non-linearity, Sparsity, and Computational efficiency.



- **Softmax**
  - Softmax is the last activation function for a neural network that converts the output of the model into a probability distribution over multiple classes. It is ideal for multi-class classification tasks, allowing the model to predict probabilities for each class.
- **Adam (Adaptive Moment Estimation)**
  - Adam is an optimization algorithm It computes adaptive learning rates for each parameter based on the first and second moments of the gradients. It is used for Efficiency, Adaptive learning rates, and Good performance.
- **Categorical Cross-Entropy**
  - Categorical cross-entropy is a loss function that measures the difference between the predicted probability distribution and the true distribution of the classes. It is specifically designed for multi-class problems where each instance belongs to one class among multiple classes.

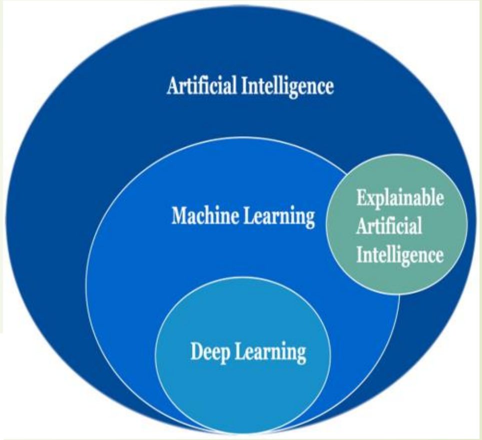
Transfer Learning Models

Models	Architecture Overview	Advantage	Use case	Other Version
Inception-V3	Expands both depth and width using "Inception modules" with multiple kernel sizes to capture features at various scales.	Efficient in handling large image datasets	Efficient for complex tasks	Inception-V1 and Inception-V2
ResNet152-v2	Solve the vanishing gradient problem and enhance performance by refined batch normalization and activation ordering.	With its 152 layers, is effective for complex feature extraction and improves model generalization.	Capture intricate details in images.	ResNet 50, ResNet 101, ResNet151-v2
VGG-16	Simpler architecture with 16 weight layers using alternating convolutional and max-pooling layers, small 3x3 filters.	Simple and effective in image classification	well-suited for transfer learning	VGG-19

Table 6: Overview of the TL models

Explainable Artificial Intelligence

- Explainable AI (XAI) is essential in enhancing the interpretability of deep learning models, particularly in sensitive applications such as plant disease detection. As deep learning models often operate as black boxes, understanding their decision-making processes can help build trust among users, facilitate knowledge transfer, and ensure ethical deployment



- Interpretation of Model Predictions.
- Identifying Areas for Improvement.
- Enhancing User Trust and Adoption.
- Supporting Diagnostic Decision-Making.
- Facilitating Education and Training.

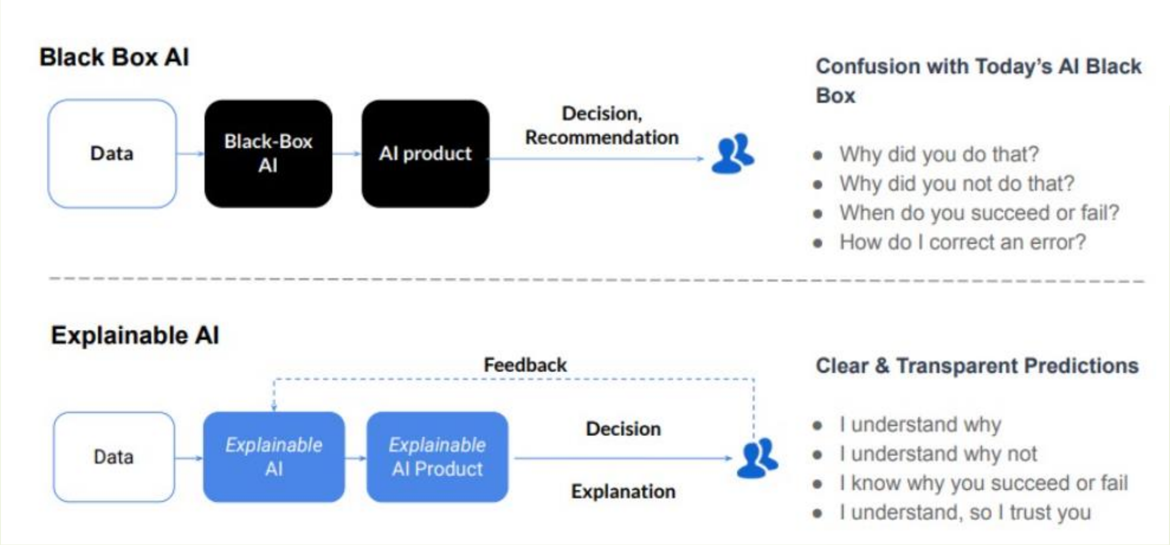


Figure 4: explainable AI

Model Training and Implementation

- **Training Configuration**

Parameter	Value/Description
Batch Size	32
Optimizer	Adam
Loss function	Categorical Cross-Entropy
Epochs	20

Table 7: training configuration

- **Hard-ware Description**
  - We have used an Intel Core i5 processor, 12GB of RAM, and Python version 3.8.15.
  - And we have Used TensorFlow 2.3.0 and Keras 2.4.0.

Epochs Wise Model Performance

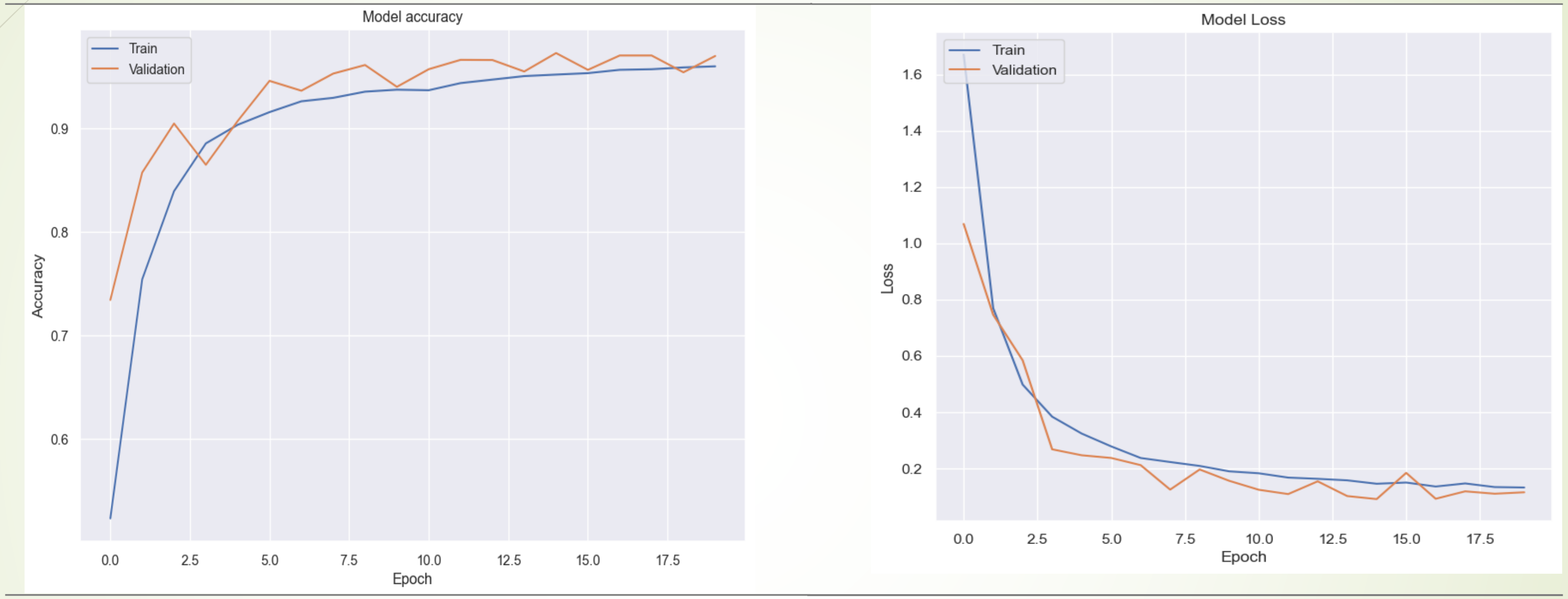


Figure 5: model performance of proposed CNN

- ✓ The model's accuracy consistently improves across epochs, starting from 43.14% in the first epoch to 95.68% by epoch 20, demonstrating the model's ability to learn effectively as training progresses.
- ✓ The training loss decreases from 1.67 in the first epoch to 0.13 by epoch 20, indicating that the model is minimizing errors and improving performance
- ✓ The validation accuracy reaches a peak of 96.83% by epoch 15, indicating strong performance on unseen data.

Epoch Wise Pre-Trained model performance

- After 20 epochs of training ResNet152-v2 achieved 94% of training accuracy along with 93% validation accuracy.

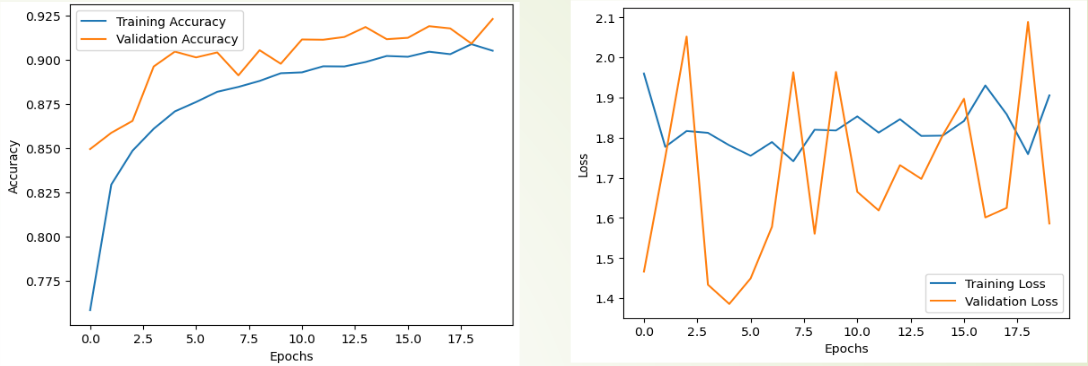


Figure 6: ResNet152-v2

- After 20 epochs of training VGG16 achieved 91.75% of training accuracy along with 91.56%.

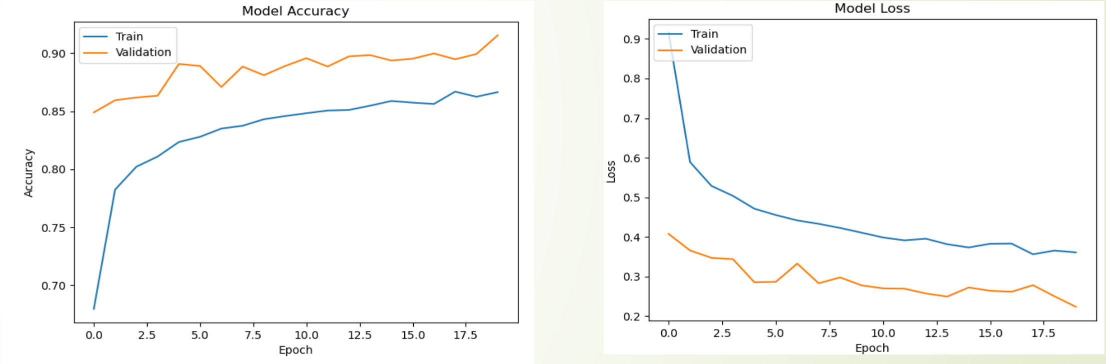


Figure 7: VGG16

- After 20 epochs of training Inception-v3 achieved 88% of training accuracy along with 87.35%.

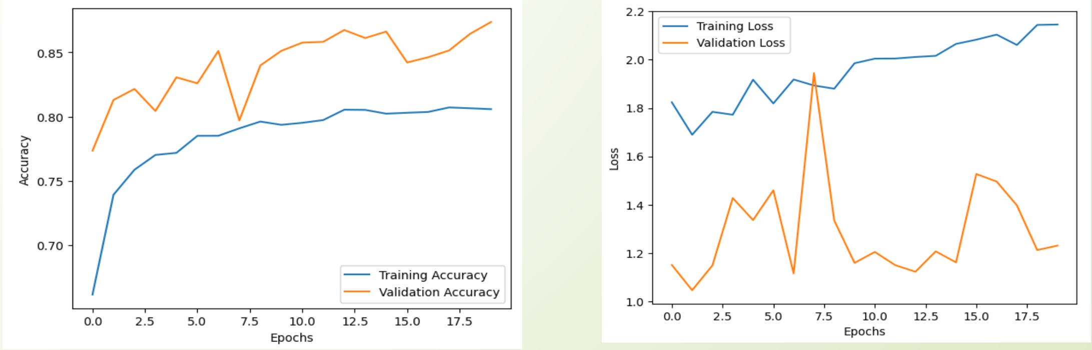


Figure 8: Inception-v3

Results & Evaluation

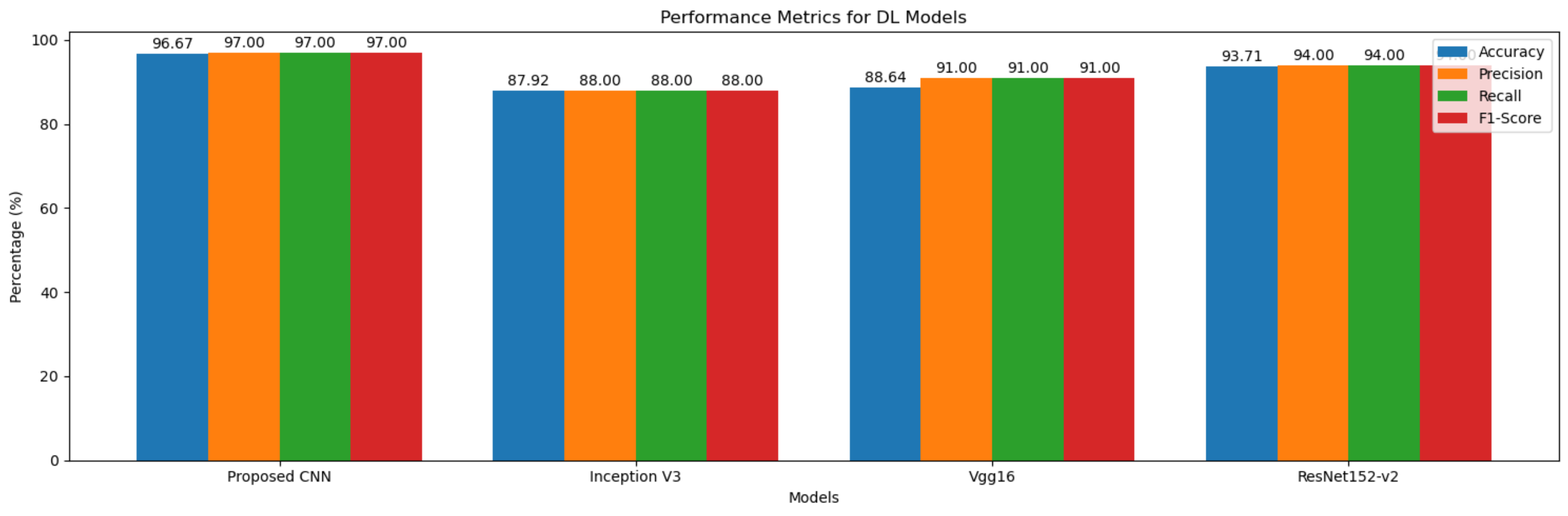


Figure 9: Graphical presentation of proposed CNN and other DL model's performance

- Our proposed CNN model achieved higher precision compared to other DL models which is 97%.
- Our proposed CNN model achieved higher recall compared to other DL models which is also 97%.
- Our proposed CNN model achieved higher accuracy compared to other DL models which 96.67% .

Precision , Recall, F1 Score

Model	Precision	Accuracy	Specificity (True negative rate)	Sensitivity (True positive rate)	F1- score
Proposed CNN	97%	96.11%	97%	97%	97%
ResNet152-v2	93.71%	94%	94%	94%	94%
VGG16	88.64%	91%	91%	91%	91%
Inception-v3	87.92%	88%	88%	88%	88%

Table 8: Precision, Recall, F1 Score table

- Our proposed CNN model achieved higher accuracy, and precision compared to other DL models which are 96.11% and 97%.
- ResNet152-v2 achieved higher accuracy and precision then VGG16 and Inception-v3 which are 93.71% and 94%.
- We also observe that VGG16 achieved a good result with 88.64% accuracy.
- Throughout the research we find that Inception-v3 achieved the lowest result in all matrices of performance.

Confusion Metrix

- A confusion matrix is a performance evaluation tool in machine learning, representing the accuracy of a classification model.
- It displays the number of true positives, true negatives, false positives, and false negatives.
- This matrix aids in analyzing model performance, identifying mis-classifications, and improving predictive accuracy.

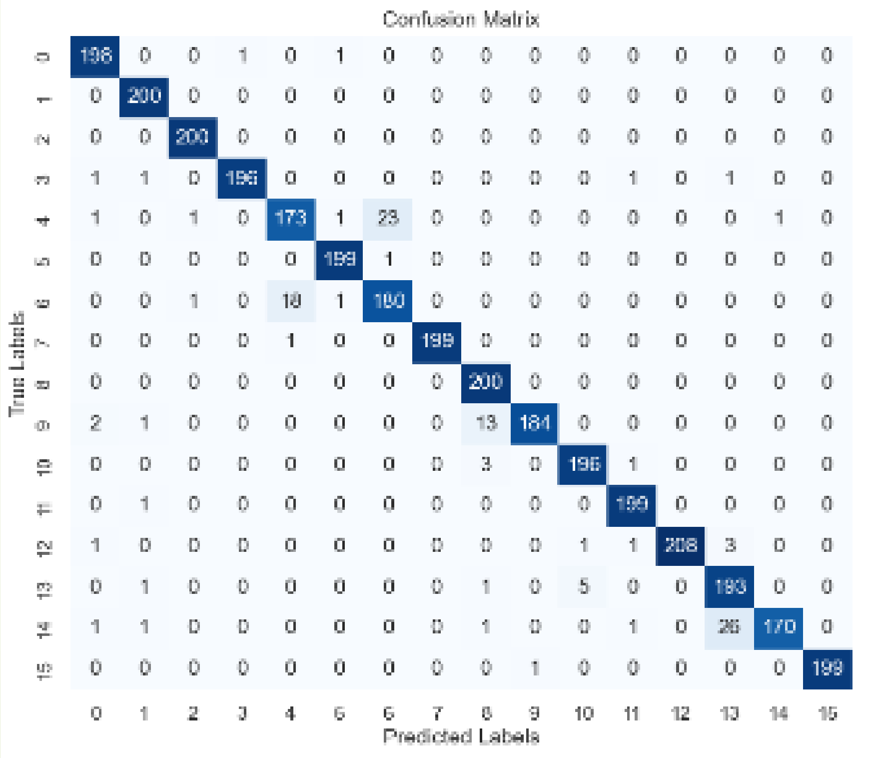


Figure 10: Confusion Matrix of Proposed CNN

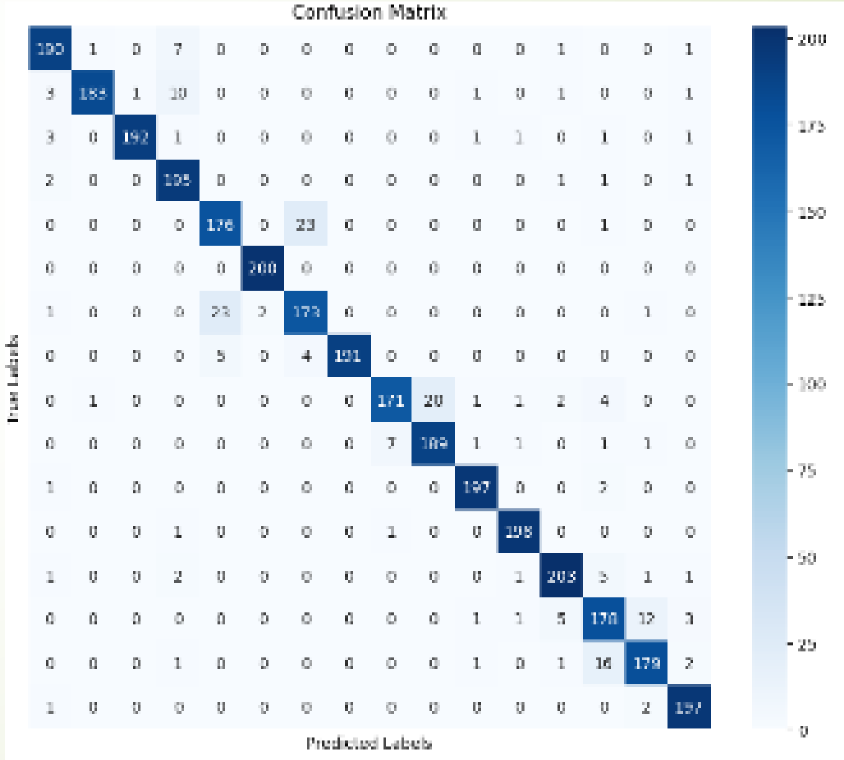


Figure 11: Confusion Matrix of RestNet152-v2

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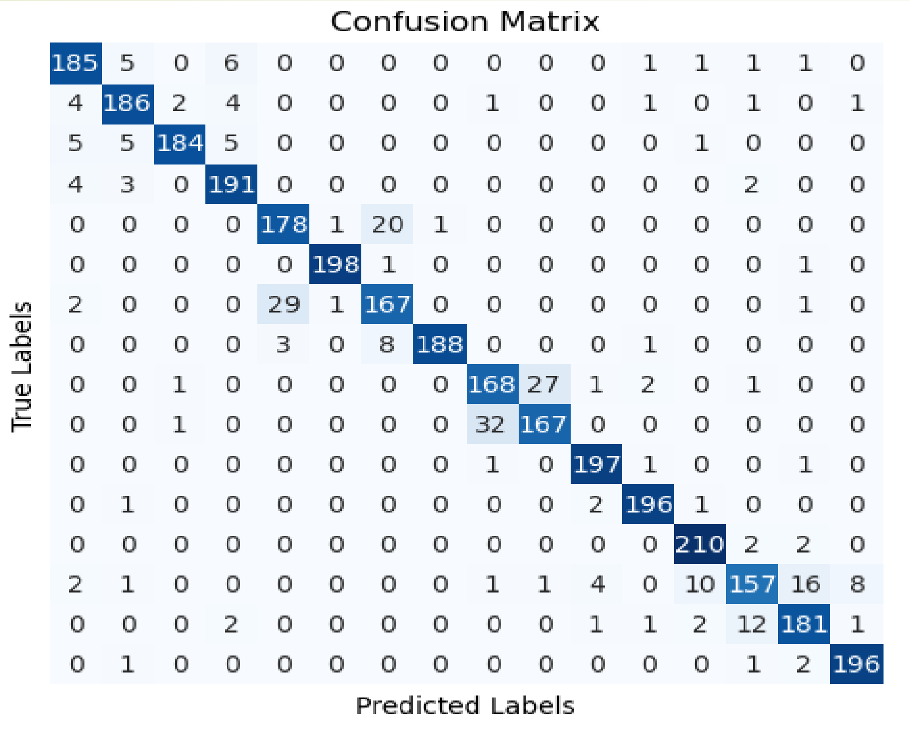

Figure 12: Confusion Matrix of Proposed VGG16

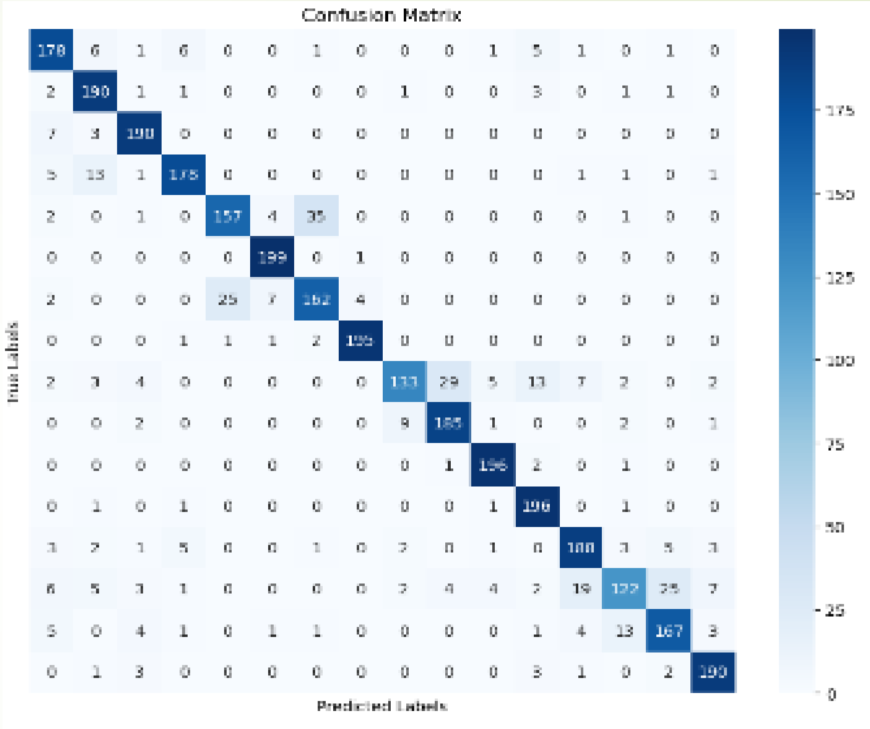

Figure 13: Confusion Matrix of Inceptionn-v3

- ❑ We have tested out models using 200 test images in each class.
- ❑ Our proposed CNN model provides 100% correct prediction on four classes and those are class 1 apple_black_rot class 2 Apple_Cedar_apple_rust class 8 Grape_Black_rot and class 12 Tomato_Bacterial_spot.

ROC-AUC Curve

- The ROC (Receiver Operating Characteristic) curve is like a graph that shows how good a model is at telling things apart. A graphical plot illustrating the trade-off between True Positive Rate and False Positive Rate at various classification thresholds.
- AUC (Area Under the Curve): A single metric representing the overall performance of a classification model based on the area under its ROC curve. A higher AUC value, closer to 1.0, indicates superior performance. The best possible AUC value is 1.0, corresponding to a model that achieves 100% sensitivity and 100% specificity.
- True Positive Rate (Sensitivity): Proportion of actual positives correctly identified by the model.
- False Positive Rate: The model incorrectly classifies the proportion of actual negatives as positives.
- Specificity (True Negative Rate): Proportion of actual negatives correctly identified by the model.

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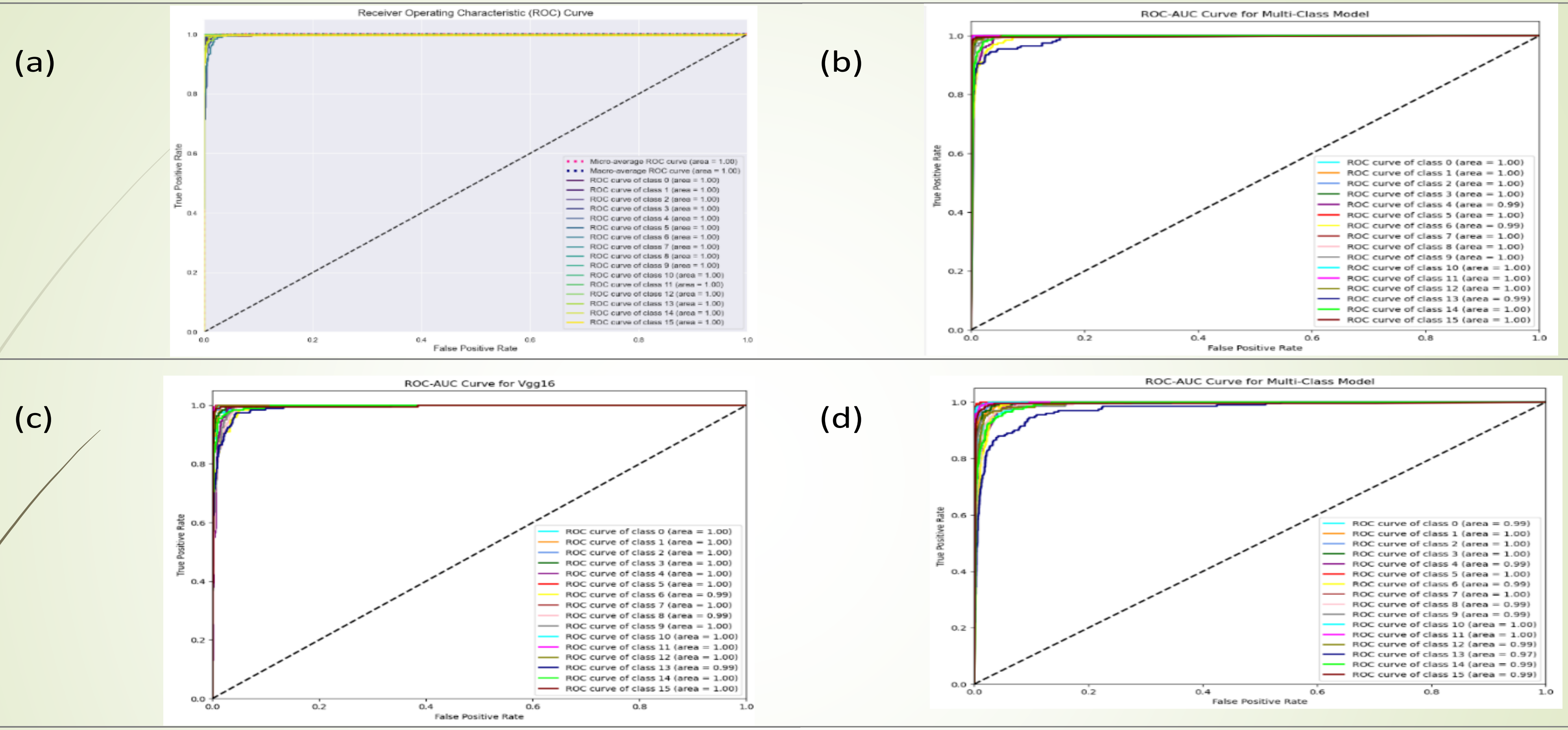
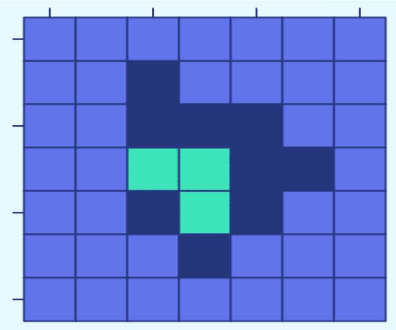


Figure 14: ROC-AUC curve (a) Proposed CNN, (b) ResNet152-v2, (c) VGG16, and (d) Inception-v3

Here we plot the ROC curve for the given class against the rest. Plot the ROC curves for each class on the same graph. Each curve represents the discrimination performance of the model for a specific class. Examine the AUC scores for each class. A higher AUC score indicates better discrimination for that particular class.

Explainable AI visualization

- **Grad-CAM**
  - **The gradient-weighted class activation map (Grad CAM**) produces a heat map that highlights important regions of an image using the target gradients (dog, cat) of the final convolutional layer.
  - The **Grad CAM** method is a popular visualization technique that is useful for understanding how a convolutional neural network has been driven to make a classification decision.



- **Layer-CAM**
  - **Layer-CAM is a class activation map (CAM)** method used to visualize which parts of an input image are contributing to a neural network's prediction, with an emphasis on activation in individual layers rather than relying only on the final convolutional layer.
  - It's a more refined method than Grad-CAM, as it can generate better localization of regions by focusing on the activations of intermediate layers.

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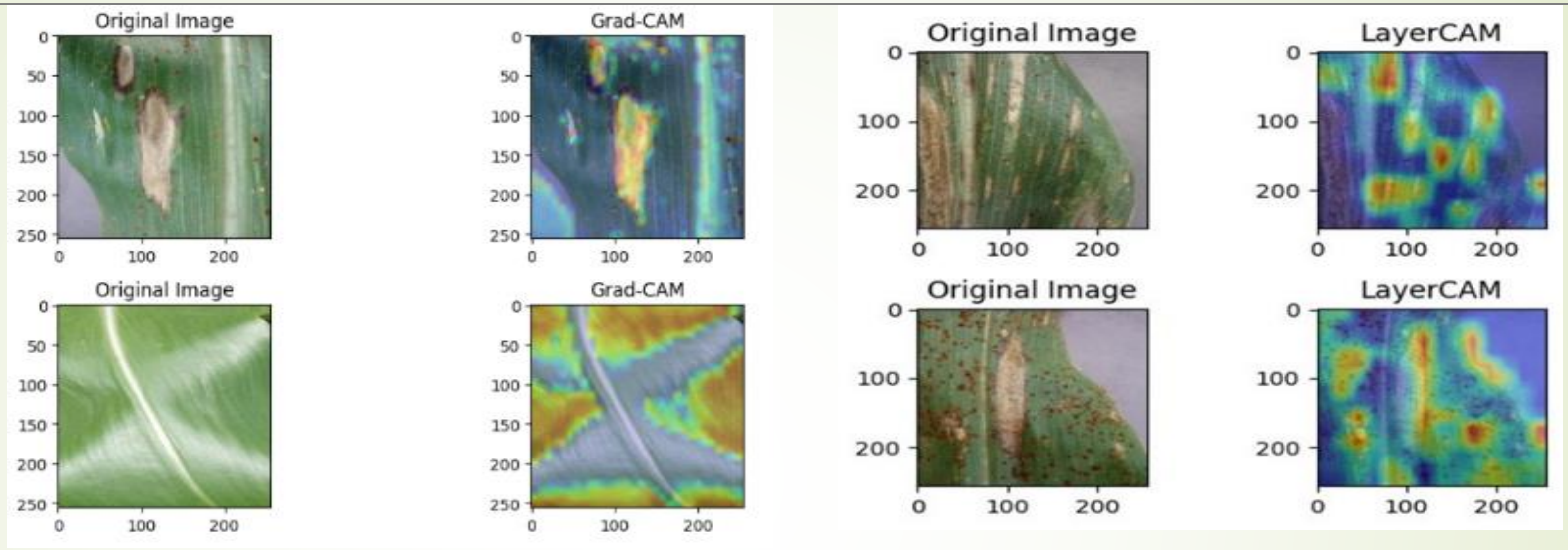
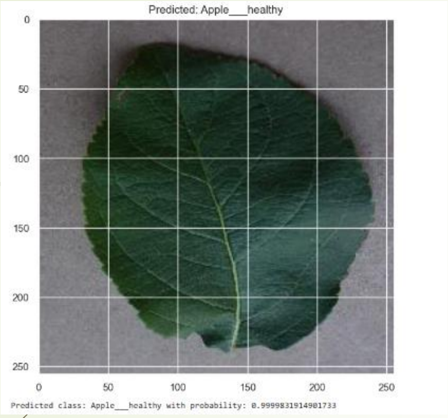


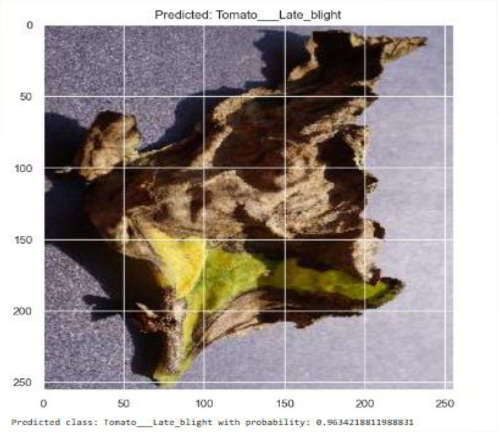
(a) (b)

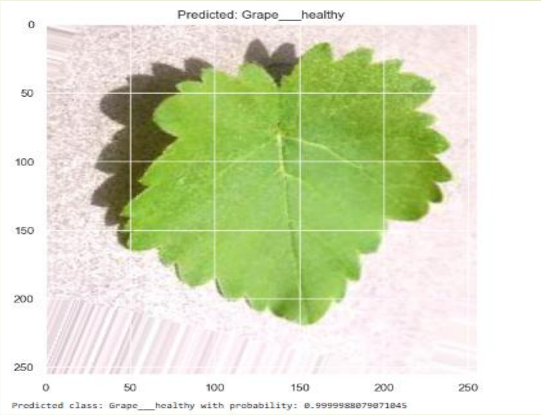
Fig 15: (a) Grad-Cam Vs (b) Layer-Cam Visualization

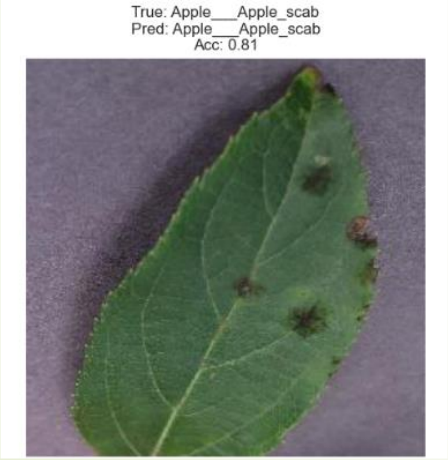
- In our research we compared Grad-CAM and Layer-CAM to visualize the focus of CNN in plant disease detection, as shown in Figure.
- In contrast, Layer-CAM improves upon Grad-CAM by incorporating activations from multiple convolutional layers, offering more detailed and precise visualizations.

Test-Result With Seen Data









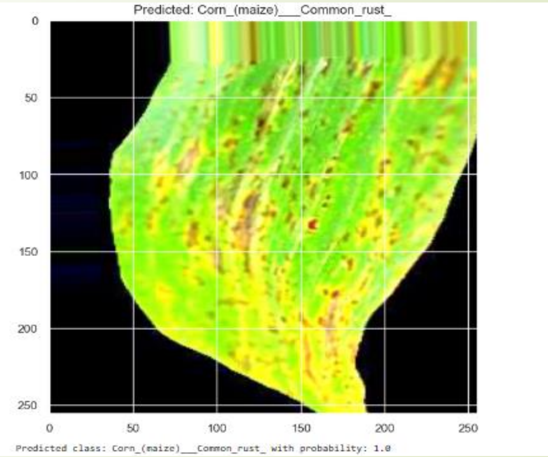


Fig 16: Test Result Seen Data

Test-Result With Unseen Data

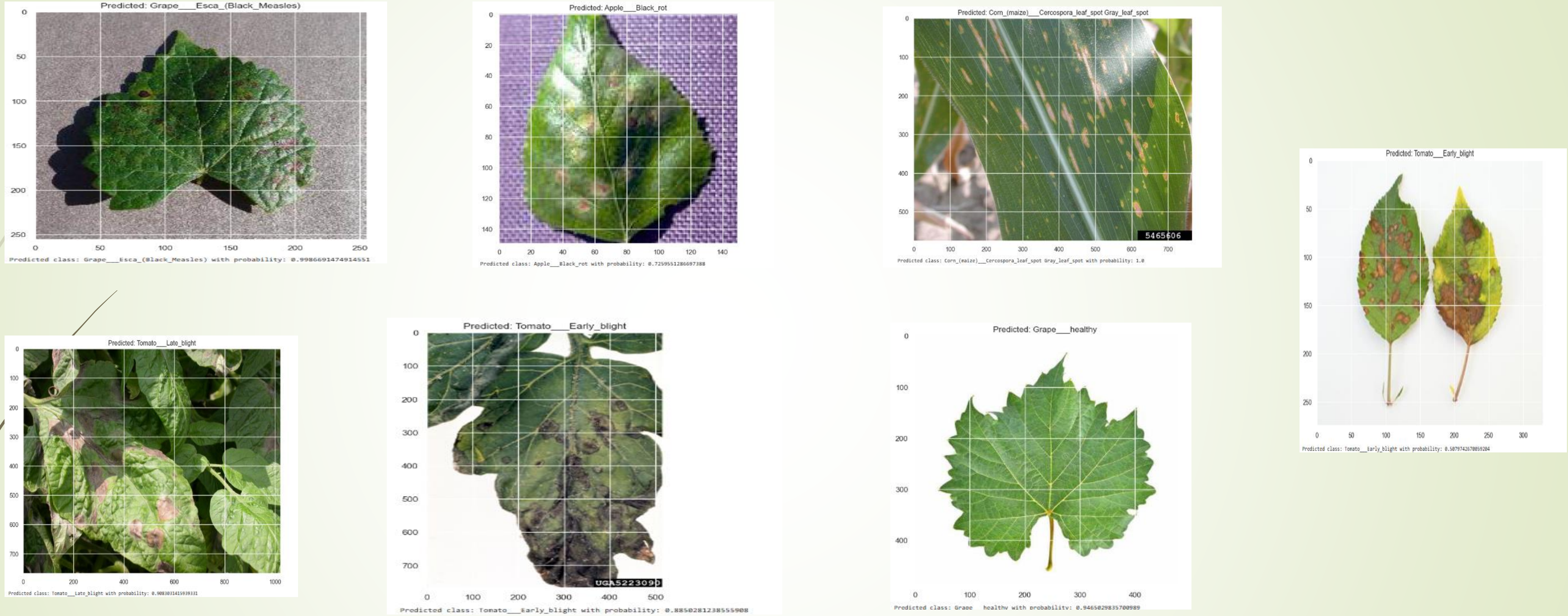


Fig 17: Test Result With Unseen Data

Conclusion

- Introduced a custom-designed CNN model for plant leaf disease classification using deep learning techniques.
- Improved model accuracy and reliability through data augmentation and image normalization.
- Outperformed existing methods with superior accuracy, precision, recall, and F1-score.
- Performance analysis using ROC curves and confusion matrices confirmed the model’s high classification ability.
- Demonstrated the model’s potential to set new standards in plant disease detection, providing reliable diagnostic insights.

Future Work

- Further refinement of the CNN architecture to enhance classification accuracy.
- Exploration of hybrid models integrating various deep learning techniques for improved results.
- Incorporating explainable AI methods (e.g., Layer-CAM) to improve model transparency and trust.
- Development of user-friendly, real-time plant disease detection applications.
- Focus on making advanced diagnostic tools accessible to farmers in resource-limited settings.

Paper Acceptance Report

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Greetings from ICISET-2024! Congratulations!

It's my pleasure to inform you that your manuscript

ID: 525
Title: Visualizing Crop Disease Detection Exploring Deep-Learning with Custom CNN Model and Grad-CAM for Enhanced Interpretability
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has been ACCEPTED for ORAL presentation at the 4rd International Conference on Innovations in Science, Engineering and Technology (ICISET-2024). The selection process of ICISET is always highly competitive and this year, only about 35% papers have been accepted out of 498 submitted papers.

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With best regards,

Chair, Technical Program Committee
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References

- Deep Learning for Plant Disease Detection Munaf Mudheher Khalid, Oguz Karan Altinbas University, 34217 İstanbul, Turkiye malmoudher97@gmail.com; oguz.karan@altinbas.edu.tr
- A Review on Machine Learning Classification Techniques for Plant Disease Detection Mrs. Shruthi U CSE Department AcIT Bengaluru, India soft.shruthi@gmail.com Dr. Nagaveni V CSE Department AcIT Bengaluru, India. nagaveni@acharya.ac.in
- Deep learning models for plant disease detection and diagnosis Konstantinos P. Ferentinos Hellenic Agricultural Organization "Demeter", Institute of Soil & Water Resources, Dept. of Agricultural Engineering, 61 Dimokratias Av., 13561 Athens, Greece
- Image-Based Tomato Leaves Diseases Detection Using Deep Learning Belal A. M. Ashqar, Samy S. Abu-Naser Department Information Technology, Faculty of Engineering and Information Technology, Al-Azhar University, Gaza, Palestine
- Multi-Class Breast Cancer Classification using Deep Learning Convolutional Neural Network Majid Nawaz, Adel A. Sewissy, Taysir Hassan A. Soliman Faculty of Computer and Information, Assiut University
- Plant Disease Detection and Classification by Deep Learning A Review LILI LI1, SHUJUAN ZHANG 2,ANDBINWANG 2 1College of Information Science and Engineering, Shanxi Agricultural University, Jinzhong 030800, China 2College of Agricultural Engineering, Shanxi Agricultural University, Jinzhong 030800, China Corresponding author: Shujuan Zhang (zsujuan1@163.com)
- Plant Disease Detection Using Image Processing and Machine Learning Pranesh Kulkarni1, Atharva Karwande1, Tejas Kolhe1, Soham Kamble1, Akshay Joshi1, Medha Wyawahare1

Thank You.