# A STUDY ON BOTTLE GOURD LEAF DISEASE RECOGNITION AND CLASSIFICATION BASED ON EFFICIENT DEEP LEARNING ALGORITHMS

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## APPROVAL

This Project titled **"A study on bottle gourd leaf disease recognition and classification based on efficient deep learning algorithms"**, submitted by Afsara Labiba, ID No: 201-15-3191 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 21 January 2024.

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## DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Mr. Amir Sohel, Lecturer (Senior scale), Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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## ABSTRACT

One of the most popular crops in Bangladesh is the bottle gourd. However, the quality and productivity of the bottle gourd crop decrease due to a variety of diseases. Therefore, a deep learning-based approach to identify disease is discussed in this study. We have collected the dataset from agricultural field and applied various preprocessing techniques like resizing, histogram equalization, augmentation etc. We have measured various statistical values like PSNR, MSE, SSIM and RMSE in the dataset for the verification of image quality after preprocessing the dataset. With the use of this research, farmers will be able to spot bottle gourd leaf diseases early on, helping them to save money. Various deep learning algorithms like VGG-16, MobileNetV2, CNN and DenseNet201 have been used here. Using the dataset consisting of 1500 images of three classes (Healthy, Anthracnose, Cercospora Leaf Spot), the models provided the accuracy of 83.33% for VGG- 16, 93.33% for MobileNetV2 ,90.67% for CNN and 93.33% for DenseNet201.The highest accuracy is provided by MobileNetV2 and DenseNet201 and it’s 93.33%.

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# CHAPTER 1
# Introduction

## 1.1 Introduction

A significant portion of Bangladesh's labor force, nearly 50% works in agriculture, which occupies more than 70% of the nation's land [1]. Many essential crops are cultivated, including rice, jute, wheat, tea, lentils, oil-seeds, vegetables, and fruits. However, pests and diseases of plants result in the loss of more than 50% of agricultural produce [2]. Therefore, to ensure the quality and quantity of crops, it is of great importance to protect plants from disease. Bottle gourd (Lagenaria siceraria) is a type of vegetable with the the lowest calories. Additionally, vitamin C (approximately 17% of RDA is found in 100 g of raw fruit), thiamin, pantothenic acid (vitamin B-5), niacin (vitamin B-3), and pyridoxine (vitamin B-6), along with minerals like calcium, iron, zinc, potassium, manganese, and magnesium, are all insignificantly present in it [3]. It lowers levels of harmful cholesterol and aids in heart health maintenance. It is also high in fiber, which is thought to support healthy digestion and blood sugar regulation. Tropical climates allow for year- round cultivation of it. But its production is affected by various diseases that can lead to significant losses.

Some of the diseases of bottle gourd are: (i)Anthracnose: On the leaves, petioles, main stem, and fruit, there are tan to brown lesions with dark dots inside [4]; (ii) Downy mildew: The upper side of the leaves have angular brown lesions, brown leaves, dead leaves connected, purple to gray spores, and gray mold on the underside of the leaves [5]; (iii) Powdery mildew : Powdery and the undersides of the leaves have white patches that are turning yellow [6] ; (iv) Cercospora leaf spot: When the disease worsens, the lesions grow until they cover a significant portion of the leaf surface. The disease first appears as tiny spots on older leaves with centers that range from light to tan brown. The centers of the lesions may become fragile and break, and they may have a black border and be wrapped around by a chlorotic area [7].

Deep learning, and more specifically Convolutional Neural Networks (CNNs), helps diagnose leaf diseases by automatically recognizing visual patterns in photos of leaves. It is capable of efficiently extracting features like discoloration or spots from multiple datasets containing both healthy and diseased leaves. This automated process enhances agricultural efficiency and crop management while enabling real-time monitoring, early disease detection, and adaptability to new diseases. We have gathered the dataset for this study from agricultural field. After that we have used various preprocessing techniques like resizing, histogram equalization, augmentation etc. Finally we have used 4 deep learning model VGG-16, MobileNet V2, DenseNet-201 and CNN and compared their performance to detect disease in bottle gourd leaf. This study aimed to develop bottle gourd leaf disease classification using deep learning algorithms.

## 1.2 Motivation

Plant diseases must be manually detected and classified, which requires patience and knowledge that isn't always available. Moreover, the accuracy of manual detection is imprecise and prone to error. It is possible to determine the existence of diseases and pests that impact the plant by categorizing the leaves based on several characteristics such size, shape, color, and texture. This can be particularly useful in identifying conditions that are hard to spot with those with no assistance. When classifying bottle gourd leaves, optimizing plant growth and crop output is crucial. In this situation, image processing using deep learning algorithms can produce more precise results than manual classification, particularly when it comes to intricate aspects like texture and color. As a result, this research will help in the identification and classification of plant illnesses, greatly enhancing disease control and crop productivity.

## 1.3 Rationale of the Study

The goal of this research is to use deep learning algorithms to identify and categorize bottle gourd leaf diseases in an efficient way. Bottle gourd is a popular vegetable in Bangladesh, but there are comparatively less studies on this specific vegetable. Our study has attempted to deal with that problems by experimenting with different deep learning methods to identify the most effective model for disease detection. We have collected the dataset from the agricultural field and applied various preprocessing techniques like resizing, histogram equalization, augmentation. Then after examining the leaf photos, we have used four deep learning models to classify the bottle gourd leaf disease. Without pursuing plant scientists, this research will help farmers identify diseases in bottle gourd leaves. As a result, it will help in early detection and management of the bottle gourd leaf disease, improve the quality and quantity of food crops produced, and eventually help in raising farmer profits.

## 1.4 Research Questions

Q.1. Which diseases of bottle gourd leaves are most often found in Bangladesh?

Q.2. Which problems are solved as a result of this study?

Q.3. How this study will help the farmers?

Q.4. How efficient and effective are deep learning models?

Q.5. What are the challenges faced in this study?

Q.6. How well do the models perform?

## 1.5 Expected Output

In this study we are working on Bottle Gourd leaf diseases detection using deep learning. Here we have used various deep learning models like VGG-16, MobileNet-V2, DenseNet-201 and CNN. We have three classes which are: Anthracnose, Cercospora leaf spot and Healthy. So, our expected outcome is to be able to differentiate between healthy and different diseased bottle gourd leaves utilizing deep learning models.

## 1.6 Report Layout

It defines what are the topic are going to discussed in this report. The topics has been separated in six chapters.

Chapter 1 - It presents introduction, motivation of the study, objective, research questions, expected outcome and layout of report.

Chapter 2 – It describes preliminaries, works that are related to this research, comparative analysis and summary of the literature review, problem scope, challenges that we have faced while implementing this work.

Chapter 3 – It highlights research subject and instrumentation needed, data collection process, statistical analysis, proposed methodology, requirements for implementation.

Chapter 4 – It describes experimental setup, experimental results & analysis, discussion.

Chapter 5 – It explains impact on society, impact on environment, ethical aspects, sustainability plan.

Chapter 6 – It talks about summary of the study, conclusions, future work.

# CHAPTER 2

# Background

## 2.1 Preliminaries

There is a significant amount of research on the identification of leaf diseases. In this section, we will look at a number of previous studies that have dealt with related topics. This includes finding the appropriate classifiers, the selection of algorithms, and the level of accuracy obtained. This helps me to understand the limitations and restrictions identified in earlier studies conducted in this particular field. In our study we have employed four deep learning models to classify bottle gourd leaf diseases.

## 2.2 Related Works

Popular modern technology that are often used to identify different crop leaf diseases include artificial intelligence and deep learning. The CNN algorithm is the best suitable model for identifying this type of leaf disease, while several studies have also used different pre-trained models.

Rony et al. [8] showed their approach for classifying bottle gourd leaf diseases. With the help of public dataset, they gathered a total of 4,363 disease pictures of the fruit for their research dataset. To produce a sharpened final image, the researchers in this study processed the unsharpened and blurry portions of the original photographs using an unsharp masking filter. Moreover, they thresholded, removed colors, and increased contrast in the photos using a green fire blue filter to improve the quality of the pictures. Various statistical formulas, including PSNR, MSE, SSIM, and SNR, were computed inside the dataset to verify the quality of the images. Finally, a modified version of a VGG-16 transfer learning architecture, called bottlenet18, was used to integrate two layers of separable and flatten layer deep learning in order to classify three distinct bottle gourd leaf diseases: anthracnose, cercospora leaf spot, and powdery mildew. Their performance metrics vary in terms of optimizers and learning rates. 93.9987% accuracy was achieved with the Adam optimizer and 0.001 learning rate when utilizing the suggested BottleNet18 architecture.

Lin et al. [9] investigated how to identify pumpkin powdery mildew using PCA and machine learning in image processing. A total of 214 sheets, 201 of which were effective were gathered for their dataset from the Pailou Test Base at Nanjing Agricultural University. They were taken in greenhouse field. In this study, the powdery mildew lesion was segmented using a hybrid color feature approach and the regional growth algorithm, which increases segmentation accuracy and provides reliable data for detecting the disease. The PCA-SVM model, which uses kernel function and PCA, was found to be more accurate and stable through comparison and a new method for identifying this disease. This paper used SVM for classification and PCA for simplifying feature extraction. They got the highest accuracy of 97.3% by using their proposed model. Limitations of this study includes the lack of original lesion image dataset as collecting lesion pictures from different times can identify diseases more precisely since they lack the other features of other frequent diseases in pumpkins as it improves classification process.

According to Liu et al. [10], the goal of that paper was to achieve the automatic identification of various diseases in the leaves of bitter gourds or balsam pear plants. To identify diseases in the leaves of bitter gourds or balsam pears in their natural habitat, a target identification technique based on Faster R- CNN is developed. Three convolution neural networks- ZF-Net, VGG CNN M 1024, and VGG-16 are employed as feature extraction models in this study. In this migration learning technique, the pre-trained ImageNet neural network architecture is employed. In addition to the little size of the leaf disease of bitter gourds. Based on the VGG-16 feature-extraction, the deep learning model with the best performance was achieved. A small dataset was used for testing. The model's accuracy was 89.70 %.

Mim et al. [11] discussed their work for recognizing sponge gourd diseases. In this paper they have used CNN and image processing techniques to identify sponge gourd diseases of the leaves and flowers. Their dataset contained 6000 leaf and flower images which they have collected from field consist of 4 classes of diseased leaves, 1 class of healthy leaf, 1 class of unhealthy flower and 1 class of healthy flower. The highest accuracy achieved by using their proposed model was 81.52%. They have planned to create Android applications and software in Bengali for rural farmers who don't speak any other language but Bengali as a future work based on this paper.

Attique et al. [12] showed their approach using an enhanced saliency technique and deep feature selection to recognize and classify diseased spots on cucumber leaves. They have proposed a new approach to preprocessing that combines HSV color space conversion, top-hat and hessian-based filtering, and local contrast. Their other contributions includes a new feature selection methodology and a novel binary segmentation method were designed and applied in this research. In this study, they were concentrating mostly on a classification and identification system for diseases of cucumber leaves. VGG-19 and VGG-M, two pre-trained models, were used to extract features and then choose the most significant features in this study. They have also used multi class SVM for identification of diseases and image segmentation using saliency method. Their proposed algorithm achieved an classification accuracy of 98.08% in 10.52 seconds. But the limitation of this study was the complex structure which takes a long time to train, which is undesirable for large datasets. Another problem was Saliency method based segmentation failed when using low contrast images.

Habib et al. [13] showed their approach of papaya disease recognition. They gathered 128 color photos of both imperfect and perfect papayas from farming fields. In order to address the papaya disease recognition problem, they offered a two-feature set with 10 features overall. The features were extracted using image processing techniques. They classified the disease using SVM and separated the disease-affected area from the collected image using the K-means clustering approach. They achieved 90% accuracy.

Shanwen et al. [14] showed the way to detect cucumber leaf disease using a dilated convolutional neural network with global pooling. From the cucumber planting bases in Yangling Agricultural High-Tech Industrial Demonstration Area, Shaanxi, China, they collected 600 infected leaves of six common cucumber leaf diseases and 100 normal leaves. In order to identify six different types of cucumber diseases- downy mildew, anthracnose, gray mold, angular leaf spot, black spot, and powdery mildew, a global pooling dilated convolutional neural network (GPDCNN) was proposed in this paper. This is achieved by combining dilated convolution with global pooling. Their suggested model substituted a global pooling layer for fully connected layers, enhancing the convolution receptive field without sacrificing discriminant creation or computing complexity. Additionally, GPDCNN incorporates the benefits of global pooling and dilated convolution. They achieved 94.65% accuracy.

Ferentinos et al. [15] showed some deep learning models for the diagnosis and identification of plant diseases. This study used basic leaf photos of both healthy and diseased plants to create specialized deep learning models based on certain CNN architectures for plant disease detection and diagnosis. The dataset used in this study includes 87, 848 photos of 25 distinct plants in 68 different classes of combinations of plant diseases from public databases. Five fundamental CNN architectures—i.AlexNet, ii.AlexNetOWTBn, iii. GoogLeNet, iv. Overfeat, and v. VGG were tested. The Torch7 machine learning computational framework was used to implement these models as well as their training and testing procedures. This study achieved the highest accuracy of 99.53%.

Adhikari et al. [16] worked an image processing system for the identification of tomato plant diseases. They collected their dataset from internet and agricultural field. They used CNN architecture by gathering information on many different diseases of tomato plants and use them in training on to CNN for creating a machine learning model. To train a model and forecast tomato plant diseases, the Darknet framework's YOLO object detection algorithm is utilized for detection purposes. They got the accuracy of 89%. The limitation of this study was that they have limited dataset and was only able to detect three classes of diseases and healthy plant of tomato.

Kutty et al. [17] mainly talked about how neural network analysis is used to classify watermelon leaf diseases such as Downey Mildew and Anthracnose. From the specified Regions of Interest (ROI), the RGB pixel color indices have been obtained and this color feature extraction is the basis for classifying the leaf illnesses of watermelon. The Statistical Package for the Social Sciences (SPSS) and the Neural Network Pattern Recognition Toolbox in MATLAB were used in the suggested automated classification model to classify diseases. Here, the model attained a 75.9% accuracy rate utilizing 200 leaf samples as datasets.

Mehedi et al. [18] showed their approach of detecting defected bitter gourd in their study. After processing photos of bitter gourd using a convolutional neural network (CNN), they produced three different models by differing the number and value of the convolutional layer. Their M3 model provided the highest accuracy which was 99.70%.

Tiwari et al. [19] discussed identification of potato leaf diseases based on deep learning. This paper presented a model that extracts relevant features from the dataset through fine-tuning (transfer learning) utilizing VGG19 or other pre-trained models. Multiple classifiers were used to assess the data, and logistic regression outperformed the others by a substantial margin in classification accuracy, reaching 97.8% throughout the test dataset.

## 2.3 Comparative Analysis and Summary

TABLE 2.3.1 : Comparative analysis of previous research works

| Author & Published Year | Dataset | Model | Accuracy | Remarks |
|---|---|---|---|---|
| Rony et al. (2021) | Bottle gourd leaf diseases | BottleNet-18 | 93.99% | Only detect three diseases |
| Lin et al. (2021) | Pumpkin diseases | PCA-SVM | 97.30% | Expanding the dataset will improve their quality of work |
| Liu et al. (2021) | Bitter gourd leaf diseases | VGG-16 | 89.70% | Increasing the dataset will make their work more efficient |
| Mim et al. (2020) | Sponge gourd diseases | CNN | 81.52% | Only two models are used |
| Attique et al. (2020) | Cucumber leaf diseases | Multiclass SVM | 98.08% | Minor effective for large and low contrast dataset |
| Habib et al. (2020) | Papaya diseases | SVM | 90% | Limited dataset |
| Shanwen et al. (2019) | Cucumber leaf disease | GPDCNN | 94.65% | A larger dataset will increase their work efficiency |
| Ferentinos et al. (2018) | Plant disease | VGG | 99.53% | There might be a overfitting problem |
| Adhikari et al. (2018) | Tomato plant disease | YOLO | 89% | Limited dataset |
| Kutty et al. (2013) | Watermelon leaf diseases | NNPR toolbox | 75.90% | Minor effective for low light images |

## 2.4 Scope of the Problem

After analyzing these papers, we have come to a conclusion that majority of the researchers have focused on detecting diseases of other plants. So, the study for detection of bottle gourd leaf diseases is comparatively less than the other plants. In this study, we have gathered the datasets of bottle gourd healthy and diseased leaves to classify bottle gourd leaf diseases using some deep learning models. This will help the farmers to identify bottle gourd leaf diseases earlier and take proper steps to prevent loss.

## 2.5 Challenges

We have collected bottle gourd leaves that contained the two diseases named anthracnose, cercospora leaf spot and healthy leaves as our work is based on bottle gourd leaves. This is the most challenging part for us because in an effort to increase the results' accuracy based on our model, we must collect accurate images of the three classes leaves. We have manually gathered the raw images straight from the agricultural field. There aren't available images online of healthy and diseased bottle gourd leaves, which have made it more difficult to gather raw images from the field. As bottle gourd is a seasonal vegetable, we have had to wait for the season for collecting the dataset. While collecting the dataset it is hard to find specific diseased leaves. Some collected images are poor quality and we have preprocessed those for working better in our models. Finding appropriate preprocessing techniques and deep learning algorithms has been our another challenges.

# CHAPTER 3
# Research Methodology

## 3.1 Research Subject and Instrumentation

The subject of this research is bottle gourd leaf disease classification based on efficient deep learning algorithms. We have used Google Colab's Python notebook for the implementation of this study. Python programming language and Tensorflow library has been used here. With the help of Keras API along with numpy library, we have implemented our deep learning models. For visualization we have used Matplotlib library. Google collaboratory has provided the support for GPU or TPU to run the deep learning algorithms.

## 3.2 Data Collection Procedure

Images of bottle gourd disease have been collected from agricultural field. We have collected 418 photos of bottle gourd leaves of three different classes (healthy, cercospora leaf spot, anthracnose) . The following are pictures of different bottle gourd leaf classes (see figure 3.2.1).

(a) Healthy (b) Cercospora leaf spot (c) Anthracnose

Figure 3.2.1: Data sample of (a) Healthy ,(b) Cercospora leaf spot and (c) Anthracnose

### 3.2.1 Disease Description

In bottle gourd leaf, there are primarily two types of diseases. These are : (i) Anthracnose and (ii) Cercospora leaf spot. The dataset of this study consists of three classes called healthy, anthracnose and cercospora leaf spot. Each of these classes contains 500 images.

In Anthracnose there is a lesions on the main stem, fruit, petioles, and leaves that range from tan to brown with dark dots inside [20]. On older leaves, the early signs of Cercospora leaf spot disease appear as tiny spots with light to dark brown centers. Large portions of the leaf surface are covered by the lesions as the disease worsens. Lesions may be surrounded by a chlorotic region with a black border, and their centers may break and become brittle. etc. [21].

According to the survey in region of Chittagong from October 2006 to June 2008, the average of leaf occurrence was 11% as detected in anthracnose of bottle gourd [22]. In three regions of Brazil in the spring and summer of 2016–17, powdery mildew damaged every bottle gourd plant, with foliar disease severity reaching as high as 50% [23]. Findings included Cercospora leaf spot in bottle gourd between 12.39 and 37.15 disease occurrence in Rajasthan [24].

## 3.3 Statistical Analysis

We have gathered almost 500 data for this study. But all of these pictures are not useful for us. While collecting the dataset some pictures have come out blurry and some are not classified properly. So, we have kept 418 images for our study. We have three classes. There are 126 images in healthy class, 149 images in cercospora leaf spot and 143 images in anthracnose. There are 30.14% data in healthy class, 35.65% data in cercospora leaf spot and 34.21% data in anthracnose. Our collected dataset is raw. For this reason, we have used a number of preprocessing methods to make sure that this dataset performs well in four deep learning models that we have used in our study.

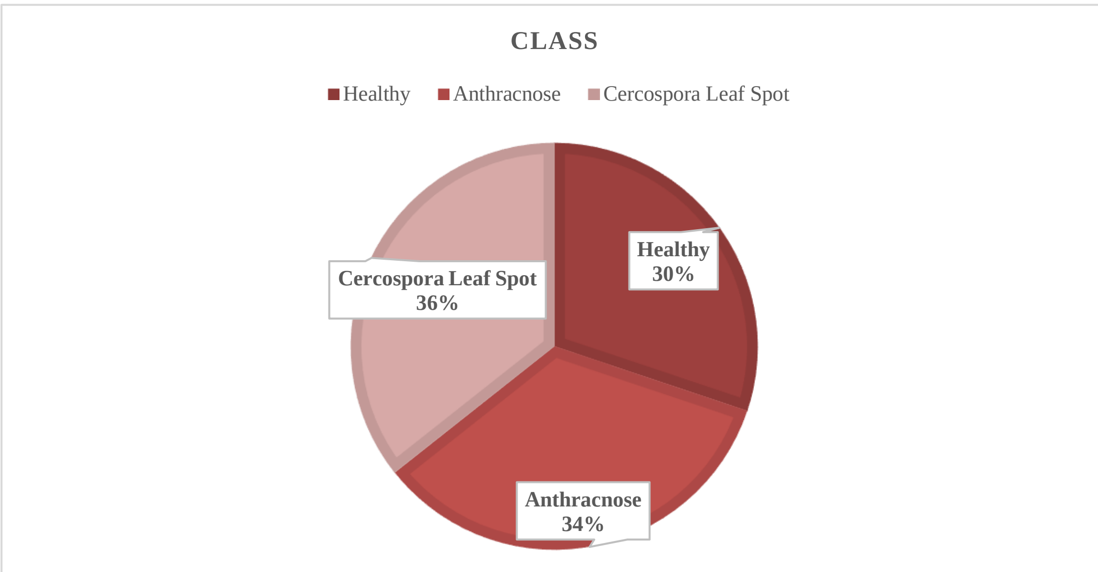



Figure 3.3.1 : Pie chart of dataset

## 3.4 Proposed Methodology

The ultimate objective of this research is to provide a useful model for early detection of bottle gourd leaf disease. As a result, several working procedures are adhered to throughout this study. Figure. 3.4.1 displays the general methodology used in this study.

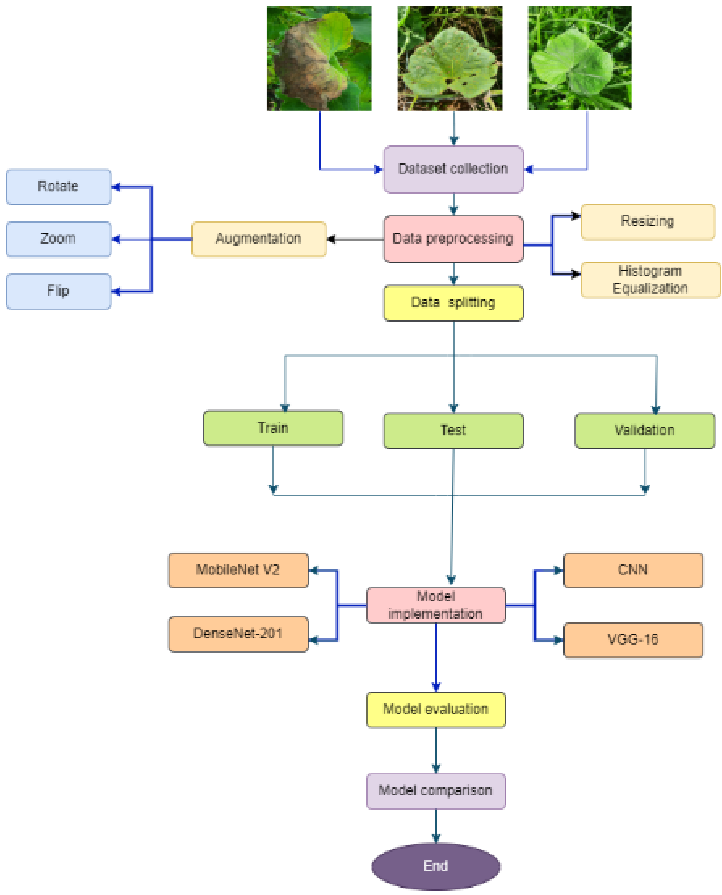



Figure. 3.4.1: System execution process of this study

## 3.5 Data Preprocessing

Preprocessing is essential to ensuring the image's quality before beginning analysis. It has allowed us to eliminate undesirable deformations and enhance significant features that are relevant to our work. It works to improve image data by eliminating unwanted distortions or emphasizing important observable aspects that are important for additional processing and verification. In our study we are using raw pictures collected from agricultural field. So, there might be some distortion or noise in our dataset due to environmental factors like low light, sunlight exposure etc. We have used various preprocessing techniques to remove these noises or distortions from our dataset including image resizing, histogram equalization. In order to expand the dataset for our study, augmentation has been applied.

### 3.5.1 Image Resize

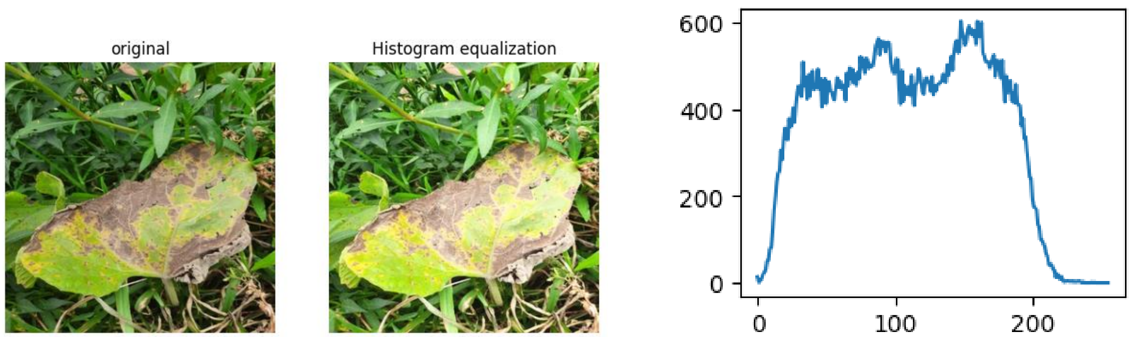
Image resizing is a basic operation that involves modifying an image's dimensions in order to make it smaller or larger. We have resized all our data into 299×299 pixels in jpg format. Deep learning models frequently use resizing to standardize input dimensions. It guarantees that sequences of photos given into the model have uniform sizes, which makes processing easier and facilitates the training of models with a variety of data, improving their performance and generalization [25]. Among these two resizing named up-sampling and down-sampling, we have used down-sampling method in our study. Figure. 3.5.1.1 shows the data sample of before and after resizing leaves.

(a) Before (b) After

Figure 3.5.1.1: Data sample of before and after resizing leaves

### 3.5.2 Histogram Equalization

Histogram equalization is a classification technique that redistributes pixel intensities to improve visual contrast. This helps draw attention to specific features, enhances the ability to recognize patterns, and eventually improves the efficiency of image-based classification models. It enhances contrast in photos. It achieves this by essentially extending the image's intensity range, or distributing the intensity values that are commonly used. This method usually results in an increase of the image's global contrast when the useful data is expressed by close contrast values. As a result, regions with less local contrast can become more contrasty. We have applied histogram equalization to improve the quality of the dataset [26]. Fig. 3.5.2.1 shows the data sample of before and after histogram equalization along with the analysis graph of histogram equalization.




(a) Before (b) After (c) Histogram Equalization Analysis

Figure 3.5.2.1: (a) Data sample of before, (b) after histogram equalization and (c) Histogram equalization analysis graph

### 3.5.3 Augmentation

In classification, augmentation is done to intentionally increase the training dataset's diversity. Augmentation is the process of applying diverse transformations, like rotation, flipping or scaling, to the preexisting images in order to improve the model's generalization to multiple input data variations [27]. Overfitting is decreased and overall performance increased through augmentation. Table 3.5.3.1 shows the number of data sample of raw data and augmented data.

TABLE 3.5.3.1: Number of raw and augmented data

| Class | Raw Data | Augmented Data |
|---|---|---|
| Healthy | 126 | 500 |
| Anthracnose | 143 | 500 |
| Cercospora Leaf Spot | 149 | 500 |
| Total | 418 | 1500 |

Here we have balanced the dataset by augmentation. This augmentation technique will help in creating varieties as well as balancing dataset for better performance of models.

## 3.6 Data Verification

Various preprocessing methods have been applied to image processing, which may have an impact on the quality of the image. Because of this, an analysis of the statistics ensures that the image quality does not decline. We measured the values of PSNR, MSE, SSIM, and SNR in this study. Comparing the preprocessed and original images provides the values of PSNR, MSE, SSIM, and SNR.

MSE (Mean Square Error) represents the error squared incrementally for the comparison between the pixels in the two images. It has a range of 0 to 1. If it is higher than 0.5, it indicates a decrease in image quality; if it is zero, it indicates noise-free, optimal quality images [28] (see equation no 1)

$$MSE = \frac{1}{ab}\sum_{i=0}^{x-1}\sum_{j=0}^{y-1}\left(O(x,y) - P(x,y)\right)^2 \qquad (1)$$

PSNR (Peak Signal to Noise Ratio) is the ratio of the maximum possible signal strength to the strength of transmitted noise that degrades the processed image's quality. The MSE value must first be determined in order to calculate the PSNR. Refer to equation number

2. For 8-bit images, the ideal PSNR range is between 30 and 50 dB. It can be considered highly satisfactory when the values are over 40 dB, but it is unacceptable and unsatisfactory when the values are less than 20 dB [29].

$$PSNR = 20\ log_{10}\left(\frac{(MAX)}{\sqrt{MSE}}\right) \qquad (2)$$

SSIM (Structural Similarity Index) evaluates how much preprocessing procedures have lowered the quality of the images. The range is from -1 to 1 [30]. Within this range, a similarity or lack of similarity is indicated by a value of 0, and perfect structural similarity is denoted by 1. When a value is near to 1, it indicates that quality of image has not been impacted by the processing steps (refer to equation no. 3).

$$SSIM_{(p,q)} = \frac{\left(2\mu_p\mu_q + c_1\right)(2\sigma_{pq} + c_2)}{\left(\mu_p^2 + \mu_p^2 + c_1\right)(\sigma_p^2 + \sigma_q^2 + c_2)} \qquad (3)$$

RMSE (Root Mean Square Error) is commonly used metric to assess a model's prediction error for quantitative data. The variations in quality between the processed and original image can be measured with its help. Equation 4 shows that the in addition to being full of errors, the lower RMSE (0) is also of good quality. [31].

$$RMSE = \left[\sum_{j=1}^{N} \left(d_{f_i} - d_d\right)^2 / M\right]^{\frac{1}{2}} \qquad (4)$$

Table 3.6.1 shows the values of MSE, PSNR, SSIM and RMSE for ten images selected randomly.

TABLE 3.6.1 : MSE, PSNR, SSIM and RMSE for ten images

| Image | MSE | PSNR | SSIM | RMSE |
|---|---|---|---|---|
| Image_1 | .43 | 39.49 | .9710 | .85 |
| Image_2 | .15 | 36.32 | .9796 | .39 |
| Image_3 | .15 | 36.31 | .9824 | .39 |
| Image_4 | .31 | 32.31 | .9425 | .40 |
| Image_5 | .28 | 33.59 | .9613 | .53 |
| Image_6 | .39 | 34.86 | .9742 | .37 |
| Image_7 | .38 | 36.09 | .9708 | .33 |
| Image_8 | .34 | 37.95 | .9714 | .38 |
| Image_9 | .41 | 33.63 | .9557 | .53 |
| Image_10 | .26 | 38.13 | .9610 | .44 |

From the table we can say that all the MSE values of the images are less than .5, PSNR values are larger than 30, SSIM values are larger than .94 and RMSE values are closer to 0 which suggests that the preprocessed images are of good quality. All of the other images in the dataset have PSNR, SSIM, RMSE, and MSE values that are within this range, indicating that our preprocessing methods are effective.

## 3.7 Data Split

We have divided the images into training , testing and validation. For training, we have taken 80% of the images. For testing, we have taken 10% of the images and for validation we have taken 10% of the images.

Table 3.7.1 shows the number of data used for training, testing and validation of the models.

TABLE 3.7.1 : Number of samples used in our study

| Class | Total Data | Training Data | Testing Data | Validation Data |
|---|---|---|---|---|
| Healthy | 500 | 400 | 50 | 50 |
| Anthracnose | 500 | 400 | 50 | 50 |
| Cercospora Leaf Spot | 500 | 400 | 50 | 50 |
| Total | 1500 | 1200 | 150 | 150 |

## 3.8 Model Description

Four models VGG-16, MobileNet V2, CNN and DenseNet- 201 have been used in this study to determine which model can identify bottle gourd leaf diseases with the highest accuracy. The popularity of convolutional neural networks is growing every day.If you want to identify crop diseases more quickly and provide the appropriate treatment, nothing compares to a solution than to use a deep convolutional neural network. Also, a lot of pre-trained models make the research easier. VGG-16, MobileNet V2, CNN and DenseNet-201 have all been used in this study to determine which produces the best results.

Deep learning algorithms like convolutional neural networks (CNNs) are usually employed in a variety of programs. CNN is frequently utilized in speech recognition, video processing, object detection, segmentation, image classification, and natural language processing. Convolution, pooling, fully connected, and non-linear layers make up CNN’s four layers. The convolutional layer utilizes kernel filters to compute the image's convolution after extracting the key features from the input image. Two consecutive convolutional layers are combined in the pooling layer. The fully connected layer, also referred to as the convolutional output layer, is the third layer. The output of a neural network is defined by the activation function. These are the most popular and commonly used CNN's activation function: sigmoid, Tanh, ReLU, Leaky ReLU, Noisy ReLU, and parametric linear units. [32].

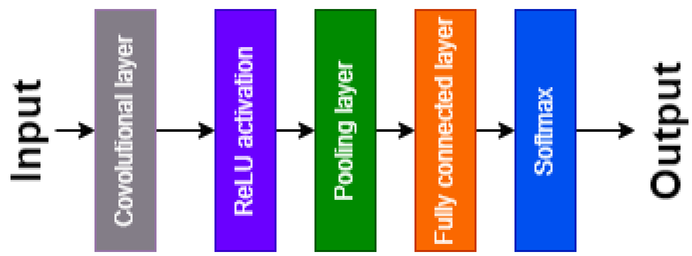



Figure 3.8.1 : Architecture of CNN

One of the greatest convolution neural network (CNN) architectures for vision models to date is the VGG16 model. Rather of having a lot of hyper-parameters, VGG16 uses convolution layers with a 3x3 filter and a stride 1 that are in the same padding and maxpool layer with a 2x2 filter of stride 2. The configurations of the convolution and max pool layers are preserved throughout the architecture. In the end, it has two fully connected layers with a softmax as the output. The 16 in VGG16 stands for the 16 weighted layers it contains.With 138 million (approximately) parameters, this network is fairly large. [33].

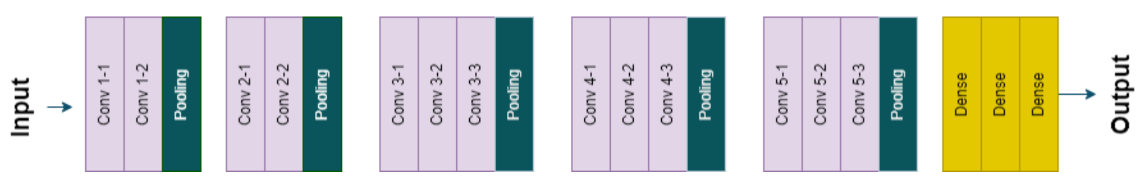



Figure 3.8.2 : Architecture of VGG-16

MobileNetV2 is an architecture for a convolutional neural network that is optimized for mobile platforms. Underneath the bottleneck layers are connected by residuals, forming an inverted residual structure. The intermediate expansion layer introduces non-linearity by filtering features through lightweight depthwise convolutions. The first convolution layer create the MobileNetV2's architecture. The residual bottleneck layers come next. [34]. Due to its lightweight deep neural network, less parameters, and enhanced classification accuracy, we employed this approach in our paper. To further reduce the number of network parameters and improve classification accuracy, MobileNet uses dense blocks from DenseNets [35]. Mobilenets are tiny models, therefore regularization is not necessary because they rarely overfit the data.

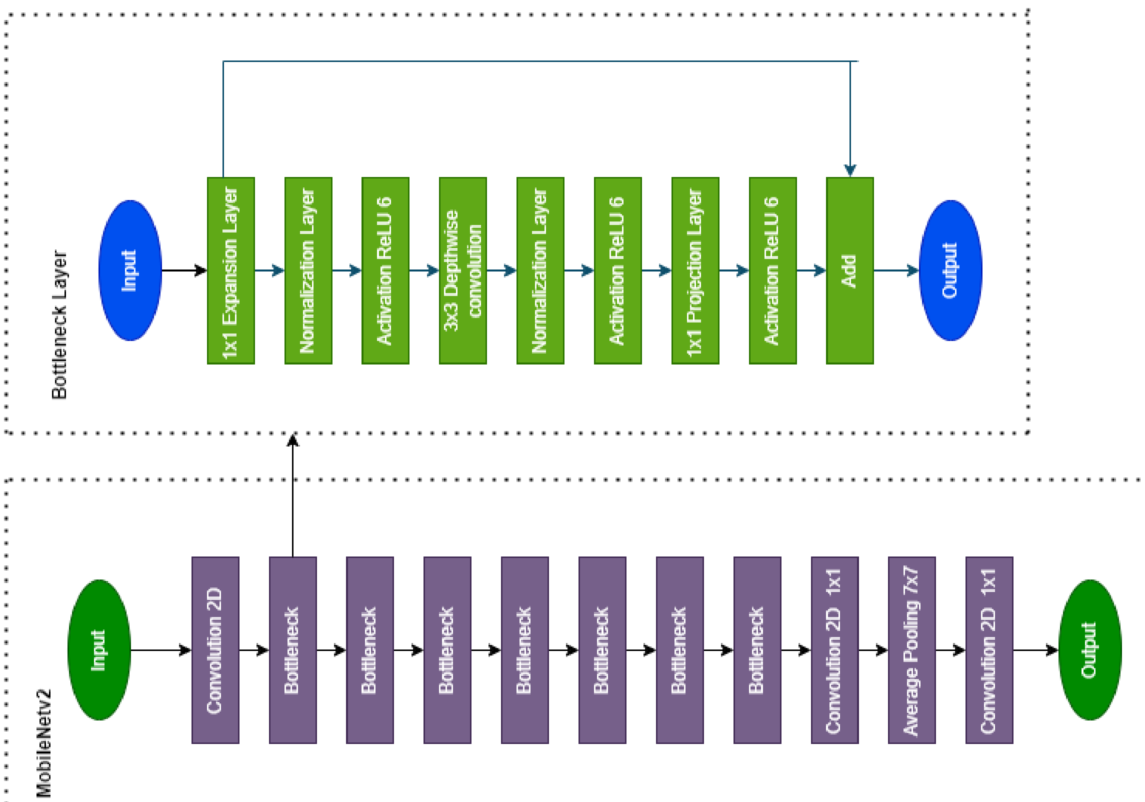



Figure 3.8.3 : Architecture of MobileNet V2

DenseNet-201 is a deep neural network architecture designed for classification of image. It belongs to the family of DenseNets, which are known for their dense connectivity between layers. In DenseNet-201 layers are closely interconnected, meaning every layer receives input from all preceding layers and provides output to every following layers [36]. This encourages reuse of features and improves information flow. Transition layers downsample the feature maps in between dense blocks to control the growth of parameters. They typically include batch normalization, 1x1 convolution for dimensionality reduction, and average pooling. Instead of fully connected layers, DenseNet-201 uses global average pooling to reduce spatial dimensions [37]. This simplifies the network and provides a compact representation for classification. Bottleneck layers (1x1 convolutions) are used to reduce the number of input channels before more computationally intensive 3x3 convolutions within dense blocks, improving efficiency. DenseNet-201's design promotes efficient learning, reduces the risk of vanishing gradients, and has shown good performance in image classification tasks.

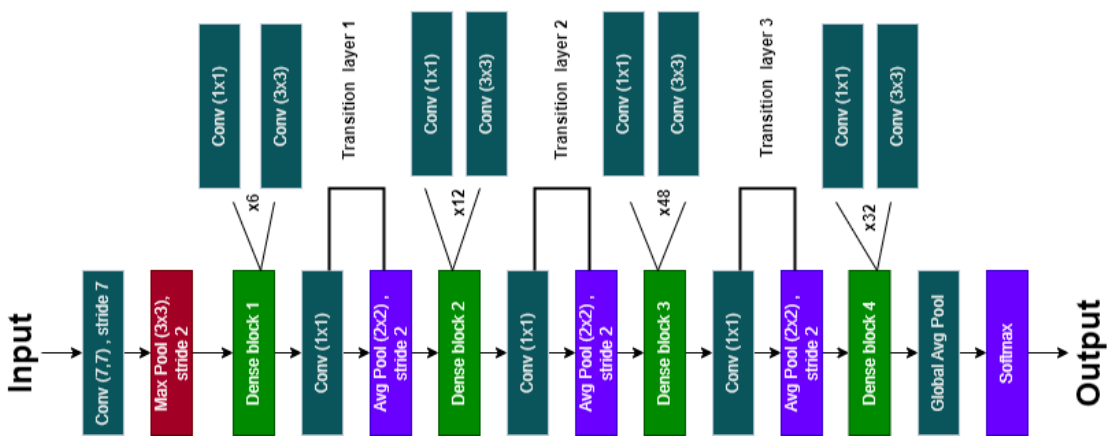



Figure 3.8.4 : Architecture of DenseNet-201

## 3.9 Feature Extraction

The CNN has been employed to retrieve appropriate dataset features for this research. The process of Convolutional Neural Networks (CNNs) starts with the input layer, where each pixel represents raw image data. Convolutional layers identify local patterns such as edges and textures by performing convolutional operations using filters or kernels. Activation functions such as ReLU are commonly used to bring in non-linearity, which improves The capability of the network to identify complex relationships in the data. Pooling layers, which frequently use methods like max pooling, help in reducing the feature maps' spatial dimensions without affecting important information. The network can learn hierarchical features and capture more complex patterns in deeper layers by stacking multiple convolutional and pooling layers. The spatial hierarchy of features is preserved during the flattening process, which converts feature maps into a one-dimensional vector. Fully connected layers process the flattened features for predictions by connecting each neuron to neurons in the layers above and below. The network’s output, which frequently represents class probabilities in classification tasks, is produced by the last fully connected layer. Based on the learned features, the output layer offers the final predictions [38]. We have employed a softmax activation function in our study to generate probabilities for every class.

## 3.10 Implementation Requirements

The study requires a few high-configuration devices. A digital camera with a good resolution is necessary for data collection. The general specifications for the CPU, GPU, and Random Access Memory (RAM) are listed below:

(i) Operating System (Windows 7 or above)

(ii) 8GB RAM

(iii) Google Colab

# CHAPTER 4

# Experimental Results and Discussion

## 4.1 Experimental Setup

We have utilized Google Colab for the implementation of deep learning models. It provides external GPU or TPU which has made the implantation faster. We have created colab notebook to run the models and mounted the google drive to get access of the dataset.

## 4.2 Experimental Results & Analysis

We've applied four deep learning models to classify bottle gourd leaf diseases in our study. These are DenseNet-201, VGG-16, CNN and MobileNet V2. Performance and results of these models are described in the sections that follow..

### 4.2.1 Performance

In many situations, performance matrices are an essential component of the estimation structure [39, 40]. We have to compute the accuracy, true positive rate, true negative rate, false positive rate, false negative rate, precision, and F1 score value depending on the confusion matrix using the equation (5–11).

$$Accuracy = \frac{TP + TN}{Total\ Number\ of\ Images} \times 100\% \qquad (5)$$

$$True\ Positive\ Rate\ (TPR) = \frac{TP}{TP + FN} \qquad (6)$$

$$True\ Negative\ Rate\ (TNR) = \frac{TN}{TN + FP} \qquad (7)$$

$$False\ Positive\ Rate\ (FPR) = \frac{FP}{TN + FP} \tag{8}$$

$$False\ Negative\ Rate\ (FNR) = \frac{FN}{FN + TP} \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$F1\ Score = 2 \times \frac{Precision \times\ Recall}{Precision +\ Recall} \tag{11}$$

Table 4.2.1.1 shows the performance metrics of DenseNet-201.

TABLE 4.2.1.1 : Performance of DenseNet-201

| Class | Accuracy | TPR | FNR | FPR | TNR | Precision | F1-Score |
|---|---|---|---|---|---|---|---|
| Anthracnose | 95.33% | 1.00 | 0 | .07 | .93 | .88 | .93 |
| Cercospora Leaf Spot | 94.67% | .86 | .14 | .01 | .99 | .98 | .91 |
| Healthy | 96.67% | .94 | .06 | .02 | .98 | .96 | .95 |

From the table we can say that the model has provided highest accuracy for detecting healthy class and lowest accuracy for detecting cercospora leaf spot. Precision is the highest in healthy class and lowest in anthracnose. It has provided the highest F1-score for healthy class and lowest F1-score for cercospora leaf spot.

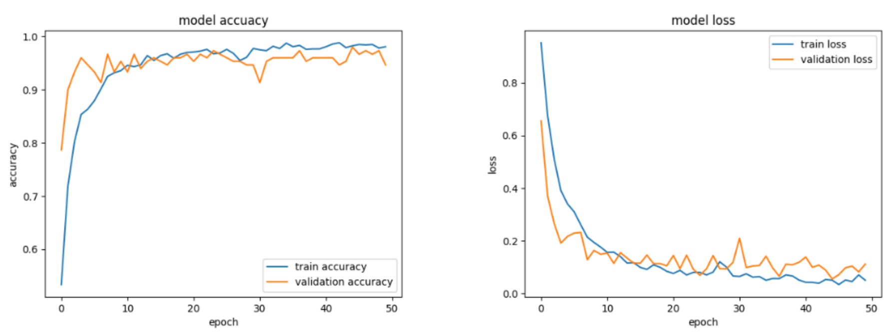



Figure 4.2.1.1 : Accuracy and losses of training and validation set in DenseNet-201

Figure 4.2.1.1 shows a graph representing the training and validation accuracy of the DenseNet-201 model. Training accuracy  is shown by blue line, and the orange line represents validation accuracy. It also shows a graph representing the training and validation loss of the DenseNet-201 model. Training loss is shown by blue line, and the orange line represents validation loss.

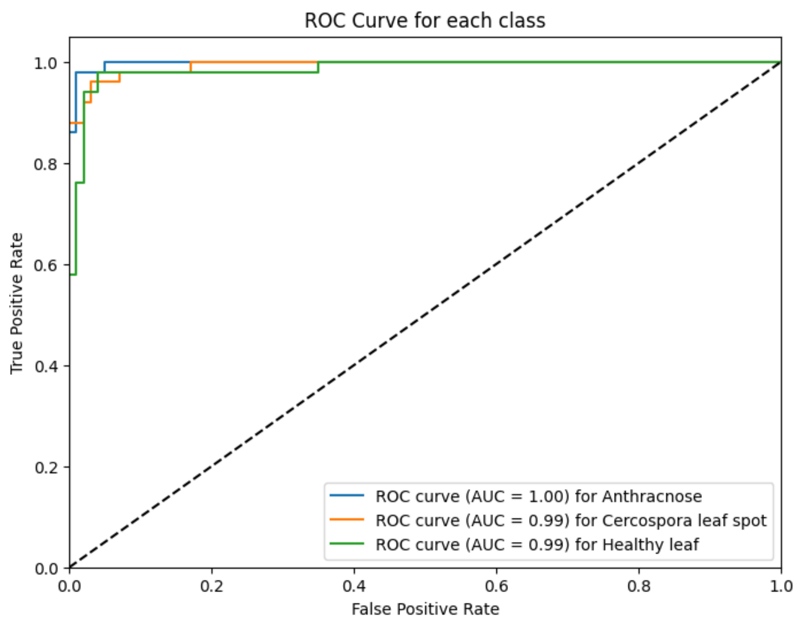



Figure 4.2.1.2 : ROC curve of DenseNet-201

Across every possible classification thresholds, the AUC or Area Under the ROC Curve offers a comprehensive per- formance measure [41]. From fig. 4.2.1.2 representing the ROC curve we can see that the AUC value of anthracnose is 1. This indicates that the prediction of this class is 100% correct. Other two classes have AUC value .99 which indicates those classes have 99% chance of correct prediction.

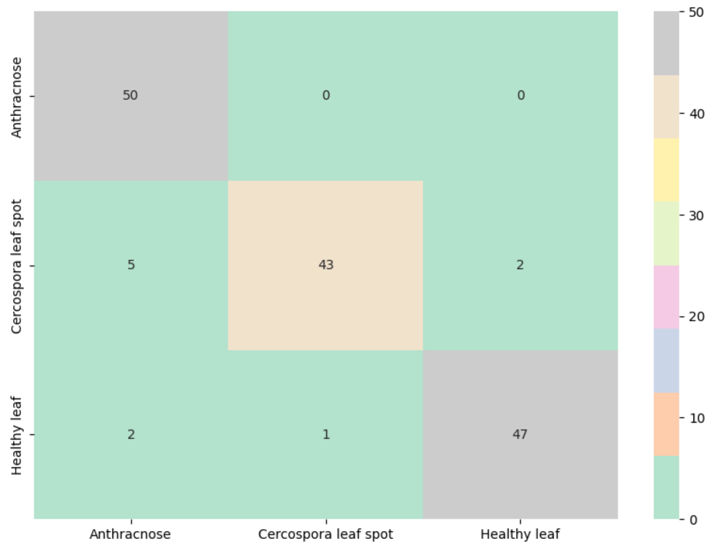



Figure 4.2.1.3 : Confusion matrix of DenseNet-201

Fig. 4.2.1.3 shows the confusion matrix of DenseNet-201. From this we have calculated various performance measures that are shown in Table 4.2.1.1. It shows the true positive for anthracnose, cercospora leaf spot and healthy class which are 50, 43 and 47 respectively. False positive for anthracnose, cercospora leaf spot and healthy class are 7, 1 and 2 respectively. False negative for anthracnose is 0, for cercospora leaf spot is 7 and for healthy leaf is 3. True negative for anthracnose is 93, for cercospora leaf spot is 99 and for healthy leaf is 98.

Table 4.2.1.2 shows the performance metrics of MobileNet V2.

TABLE 4.2.1.2 : Performance of MobileNet V2

| Class | Accuracy | TPR | FNR | FPR | TNR | Precision | F1-Score |
|---|---|---|---|---|---|---|---|
| Anthracnose | 95.33% | 1.00 | 0 | .07 | .93 | .88 | .93 |
| Cercospora Leaf Spot | 94.67% | .86 | .14 | .01 | .99 | .98 | .91 |
| Healthy | 96.67% | .94 | .06 | .02 | .98 | .96 | .95 |

This table shows that the model has provided highest accuracy for detecting healthy class and lowest accuracy for detecting cercospora leaf spot. Precision is the highest in healthy class and lowest in anthracnose. It has provided the highest F1-score for healthy class and lowest F1-score for cercospora leaf spot.

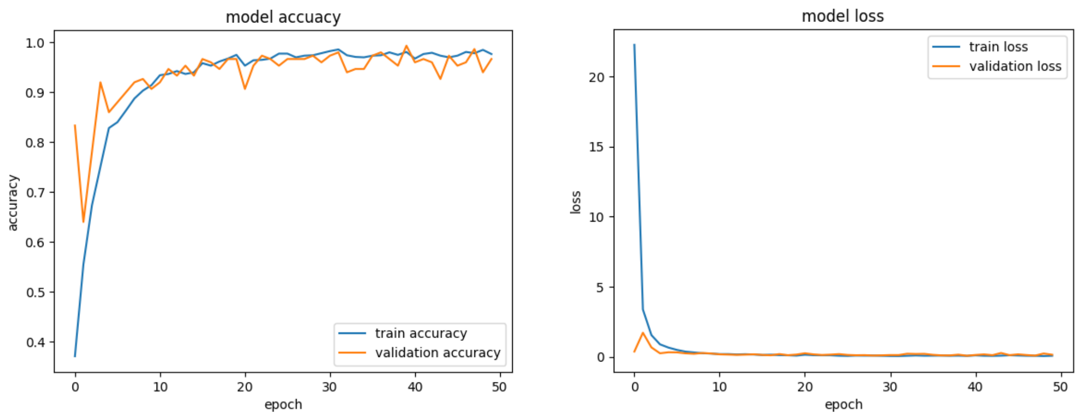



Figure 4.2.1.4 : Accuracy and losses of training and validation set in MobileNet V2

Figure 4.2.1.4 shows a graph representing the training and validation accuracy of the MobileNet V2. Validation accuracy is shown by the orange line, and training accuracy is shown by the blue line. It also shows a graph representing the training and validation loss of the MobileNet V2. Training loss is shown by the blue line, and validation loss is shown by the orange line.

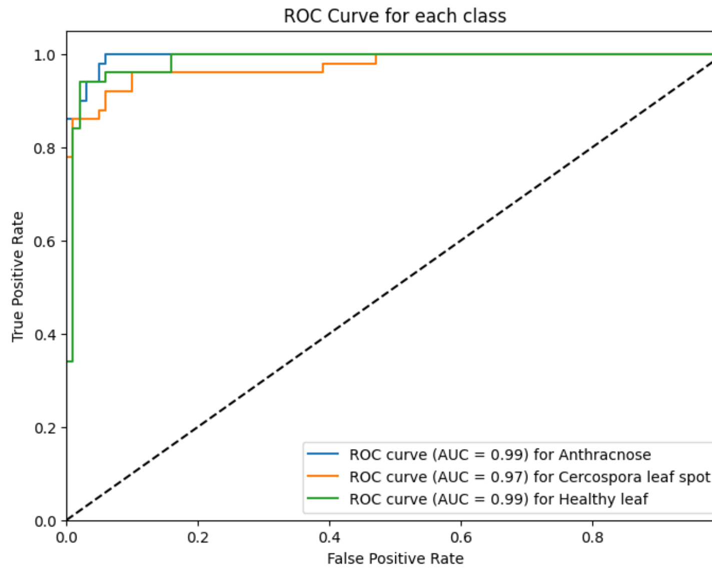



Figure 4.2.1.5 : ROC curve of MobileNet V2

From fig. 4.2.1.5 representing the ROC curve we can see that the AUC value of anthracnose and healthy leaf is .99 which indicates those classes have 99% chance of correct prediction.

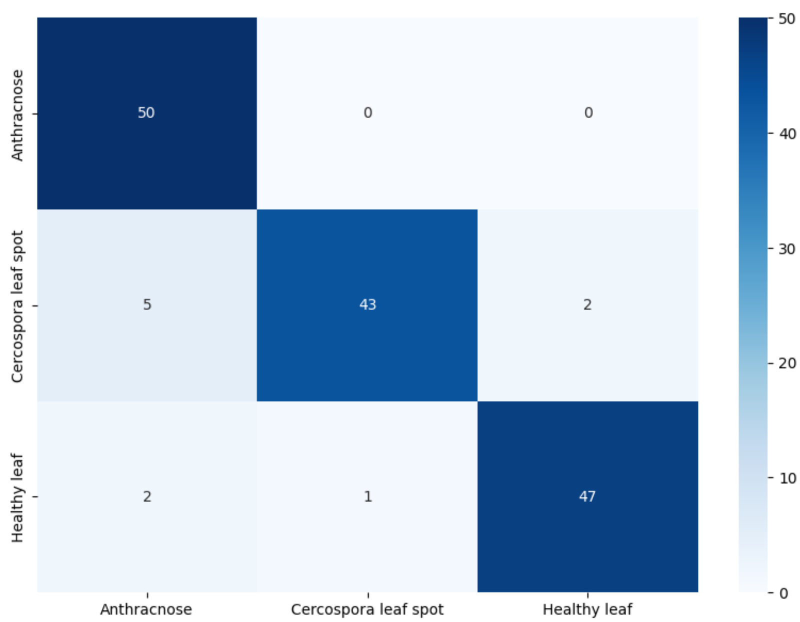



Figure 4.2.1.6 : Confusion matrix of MobileNet V2

Fig. 4.2.1.6 shows the confusion matrix of MobileNet V2. From this we have calculated various performance measures that are shown in Table 4.2.1.2. It shows the true positive for anthracnose, cercospora leaf spot and healthy class which are 50, 43 and 47 respectively.False positive for anthracnose, cercospora leaf spot and healthy class are 7, 1 and 2 respectively. False negative for anthracnose is 0, for cercospora leaf spot is 7 and for healthy leaf is 3. True negative for anthracnose is 93, for cercospora leaf spot is 99 and for healthy leaf is 98.

Table 4.2.1.3 shows the performance metrics of CNN.

TABLE 4.2.1.3 : Performance of CNN

| Class | Accuracy | TPR | FNR | FPR | TNR | Precision | F1-Score |
|---|---|---|---|---|---|---|---|
| Anthracnose | 95.33% | .98 | .02 | .06 | .94 | .89 | .93 |
| Cercospora Leaf Spot | 92% | .86 | .14 | .05 | .95 | .90 | .88 |
| Healthy | 94% | .88 | .12 | .03 | .97 | .94 | .91 |

This table shows that the model has provided highest accuracy for detecting anthracnose and lowest accuracy for detecting cercospora leaf spot. Precision is the highest in healthy class and lowest in anthracnose. It has provided the highest F1-score for anthracnose and lowest F1-score for cercospora leaf spot.

Figure 4.2.1.7 shows a graph representing the training and validation accuracy of the CNN. Training accuracy is shown by the blue line, and validation accuracy is represented by the orange line. It also shows a graph representing the training and validation loss of the CNN. Training loss is represented by the blue line, and validation loss is shown by the orange line.

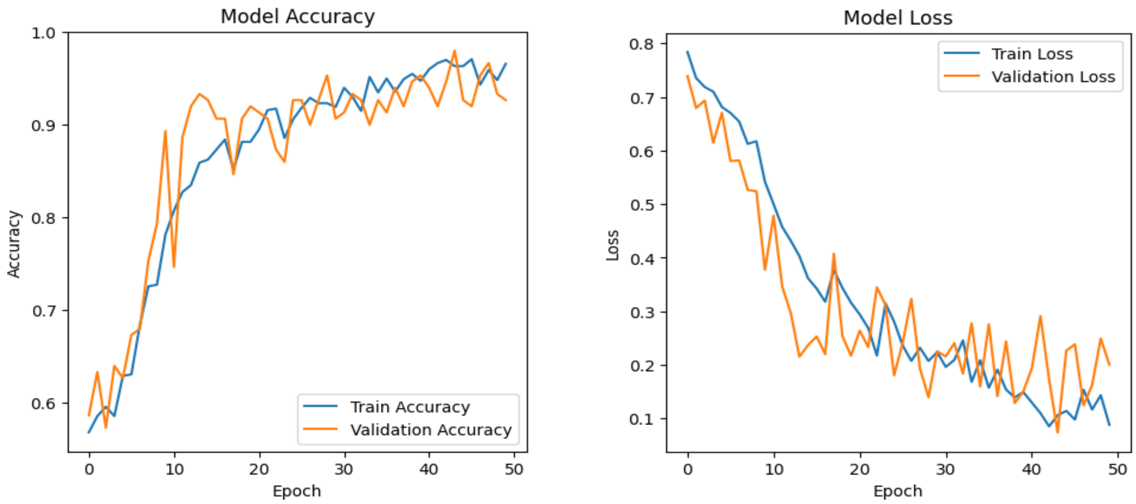



Figure 4.2.1.7 : Accuracy and losses of training and validation set in CNN

Figure 4.2.1.7 shows a graph representing the training and validation accuracy of the CNN. Training accuracy is shown by blue line, and validation accuracy is represented by orange line. It also shows graph representing the training and validation loss of the CNN. Training loss is represented by blue line, and validation loss is shown by orange line.

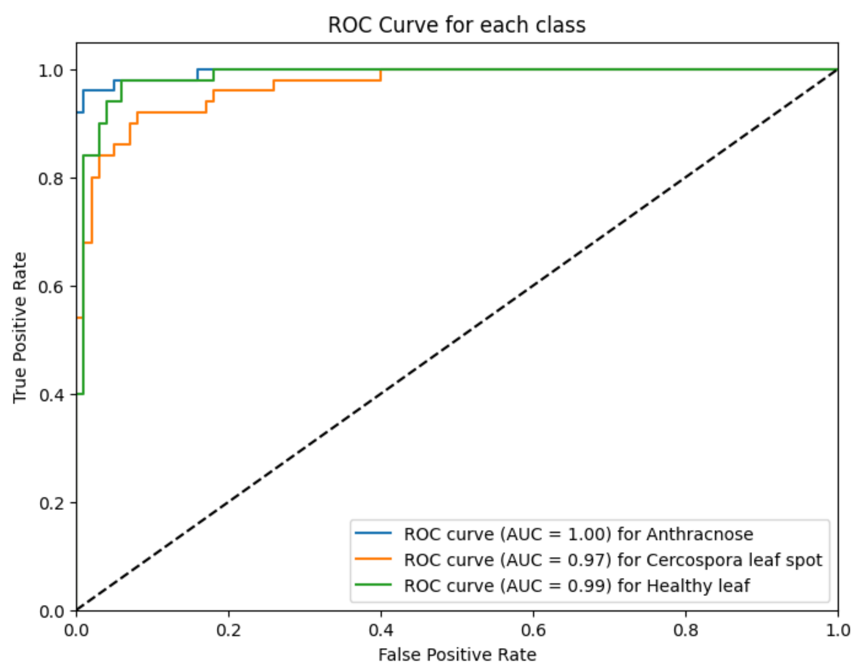



Figure 4.2.1.8 : ROC curve of CNN

From fig. 4.2.1.8 representing the ROC curve we can see that the AUC value of healthy leaf is .99 which indicates this class has 99% chance of correct prediction. Cercospora leaf spot has the AUC value of .97 which indicates that the prediction of this class is 97% correct. The AUC value of anthracnose is 1. This indicates that the prediction of this class is 100% correct.

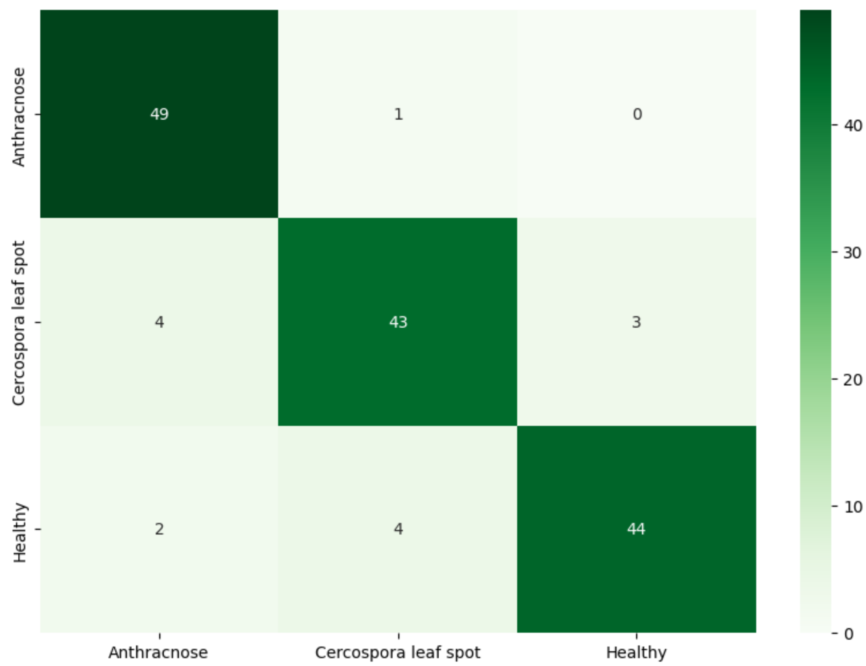



Figure 4.2.1.9 : Confusion matrix of CNN

Fig. 4.2.1.9 shows the confusion matrix of CNN. From this we have calculated various performance measures that are shown in Table 4.2.1.3. It shows the true positive for anthracnose, cercospora leaf spot and healthy class which are 49, 43 and 44 respectively. False positive for anthracnose, cercospora leaf spot and healthy class are 6, 5 and 3 respectively. False negative for anthracnose is 1, for cercospora leaf spot is 7 and for healthy leaf is 6. True negative for anthracnose is 94, for cercospora leaf spot is 95 and for healthy leaf is 97.

Table 4.2.1.4 shows the performance metrics of VGG-16.

TABLE 4.2.1.4 : Performance of VGG-16

| Class | Accuracy | TPR | FNR | FPR | TNR | Precision | F1-Score |
|---|---|---|---|---|---|---|---|
| Anthracnose | 86% | 1.00 | 0 | .21 | .79 | .70 | .83 |
| Cercospora Leaf Spot | 88.67% | .70 | .3 | .02 | .98 | .95 | .80 |
| Healthy | 92% | .80 | .2 | .02 | .98 | .95 | .87 |

From the table we can say that the model has provided high- est accuracy for detecting healthy class and lowest accuracy for detecting anthracnose. Precision is the highest in healthy class and cercospora leaf spot and lowest in anthracnose. It has provided the highest F1-score for healthy class and lowest F1-score for cercospora leaf spot.

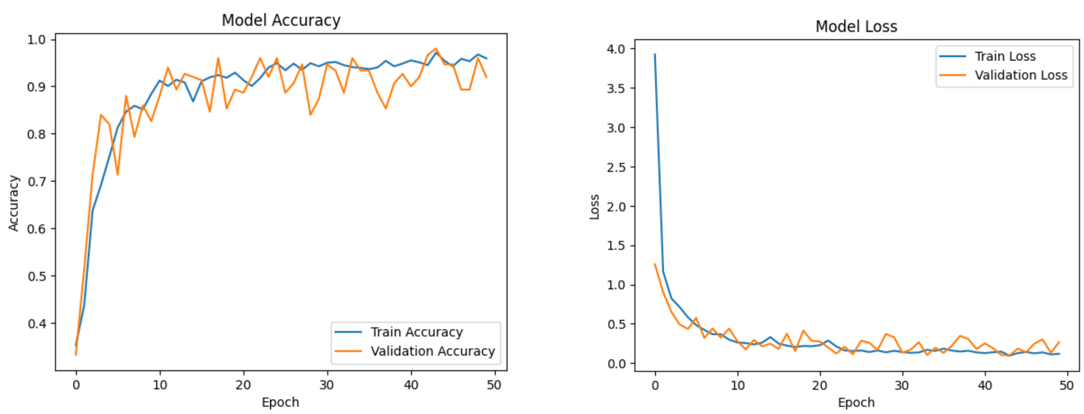



Figure 4.2.1.10 : Accuracy and losses of training and validation set in VGG-16

Figure 4.2.1.10 shows a graph representing the training and validation accuracy of the VGG-16. Training accuracy is shown by the blue line, while validation accuracy is shown by the orange line. Additionally, a graph illustrating the VGG-16's training and validation losses is displayed. Training loss is shown by the blue line, and validation loss is shown by the orange line.

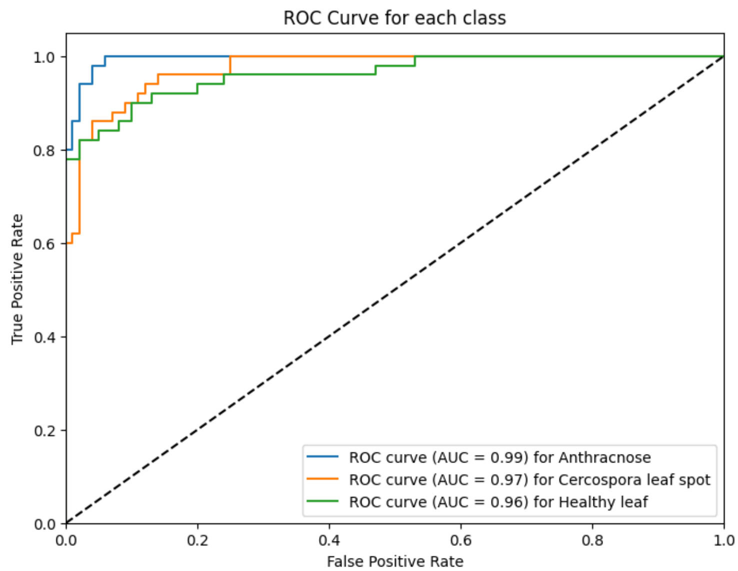



Figure 4.2.1.11 : ROC curve of VGG-16

From fig. 4.2.1.11 representing the ROC curve we can see that the AUC value of anthracnose is .99 which indicates this class has 99% chance of correct prediction.

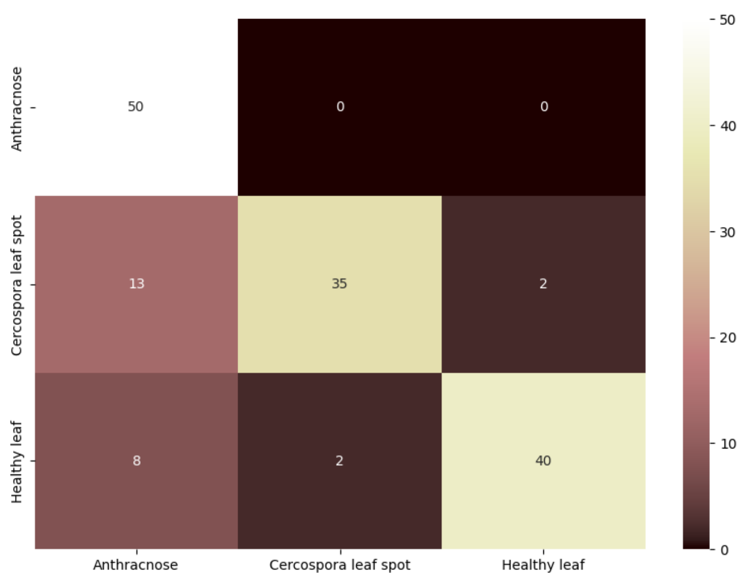



Figure 4.2.1.12 : Confusion matrix of VGG-16

Fig. 4.2.1.12 shows the confusion matrix of VGG-16. From this we have calculated various performance measures that are shown in Table VIII. It shows the true positive for anthracnose, cercospora leaf spot and healthy class which are 50, 35 and 40 respectively.False positive for anthracnose, cercospora leaf spot and healthy class are 21, 2 and 2 respectively. False negative for anthracnose is 0, for cercospora leaf spot is 15 and for healthy leaf is 10. True negative for anthracnose is 79, for cercospora leaf spot is 98 and for healthy leaf is 98.

Table 4.2.1.5 shows the overall performance of the four models.

TABLE 4.2.1.5 : Overall performance of models

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| DenseNet-201 | 93.33% | .94 | .93 | .93 |
| MobileNet V2 | 93.33% | .94 | .93 | .93 |
| CNN | 90.67% | .91 | .91 | .91 |
| VGG-16 | 83.33% | .87 | .83 | .83 |

This table shows that DenseNet-201 and MobileNet V2 has provided the highest accuracy among the four models. VGG-16 has provided the lowest accuracy. Precision is also the highest for DenseNet-201 and MobileNet V2 and lowest for VGG-16. Same for the recall and F1-score.

### 4.2.2 Comparison of performance for raw data and preprocessed data

When we have applied the models on the raw data, the models have provided less accuracy and more loss. But after preprocessing our data, the four models that we have applied in this study performed better.

Table 4.2.2.1 shows the comparison of performance for raw data and preprocessed data.

TABLE 4.2.2.1 : Comparison of performance for raw data and preprocessed data

| Model | Accuracy of Raw Data | Loss of Raw Data | Accuracy of Preprocessed Data | Loss of Preprocessed Data |
|---|---|---|---|---|
| DenseNet-201 | 59.52% | 4.28 | 93.33% | .285 |
| MobileNer V2 | 71.43% | 4.93 | 93.33% | .268 |
| CNN | 67.43% | .84 | 90.67% | .430 |
| VGG-16 | 64.28% | 1.91 | 83.33% | .239 |

This table shows that the accuracy have increased for all the models in preprocessed data and loss have decreased.

### 4.2.3 Error Analysis

An error happens if the algorithm misclassifies or produces inconsistent data. Despite using the most effective model to identify bottle gourd leaf diseases, this study contains some errors. As there are limitations to technology as well, the machine becomes confused, particularly when the term is used to identify diseases or categorize various class types. The misclassification rate indicates the likelihood at which the confusion matrix mispredicts the true positive and negative outputs [42]. It can be calculated by using equation no 12.

$$Misclassification\ Rate = \frac{FP + FN}{Total\ Number\ of\ Images} \qquad (12)$$

Misclassification Error Rate is 6.67% for DenseNet-201, 6.67% for MobileNet V2, 16.67% for VGG-16 and 9.33% for CNN.

## 4.3 Discussion

We have used four deep learning models (DenseNet-201, MobileNet V2, CNN and VGG-16) in our study to classify bottle gourd leaf diseases. MobileNet V2 and DenseNet-201 have provided the highest accuracy which is 93.33%. VGG-16 has provided the lowest accuracy which is 83.33%. Misclassification rate is the highest for VGG-16 which is 16.67%. MobileNet V2 and DenseNet-201 have the lowest misclassification rate which is 6.67%.

# CHAPTER 5

# Impact on Society, Environment and Sustainability

## 5.1 Impact on Society

Our research on applying deep learning to classify bottle gourd leaf diseases has applications in both agriculture and society. Due to farmers' inexperience or delays in detecting diseases, numerous bottle gourd fields have recently been destroyed. We anticipate that our research will be highly beneficial to farmers, as the majority lack formal knowledge about diseases. Because it's crucial to identify diseases before they spread and have a chance to fully develop. This study provides information related to bottle gourd leaf diseases like anthracnose and cercospora leaf spot. Farmers can minimize crop losses and maximize resource utilization by immediately responding to diseases that they accurately identify early on. This increases yields and lowers wasteful spending, which benefits the economy in addition to improving food security. Moreover, sharing our research results encourages improved agricultural practices, increases knowledge, and provides training programs with instructional materials. In conclusion, the agricultural sector benefits directly from our research in terms of crop health, resource efficiency, economic outcomes, and knowledge transfer.

## 5.2 Impact on Environment

Our work promotes more environmentally friendly agriculture by providing accurate disease detection and focused interventions. As part of this, less pesticide is used, resource efficiency is maximized, biodiversity is supported, soil health is improved, and sustainable farming methods are promoted. All of these results lessen agriculture's negative environmental effects and support the more general objectives of ecological preservation and sustainability. Therefore, our study has had a significant environmental impact.

## 5.3 Ethical Aspects

Obtaining informed consent is essential when collecting data or samples from farmers' fields and agricultural systems. That means we have to provide a clear explanation of the goal of our research project. In addition, we have to talk about the importance of the necessary data sets and sample collection techniques and how the findings can improve farming practices. By openly participating in this process and being fully aware of their rights, farmers can also express their opinions. We would like to maintain ethical standards and look for suitable ethical guidance and review. The planning, carrying out, and reporting stages of research all involve ethical considerations.

## 5.4 Sustainability Plan

In order to establish a sustainable plan for our research, we will update and expand our dataset on a regular basis, optimize models for efficiency, interact with local communities, support open access, offer education and training, encourage for supportive policies, and continuously assess the effects on the environment and socioeconomic conditions. This approach ensures long-term validity, ethical use, and beneficial contributions to sustainable practices in bottle gourd leaf disease classification.

# CHAPTER 6

# Summary, Conclusion, Recommendation and Implication for future Research

## 6.1 Summary of the Study

We have done a study of bottle gourd leaf disease recognition and classification based on efficient deep learning algorithms. To do this, we have collected images of bottle gourd healthy and diseased leaves from agricultural field. After preprocessing the dataset, we have applied four deep learning models. For the verification of the image quality after preprocessing, we have calculated PSNR, MSE, SSIM and RMSE of the dataset. Despite facing several challenges, we have tried our best to implement this study. The best result is achieved by DenseNet-201 and MobileNet V2 with an accuracy of 93.33%.

## 6.2 Conclusion

This study has found efficient ways to identify and label bottle gourd disease using deep learning algorithms. Bottle gourd is a popular vegetable in Bangladesh, but there are comparatively less studies on this specific vegetable. In this research, we have solved that problems by experimenting with different deep learning algorithms to find efficient models for disease detection in bottle gourd leaves after analysis of the leaf pictures. With the help of this effort, farmers won't have to chase after plant scientists to identify diseases in bottle gourd leaves. As a result, it will enable them to quickly address the plant's diseases, improving the quality and yield of food crops produced and contributing in expanding farmer profits. The highest accuracy is provided by DenseNet-201 and MobileNet V2 which is 93.33%. The lowest accuracy is provided by VGG-16 which is 83.33%. The performance of the algorithms are compared using a range of assessment criteria, including the F1 score, recall, accuracy, precision, and confusion matrix.

## 6.3 Implication for Further Study

We are hoping to expand the dataset and classes of our work for further study. This will enable farmers to identify more diseases of bottle gourd leaf. In addition, we want to implement a mobile app as well as web application based on this study. With the help of the app if a user gives input a bottle gourd leaf, the app will detect if the leaf is healthy or not and will show output based on that. This way farmers will be able to detect disease efficiently.

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