DETECTING MANGO LEAF DISEASES USING DEEP LEARNING: A NOVEL APPROACH FOR AGRICULTURAL HEALTH MONITORING

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "**DETECTING MANGO LEAF DISEASES USING DEEP LEARNING: A NOVEL APPROACH FOR AGRICULTURAL HEALTH MONITORING**", submitted by **SAURAV SARKAR, ID: 213-15-4285** and **PRANTA GHOSH, ID: 213-15-4341** 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 29-06-2024.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Mr. Md. Sazzadur Ahamed, Assistant Professor, 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

Mango leaf diseases suffer from a multiple challenge in diagnosis due to different types of crops, changing agronomic disease indices and several environmental factors that influence them. It is still hard to detect them early since extant methods depend on data restricted by geography thereby making them inefficient. This is essential for timely detection and control of such diseases in order to prevent huge financial losses that result among farmers. This research introduces an innovative strategy using deep learning and image processing technologies towards that end. Using CNN (Convolutional Neural Network) model, the study achieved a remarkably high 98.75% accuracy in separating healthy mango leaves from those with diseases. Rigorous tests were carried out over a range of leaf conditions to verify the effectiveness of the model. The technology has helped apply the algorithm onto 3000 leaf pictures which assist in identifying whether mango leaves are healthy or diseased when illness starts thus this is early disease detection. This innovation does not simply provide a timely and effective solution to enhance the management of diseases in mango farming, but also sets a benchmark for comparable advances in the broader agricultural milieu. The importance of this new technique in revolutionizing plant disease identification and prevention highlights its significance in agricultural development. By overcoming geographical barriers and embracing state-of-the-art technology, this study begins a fresh chapter in agricultural practices; It is hoped that it will help farmers enable farmers to manage their diseases better and produce more sustainable crops.

Keywords - Mango Leaf Disease Detection, Deep Learning Techniques, Agricultural Image Processing, CNN in Leaf Disease Detect, Deep Learning, Plant Health Monitoring.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

One of the world's mango production giants is Bangladesh, which is often referred to as Mango Island, producing one million tons annually. In their hearts the Bangladeshi people love this fruit and brightly it adorns their tables. Therefore, there is a silent enemy in the process of growing mangoes; this enemy is called Mango leaf disease. There are many threats to these trees' health and productivity in the midst of beautiful outgrowths that decorate the country side. These pathogens include fungi, bacteria and viruses that mostly attack mango leaves. Several kinds of diseases impact on mango leaves starting from minor lesions in form of marks or color changes to meltdown which cause injuries ultimately affecting all livelihoods for mango farmers all over the country. Anthracnose, powdery mildew, bacterial black spot and mango malformation diseases are some of these diseases that affect mango trees in Bangladesh leading to economic losses and reduction of fruit quality. Nevertheless, despite being battered by various types of diseases causing harm to its crops, Bangladeshi farmers have shown strength and wits against them. Adoption of integrated pest management practices, using disease-resistant varieties and application.

1.2 Motivation

The main reason behind examining mango foliar diseases is the huge impact of these diseases on productivity and fruit quality of this plant. Instances include Lasiodiplodia Theobroma induced mango dieback which can cause immense harm, yield reduction as well as death of plants. Early detection and control of these conditions is essential in minimizing financial losses to farmers and ensure availability of disease-free mangoes. We are concentrating on using new technologies like image processing and deep learning to develop reliable techniques for detecting diseases that will assist farmers in saving their harvests from being ruined by them. The agricultural sector can safeguard its production in mangoes and maintain high quality of this common fruit through a fast grasp and handling of leaf problems in MANGO plants.

1.3 Rational of the Study

The motive behind investigating the diseases affecting mango leaf's is to come up with methods for detection and management that are effective. Mango is a major fruit crop in the world, which is mainly produced in Bangladesh the biggest producer accounting for global supply. Mango foliar diseases contribute considerably towards destruction of plants reducing yield and bringing about death of even plants [1]. The study seeks to address this issue by using advanced technologies such as image processing and deep learning to automatically detect leaf diseases on mango trees [2], [3], [4] Detection of disease at early stage helps farmers avoid losses but also retains quality. Uncontrolled use of pesticides is currently diminishing Bangladesh export value[2]. The study aims at assisting farmers decrease their losses, increase productivity and ensure sustainability of mango cultivation through developing efficient disease detection systems[2], [4].

1.4 Research Question

- How is the dataset collected?
- How do you make classes model on mango leaf dataset?
- What number of categories are there in this dataset?
- How does it work benefit agricultural industry and people?
- Which are the most common diseases in mango leaf?

1.5 Expected Output

This study is based on the classification of leaf diseases of mango. Here the leaves are divided into five categories: healthy, anthracnose, bacterial canker, dieback and gall midge. We are trying to develop an excellent deep learning technique for determining diseases in mango leaves. Here we used CNN, EfficientNetB0, RestNet50, EfficientNetB7, EfficientNetV2B3, Vgg16, DenseNet121.

1.6 Report Layout

The subsequence chapters of this paper organized as follow:

- Chapter 1: Introduction, Motivation, Rational of the Study, Research Question, Expected Output, Report Layout.

- Chapter 2: Preliminaries, Related Work, Comparative Analysis & Summary, Scope of the Problems, Challenges.
- Chapter 3: Introduction, Research Subject and Instrumentation, Data Collection Procedure, Data Preprocessing, Models, Implementation Requirements.
- Chapter 4: Introduction, Descriptive Analysis, Experimental Result, Discussion.
- Chapter 5: Impact on Society, Impact on Environment, Ethical Aspects, Sustainability Plan.
- Chapter 6: Summary of the Study, Conclusion, Implication for further Study.

CHAPTER 2
BACKGROUND

2.1 Preliminaries

Research in classifying good and bad mango leaves is important because it helps to identify leaf diseases easily. Deep learning and machine learning have already been used extensively in crop science and agricultural industry. A large amount of information is available from this study.

2.2 Related Work

Saleem et al. (2021) compare Machine learning-based disease detection (MLDR) and support vector machine (SVM) has been used for plant disease detection. SVM showed promising results in detecting a variety of plant diseases including mango leaf disease with a mean accuracy of 80%. The InceptionV3 model demonstrated high accuracy (96.75%) in detecting mango leaf diseases, outperforming SVM in some cases. Future research directions may involve examining texture-based as well as color-based features which could improve plant leaf disease diagnosis accuracy[3].

Mishra et al. (2021) sorted out the automatic detection of plant diseases, especially in Mango plant species to enhance agricultural production and ease the burden of farmers. This introduces a wavelet transform image segmentation technique for disease detection and a Wavelet Neural Network (WNN) model for disease classification, with an accuracy reaching 98% on identification of mango leaf diseases. The suggested WNN model utilizes a novel wavelet function in hidden nodes that ensures faster convergence and requires less number of hidden nodes as compared to other models. It concludes by highlighting the high classification accuracy at 98%, faster computational time at 12,6587 seconds, and can be used for other medical imaging databases in future[5].

JM. Gining et al. (2021) On the development of Harumanis mango leaf disease recognition system using image processing techniques in helping farmers detect diseases in mango leaves. The system achieves 68.89% accuracy in detecting and classifying diseases, with future plans to add more diseases. Harumanis mango leaves are prone to diseases like anthracnose, scab and powdery mildew, which reduce crop productivity. MATLAB's Image Processing Toolbox has been used for image pre-processing, segmentation, feature extraction and classification processes within the system. The method involves obtaining images for analysis first, then preprocessing them before extracting features from them through segmentation and finally identifying the disease under consideration by classifying it via digital imaging technology[6].

Rajbongshi et al. (2021) have done the identification of mango leaf diseases using convolutional neural network (CNN) models with transfer learning approach. Different CNN models like DenseNet201, InceptionResNetV2, InceptionV3, ResNet50, ResNet152V2 and Exception were utilized for disease classification whereby DenseNet201 recorded the highest accuracy rate of 98.00%. The study workflow encompassed image acquisition, segmentation and feature extraction for disease detection using a data set consisting of 1500 images of diseased/healthy mango leaves with classes such as anthracnose; gall machi; powdery mildew and red rust. The paper also covers mathematical representation of batch normalization output among other subjects including evaluating performance metrics like accuracy, precision, F1 score, sensitivity, specificity, FNR and FPR in each model. In general, the study highlights on prompt identification as well as early diagnosis of diseases in plants to increase yield and quality through mechanization and advanced CNN models[7].

Mia et al. (2020) This paper presents a system for mango leaf disease recognition using an ensemble neural network (ENN) and support vector machines (SVM). The study focuses on identifying several ailments of mango leaves by capturing the images of the affected leaves and training a machine learning system to identify symptoms automatically. The suggested system attains an average accuracy of 80% in detecting and classifying various diseases of mango leaves, thus enhancing agriculture through time saving and better treatment of diseases. Support vector machines (SVM) are utilized within the NNE to detect four types of mango leaf diseases, including Dag disease, Golmachi, Moricha disease, and Shutimold.The designing of this system helps to identify and classify diseases accurately with regard to enhancing the production of mangos' as well as agricultural sector's development. The research points out that more training data should be added to enhance accuracy; future work is also recommended for comparing texture-based techniques versus color features in order to enhance recognition accuracies[8].

S. Arivazhagan et al. (2018) Focus on automating the identification of leaf diseases in Mango plants using a deep learning approach, particularly a Convolutional Neural Network (CNN). It has been spotlighting how early and accurate detection of leaf disease could help to improve crop yield and quality by discussing automation benefits on big farms. The CNN model developed achieved an impressive accuracy of 96.67% in identifying five different leaf diseases in Mango plants, showcasing its potential for real-time applications. In this paper, the CNN model uses for mango leaf disease recognition is explained comprehensively with attention paid to the RELU activation function as well as batch normalization that are important factors ensuring fast and accurate recognition outcome. Consequently, one can conclude that CNNs are favored for applications like these due to their capacity to automate feature extraction without any need for extensive preprocessing of images which results in faster convergence rates and good training performance[9].

Swathi et al. (2020) Diseases detection in mango plants using modified Multi Support Vector Machine (SVM). It is vital to identify the diseases of Mangifera Indica so as to prevent the losses in yield, however, this process is time consuming, particularly when it comes to larger farms. The SVM algorithm is used for detecting diseases whereby training set images are utilized for updating weights in their bid to achieve precise diagnosis of the diseases on test images. Image segmentation plays a central role in recognizing which parts of the plant have been affected by disease. Multiple algorithms like histogram-based methods, edge detection and clustering have been discussed in literature. Specifically, this paper uses a spot detection algorithm for cluster analysis to identify diseased areas on mango leaves. Detection process involves various steps like image pre-processing, contrast enhancement and histogram equalization that will improve disease image intensities. Extraction and classification require large amount of training data for accurate feature selection using Neural Network Analysis. Classification is achieved through image processing techniques, feature extraction and classification[10].

Gulavnai et al. (2019) Using deep learning models, specifically Convolutional Neural Networks (CNN), for automated identification of mango diseases. The study exploited a dataset with many images of mangoes in different forms and states affected by several diseases to teach the CNN. Data augmentation techniques helped convert the native mango dataset into a new set that is referred to as “the Mango leaflet dataset,” which contains pictures of the leaves of mango plants. ResNet18, ResNet34 and ResNet50 were among some of the various CNN architectures employed where accuracy was recorded at rates varying from 90.88% to 91.50% in classifying problems that affect mangoes. The results indicate that using ResNet50 for transfer learning is effective in giving an accurate automatic diagnosis on Mango disease, hence an appropriate way to detect field diseases through CNN. On its part, this document recommends developing a mobile-friendly model that will use India’s best CNN architecture in monitoring progression of mango diseases[11].

Veling et al. (2019) carried out studies for the techniques of detection and diagnosis of mango diseases in order to prevent a decrease in production. The aim is to emphasize why control measures on this problem has to start early during the season to improve quality and quantity because many farmers are illiterate. In order to detect diseases, this system uses image processing methods such as contrast enhancement and GLCM matrix features. The extracted features include contrast, correlation, energy, entropy, homogeneity, cluster prominence, cluster shade, variance and dissimilarity. This paper also discussed about using SVM as a classifier with 90% accuracy rate from 92 samples on test. MATLAB based GUI is employed for the identification and control of different diseases like Anthracnose, Powdery Mildew, Black Banded and Red Rust. To achieve successful disease detection while reducing dimensionality feature selection algorithms like GLCM and Sequential Forward Selection are used[12].

Zhang et al. (2017) “Improving the identification accuracy of maize leaf diseases using deep convolutional neural networks (CNNs) like GoogleNet and Cifar10”. In previous works, digital image processing combined with different neural network models have been used to achieve up to 95.3% accuracies but with limitations in recognizing a wide range of maize diseases. Deep learning techniques can be utilized for accurately identifying plant diseases, improving plant protection as well as expanding computer vision in precision agriculture. It sets forth two improved CNN models that enhance the recognition of maize leaf disease by adjusting its model parameters, changing pooling combinations, adding dropout operations and reducing classifiers. The paper compares modified models with an unmodified one; it aims at achieving greater accuracy fewer parameters and shorter training duration[13].

Gandhi et al. (2018) is important because it addresses the major problem of crop loss due to diseases, especially in India where agriculture has not progressed as much as other sectors. The author presents a plant disease identification system based on images with an emphasis on generating local datasets for Indian farmers through Generative Adversarial Networks (GANs) that can interpolate poorly represented local images. To classify, the approach utilizes Convolutional Neural Networks (CNNs), which are also intended to be used as a mobile app for detecting diseases on leaves at an early stage and mitigating losses. A case study examined MobileNets architecture which applied depth-wise separable convolutions to decrease the computation time and model size compared to traditional CNNs such as Inception models. Thus, it shows how deep learning technologies like CNNs and GANs could be effective in automating plant disease detection in order to improve food security necessary for supporting farmers[14].

Kestur et al. (2018) uses a deep convolutional neural network called MangoNet for mango detection and counting. The suggested methodology was evaluated with F1-score, precision and recall metrics. The results reveal that MangoNet has outperformed the other method (Arch4) on accuracy (73.6%) and F1-score (0.844). It showed resilience to different scales, illumination and densities of mangoes thereby making it practical useful in applications. This work proposes further possibilities such as panoramic imaging, whole orchard yield estimation etc[15].

Ozguven et al. (2019) automatic detection and classification of sugar beet leaf spot disease was done through the use of an Updated Faster R-CNN model in this study. This deep learning method surpassed other models with an accuracy rate of 95.48%. Changing parameters in the CNN architecture enabled the model to detect diseased areas better regardless of challenges like differing sunlight intensity and image quality. The method was tested on 155 images and showed a high correct classification rate. This can be utilized for real-time disease detection and intervention in large production areas, thus improving plant protection applications[16].

Sujatha et al. (2020) deep convolutional neural network known as MangoNet to detect and count mangoes in the gardens. Picture segmentation preceded connected object detection. It was trained on mango images tagged with annotations, and achieved improved accuracy and consistency over traditional methods when tested. Results displayed that MangoNet can handle different scales, illumination and occlusion since it got 73.6% accuracy and F1-score of 0.844.This shows potential for practical use in the field of yield estimation. Possible areas of work include pan-detection in panoramic images for an extensive orchard estimation about crop productivity[17].

Fiona et al. (2019) using digital image processing methods particularly image acquisition, preprocessing, segmentation and feature extraction which culminate in classification using an Artificial Neural Network (ANN). The findings showed a high accuracy of 90% in classifying the state of oranges as ripe, unripe or infected. In abstract terms the study reveals how image processing is applied to enhance agricultural efficiency and decrease human labor as well as improve sorting precision. In conclusion, ANN algorithms greatly boost disease detection and fruit sorting thus indicating room for further development of treatment recommendations[18].

Arnal Barbedo et al. (2019) Digital image processing and an artificial neural network (ANN) were used in the study to classify ripe, unripe, or diseased oranges. Among the methods employed are image acquisition, preprocessing, segmentation as well as classification. BIC was applied for feature extraction and RGB color space was used by the ANN which was trained using 400 images. In terms of classification, it recorded a 90% accuracy level. The abstract article centered on smart farming’s prospect of maximizing both quality and quantity of harvest. In conclusion, it is important that there is further research that can automate treatment recommendations based on disease detection[19].

Reo et al. (2020) detected using modified multi-support vector machine (SVM) algorithm. The methods used include image acquisition, pre-processing, segmentation, feature extraction and classification. The modified SVM achieved 98.57% accuracy with 670 images. The abstract focused on early disease detection for crop loss prevention purposes. In conclusion, it was observed that the method had a high level of accuracy and recommended some improvements like including SOFTMAX for better classification results. As shown in this study, machine learning is effective in agriculture and it has potential for wider use in crop management contexts[20].

2.3 Comparative Analysis & Summary

The comparison analysis here where we compared our thesis, “Deep Learning for Detection of Mango Leaf Disease: A Comparative Study Using Convolutional Neural Networks Models” with the reviewed papers and determining where are its models best applicable.

The most accurate accuracy (98.75%) among all other papers was shown by Our suggested model (EfficientNetB0), hence it outdid other methods in classifying mango leaf diseases. In this case the high precision could be attributed to utilization of sophisticated architectures such as EfficientNetB0 during our deep learning investigations which were more efficient than the traditional models like KNN, ANN, used by other studies. Other works investigated several plant diseases; however, this study focused only on mango leaf disease detection with a high accuracy meaning that it has strong applicability and relevance within this domain unlike others that had broader coverage but with lower accuracy. The table 2.1 below displays related work comparison

Table 2.1: Comparison between Our work & others work

Domain	Dataset	Models	Accuracy	Author
Detection	Kaggle Dataset	SVM	90%	Gandhi et al. (2018)
Detection	11,096 images	deep CNN	91.45%	Kestur et al. (2018)
Detection	Kaggle Dataset	ResNet18 CNN	91%	Gulavnai et al. (2019)
Detection	670 images	SVM algorithm	97%%	Swathi et al. (2020)
Detection	1200 images	CNN model	96.67%	S. Arivazhagan et al. (2018)

Detection	Online Dataset	SVM	80%	Mia et al. (2020)
Detection	17,572 images	DenseNet201	98.00%	Rajbongshi et al. (2021)
Detection	629 images	CNN model	68.89%	JM. Gining et al. (2021)
Detection	1130 images	WNN model	98%	Mishra et al. (2021)
classification	155 images	R-CNN model	95.48%	Ozguven et al. (2019)
classification	609 images	RF SGD SVM VGG-16	76.8% 86.5% 87% 89.5%	Sujatha et al. (2020)
classification	400 images	ANN model	90%	Fiona et al. (2019)
Detection	1567 images	CNN model	75%	Arnal Barbedo et al. (2019)
Detection	1200 images	SVM	97%	Reo et al. (2020)
Detection	3000 images	EfficientNetB0 ResNet50 EfficientNetB7 EfficientNetV2B3 VGG16 DenseNet121	98.75% 98% 94.22% 79.16% 73.75% 39.16%	**Our study**

In general, Our thesis provides a remarkable contribution to the field of mango leaf disease detection using CNNs. My study is a benchmark in this area of research due to the high accuracy of our proposed model, which specifically focuses on mango leaf diseases. It indicates that combination of state-of-the-art deep learning models can yield better results than the traditional single-model approaches.

2.4 Scope of the Problems

Mango leaf disease problems are complex and it affects mango production globally. The objective of this study is to ascertain early-stage occurrence of diseases on mango leaves. This has contributed to loss of significant amounts of the harvested crop, which can range from 30% up to 40% because different types of diseases attack mango leaf. These conditions cause huge economic losses and impair general health status of the trees. However, these current manual observations done by farmers and agricultural scientists are time-consuming, costly, and often inaccurate in identifying various diseases. The present research emphasizes how deep learning tools including image processing or convolutional neural network (CNN) models could be used effectively for mango leaf population disease detection. Thus, our aim for this study was to provide an overall perspective that might help in improving control strategies for diseases such as these in mango farming.

2.5 Challenges

▪ Getting accuracy of model over 98.75%.

▪ Implementing efficiently.

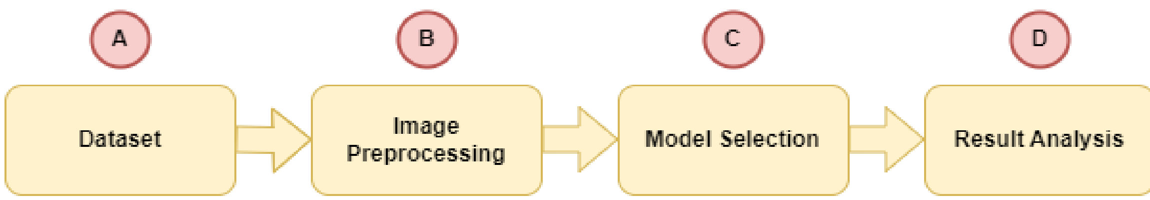
▪ A thorough review of the literature.

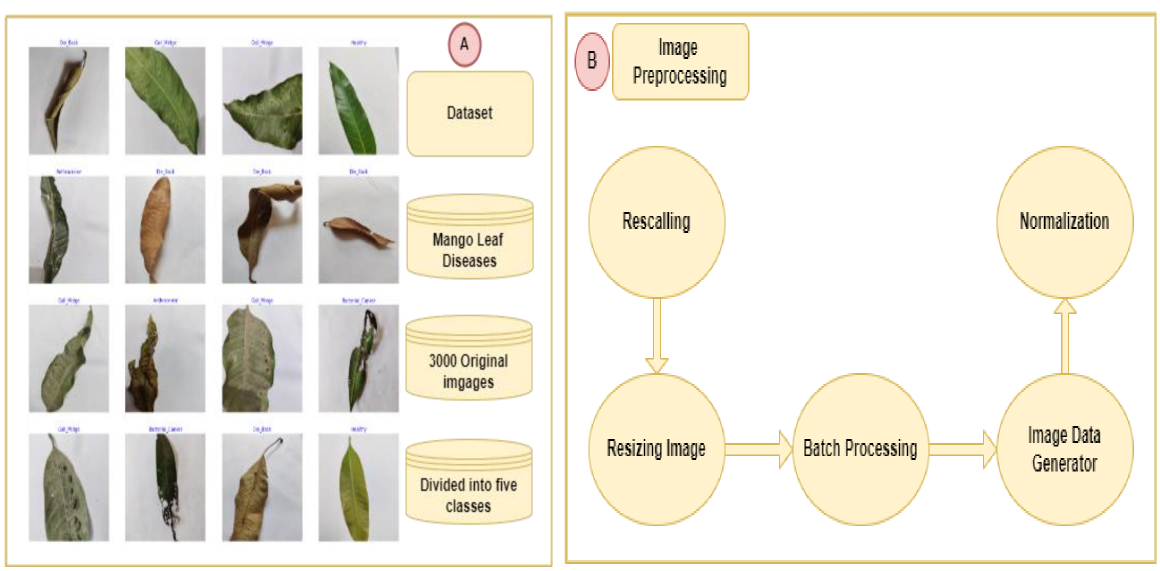
▪ Identifying gaps in other studies.

CHAPTER 3:
RESEARCH METHODOLOGY

3.1 Introduction

The section is giving a brief description of the objectives of the study and how they were achieved by the methodology which was thorough enough. This will be followed by scrutinizing our method of data collection reliability and classification of mango plant diseases. In this research, a convolutional neural network (CNN) is used to categorize 2D pictures that assist in identifying the mango leaf sickness. By using this method, we can treat or eliminate diseases from images of leaves effectively. Other subsequent studies on photo processing and sorting have utilized results from this specific study. Due to their detailedness and effectiveness, all data gathering procedures used in this research are reliable.





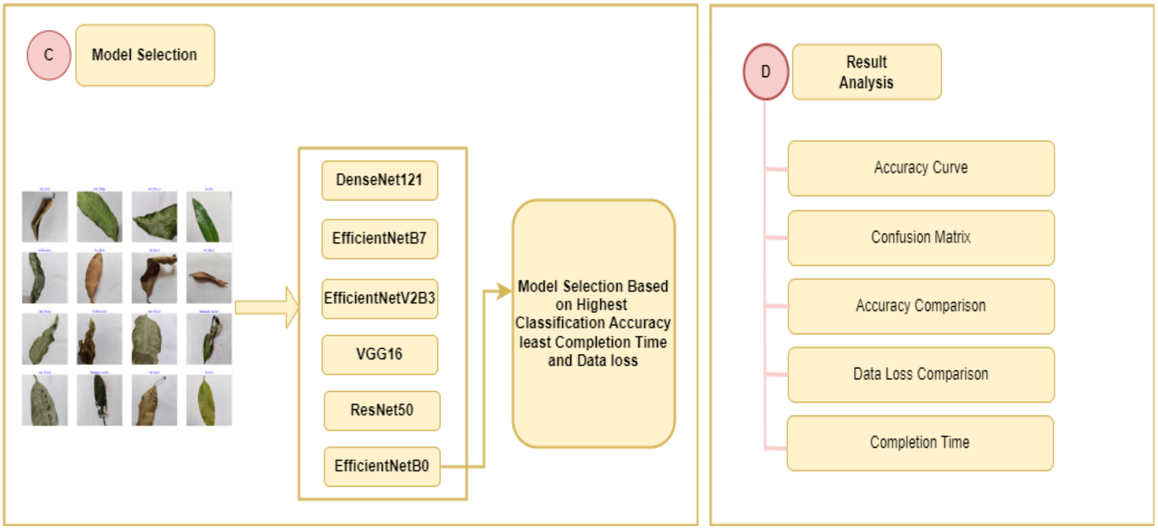


Figure 3.1: Working Procedure

3.2 Research Subject and Instrumentation

The subject of our research is “Deep learning for detection of mango leaf disease: a comparative study using Convolutional Neural Networks models” and will be determined by the model whether the leaf is free from diseases or not so that we can compare with CNNs models & proposed model.

Instruments:

For this project, We used some of the suggested models along with actual pictures of sick and healthy leaves to determine if it was a disease or not. To work on a deep learning model, you need to have a fast PC, GPU and other parts which are necessary. It will be difficult to set up without them. Besides, these are some of the methods and instruments that are necessary for successful completion of the research:

Hardware Requirements:

- hp pavilion gaming 15
- AMD Ryzen 5 5600H with Radeon Graphics 3.30 GHz
- RAM 8.00 GB (7.34 GB usable)
- 64-bit operating system, x64-based processor
- ROM 512 GB SSD

Software & Libraries Requirements:

- Python version (3.10.12)
- Google Collab
- Operating system: Windows 11 Pro (23H2)
- TensorFlow (2.15.0)
- NumPy
- Pandas
- Matplotlib
- Internet Connection

3.3 Data Collection Procedure

OnePlus Nord (AC 2001) camera was used to capture images of mango leaves to create a real capture image dataset. In order to collect these types of mango leaves, we went to various mango gardens and also got several kinds of the unhealthy and healthy leaves from our area's mango trees. Then, we took clear pictures by putting infected mango leaves on white paper. We captured in total 3000 images including: 600 images for healthy leaf, 600 images for gallize, 600 images for dieback, 600 images for bacterial canker, and 600 images for anthracnose that are all unique. OnePlus Nord camera specifications include a48 MP primary camera with a26mm f/1.8 lens having a PDAF, OIS and a1/2.0."

Figure 3.3: Categories of Leaf

3.4 Data Preprocessing

About 3000 field images were captured for our testing purposes. We have divided them into five categories. We trained 480 using a total of 2400 data points (about 80%) and tested with 600 data points (20%) out of a total of 3000 data points. We divided everything into five categories: healthy leaves, gallize, dieback, bacterial canker and anthracnose.

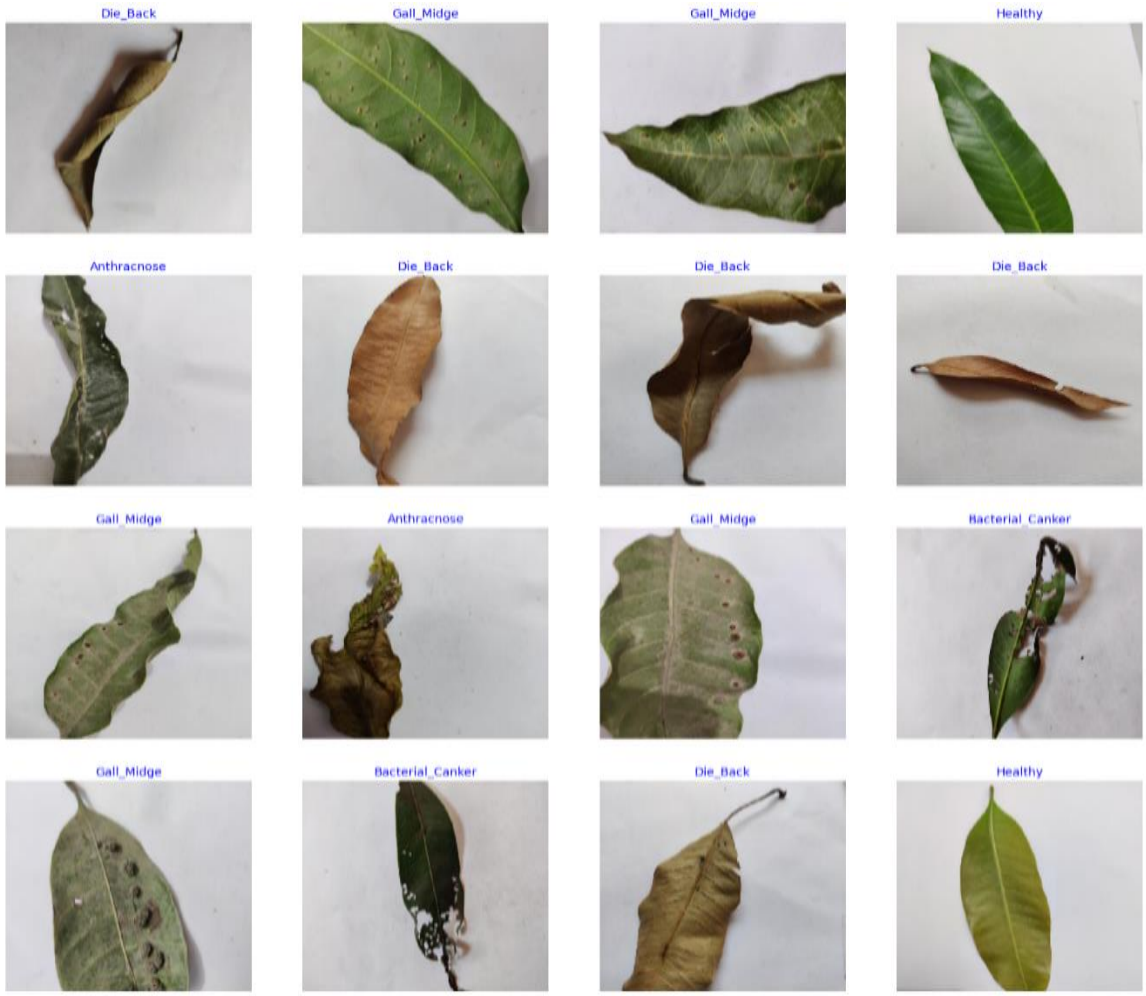


Figure 3.4: Processed Images

This is the data group of mango leaf diseases. We have collected information about various diseases in our collection. The following graph shows how the diseased leaf are divided into different groups.

Table 3.4: dataset description

Dataset	Classes	Original Images
Real Capture Image Dataset	Anthracnose	600
	Bacterial Canker	600
	Die Back	600
	Gall Midge	600
	Healthy	600
Total		**3000**

3.5 Models

Most commonly applied in interpreting visual images, CNNs are among the deep neural networks. The architecture typically includes an input layer followed by several convolutional layers, pooling layers, fully connected layers, and finally an output layer that makes a prediction. It shows the flow from the input images to the predicted class. For example, input images undergo a convolutional layer which is designed for automatically and adaptively learning spatial hierarchies of features from input images according to a diagram in the paper. Following this step, there is another set of convolutional and pooling layers through which this process repeats itself on.

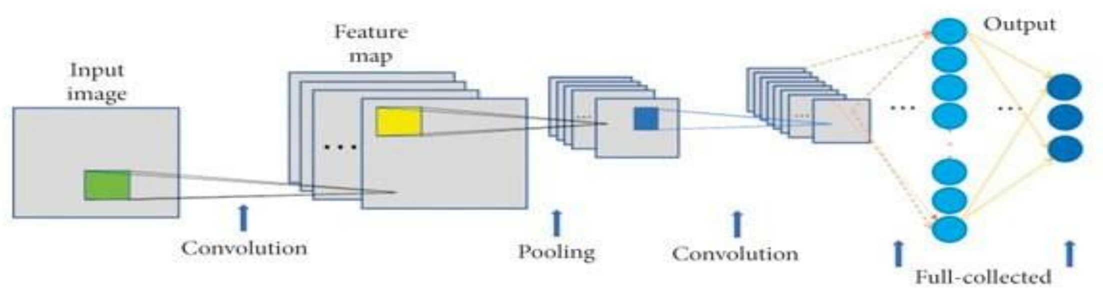


Figure 3.5: CNN Model Workflow

The representation is flattened into a vector and passed through fully connected layers after the last pooling layer; where more complex representations are learned. Often, the final layer is a SoftMax or logistic regression layer which gives a probability distribution over the classes. The output 'Leaf' indicates that this CNN is used in classifying images of leaves, maybe as part of plant recognition system or a scientific study focused on classifying species of plants. In my studies I am implementing some of the CNN architecture to detect leaf.

3.5.1 Proposed Model (EfficientNetB0):

Several ways can be used to identify diseases which affect mango leaf. Methodology The proposed model (EfficientNetB0) is implemented here. Code for implementation of there could be some methods of detection. Here are the steps of code:

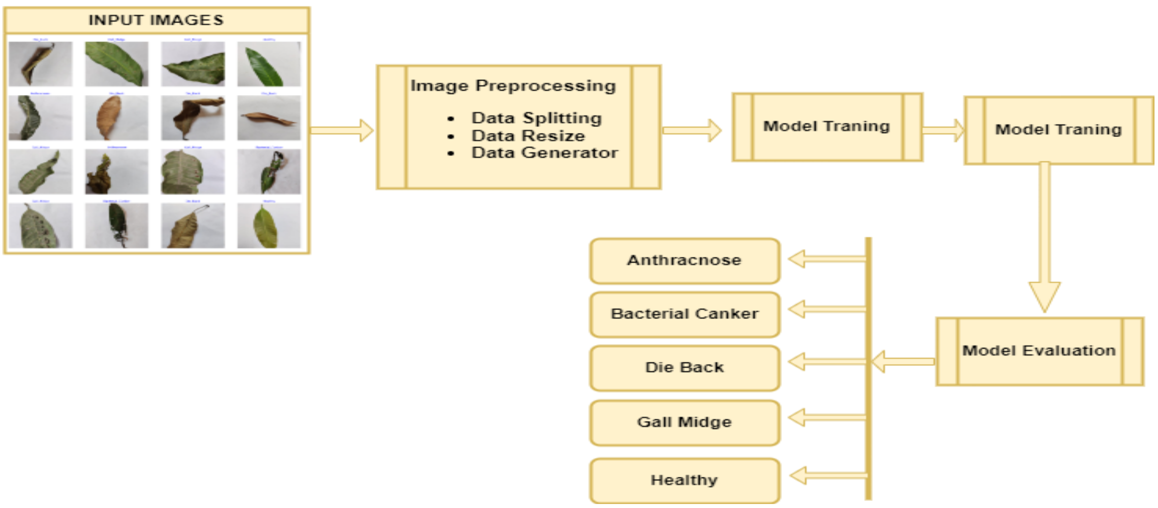


Figure 3.5.1: Proposed Model Workflow

Environment Setup and Loading Data

Get started on establishing a locale, installing all indispensable libraries (such as TensorFlow, karas, NumPy etc.) and mounting Google Collab Drive for data access. Load the mango leaf dataset that is always kept separately on drive. Healthy and unhealthy pages are contained in separate folders. The data has to be preprocessed; it involves sizing up the structures and exploratory data analysis.

Model Selection

Choose a base CNN model suitable for image classification task such as proposed model (EfficientNetB0). Add custom layers such global average pooling and dense layers to the base model thus making it binary classification (healthy leaf, gall mize, die back, bacterial canker, anthracnose).

Model Training and Fine-Tuning

Set up the model for both model training and fine-tuning, specify trainable layers, optimizer (e.g. ADAM), loss functions (categorical cross entropy), and metrics (accuracy, precision, recall). Develop models that are trained on fixed batch sizes using train datasets with steps per epoch. Avoid overfitting through callbacks like early stopping Fine-tune the model by adding custom layers to some upper unfreeze layers from the base model.

Model Evaluation and Visualization:

Compute the model performance in terms of such important aspects as loss, precision, recall and accuracy over a single test or validation dataset. Visualize how well the model has been doing during its epochs of training and validation by sketching a graph representing these two measures.

Prediction and Analysis:

Apply this trained model to predict new categories of mango leaves. Such classes may include Healthy leaves, Gall Mize, Die back, Bacterial canker as well as Anthracnose. Alternatively, confusion matrix and classification report can be generated for evaluation model performance in more detail. Functions for user's convenience the verification result shows the image along with its predicted class. Finally, after showing Figure (---), block design of proposed model all steps to be shown in method used in this study.

3.5.2 EfficientNetB0:

EfficientNetB0 is a neural network architecture of convolutional type belonging to the family EfficientNet. Being developed by Google researchers, EfficientNets try to offer state-of-the-art results while being small in terms of computation.

Specifically, EfficientNetB0 is the base model among the EfficientNet series. It is designed to strike a balance between model size (number of parameters) and model performance. In spite of its comparatively smaller capacity as compared to some other complex models, EfficientNetB0 has exhibited excellent performance on diverse computer vision tasks such as image recognition, object localization and segmentation.

EfficientNet fundamentally introduces compound scaling which uniformly scales up all dimensions including depth, width and resolution in a mathematically sound manner. Thus, compared with traditional scaling methods, these techniques enable improved efficiency for future EfficientNet models accompanied by parameter reductions.

Due to this trade-off between accuracy and efficiency that this model presents thus making it desirable for deployment on mobile phones or embedded systems where computing resources are scarce.

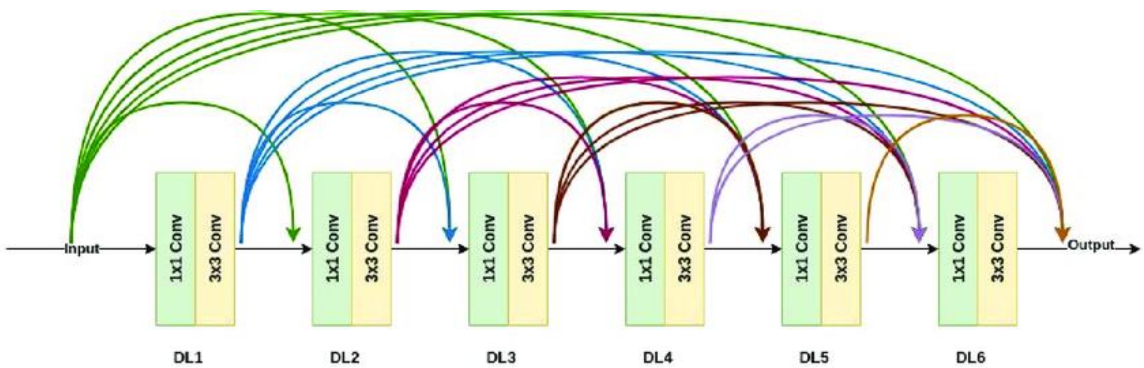


Figure 3.5.2: EfficientNetB0 model architecture

3.5.3 ResNet50:

ResNet50 is an architecture of a Convolutional Neural Network (CNN) belonging to the ResNet (Residual Network) family. It was introduced by Microsoft Research Technology, as one piece in the larger ResNet family which have deeper variations such as ResNet101 and ResNet152.

The name “”50”” in ResNet50 implies that it has 50 layers in all. However, unlike traditional deep neural networks where increasing the number of layers might lead to degradation in performance due to vanishing gradients or overfitting, ResNet50 introduces the concept of residual learning.

Residual learning addresses this problem of gradient vanishing by providing skip connections, or shortcuts, that allow for more direct propagations of gradients during training time. Thus, a layer’s output becomes the sum of its original input and its own representation producing a residual block. These skip connections allow the network to learn residual functions instead of directly mapping inputs to outputs, resulting in an easier training process for deeper networks.Multiple residual blocks make up Resnet 50; each with several convolutional layers as well as batch normalization followed by ReLU activation functions. Additionally, pooling layers are present while fully connected ones are provided at the end for classification purposes.

Many computer vision tasks can be accomplished using the ResNet50, such as image classification, object detection and image segmentation. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) of 2015 saw it come out on top for large scale image classification.

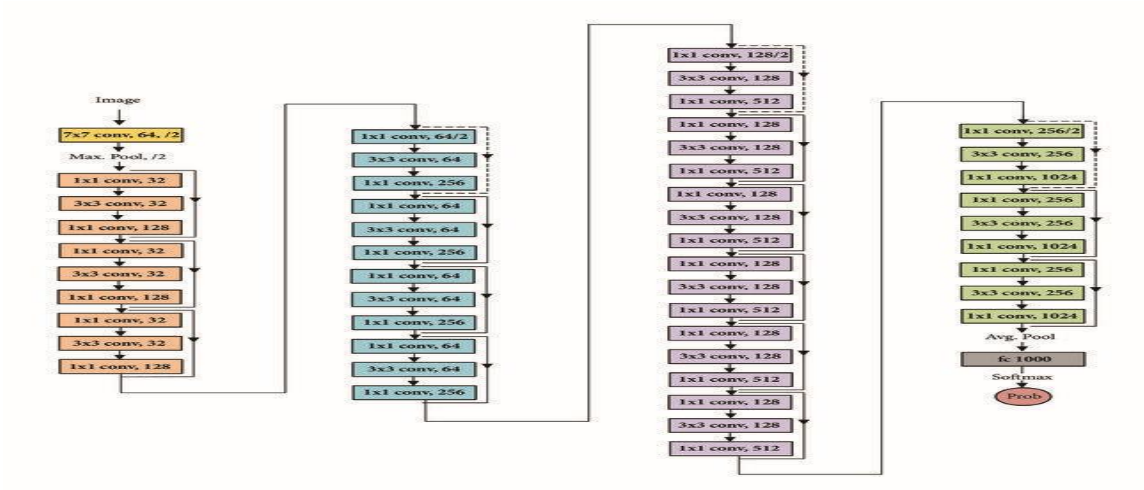


Figure 3.5.3: ResNet50 model architecture

Generally, ResNet50 is cherished for its ability to train deep neural networks effectively through its depth and accuracy in a bid to improve performance. Its adaptability and extension to multiple application domains have made it a reference point architecture in the field of deep learning.

3.5.4 EfficientNetB7:

The most significant in the EfficientNet family of neural network architectures is EfficientNetB7. Like other versions, EfficientNetB7 aims at maintaining speed and size balance, which ensures that it performs much better than its competitors.

Unlike smaller variants such as EfficientNetB0, EfficientNetB7 has a significantly higher number of parameters. This is achieved via compounding scaling concept which combines depth, width and resolution scaling. As such, it guarantees high performance in different computer vision tasks like image classification, object detection, and segmentation. Notwithstanding its bigger size, EfficientNetB7 upholds computational efficiency that is crucial for deploying deep learning models into resource-constrained environments. This makes it suitable for a wide range of applications, from cloud-based services to edge devices such as smartphones and IoT devices. The EfficientNetB7 model has been designed to perform well in tasks that are very accurate just like fine-grained image classification or medical imaging analysis. Nevertheless, the training and deployment of EfficientNetB7 may be more computationally expensive than smaller models which necessitates tradeoffs between model size, accuracy and computational costs while selecting an appropriate architecture for a given task.

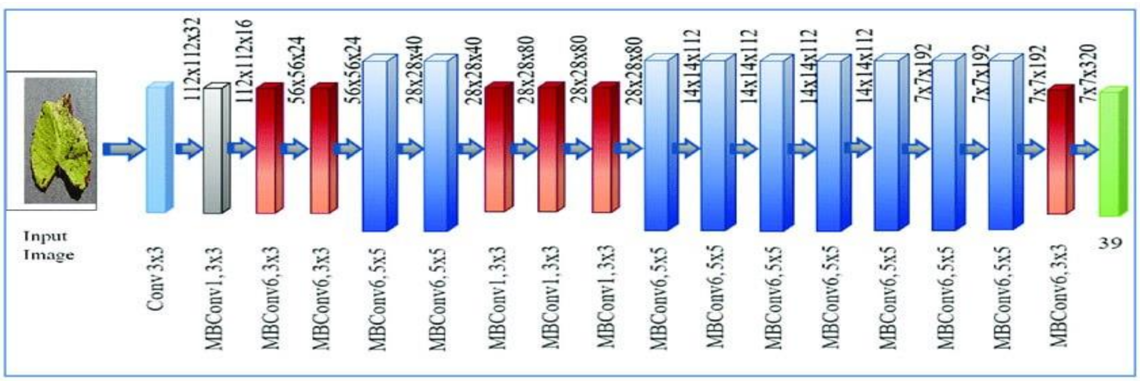


Figure 3.5.4: EfficientNetB7 model architecture

3.5.5 EfficientNetV2B3:

EfficientNetV2B3 falls under the EfficientNetV2 family of neuro network architectures. The original idea behind EfficientNet models was to improve on their efficiency while at the same time enhancing their performance in relation to computational resources as well as accuracy.

Specifically, EfficientNetV2B3 is the particular configuration within EfficientNetV2 referred by “B3” which denotes size or scaling factor. Just like the original EfficientNets, these models employ compound scaling approach that keeps a balance on model depth, width and resolution, hence optimizing their performance.

EfficientNetV2B3 is a larger, more powerful variant of EfficientNetV2B0 and ones like it. Its design still aims at being computationally efficient. This is achieved by carefully balancing the number of layers, channels, and resolution to maximize performance while minimizing the number of parameters and computational cost.

EfficientNetV2B3 can be employed in many computer vision tasks such as image classification, object detection and segmentation.

It can be deployed on different platforms because it is versatile and efficient enough to run on cloud servers or edge devices such as smartphones or IoT devices. In general, EfficientNetV2B3 is a state-of-the-art neural network architecture that compromises excellently between accuracy and computational efficiency hence making it a useful tool for various machine learning tasks.

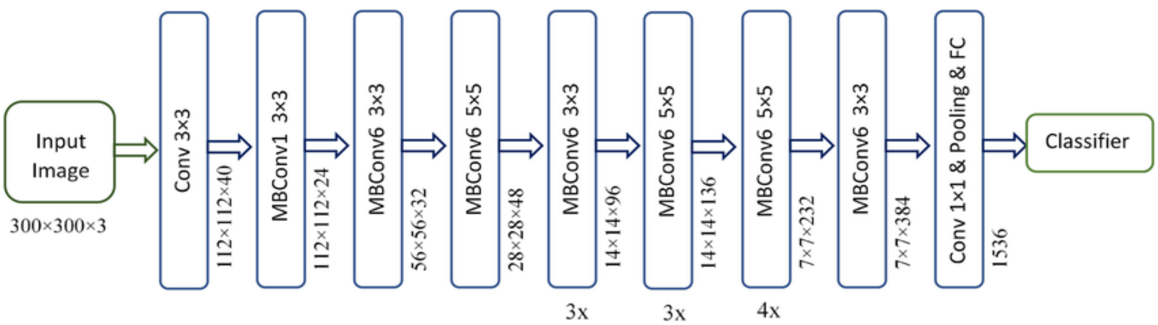


Figure 3.5.5: EfficientNetV2B3 model architecture

3.5.6 VGG16:

VGG16 is a CNN architecture, which is a convolutional neural network that was developed by the Visual Geometry Group (VGG) at the University of Oxford. It is part of VGG's models family which includes variations like VGG19, with 19 layers and smaller ones such as VGG11.The '16' in VGG16 stands for the total number of layers including convolutional layers, pooling layers and fully connected layers in the network. Specifically, there are 13 convolutional layers followed by 3 fully connected layers.It has a simple uniform architecture. It uses small 3x3 convolutional filters with stride 1 and same padding throughout the network. There are also pooling layers which help to decrease spatial dimensions of feature maps in each layer.

Though simple, it has shown its capabilities through; ILSVRC-2014 ImageNet Large Scale Visual Recognition Challenge where it took second place (Russakovsky et al., 2015).
VGG16 is influential in the evolution of CNN architectures, and has been a yardstick for many succeeding models. However, compared to ResNet or EfficientNet which are modern architectures, it is seen as relatively deep and computationally expensive. On the other hand, VGG16 remains a useful benchmark and pedagogical tool towards understanding deep learning and convolutional neural networks.

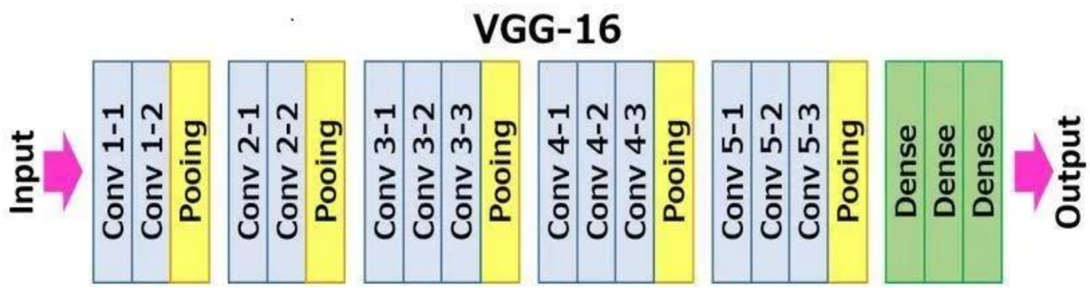


Figure 3.5.6: VGG16 model architecture

3.5.7 DenseNet121:

DenseNet121 is one of the convolutional neural network architectures belonging to DenseNet family (Densely Connected Convolutional Networks). DenseNet architectures have been developed by researchers from Facebook AI Research (FAIR) that are characterized with densely connected layers where every layer is connected to all others in forward propagation manner.
On the other hand, DenseNet121 contains 121 layers including convolutions, pooling, batch normalization and fully connected ones.
Dense connectivity is one of the major attributes of DenseNet architectures. In usual convolutional neural network, every layer is connected only to subsequent layers. However, in DenseNet architectures every layer is directly connected to all other layers that come after it. This dense connectivity supports ubiquitous usage of features throughout the network thus making parameter usage more efficient and gradient flow better during training.
DenseNet121 has been extensively used for a range of computer vision tasks such as image classification, object detection and segmentation. It has demonstrated excellent results on

benchmark datasets like ImageNet and has been employed as a backbone architecture in many recent models.

All in all, DenseNet121 can be described as a potent yet effective neural network design that achieves both high accuracy and parameter efficiency which makes it highly popular for numerous applications within computer vision domain.

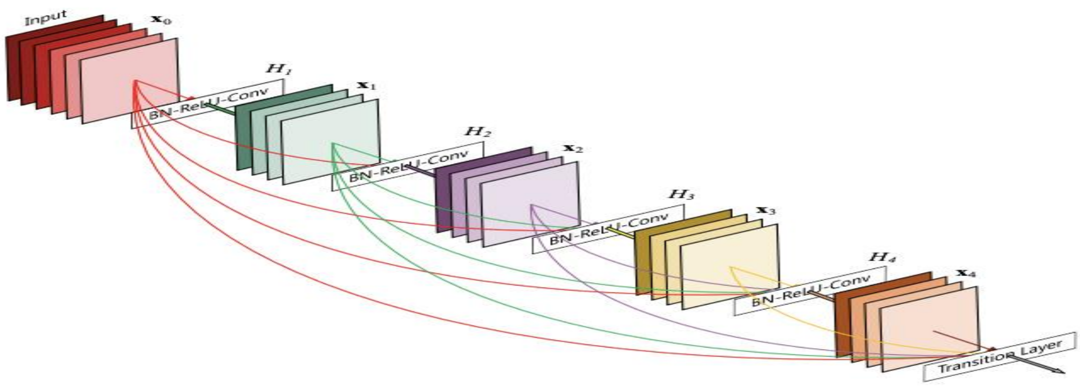


Figure 3.5.6: DenseNet121 model architecture

3.6 Implementation Requirements

It does certain job as many deep learning models and types are available. Six different kinds of the project idea were the proposed ones. These seven models are very good at figuring out what they are when given pictures of illnesses. Majority of my files contain pictures of mango leaves that I have taken in the field and in my yard. This model provides most accurate results by using machine learning to correctly classify images and identify diseases.

- hp pavilion gaming Laptop
- Internet Connection
- Google Collab
- Python

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction

Before we proceed to this point, let's briefly review the research methods employed in this study. This chapter will discuss the achievements and outcomes of these projects enabled by the deep learning. Most emphasis is placed on deep learning model that is proposed. DenseNet121, ResNet50, EfficientV2B3, EfficientNetB7, EfficientNetB0 and VGG16 were used as image classification models. We are going to reconsider part of that Part, which will additionally look into other measures. We should be very accurate after training our model with training data. A desktop or laptop computer is required when modeling deep learning algorithms. All of those are equipped with appropriate tools like this one too! Powerful graphics processing unit is necessary for training purposes. On a simple window we began training our proposed model while. Since it takes a long time to process and can lead to false results Google Colab trains our models. Google colab was crucial in our success of Project Model Training.

4.2 Descriptive Analysis

Use of the confusion matrix can help evaluate the operation of a deep learning classifier. It shows how many objects are in each class. In this case, the confusion matrix is to be employed to identify True Positives (TP), True Negatives (TN), False Positives (FP) and also False Negatives (FN). Accuracy: This factor rates the model by counting its number of accurate statements. Accuracy= ((TP+TN) / (TP+TN+FP+FN)) x 100% Precision: Gives an accuracy measure for correctly recognizing cases as positive against false positives on the positive pulse alone. The portion of accurate forecasts made by a good model whose main aim has been information gathering. The formula is given as, Precision= (TP /(TP+FP)) x 100% Recall: This recall is calculated by dividing true positives with false negatives value. It shows how comprehensive a model is Recall = (TP/(TP+FN)) x 100%. F1-Score: It averages memory and precision when calculating the F1-score. Contributing to the F1 score, false positives and negatives are not absent here. ((2 * Precision * Recall) / (Precision + Recall) x 100% False Negative Rate (FNR): The proportion of negative examples incorrectly classified by a model is given as a negative rate. It has also been referred to as the FNR. FNR = (FN / (FN + TP)) x 100% Negative Predictive Value (NPV): NPV in the testing community is defined as real negatives over population size with false negatives. NPV = (TN / (TN + FN)) x 100% False Discovery Rate (FDR): This calculation involves dividing total number of right ones by total numbers of wrong ones to get the false discovery rate. FDR= (FP / (TP + FP)) x 100%.

4.3 Experimental Result

The final result is an essential component of every project. It is known to everybody that no machine can produce results that are 100% correct. While our study's outcomes were great, We did not always use the appropriate way. We are using six different models in order to come up with the best results. These models include DenseNet121, EfficientNetB7, EfficientNetV2B3, EfficientNetB0 VGG16 and ResNet50 models. With each model giving us dissimilar results. Where we obtain the highest accuracy in "EfficientNetB0 model" which gives 98.75% accuracy– maximum precision rate. Planner for supreme performance was tested here too. The worst of all was The DenseNet121 model we used. It had an accuracy of 39.16%.

Table 4.3: Test result of different models and optimizer

Model Name	**Test Loss**	**Test Accuracy**
EfficientNetB0	38.43%	98.75%
ResNet50	61.06%	98%
EfficientNetB7	106.10%	94.22%
EfficientNetV2B3	84.80%	79.16%
VGG16	95.58%	73.75%
DenseNet121	151.14%	39.16%

4.3.1 EfficientNetB0:

Here is our first-rate model amongst the other six ordinary models that gave me 99.17% Val accuracy, We run 10 epochs & all time the accuracy increases & Val loss becomes low. Below, We present the last ten epochs on the Table & train loss, train accuracy value loss and value accuracy will be listed thereon. Finally, We get a 98.75% accuracy or precision and recall.

Table 4.3.1: Train & Val accuracy of EfficientNetB0 model

Train Loss	Train Accuracy	Val Loss	Val Accuracy
6.9766	0.8742	6.0436	0.9278
4.9596	0.9629	4.2265	0.9917
3.6177	0.9796	3.0799	0.9917
2.6653	0.9837	2.2379	0.9833
1.9355	0.9917	1.6092	0.9917
1.3970	0.9921	1.1565	0.9972
1.0200	0.9933	0.8502	0.9917
0.7485	0.9975	0.6055	1.0000
0.5580	0.9967	0.4647	0.9944
0.4395	0.9946	0.3722	0.9917

It indicates how far apart the model's train and validation results are from each other after training it. It is always better than the confirmation except for the test.

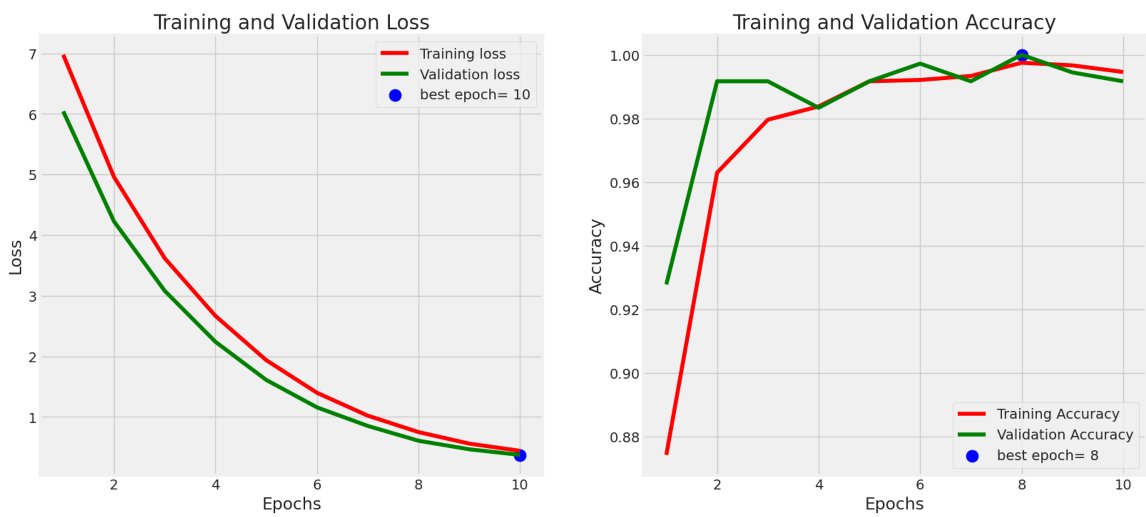


Figure 4.3.1: EfficientNetB0 model Accuracy & Loss

The uncertainty matrix has two variables regarding both real name and expected label. Through this grid we can figure out metrics like memory usage, f1-score, accuracy etc.

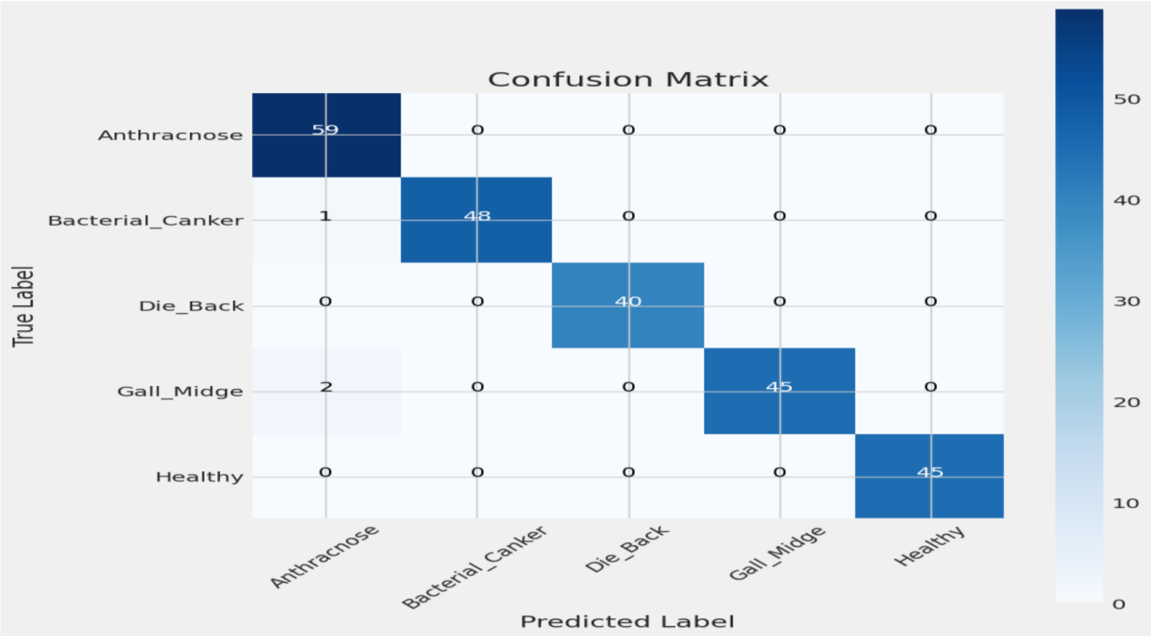


Figure 4.3.1: EfficientNetB0 model confusion matrix

4.3.2 ResNet50:

I got 98.94% Val_ accuracy with the second most eminent model called ResNet50. Ten epochs were done in this model and there were 10 steps per epoch for each of them. The table below shows the last ten epochs of the model. From here, I can see that training and Val accuracy are both increasing while at every epoch there is a reduction in training and Val loss. In conclusion, summarizing all accuracies; it is above 98%.

Table 4.3.2: Train & Val accuracy of ResNet50 model

Train Loss	Train Accuracy	Val Loss	Val Accuracy
6.7604	0.8388	5.6516	0.9500
4.9741	0.9304	4.2387	0.9694
3.7659	0.9500	3.2175	0.9639
2.8566	0.9600	2.4285	0.9750

2.1741	0.9696	1.8552	0.9639
1.6618	1.6618	1.4309	0.9694
1.3021	0.9700	1.1166	0.9694
1.0301	0.9767	0.8960	0.9806
0.8322	0.9771	0.7344	0.9694
0.6921	0.9821	0.6211	0.9694

The model is trained and then presented both train and validation loss comparisons and, accuracy comparison. In all cases, train accuracy is higher than validation accuracy.

Figure 4.3.2: ResNet50 model Accuracy & Loss

The confusion matrix has two dimensions; one for true label and another for predicted label. Precision, recall fi-score etc. can be measured by calculating this matrix.

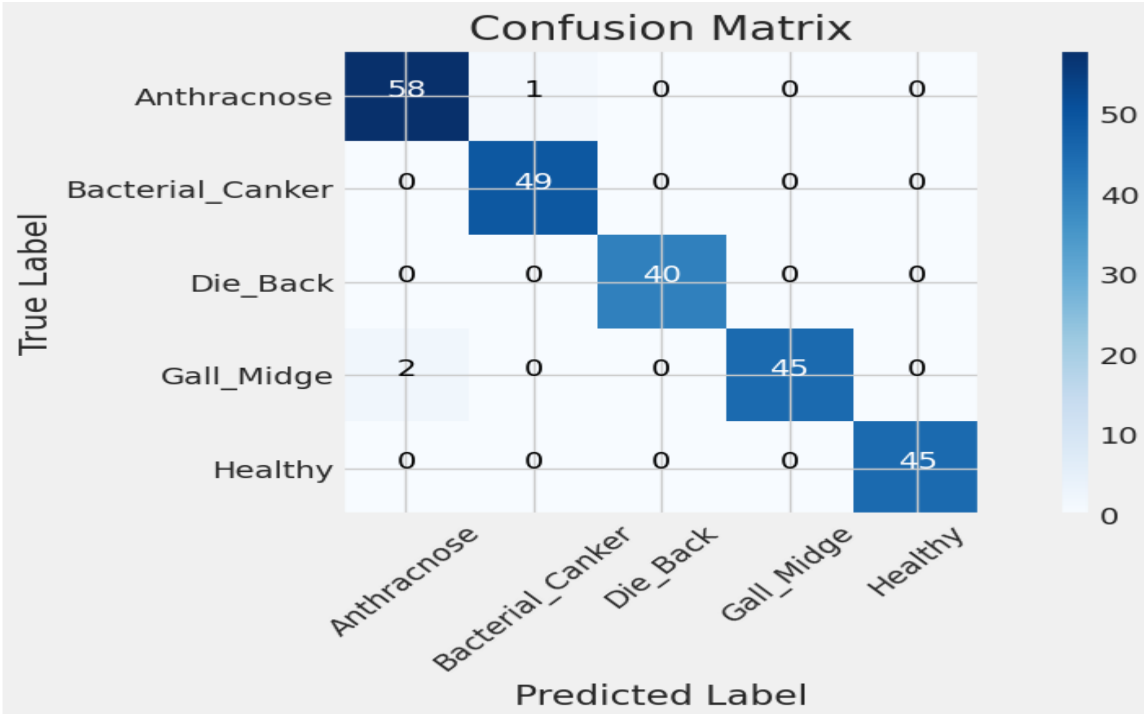


Figure 4.3.2: ResNet50 model confusion matrix

4.3.3 EfficientNetB7:

EfficientNetB7, the third-best model, gives me 93.75% Val accuracy. This model has run for 10 epochs consisting of 10 steps each. Here are the ten most recent epochs from the model. Here, we can observe that there is a decrease in training and Val loss on one hand as there is an increase in training and Val precision on the other hand. It is more than an accuracy rate of 94.22 % when you calculate all the accuracy values possible to achieve above this percentage.

Table 4.3.3: Train & Val accuracy of EfficientNetB7 model

Train Loss	Train Accuracy	Val Loss	Val Accuracy
5.1653	0.7195	4.2440	0.8711
0.8711	0.8338	3.3756	0.8956
3.2197	0.8624	2.7594	0.9400
2.7029	0.8924	2.3782	0.9244

2.3050	0.8929	2.0250	0.9311
1.9907	0.8971	1.7455	0.9267
1.7336	0.9010	1.5263	0.9333
1.5262	0.9043	1.3377	0.9356
1.3278	0.9152	1.1718	0.9533
1.2156	0.9043	1.0718	0.9311

Train and validation loss as well as accuracy are often compared together by different people. It is always true that the train accuracy is better than the confirmation accuracy because

Figure 4.3.3: EfficientNetB7 model Accuracy & Loss

Accordingly, the confusion matrix has two dimensions for both true label and expected label. By working out this grid I can find out about accuracy, memory, fi-score, and so on which seem to be important factors in determining whether or not a person should buy a particular item.

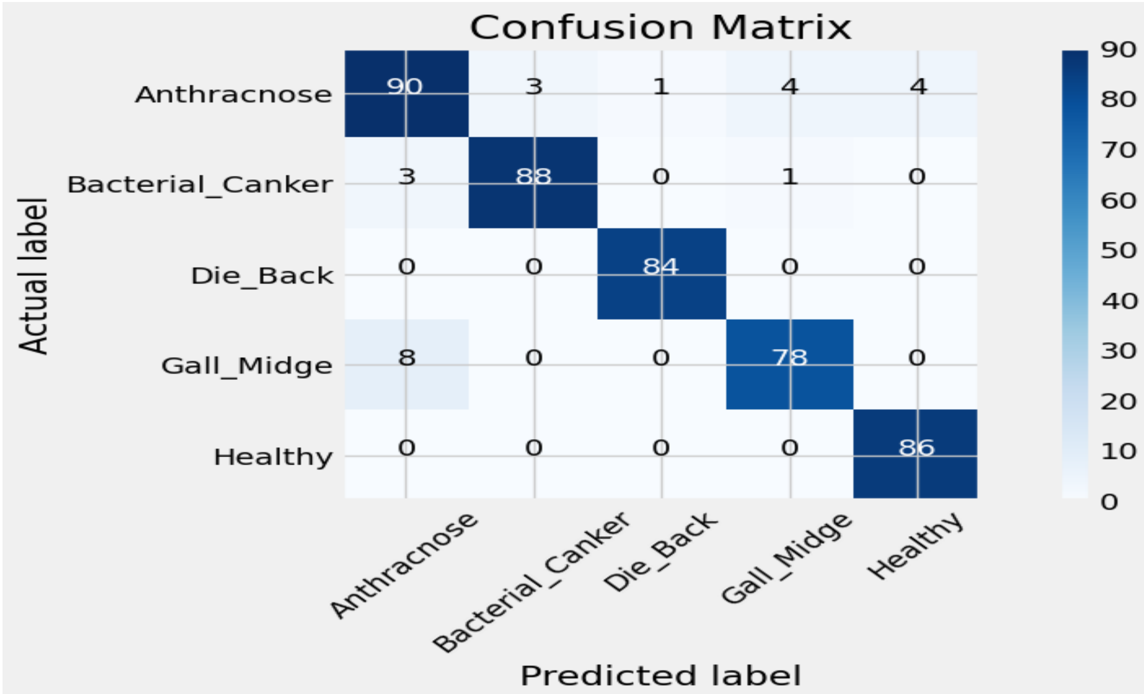


Figure 4.3.3: EfficientNetB7 model confusion matrix

4.3.4 EfficientNetV2B3:

It has an accuracy of 79.16% which happens to be the fourth best among the four models being developed. The model was run ten times instead of just ten and each time it took thirty-three steps. Ten pictures showing some of the most recent epochs in our model are shown below this paragraph. In summary, we can see from training and Val loss that they are both decreasing whereas training and Val accuracy show their upward trend. On Average, this is more than everything right answers at once.

Table 4.3.4: Train & Val accuracy of EfficientNetV2B3 model

Train Loss	Train Accuracy	Val Loss	Val Accuracy
2.8455	0.5429	1.8096	0.6583
1.4338	0.6321	1.4462	0.6944
1.2725	0.6413	1.2407	0.6972
1.1897	0.6679	1.0649	0.7139

1.1352	0.6662	0.9717	0.7389
1.0852	0.6875	0.9109	0.7333
1.0390	0.6988	0.8821	0.7556
1.0215	0.7025	0.8672	0.7667
1.0079	0.6862	0.8415	0.7667
0.9834	0.7200	0.8348	0.7556

The train run has not been shown here as well as the difference between its accuracy and loss compared to those of confirmation runs after conducting them on this model. Train accuracy on this one, as expected, is always higher than guaranteed accuracy

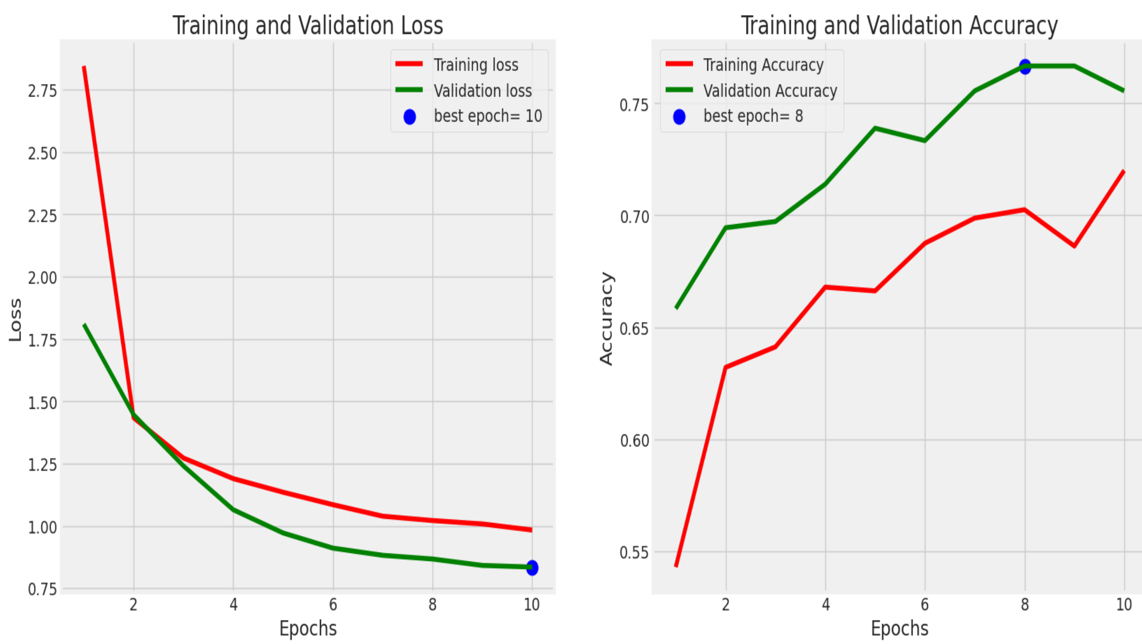


Figure 4.3.4: EfficientNetV2B3 model Accuracy & Loss

This matrix demonstrates two elements; actual identity and assumed label. It is helpful for identifying such details as: precision; recall; f-scores as well as other things.

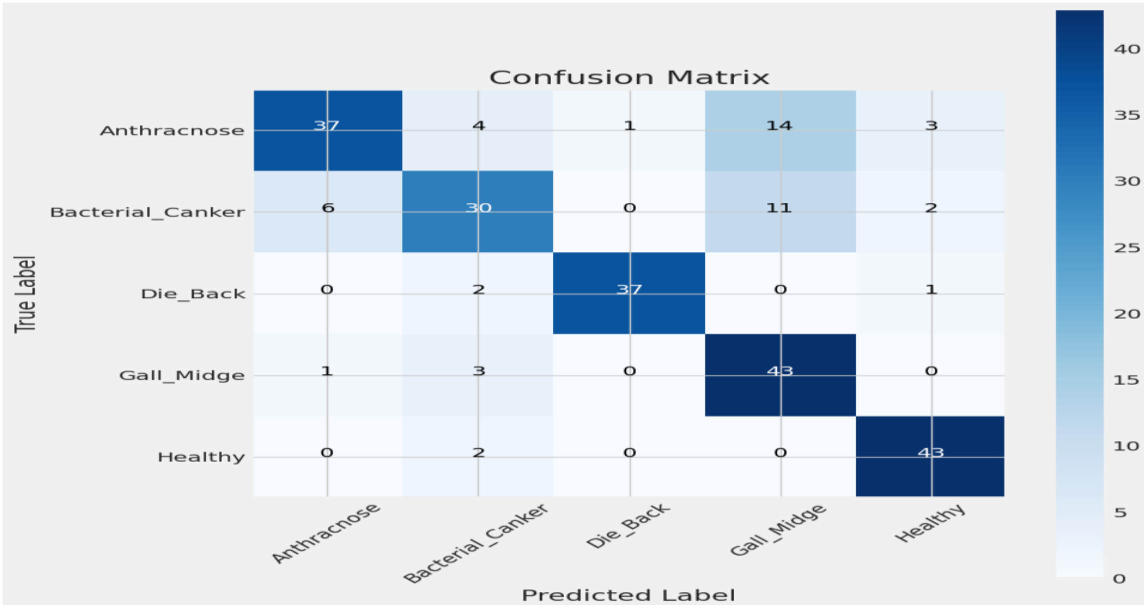


Figure 4.3.4: EfficientNetV2B3 model confusion matrix

4.3.5 VGG16:

Five is VGG16, and it operates at 73.75%. The model's last ten epochs are illustrated in the subsequent set of snaps. It can be seen that training and Val loss go down while training and Val accuracy goes up. Starting from accuracy which stands at 77.08% and Val accuracy which also stands at 77.08%. Mean score is more than 75% but less than80%.

Table 4.3.5: Train & Val accuracy of VGG16 model

Train Loss	Train Accuracy	Val Loss	Val Accuracy
3.1153	0.5308	2.0932	0.6361
1.6692	0.6608	1.7084	0.6556
1.4070	0.6904	1.4446	0.6750
1.2595	0.7113	1.2521	0.7000
1.1694	0.7196	1.1353	0.7333
1.1142	0.7308	1.0628	0.7333
1.0648	0.7337	1.0251	0.7361
1.0231	0.7467	0.9887	0.7472

0.9851	0.7608	0.9610	0.7611
0.9567	0.7542	0.9431	0.7639

The gap between precision and loss in train and proof runs is shown after the model has been trained. Train accuracy always higher than the test one

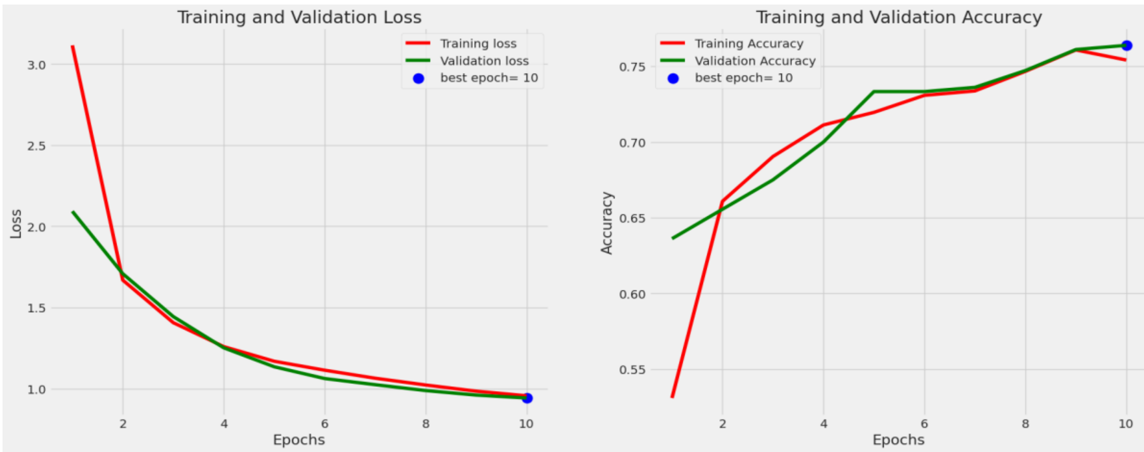


Figure 4.3.5: VGG16 model Accuracy & Loss

Uncertainty matrix tells us that the true name as well as supposed label consist of two parts. We can use this chart to study spelling, memory, f-score, etc.

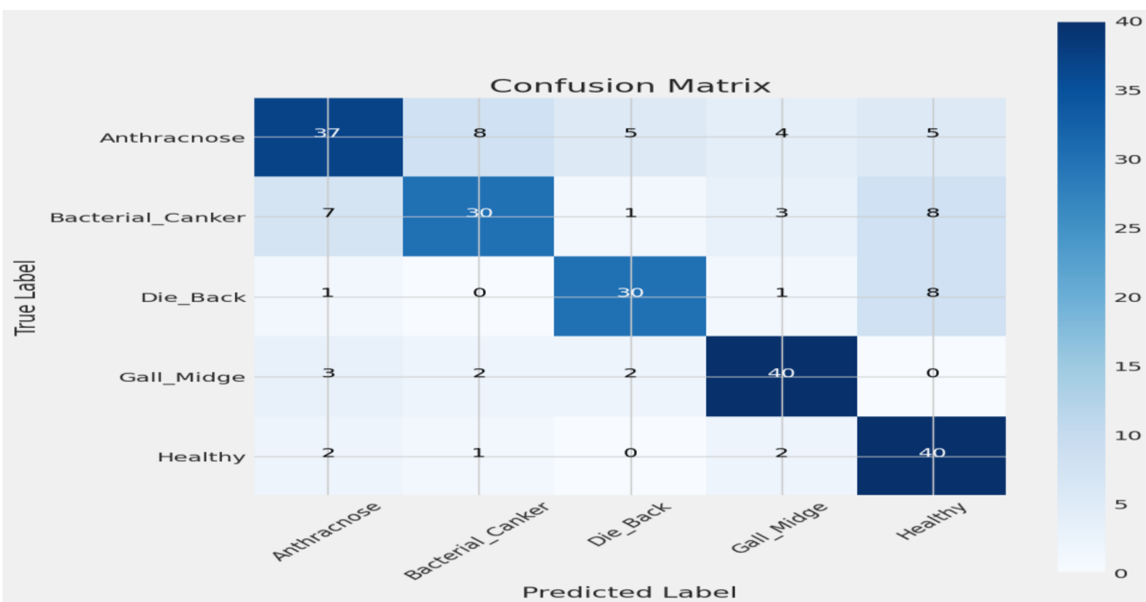


Figure 4.3.5: VGG16 model confusion matrix

4.3.6 DenseNet121:

The one that is DenseNet121 and it works 39.16% of the time – this is the sixth one. The last ten epochs of the model are shown in the following sequence of pictures. It's evident that training and Val loss are being reduced, while training and Val accuracy are growing. If you look at the state of accuracy, it has decreased from 66.66%, and Val accuracy has dropped from 45.83%. The average score is below 50% but above 40%.

Table 4.3.6: Train & Val accuracy of DenseNet121 model

Train Loss	Train Accuracy	Val Loss	Val Accuracy
2.6271	0.3500	1.6169	0.4139
1.5516	0.3963	1.5194	0.4000
1.5149	0.4071	1.4760	0.4111
1.4957	0.4083	1.4590	0.4194
1.4813	0.4108	1.4413	0.4278
1.4696	0.4146	1.4354	0.4389
1.4711	0.4121	1.4309	0.4361
1.4576	0.4158	1.4259	0.4389
1.4509	0.4179	1.4184	0.4361
1.4430	0.4171	1.4126	0.4417

For after the model had gone through a learning process, we see how the precision differs with loss between train as well as validation runs. Train accuracy is always higher than test accuracy.

Figure 4.3.6: DenseNet121 model Accuracy & Loss

Both parts contain real names and false labels on their uncertainty matrix. The spelling, memory, fi-score; We can use this grid to learn about other things.

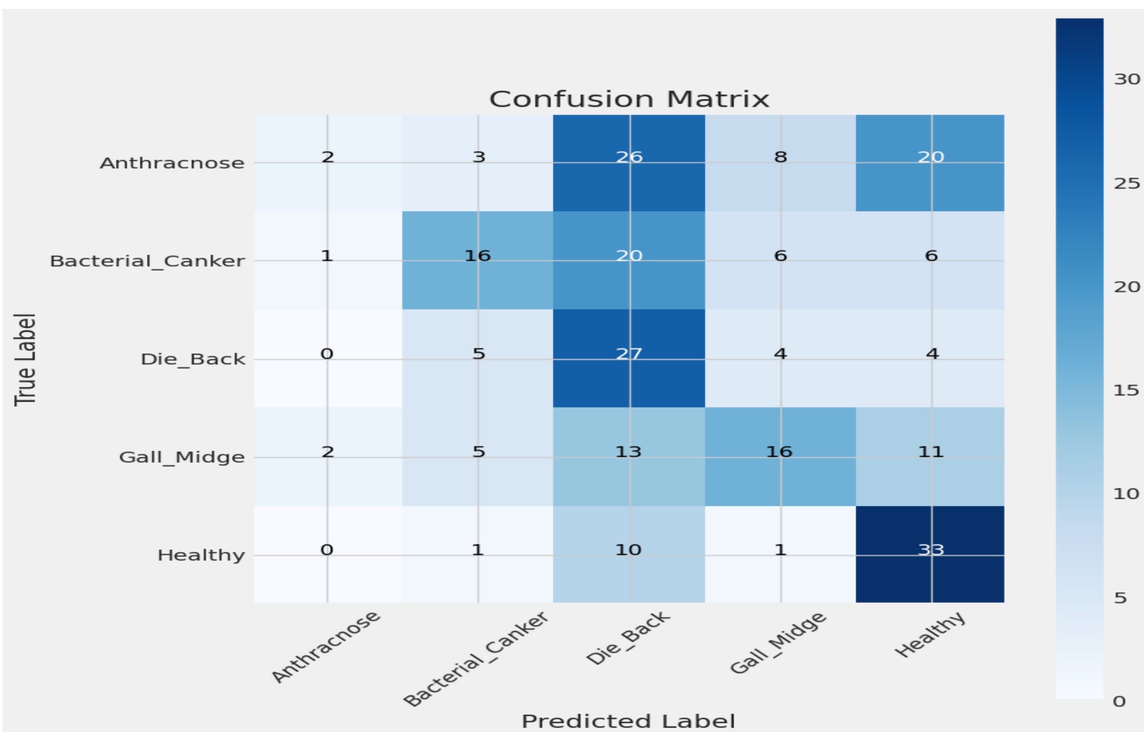


Figure 4.3.6: DenseNet121 model confusion matrix

4.4 Discussion

Our proposed model performs the best since it has the highest accuracy and EfficientNetB0 outperforms other models in terms of accuracy, F1 score, and recall amongst the seven CNN models. The most accurate model with a negative predictive value is EfficientNetB0. Studies carried out on the method used show that it can help us understand how people have an opinion about Coax. Furthermore, growers can sort through leaves to decide if the leaf is infected or not. Meanwhile farmers would safeguard their produce if they realist there is a disease. As such, more fruits will also be available due to an increase in their number. Initially some pictures of mango leaves were scanned and labeled. These images were sourced from a collection of datasets. The prediction becomes accessible for viewing upon uploading this image.

Fig. 4.4. Predicting actual leaf classes

From figure (Fig. 4.4), one can easily notice that our model perfectly predicts whether the disease will occur or not; “healthy” as shown by actual symbol while “healthy” according to our own model.

Table 4.4: Comparison between Our work & Related best other work

Domain	**Dataset**	**Models**	**Accuracy**	**Author**
Detection	670 images	SVM algorithm	97%%	Swathi et al. (2020)
Detection	17,572 images	DenseNet201	98.00%	Rajbongshi et al. (2021)
Detection	1130 images	WNN model	98%	Mishra et al. (2021)
Detection	1200 images	SVM	97%	Reo et al. (2020)
Detection	1200 images	CNN model	96.67%	S.Arivazhagan et al. (2018)
Detection	**3000 images**	**EfficientNetB0**	**98.75%**	**Our Study**

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

For global agriculture, mango leaf diseases are a huge challenge which needs immediate and precise identification before it leads to disastrous consequences. The effect of mango leaf diseases including anthracnose disease on society in Bangladesh and globally is noteworthy. In Bangladesh, losses in yield due to mango anthracnose disease (MAD) and stem end rot diseases are very high; they may range from 25-30% of mango yield. This causes a strain on the economy of farmers, undermining future prospects for the country's mango farming enterprises. The economic significance of anthracnose with respect to mango is demonstrated by the differences between export and domestic markets where second grade fruits are still sold locally despite such losses. Being expensive, managing MAD could have severe repercussions for the economy, especially if small scale farmers cannot afford investing in control strategies resulting into serious economic impacts. Research is ongoing regarding light weight deep learning models as well as convolutional neural networks that can be used to enhance classification as well as detection of Mango Leaf Diseases which will lead to better agricultural practices reducing these diseases' negative effects on quality and quantity.

5.2 Impact on Environment

The environment is greatly affected by mango leaf diseases like anthracnose. The spread of these diseases has huge implications for ecosystems. The use of fungicides in controlling mango leaf diseases has environmental consequences due to excessive application leading to the development of strains resistant to fungicides, which may imply the use of more potent or dangerous compounds that can amount to increased negative effects on the environment.

Furthermore, humid regions harbor pests like anthracnose for mango trees, spreading such infections thereby causing ecological imbalances. For instance, loss in fruit yield caused by these infections may result in food insecurity and loss of habitat for other organism's dependent on them.

In summary, economic implications characterizing mango leaf diseases are accompanied by significant environmental impacts that necessitate adoption of sustainable management practices for both agriculture and the ecosystem at large.

5.3 Ethical Aspects

Mango leaf disease research has a moral dimension. In order to avoid wrong conclusions, it is imperative to ensure accuracy of the information derived. Research also needs to take into account the local communities and ecosystems where they are taking place. And this means looking at what else might happen in society if it does go wrong. By so doing, the study not only becomes credible but also contributes positively to both humanity and nature. It’s all about being accountable and considering every situation in the research.

5.4 Sustainability Plan

The long-term plan for finding mango leaf diseases stresses on constant improvement and change. This implies that there should always be alternative ways of handling agricultural problems whenever they emerge. Additionally, one of the objectives for the forthcoming years is integrating these approaches with other tools and techniques. There is also need to work together with small-scale farmers to ensure proper use of these technologies that will be useful but safe for our environment. The objective of this technique is therefore maintaining healthiness of mango trees over time, thus keeping them as renewable sources for many years ahead as well as eco-friendly ones too.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

The main objective of this research was to investigate the application of Convolutional Neural Networks (CNNs) in the classification and diagnosis of various diseases that affect mango leaves. We have used several advanced deep learning models such as EfficientNetB0 (Proposed model), DenseNet121, VGG16, ResNet50, EfficientNetB7 and EfficientNetV2B3.These models were trained and tested rigorously on a comprehensive dataset before their performance could be evaluated using accuracy, precision, recall and F1-score metrics. From the results it is evident that Proposed model based on EfficientNetB0 attained higher accuracy compared to others thus indicating its suitability in mango leaf disease identification. This implies that among the models considered for this study, EfficientNetB0 seems more appropriate in dealing with this kind of classification task. According to this research, deep learning methods have potential to identify diseases affecting mango leaves with high levels of precision which is a significant development in agriculture. In addition, these models can effectively play an essential role in preventing or managing diseases by providing accurate detection of disease thus enabling timely interventions for farmers and other stakeholders in agriculture who would want to save their crops from diseases. The outcomes recommend integration of such technologies might result in improved crop health hence enhanced agricultural productivity.

6.2 Conclusion

The experiment proved the usefulness of deep learning models especially Convolutional Neural Networks (CNNs) in terms of classifying and detecting mango leaves diseases. Out of the various models tested, EfficientNetB0 model proposed indicated superior performance with a precision of 98.75%. Therefore, this high level of accuracy implies that EfficientNetB0 provides an effective way to detect early diseases in mango leaves. These results indicate that there is room for improvement in the agricultural sector with regards to disease control methods. The study also underscores the role of advanced technological integration into agriculture as a means towards enhancing crop management and productivity. Besides, this application has huge implications on sustainable farming practices and overall improvement in quality crop production where CNNs are used for plant disease detection. Consequently, these models can enable accurate and early detection of diseases which would then result in reduced excessive need for pest control chemicals thus promoting environmentally friendly farming practices. In essence, it suggests that technology can revolutionize agriculture leading to further investigations on this subject matter.

6.3 Implication for further Study

Advanced deep learning techniques such as Convolutional Neural Networks (CNNs) and transfer learning will be used to build a more accurate mango leaf disease detection model. These methods, which are used jointly should dramatically enhance the model’s effectiveness. Furthermore, we intend to make our data set larger by including additional images of mango leaves and fruits. In this way, it will be possible to come up with a reliable classification system that can distinguish between illnesses in different plant organs using a broad-based dataset. The main objective is therefore to design real-time recognition approaches that can be employed in practical agricultural contexts for accurate diagnosis of diseases related to mangos in time. Thus, this approach can not only improve the dependability of our system but also extend useful assistance to farmers and other stakeholders in agriculture about better management and control of mango diseases.

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