

**Crop Disease Recognition using Deep Learning**

**BY**

**S. M. SOHAN**

**ID: 173-15-10446**

**AND**

**MD. MONSAKIB RAHMAN**

**ID: 173-15-10436**

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering <sup>[Font-14]</sup>

Supervised By

**Md. Tarek Habib**

Assistant Professor

Department of CSE

Co-Supervised By

**Ms. Nusrat Jahan**

Sr. Lecturer

Department of CSE



**DAFFODIL INTERNATIONAL UNIVERSITY**

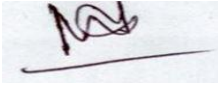
**DHAKA, BANGLADESH**

**DECEMBER 2021**

## **APPROVAL**

This Project titled “**Crop Disease Recognition using Deep Learning**”, submitted by \* **S. M. Sohan, ID:173-15-10446\*** and \***Md. Monsakib Rahman, ID:173-15-10436\*** 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 \***Sunday 2 January 2022\***.<sup>[Font-12]</sup>

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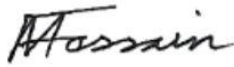
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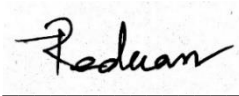
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---

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Department of Computer Science and Engineering

Faculty of Science & Information Technology

Daffodil International University



---

**External Examiner**

**Dr. Mohammad Shorif Uddin**

**Professor**

Department of Computer Science and Engineering

Jahangirnagar University

## DECLARATION


We hereby declare that, this project “**Crop Diseases Detection using Machine Learning**” has been done by us under the supervision of **Md. Tarek Habib, 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.



**Supervised By**

---

**Md. Tarek Habib**  
Assistant Professor  
Department of CSE  
Daffodil International University



**Co-Supervised By**

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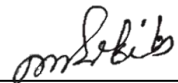
**Ms. Nusrat Jahan**  
Sr. Lecturer  
Department of CSE  
Daffodil International University



**Submitted By**

---

**S.M. Sohan**  
ID: 173-15-10446  
Department of CSE  
Daffodil International University



---

**Md. Monsakib Rahman**  
ID: 173-15-10436  
Department of CSE  
Daffodil International University

## ACKNOWLEDGEMENT

First we express our heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year project/internship successfully.

We really grateful and wish our profound our indebtedness to **Md. Tarek Habib, Assistant Professor**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of “*Artificial Intelligence, Machine Learning, Deep Learning, Image processing, Convolutional Neural Network.*” to carry out this project. His endless patience ,scholarly guidance ,continual encouragement , constant and energetic supervision, constructive criticism , valuable advice ,reading many inferior draft and correcting them at all stage have made it possible to complete this project.

We would like to express our heartiest gratitude to God, our supervisor Dr. Touhid Bhuiyan teacher and Head, Department of CSE, for his kind help to finish our project and also to other faculty member and the staff of CSE department of Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

## **ABSTRACT**

Bangladesh is an agricultural country. Agriculture is considered to be the backbone of our country. Crops play an important role in our daily routine providing us with nourishments. Because of being environmental condition crops are affected by many serious diseases. After affecting the crops the production and development of crops are totally reduced. Farmers are not able to detect these diseases at an early stage because they don't have any modern technology to detect the diseases and they don't take any necessary steps to solve the problem. Artificial Intelligence has become the new leader of data analytics in this technological race. Now there are many technologies play a major role and techniques like Machine Learning, Deep Learning, Computer Vision algorithms, Image processing, Convolutional Neural Network Algorithm. Healthy as well as diseased leaves are captured using cameras from real-time environments. The captured images undergo processes like preprocessing and segmentation. After segmentation, using Machine learning algorithms in which healthy and diseased leaves are detected. This system helps to reduce the difficulties faced by the farmers during crop cultivation which helps in increasing the crop yield. This study aims to reduce the physical and mental harassment of farmers. Our proposed model has achieved fairly high Accuracy.

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# CHAPTER 1

## INTRODUCTION

### 1.1 Introduction

Agriculture is a fascinating topic of study in today's globe. Over 8 billion people are expected to live on the planet. The major and most pressing issue for those people is food, which is dependent on agriculture. It is one of Bangladesh's most significant vocations, covering over 60% of the country's territory. Farming is the nation's major source of income. Farmers raise a variety of crops to meet their needs. Farming has grown more challenging for farmers as the environment has changed owing to issues such as pollution, global warming, natural catastrophes, and so on. Several kinds of pathogens have infected its leaf, fruit, and stem, causing illnesses. Bacteria, fungus, viruses, and other microorganisms are the most common causes of leaf diseases. In this concept, the farmer takes a photo of a leaf from a crop that he has seeded in his farm. He takes the photo, and the system determines which plants are healthy and which are diseased. For identifying healthy and unhealthy crops, approaches such as Machine Learning Algorithms, Image Processing, Deep Learning, and others are used. In this industry, machine learning is critical.

### 1.2 Motivation

In our country named Bangladesh is mainly an agricultural country. The big amount of people here live in village and agriculture dependent occupation. They lead their life under rated. Their all needs depend on it which they sell and get money from it . If they are related in this occupation where has billon of people's daily food. We see the rural area where people plant many types of crop but do not get enough production. Because of the main problem is crop disease. This is very sufferingful for people. And they can not connect with agricultural officer properly. If they connect with the officer but solution takes long time. The manual process of agriculture is not the right process now. Because they can not detect

the right diseases and can not take proper necessary steps to solve the problem in time. So it should be automated and without time consuming process to detect the diseases and get the actual information.

### **1.3 Rationale of the Study**

Deep Learning, Computer Vision Algorithms, Image Processing, Convolutional Neural Network (CNN), which is considered a branch of Artificial Intelligence (AI), is a field of CSE that deals with information extraction based on example recognition. After a repeated examination of information and specialists' assignments, a PC gained from previous blunders that job was recently assumed to be too complicated for machines to measure. Because of its great accuracy, CNNs are employed for picture categorization and identification. Machine learning is the process from which a machine learns from the data it is given on its own. Unlike other languages, it improves through practice rather than being expressly coded.

The user gives the system with training data, which aids in its training. The accuracy of the results is ensured by a vast amount of training data. We reasoned that we might identify actions using a deep convolution neural network (CNN).

### **1.4 Research Questions**

1. Does your system provide an actual result when given sample data?
2. Can a machine learning system be used to identify agricultural diseases?
3. Does each algorithm perform flawlessly (yes/no)?
4. Do we have a flawless manual detection system for all crop diseases? Because it has been provided a set of valid data, the system should be given a genuine output. It uses a machine learning system to detect agricultural illnesses by comparing images of healthy and diseased crops. The data from the tests is sent into the trained system. The outcome is determined on how well the system has been educated. When the system receives images as input, image processing techniques must be used to process the images. We trained our

machine with a vast amount of data sets and achieved a high level of accuracy, and I am certain that our computer will be able to recognize healthy and diseased crops with ease.

We employed the Convolutional Neural Network (CNN) method and got decent results in terms of accuracy and feedback.

## **1.5 Expected Outcome**

Our crop diseases identification technology aids in the generation of an expected outcome based on input data from our dataset. To generate a more accurate outcome, we employed 65 percent training data, 13 percent test data, and 22 percent genuine data. The degree of accuracy is entirely reliant on the training data set, according to our findings. Our computational system can be accessed after most of the guidelines developed have been completed. We used a variety of ways to achieve accurate results. Vgg16 and Mobilenet are two models from the CNN algorithm that we use in our system. We achieve greater accuracy via vgg16 in the Mobilenet model. We obtained about 97 percent accuracy from the data we used to develop this method.

## **1.6 Report Layout**

**Chapter 1:** In this section, we spoke about why we wanted to do this project, its goals, and the expected outcome of our work.

**Chapter 2:** In this section, we have given the foundation of our study and examined other relevant studies, similar investigations, the scope of the issues, and the obstacles.

**Chapter 3:** we discuss our study topic and instrument, as well as the data gathering, data analysis, and effective implementation.

**Chapter 4:** In this chapter, we will summarize our study experimental results and descriptive analysis.

**Chapter 5:** In this chapter, we discuss the summary of predictions and conclusions, as well as the study procedure in general.

## CHAPTER 2

### BACKGROUND

#### 2.1 Introduction

Agriculture is a occupation that is more important than any other occupation. Because we know that there are mainly five types of human rights. But the first and very important from these five is Food. The needs of food is mainly come from agriculture. The activity of producing plants and cattle is known as agriculture. In the establishment of sedentary human civilization, where have a significant factor known as agriculture. From tamed species by creating food surpluses since it should be enabled humans to dwell in cities. A long history of agriculture started thousands of years. The farmers do their job properly to plant crop and focus on it. The world even any development all over the world but it can not lead without food. So farmer's should plant crops to hold the development and civilization. But there are many challenges on it. The development of plant crops has natural problem like environmental disaster the problem of insects. So we need to develop in this side. We have undertaken this research project throughout which we will try to figure out the most important features that detect the diseases of crop and it is Bangladesh's most important industries.

Our linked studies, the project description, and the research problems will all be included in this part. Underneath the complementary work area, we shall examine various published papers which are relevant with this study. We will discuss our project summary in the summary section, and we will discuss how we will develop it in the challenge section.

#### 2.2 Related Works

Crop diseases Detection is the system which is the crucial research area in Bangladesh is a kind of framework where we can undoubtedly realize about the healthy and affected crops and take necessary steps as soon as possible. Machine learning has been used to detect

agricultural diseases in a number of studies and research projects. R. Poonguzhali and A Vijayabhanu [2] shown that the Crop Condition Assessment using Machine Learning system has five components. They really are. Obtaining Images Image Preparation Segmentation of images Classification of Feature Extraction. Real-time paddy leaf photos from surrounding fields are acquired in Image Acquisition. There are photographs of both healthy and sick leaves in this collection. Among of all diseases the considered diseases are Leaf Blast and Brown Spot. Both healthy and sick photos are included in the training dataset. The pictures are trained using the Convolutional Neural Network (CNN) technique. The photos have been trained and categorised effectively. The healthy image and the affected image which is detected by the system.

Radhika Deshmukh and Manjusha Deshmukh [4] shown that rice leaf diseases may be diagnosed using the K-means and artificial neural network algorithms in 2015. Brown Spot is the illness that is most prevalent in this area. This article the main topics are classification, segmentation, image preprocessing, Image acquisition, and feature extraction, using ANN. For picture segmentation, the K-means method is utilized. The findings of this article show that illness detection may be done quickly. Images of paddy leaves acquired using cameras are processed on a distant server. The illnesses like Rice Sheath Blight, Rice Blast, and Brown Spot are discussed here. Sanjana, Y., Ashwath Sivasamy, and Sri Jayanth [6] photographed 500 sick paddy leaf photos in the same year. From central server image selection, picture capture, crop, zoom and expert crop image sharing get notice that method is utilized here. Both the training and analysis stages need image processing, which is handled by the expert groups. This procedure is straightforward and inexpensive.

Guo, Yan, et al. [8] in 2020 introduce the plant diseases detection using a deep learning based model with high training efficiency, unsupervised, good universality and high accuracy. However, there are various obstacles to the precision and practicality of plant disease detection in today's complex environment. To address these issues and enhance the



identification technique, this study proposes a recognition model including RPN, CV, and TL algorithms that can successfully handle the problem of plant disease identification in a complex environment.

Nikhil Patil, Rajib Ali, Vaibhav Wankhedkar, and Prof. Deepali Nayak [10] presented Crop Disease Detection using a CNN system based on Deep Learning in a study published in 2019. Farmers can profit from the suggested technology since it gives real-time crop disease information. The revealed technique has an accuracy rate of 89 percent when compared to traditional crop disease detection technologies, meaning a right detection rate of 9%.

In our paper, we have collected data and this dataset given to the system where using deep learning algorithm most likely Convolutional Neural Networks (CNN) algorithms which is most popular than other algorithm. So in our paper, we have shown that the detection of crop diseases is a system where we detect healthy and affected crops.

### **2.3 Research Summary**

Here we work for the topic of crop diseases detection. Actually it is very important for every nations and every country. Because the problem of food is a main fact. So the world is going to developed and we need to take to step and other we have a lot of population. So we should to digitalized and modernized the field of agriculture. Here we see there are some of work already. We need to develop it.

### **2.4 Challenges**

While our research to finish we are suffering from many challenges. In our detection accuracy improving one aspect is the most difficult that is data collection. In Bangladesh, data collecting is a time-consuming operation. There have not available collected data in any Govt. or private company in our country which is helpful for our project. As a result

we went many people and farmers to collect data manually and then we store it in our PC. For this reason we contacted some Govt. office for many time that is so much time consuming. We didn't get perfect data. There had also many missing data. Then we collect data from online and went to the field to collect real time data. But this is also time consuming because the crops, fruits and other plants do not grow in same time and same season. There are almost plants grow different times and then there all images are not suitable to taken. All the healthy and affected sign of crops could not taken. so this have to finish to take many times. Finally we finish the data collection process that is time consuming. As a result, the proposed architecture has been subjected to a different procedure. Finally, a process for obtaining accurate value has been established. As a result the method of working faces many Several obstacles.

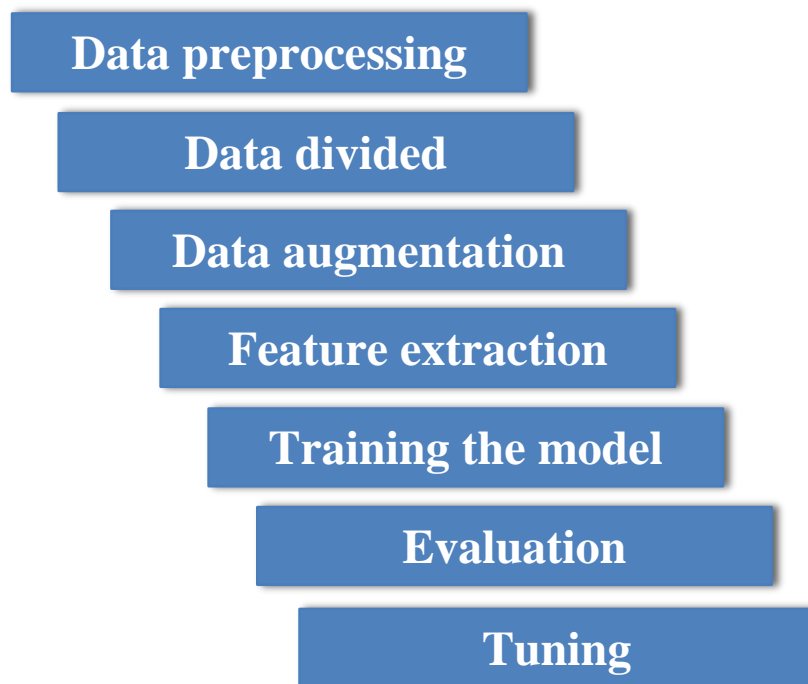
## CHAPTER 3

### RESEARCH METHODOLOGY

#### 3.1 Introduction

We shall detail our study technique and processes in this section. This course will also cover research project tools, data collecting, study subject, pre\_processing, processing, statistical-analysis, and execution.

We can see the entire process at a look in Figure 3.1.



**Figure 3.1:** Methodology at a Glance.

**Step 1:** Data preparation: all photos in the dataset are downsized to 224x224 pixels.

**Step 2:** The data is split into two portions, with 65 percent of the data being used for training, 22 percent for valid data, and 13 percent for testing.

**Step 3:** Data augmentation: To minimize overfitting, the Training set is augmented by rotating, resizing, and adding random noise to the photos.

**Step 4:** Feature extraction: Using convolutional operations, features would be extracted in the initial layers of the CNN architecture.

**Step 5:** Train the model: We'll utilize a LeNet-based architecture in this example [9]. We will test the network using Training data set characteristics whenever the architectural style has just been developed.

**Step 6:** Evaluation: The accuracy of the model will be assessed using the Test set.

**Step 7:** Tuning: If the results aren't what you want, tweak the architecture by adjusting kernel size and nodes in the last completely linked layer.

### **3.2 Subject of Study and Instrumentation**

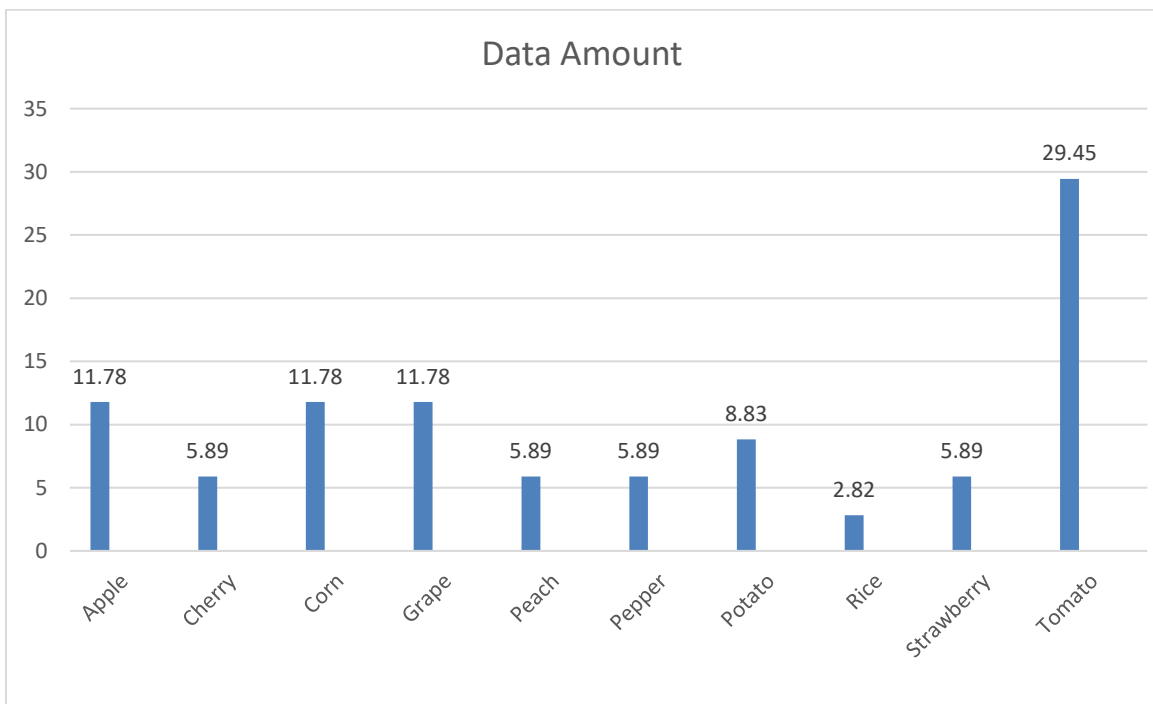
We can see that information is the most important aspect of the test. Finding spectacular data and a fantastic technique or model for our research job is an extremely important component for an expert. We'll also need to go at similar test papers. At this point, we must make the following decisions:

- Which information should be gathered?
- How can you be confident that the information you've gathered is correct?
- What is the best way to organize each piece of information?
- How should each piece of information be labeled?
- How much data do we need to get a high level of accuracy?

### **3.3 Data Collection Procedure**

Data collection process was very lengthy and time consuming because our main data type was image type. So there the most data used in this project are collected from various online resources and real time field in our country (Bangladesh). Most of the data are collected from many nursery and agricultural field. We have to wait many time when the crop like

rice, potato, tomato, corn, pepper, peach are grown. Because they grow different times. But we get so many data like apple, cherry, grape, strawberry and other from online resources. In Covid-19 pandemic situation, we have collected all over 10 categories of crops. And They have healthy and affected classes. The amount of these classes are 37. we have collected almost 78000+ data in which we have used all of them data in our research. The Collected data remain on 10 crops and there have Apple(11.78%), Cherry(5.89%), Corn(11.78%), Grape(11.78%), Peach(5.89%), Pepper(5.89%), Potato(8.83%), Rice(2.82%), Strawberry(5.89%), and Tomato(29.45%) data of total amount of data.








**Figure 3.2:** Vgg16 Model for Cherry

### 3.3.1 Classes

There are 37 classes in the dataset that was retrieved. Furthermore, the data was segregated into three independent data sets: "training and valid data set for model construction, and test dataset for model evaluation."

**Table 3.1:** Classes And Damo Data

Classes	Data
AppleBlackrot	
AppleHealthy	

<p>AppleScab</p>	
<p>CedarAppleRust</p>	
<p>Cherry_healthy</p>	

Cherry\_powdery\_mildew



Corn\_common\_rust



Corn\_gray\_leaf\_spot





Corn\_healthy



Corn\_northern\_leaf\_blight



Grape\_black\_rot



Grape\_isariopsis\_leaf\_spot



Grape\_healthy



Peach\_bacterial\_spot



Peach\_healthy



Bell\_pepper\_bacterial\_spot



Bell pepper Healthy



Potatoes\_with\_early\_blight






Potatoes\_healthy



Potato\_late\_blight



<p>Rice_brownspot</p>	 A close-up photograph of a rice leaf against a light grey background. The leaf shows several distinct, elongated brown spots, characteristic of rice brown spot disease.
<p>Rice_healthy</p>	 A close-up photograph of a healthy rice leaf against a light grey background. The leaf is a uniform green color and shows no signs of disease or damage.
<p>Rice_hispa</p>	 A close-up photograph of a rice leaf against a light purple background. The leaf shows signs of damage, including a prominent, dark, elongated lesion, characteristic of hispa damage.

Rice\_leafblast



Strawberry\_leaf\_scorch



Strawberry\_leaf\_healthy



Tomato\_bacterial\_spot



Tomato\_early\_blight



Tomato\_healthy



Tomato\_late\_blight



Tomato\_leaf\_mold



Tomato\_mosaic\_virus





Tomato\_septoria\_leaf\_spot



Tomato\_spider\_mites



Tomato\_target\_spot



Tomato\_yellow\_curl\_virus

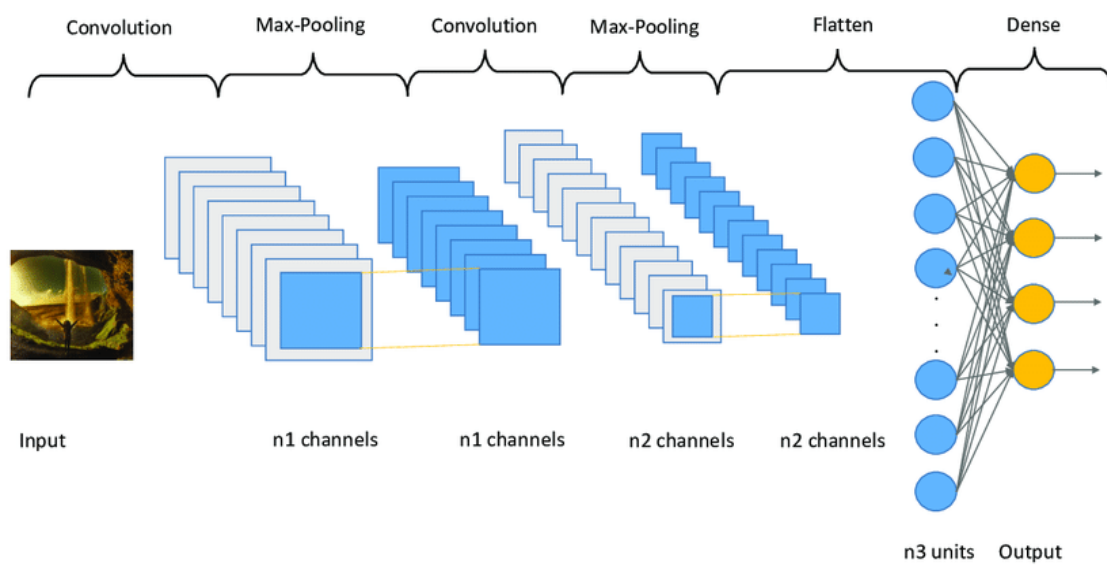


### 3.3.2 Data Preprocessing

#### 3.3.2.1 Vgg16 Model

We investigated a number of algorithms for detecting crop disease, including the use of Convolutional Neural Networks (CNN) with a customized architecture in the detection of leaf disease from leaves, as well as the VGG Architecture with 16 layers (VGG 16), which is proposed to classify infected crops with various diseases. VGG Architecture employs 3 X 3 Convolutional layers that are placed on top of each other in order of increasing pattern depth. It has already been determined that trained to a VGG 16 is tough, certainly in terms of Integration on the deeper networks; consequently, train the smaller form of VGG with less fully - connected layers beforehand to make the training easier. Pretraining is the process of converging smaller networks and then using them to initialize bigger deep networks. VGGNet has two key disadvantages.

- i. Training is quite sluggish.
- ii. In terms of disk/bandwidth, there are a lot of network architectural weights.



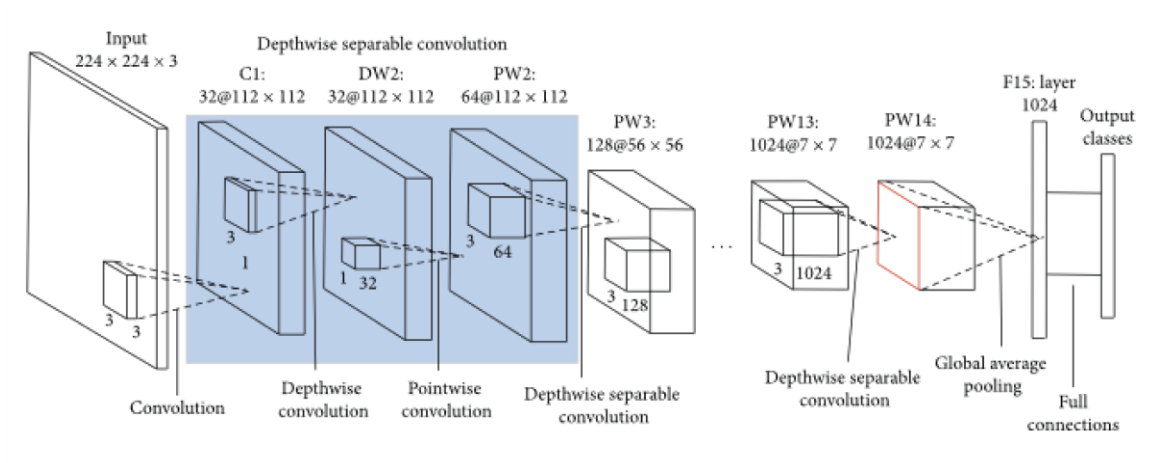
**Figure:3.3 Vgg16 Model**

ResNet is used to overcome the disadvantages of VGG and lower the error rate. On the ImageNet Dataset, it has a 3.57 percent error rate. ResNet, like VGG, is made up of numerous layers piled on top of each other. The network learns numerous low/mid/high level characteristics at the conclusion of these levels. Residuals can be nothing more than the subtraction of each input layer's feature learnt. ResNet accomplishes this by linking the  $n$ th and  $(n+x)$ th layers. This means that training this type of network is easier than training other types of networks, and it also solves the problem of error rate by lowering it.

### 3.3.2.2 Mobilenet Model

Two layers of depth wise separable convolutions make up the MobileNet model. Convolutions are divided into two types: depthwise and pointwise. In MobileNets depthwise convolution, a single filter filters each input channel. The outputs of the depthwise convolution are then blended by the pointwise convolution utilizing a  $1 \times 1$  convolution. By describing the network in such fundamental ways, we may easily study network structure to determine a pleasant network. Except the last completely connected

layer, as it has no nonlinear characteristics as well as feeds into something like a softmax function for classification, the rest of the layers are fully linked, all layers in MobileNet are followed by batchnorm and ReLU nonlinearity. A factorized layer with depthwise convolution, 1 X 1 pointwise convolution, batchnorm, and ReLU nonlinearity is compared to a layer with conventional convolutions, batchnorm, and ReLU nonlinearity after each convolutional layer. In the hidden layer convolutions and the first layer, strided convolution is used to address down sampling. Before the totally linked layer, a last average pooling decreases the spatial resolution to one. When depthwise and pointwise convolutions are counted independently, MobileNet has 28 layers. In comparison to typical 3D convolution, MobileNet uses the depthwise separable convolution approach to greatly minimize the redundancy of the convolution kernel. It not only decreases the model's size and optimizes the latency, but it also increases the model's recognition accuracy.

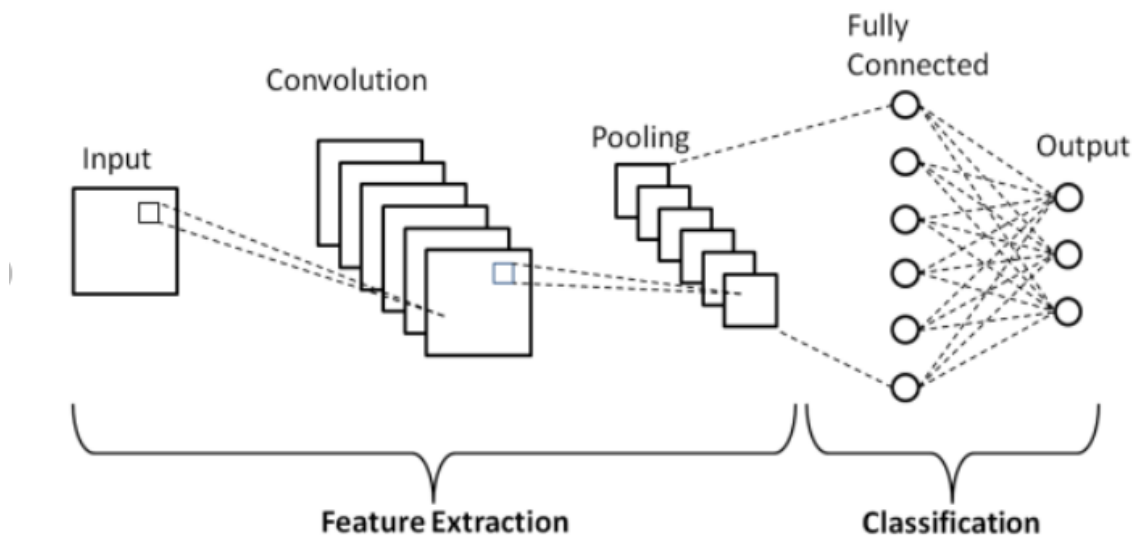


**Figure 3.4:** Mobilenet Model

In comparison with conventional three - dimensional convolution, MobileNet uses the depthwise separable convolution approach to greatly minimize the redundancy of the convolution kernel. It not only decreases the model's weight and minimizes the latency, but it also increases the model's recognition accuracy.

### 3.3.3 Model Learning

The Architecture accepts an image with a resolution of 224 by 224 pixels as input. To filter the picture, data preprocessing and data augmentation are used. Data Augmentation is the addition of noise data and the flipping of a picture to make it more relevant. There are two Convolution layers in total in the described design. The Abstract features are extracted from the image using Convolution layer 1 with an input shape of 224 X 224 X 3 and a depth of 32. Later, the Convolution Layer 1 result is down sampled and 2 X 2 Maxpooled Layer is applied. Convolution Layer 2 receives this output and extracts additional detailed characteristics from the input shape of 112 X 112 with a Depth of 64. This Input is also passed on to successive Convolutional Layers. To limit the quantity of Overfitting, the Dropout Layer is also used. Some perceptron's are activated in Dropout, which increases overall performance. The input from the previous layers is flattened and sent to the fully linked layers, which do the actual categorization.



**Figure 3.5:** Convolutional Neural Network (CNN)

The right photograph of the leaf was obtained. The image will then be scaled in the suitable format before being sent to a server where a Convolutional Neural Network method will

be applied. Every Convolutional Neural Network design includes four primary components and is separated into two parts: feature extraction and classification.

1. The operation of convolution.
2. Pooling to the maximum (Down sampling)
3. ReLu (Non Linearity)
4. The classification system (fully connected layer)

### **3.3.4 Data Organizing**

We'll need a lot of iterations, time, and effort to complete a good deep learning project. To help this process go more smoothly, we should aim to make the most of our resources. We'll be able to do this with the aid of a strong step-by-step process. Our projects become more productive, repeatable, and understood as a result of it. Even if our job is imprecise, it will elicit many assessment criteria, optimization and loss functions, data gathering and generating processes, and so on. Three folders have been created to organize the data. Train, validate, and test are the three terms. There are 10 crop categories and 37 classifications in our crop disease detection system. There were three folders for each class. Train has 1500 data, valid has 500 data, and test folder includes 300 data for each class. For improved efficiency and accuracy, we structure it so that almost all classes hold the same amount of data.

### **3.3.5 Data Storing**

Data storage is the most important phase in a deep learning project since data is the most important aspect. We won't be able to acquire the intended outcome if the data set isn't kept up to date. As a result, we should be more concerned with data storage and the amount of data accessible, so that we can evaluate the data and properly keep it. We keep all of the data on Google Drive in this section since it makes our work simpler. Our may use those online data that is stored in our project because we downloaded all of the data as jpeg files

in Google Drive. We then saved them on Google Drive so that they wouldn't be lost. We may then use those data in our project work by coding them using a simple step or code.

### **3.3.6 Machine Learning Algorithms**

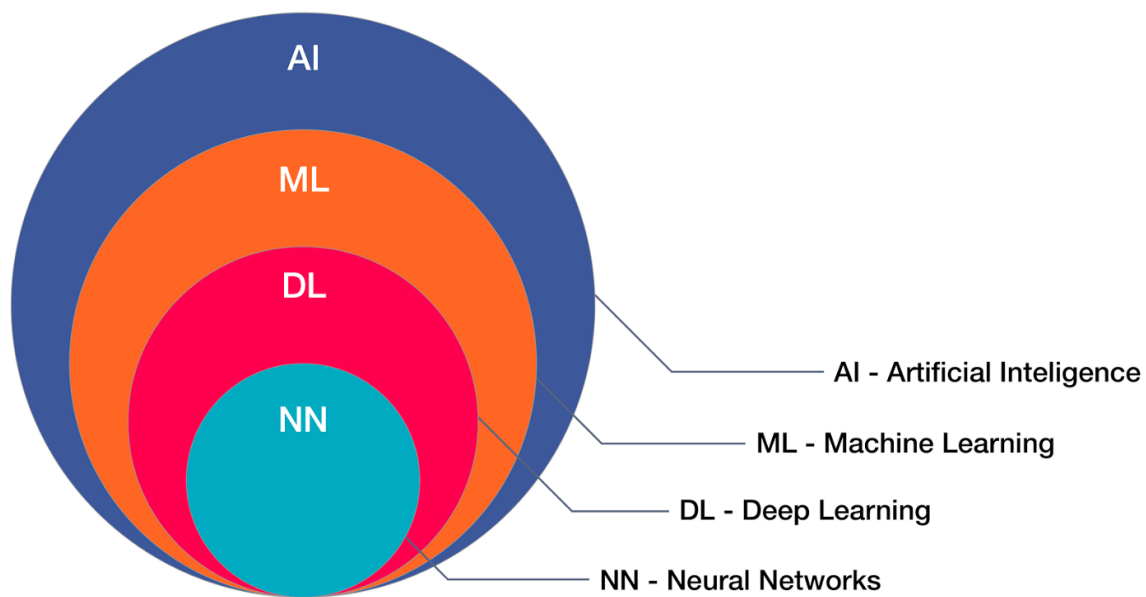
#### **3.3.6.1 Machine Learning**

Computer science has a sub-field named Machine Learning (ML) area of Artificial Intelligence. Machine learning (ML) is a method of giving machines the capacity to learn a task and improve their performance on it automatically. This field is primarily data-driven. ML algorithms are given many sorts of data for various goals. Numerical, text, picture, video, and sequence data are examples of these types of data. Then, using machine learning algorithms, this data are analyzed for patterns and predictions are made on previously unknown data. If the accuracy isn't good enough, the algorithms refine their learning patterns or equations and restart the prediction process. Prediction is only one of ML's capabilities; it also includes classification, grouping, regression, and other functions. ML is diametrically opposed to classical computing. Because the algorithms learn on their own, ML does not require any human intervention. Traditional computing, on the other hand, relies on humans to deliver and manage everything. Machines or computers are given data which in ML computing with data related outputs and as a consequence the computer produces programs or models. Traditional computing, on the other hand, necessitates the input of data and programs expressed as computer codes, as well as the output of associated data. Here, programs are mostly human-authored instructions expressed in the form of code.

#### **3.3.6.2 Deep Learning**

Deep Learning (DL) is a branch of Machine Learning (ML) that studies the deep structures of Artificial Neural Networks (ANNs). Deep learning is a flourishing subject at the moment, with deep learning being used in almost all projects and problem statements. Many of us, including ourselves, would choose a traditional neural network as a deep

learning approach for answering any computer vision problem statement. A convolutional neural network is a sort of deep learning that works by collecting properties from pictures, creating a neural network by assigning weights to them, then convolving them with a filter to categorize and identify them. Any image or video processing data the first choice for dealing which is CNN. The transfer learning model is very simple to use and modify utilizing our layers. Algorithms for machine learning come in a range of forms and sizes. The Convolutional Neural Network (CNN) approach that we used in this situation. Including NumPy, Pandas Tensorflow and other Python libraries and algorithms were utilized.



**Figure 3.6:** Relational of AI, ML, DL and NN.

### 3.4 Implementation Requirements

- **Python 3.8 is the latest version.**

Python 3.8 is a version of Python. It is a programming language with a high level of abstraction. It is used by the majority of researchers to conduct their study. It is a highly recommended programming language for AI-based work, and it is extremely popular among the new generation of programmers due to its ease of learning and comprehension.



- **Visual Studio Code allows Jupyter Notebooks.**

Jupyter (previously IPython Notebook) is an open-source tool that allows us to seamlessly merge Markdown text and executable Python source code in a notebook. Visual Studio Code is a standalone source code editor that works on Windows, macOS, and Linux and enables working with Jupyter Notebooks natively as well as through Python code files. As a result of the little weight, we are able to operate efficiently here.

- **Requirements for Hardware and Software**

- System of Operation (Windows 10)
- Hard Disk Drive (Minimum 8 GB)
- Ram is a character in the film Ram (More than 4 GB)

## **CHAPTER 4**

# EXPERIMENTAL RESULT AND DISCUSSION

## 4.1 Experimental Setup

We gathered the data first in order to use the model and run the code. The following is the system:

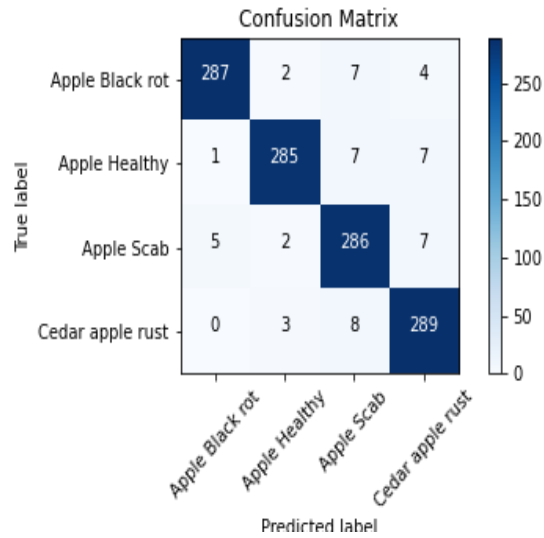
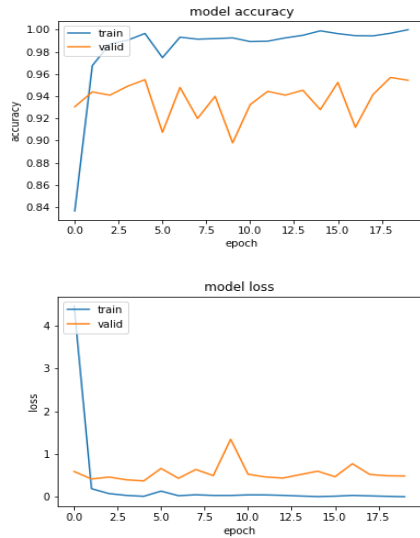
- The system named crop diseases detection as we have worked with so our main data is image type.
- We collected the data from online and some data collect from field in real time.
- Then the data will be stored in google drive so that it would not lost.
- After that we organize the data.
- At that point we have finished and standardized the data so we can start the preparation.
- At that point we have preprocessed our data

## 4.2 Experimental Result and Analysis

In our project crop diseases detection we used the Convolutional Neural Network (CNN) Algorithm. There have we used two model. They are Vgg16 and Mobilenet. So after using these two model the accuracy, model loss and confusion matrix below:

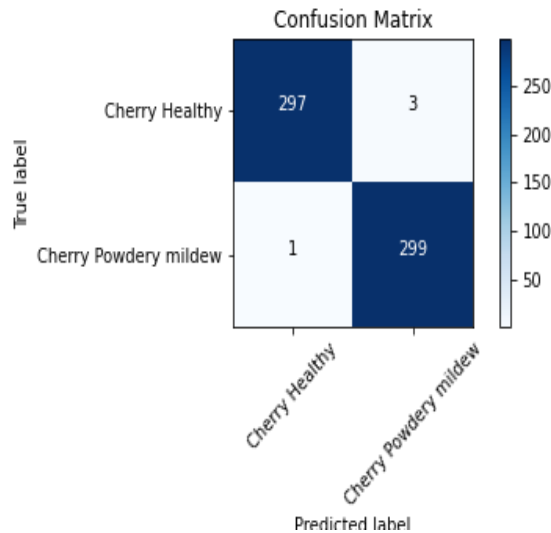
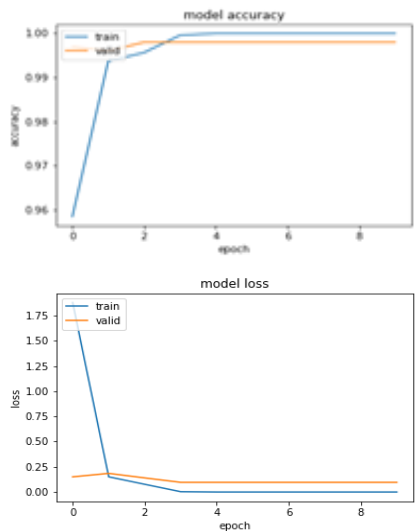
### 4.2.1 Using Vgg16 Model

Here we see that we used here Vgg16 model which have a better performance that is shown. We see that the model accuracy, model loss and confusion matrix below in Figure 4.1.1. After using Vgg16 model in Apple we evaluate in accuracy where followed that in first two epoch the train accuracy gained 97% and the valid accuracy is 94%. After that the epoch of five it is overtrained and fall down. But after 20 epochs then the train accuracy raised in 100% and valid accuracy is 95%. Also in model loss the train and valid lost almost remain on below 1. Our test accuracy of Apple is 95.58%.



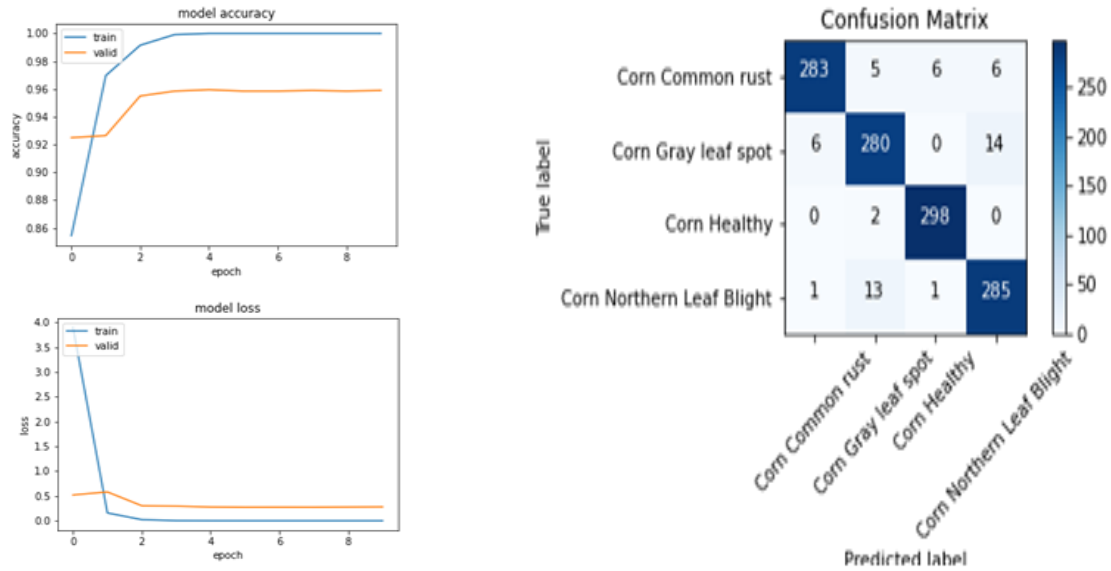
**Figure 4.1.1:** Accuracy, Loss, Confusion Matrix of Vgg16 Model for Apple

In Cherry Figure 4.1.2 we followed that in first two epoch the train accuracy and valid accuracy gained to above 99.40%. But after 10 epochs then the train accuracy raised in 100% and valid accuracy is 99.70%. Also in model loss the train and valid lost almost remain on below 0.25. Our test accuracy of Cherry is 99.33%.



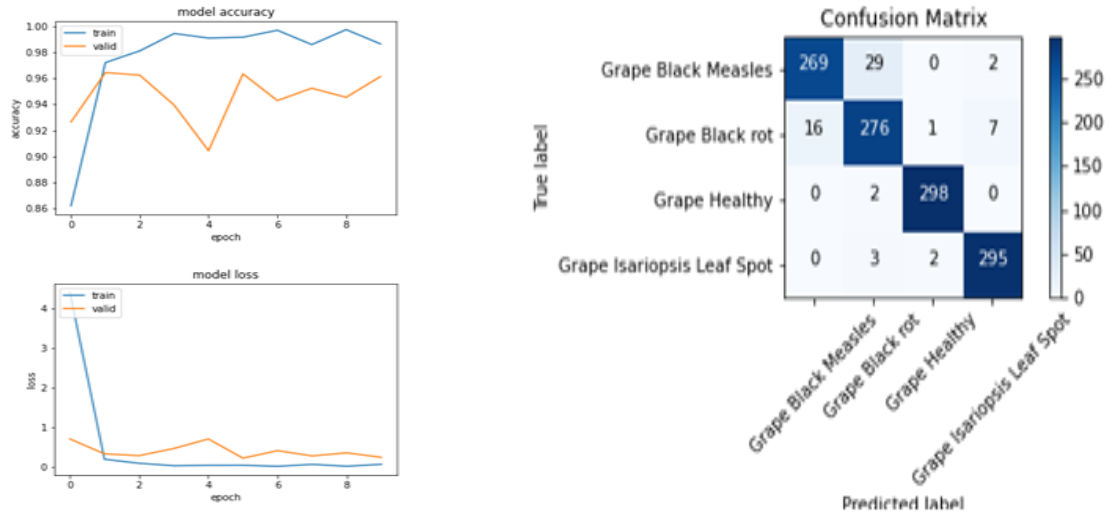
**Figure 4.1.2:** Accuracy, Loss, Confusion Matrix of Vgg16 Model for Cherry

In Figure 4.1.3 we see that in Corn the first two epoch the train accuracy gained 97% and the valid accuracy is 93. But after 10 epochs then the train accuracy raised in 100% and valid accuracy is 96%. Also in model loss the train and valid lost almost remain on below 0.25. Our test accuracy of Corn is 95.50%.



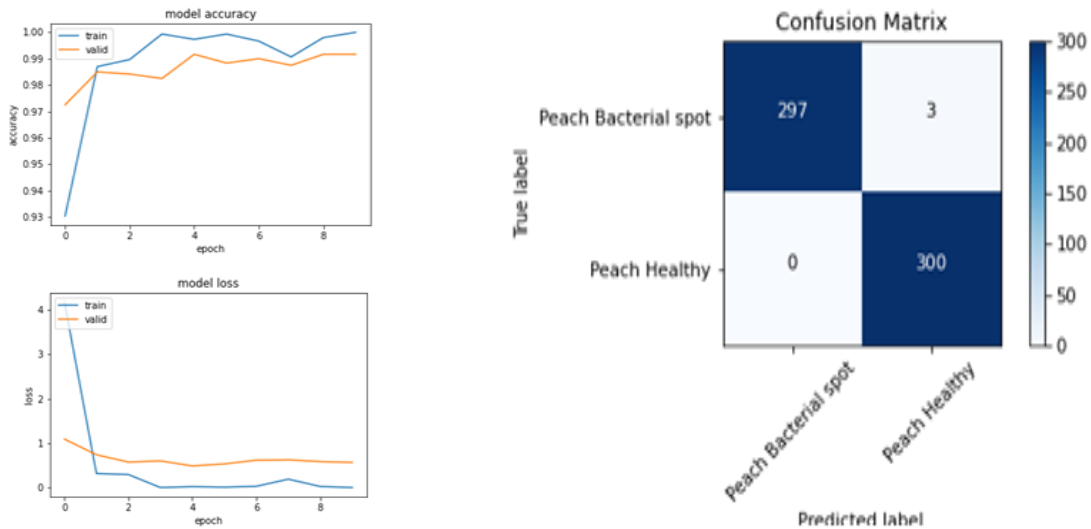
**Figure 4.1.3:** Accuracy, Loss, Confusion Matrix of Vgg16 Model for Corn

In Grape Figure 4.1.4 in first two epoch the train accuracy gained 97% and the valid accuracy is 96%. After that the epoch of four valid accuracy is going down. But after 10 epochs then the train accuracy raised in 98.20% and valid accuracy is 96%. Also in model loss the train and valid lost almost remain on below 1. Our test accuracy of Grape is 94.83%.



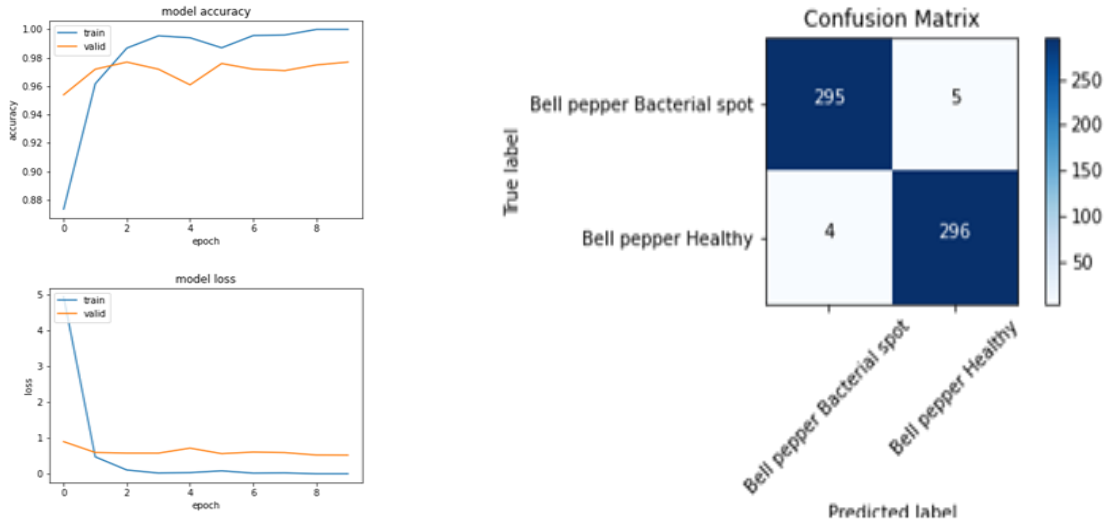
**Figure 4.1.4:** Accuracy, Loss, Confusion Matrix of Vgg16 Model for Grape

We followed that Figure 4.1.5 in Peach first two epoch the train accuracy gained 98.70% and the valid accuracy is 98.50%. But after 10 epochs then the train accuracy raised in 100% and valid accuracy is 99%. Also in model loss the train and valid lost almost remain on below 1. Our test accuracy of Peach is 99.50%.



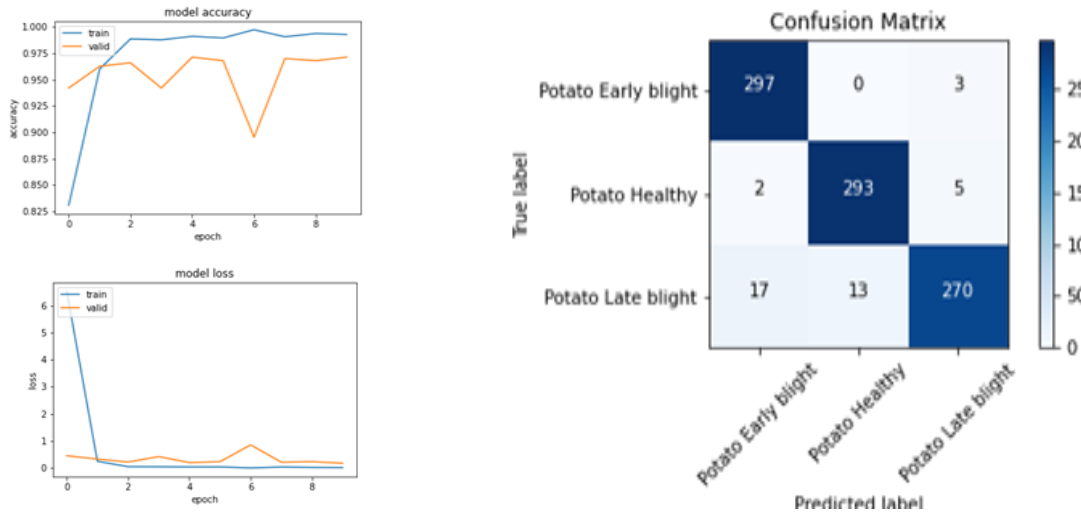
**Figure 4.1.5:** Accuracy, Loss, Confusion Matrix of Vgg16 Model for Peach

Figure 4.1.6 the Pepper first two epoch the train accuracy gained 97% and the valid accuracy is 96%. After that the epoch of four valid accuracy is 96%. But after 10 epochs then the train accuracy raised in 100% and valid accuracy is 97%. Also in model loss the train and valid lost almost remain on below 1. Our test accuracy of Pepper is 98.50%.



**Figure 4.1.6:** Accuracy, Loss, Confusion Matrix of Vgg16 Model for Pepper

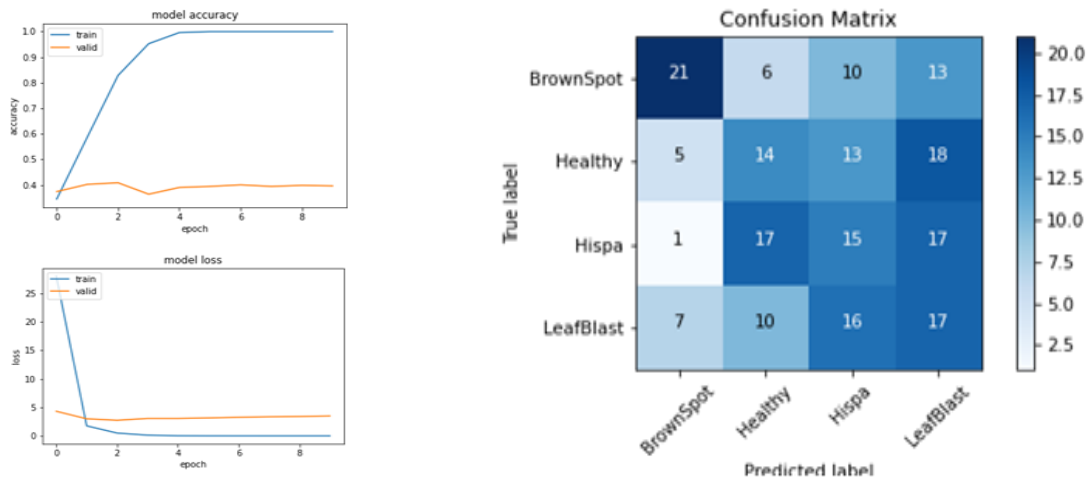
When we take the crop named Potato in Figure 4.1.7 first two epoch the train accuracy gained 98% and the valid accuracy is 96%. After that the epoch of four valid accuracy is going fall down. But after 10 epochs then the train accuracy raised in 98% and valid accuracy is 96%. Also in model loss the train and valid lost almost remain on below 1. Our test accuracy of Potato is 95.56%.



**Figure 4.1.7:** Accuracy, Loss, Confusion Matrix of Vgg16 Model for Potato

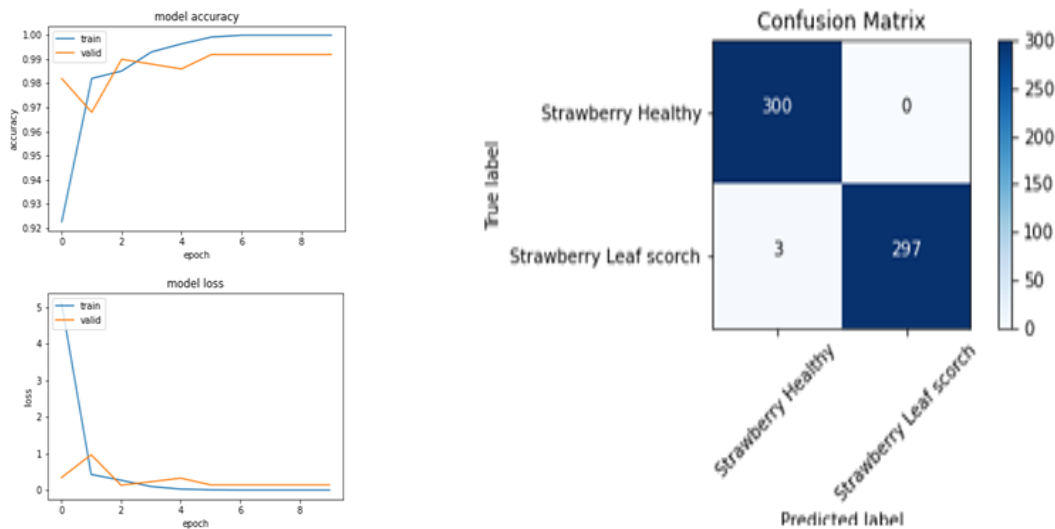
Figure 4.1.8 in Rice first two epoch the train accuracy gained 82% and the valid accuracy is 40%. But after 10 epochs then the train accuracy raised in 100% and valid accuracy is

40%. Also in model loss the train and valid lost almost remain on below 5. Our test accuracy of Rice is 33.50%.



**Figure 4.1.8:** Accuracy, Loss, Confusion Matrix of Vgg16 Model for Rice

Figure 4.1.9 Strawberry first two epoch the train accuracy gained 98% and the valid accuracy is going down to 97%. But after 10 epochs then the train accuracy raised in 100% and valid accuracy is 99%. Also in model loss the train and valid loss almost remain on below 1. Our test accuracy of Strawberry is 99.50%.



**Figure 4.1.9:** Accuracy, Loss, Confusion Matrix of Vgg16 Model for Strawberry

In Tomato Figure 4.1.10 we followed that in first two epochs the train accuracy gained 96% and the valid accuracy is going down to 82%. But after 20 epochs then the train

accuracy raised in 99% and valid accuracy is 84%. Also in model loss the train and valid lost almost remain on below 1. Our test accuracy of Tomato is 83.10%.

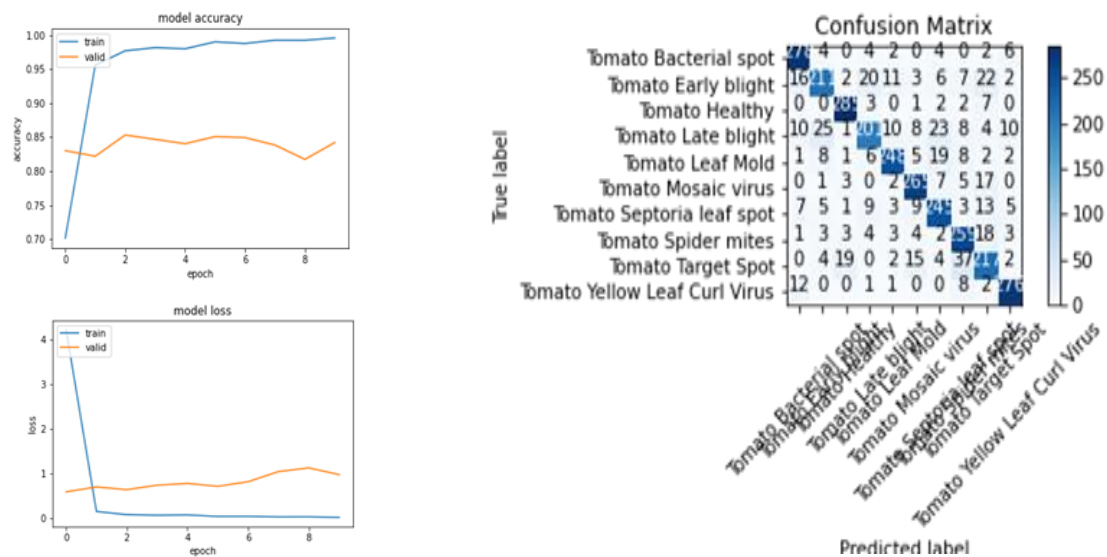


Figure 4.1.10: Accuracy, Loss, Confusion Matrix of Vgg16 Model for Tomato

Table 4.1: Accuracy Table for Vgg16 Model

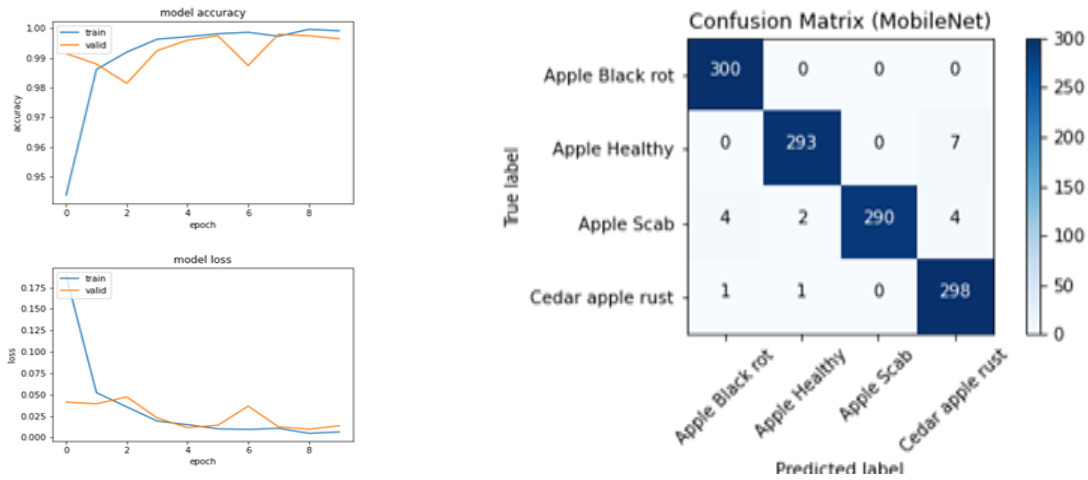
Crop Name	Accuracy(%)
Apple	95.58
Cherry	99.33
Corn	95.50
Grape	94.83
Peach	99.50
Pepper	98.50
Potato	95.56
Rice	33.50
Strawberry	99.50
Tomato	83.10

## 4.2.2 Using Mobilenet

Here we see that we used here Mobilenet model which have a much better performance that is shown. We see that the model accuracy, model loss and confusion matrix below in Figure 4.2.1. After using Mobilenet model in Apple we evaluate in accuracy where followed that in first two

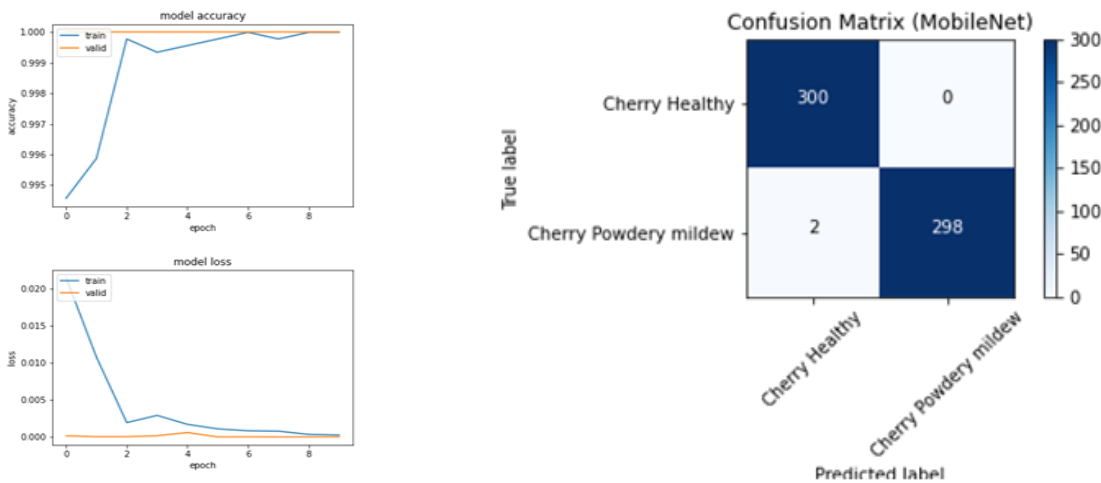


epoch the train accuracy gained 98.50% and the valid accuracy is going down to 98.10%. But after 10 epochs then the train accuracy raised in 99.80% and valid accuracy is 99.50%. Also in model loss the train and valid lost almost remain on below 0.050. Our test accuracy of Apple is 98.42%.



**Figure 4.2.1:** Accuracy, Loss, Confusion Matrix of Mobilenet Model for Apple

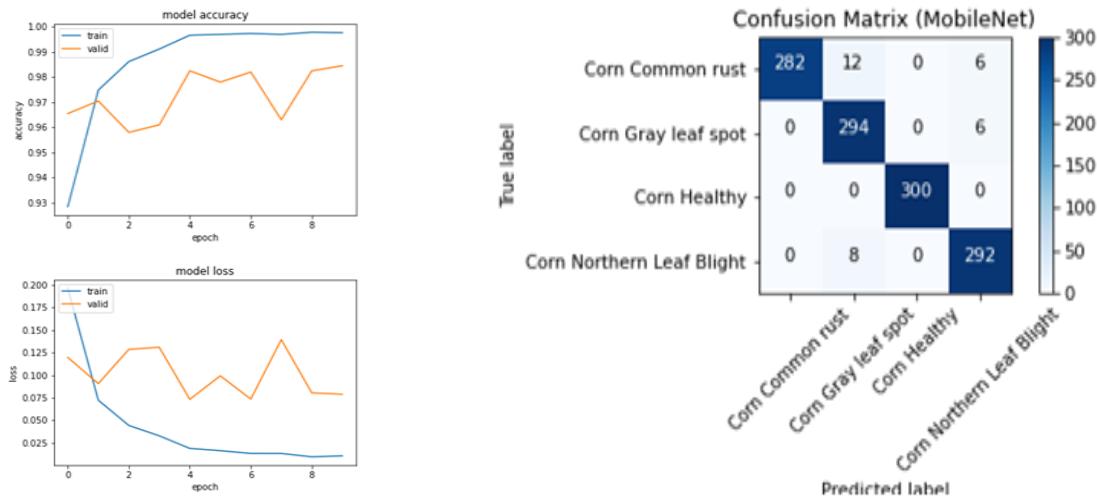
In Cherry Figure 4.2.2 we followed that in first two epoch the train accuracy is 99.58% and valid accuracy gained to 100%. But after 10 epochs then the train accuracy raised in 100% and valid accuracy is 99.98%. Also in model loss the train and valid lost almost remain on below 0.005. Our test accuracy of Cherry is 99.66%.



**Figure 4.2.2:** Accuracy, Loss, Confusion Matrix of Mobilenet Model for Cherry

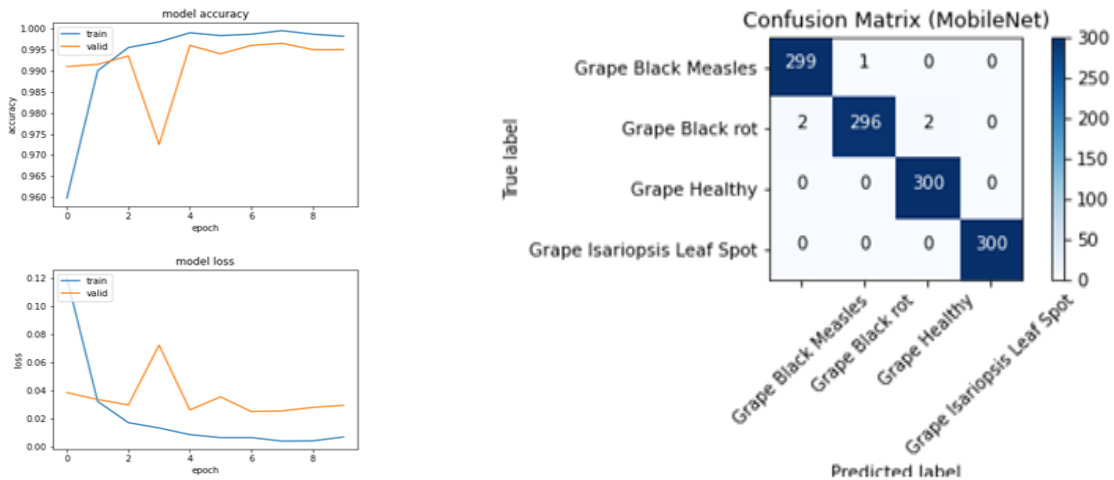
In Figure 4.2.3 we see that in Corn the first two epoch the train accuracy gained 97.50% and the valid accuracy is 97%. But after 10 epochs then the train accuracy raised in 100% and valid

accuracy is 98.10%. Also in model loss the train and valid lost almost remain on below 0.125. Our test accuracy of Corn is 97.33%.



**Figure 4.2.3:** Accuracy, Loss, Confusion Matrix of Mobilenet Model for Corn

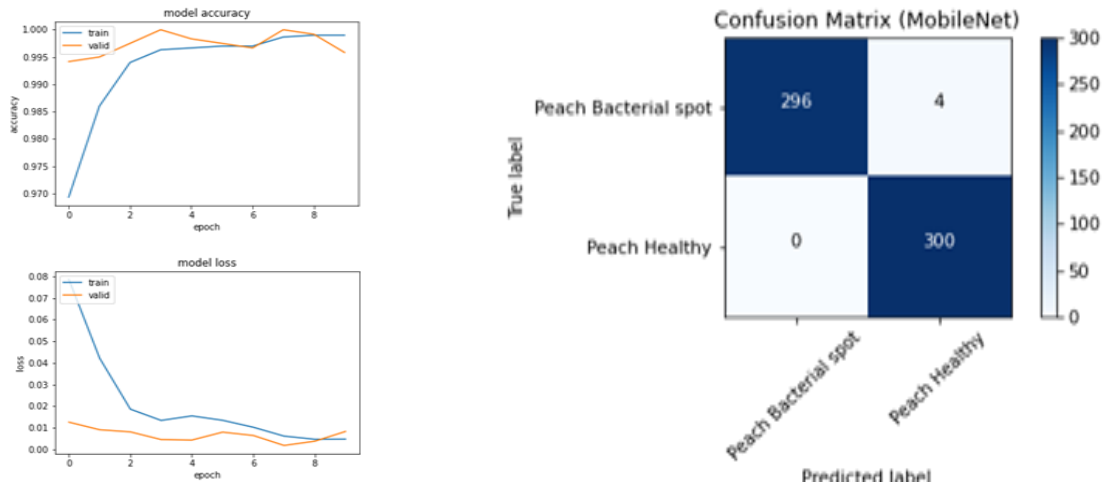
In Grape Figure 4.2.4 in first two epoch the train accuracy gained 99% and the valid accuracy is 99.20%. After that the epoch of three valid accuracy is going down to 97.20%. But after 10 epochs then the train accuracy raised in 99.70% and valid accuracy is 99.40%. Also in model loss the train and valid lost almost remain on below 0.07. Our test accuracy of Grape is 99.58%.



**Figure 4.2.4:** Accuracy, Loss, Confusion Matrix of Mobilenet Model for Grape

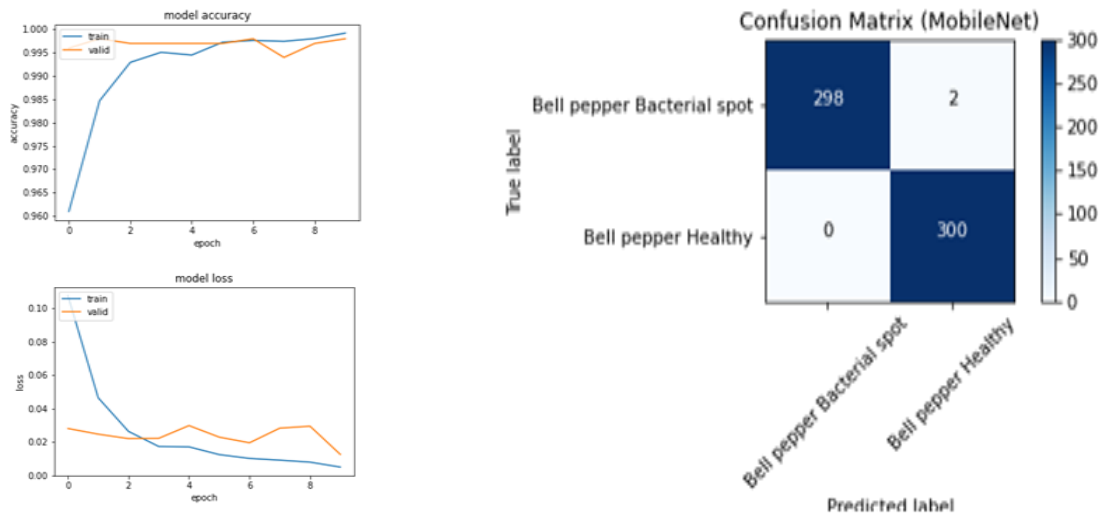
We followed that Figure 4.2.5 in Peach first two epoch the train accuracy gained 98.60% and the valid accuracy is 99.50%. But after 10 epochs then the train accuracy raised in 99.75% and valid

accuracy is 99.40%. Also in model loss the train and valid lost almost remain on below 0.04. Our test accuracy of Peach is 99.33%.



**Figure 4.2.5:** Accuracy, Loss, Confusion Matrix of Mobilenet Model for Peach

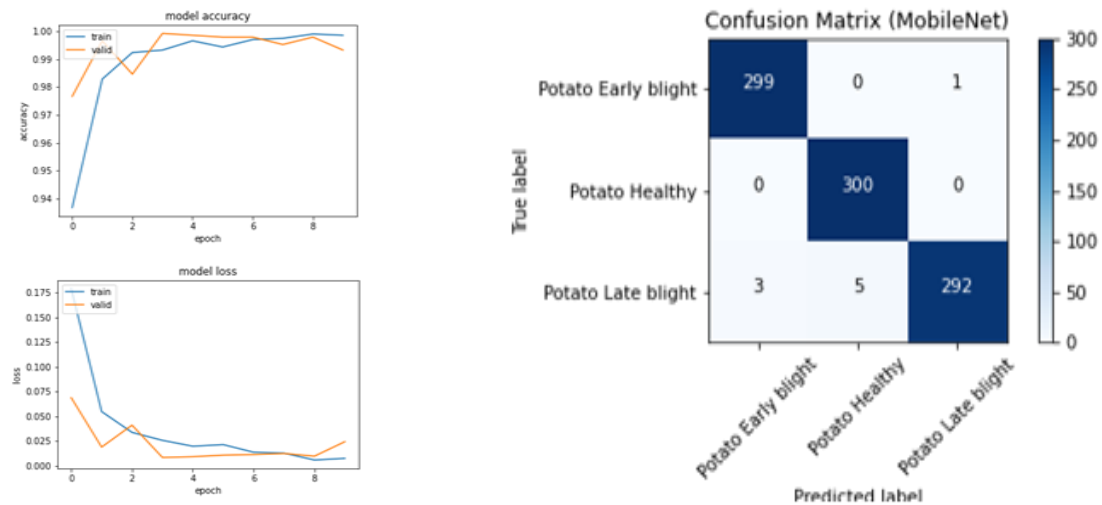
Figure 4.2.6 the Pepper first two epoch the train accuracy gained 98.50% and the valid accuracy is 99.70%. After that the epoch of four valid accuracy is 99.40%. But after 10 epochs then the train accuracy raised in 99.90% and valid accuracy is 99.70%. Also in model loss the train and valid lost almost remain on below 0.05. Our test accuracy of Pepper is 99.66%.



**Figure 4.2.6:** Accuracy, Loss, Confusion Matrix of Mobilenet Model for Pepper

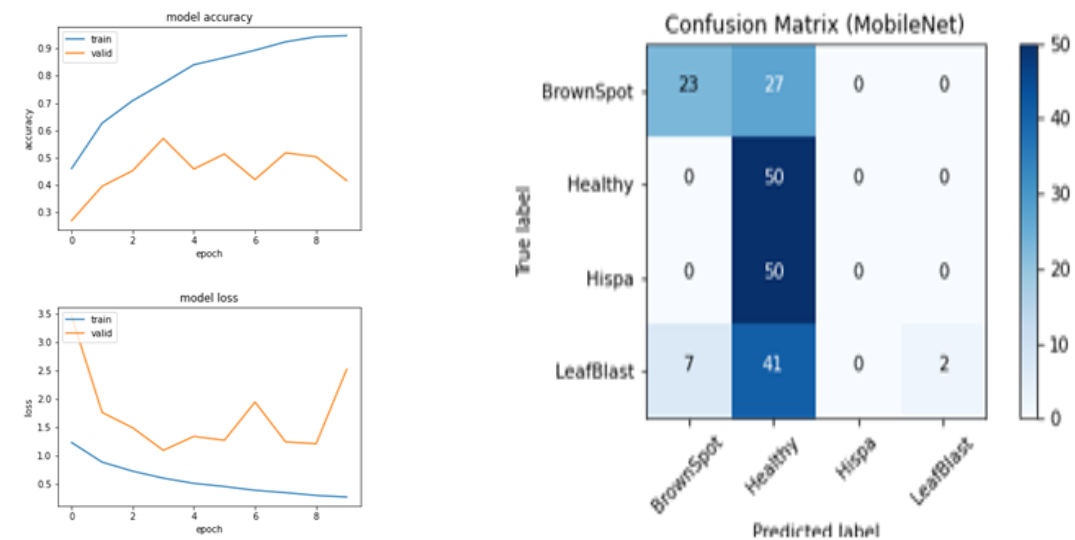
When we take the crop named Potato in Figure 4.2.7 first two epoch the train accuracy gained 98.20% and the valid accuracy is 99.50%. After two epoch valid accuracy is going fall down to

98.40%. But after 10 epochs then the train accuracy raised in 99.90% and valid accuracy is 99%. Also in model loss the train and valid lost almost remain on below 0.060. Our test accuracy of Potato is 99%.



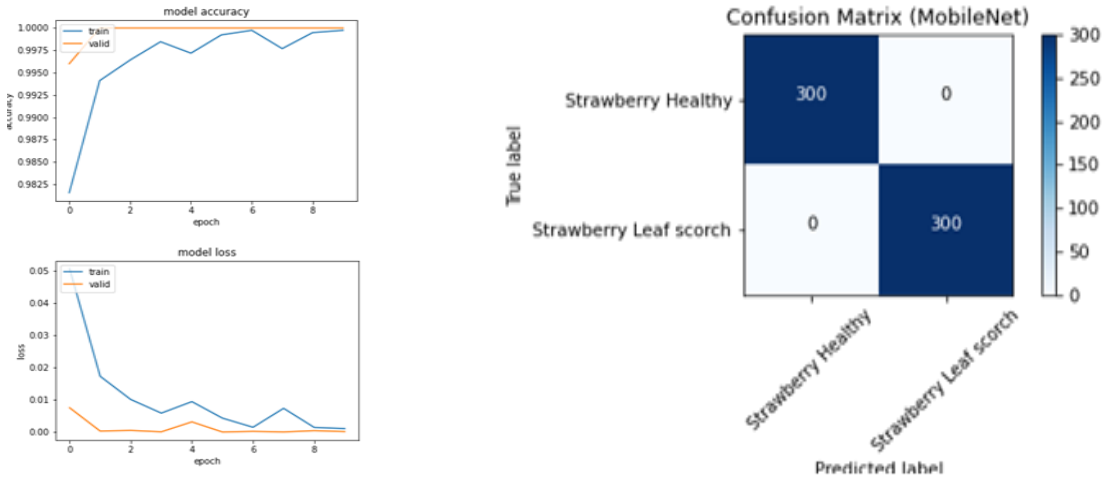
**Figure 4.2.7:** Accuracy, Loss, Confusion Matrix of Mobilenet Model for Potato

Figure 4.2.8 in Rice first two epoch the train accuracy gained 62% and the valid accuracy is 40%. But after 10 epochs then the train accuracy raised in 97% and valid accuracy is 41%. Also in model loss the train and valid lost almost remain on below 2.0. Our test accuracy of Rice is 37.50%.



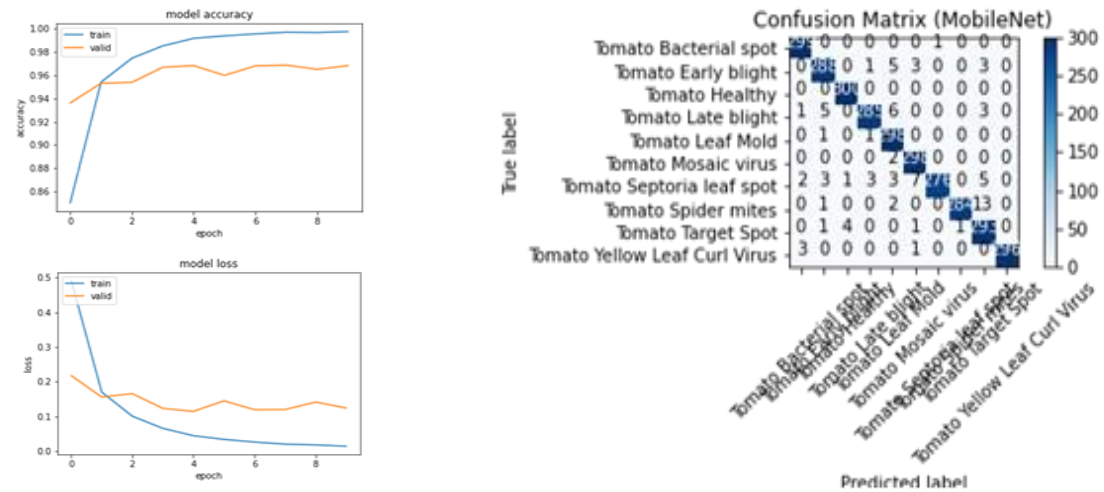
**Figure 4.2.8:** Accuracy, Loss, Confusion Matrix of Mobilenet Model for Rice

Figure 4.2.9 Strawberry first two epoch the train accuracy gained 99.40% and the valid accuracy is 100%. But after 10 epochs then the train accuracy raised in 100% and valid accuracy is 99.98%. Also in model loss the train and valid loss almost remain on below 0.02. Our test accuracy of Strawberry is 100%.



**Figure 4.2.9:** Accuracy, Loss, Confusion Matrix of Mobilenet Model for Strawberry

In Tomato Figure 4.1.10 we followed that in first two epoch the train accuracy gained 97% and the valid accuracy is 95%. But after 10 epochs then the train accuracy raised in 100% and valid accuracy is 96%. Also in model loss the train and valid lost almost remain on below 0.2. Our test accuracy of Tomato is 97.23%.



**Figure 4.2.10:** Accuracy, Loss, Confusion Matrix of Mobilenet Model for Tomato

**Table 4.2:** Accuracy Table for Mobilenet Model

Crop Name	Accuracy(%)
Apple	98.42
Cherry	99.66
Corn	97.33
Grape	99.58
Peach	99.33
Pepper	99.66
Potato	99.00
Rice	37.50
Strawberry	100.00
Tomato	97.23

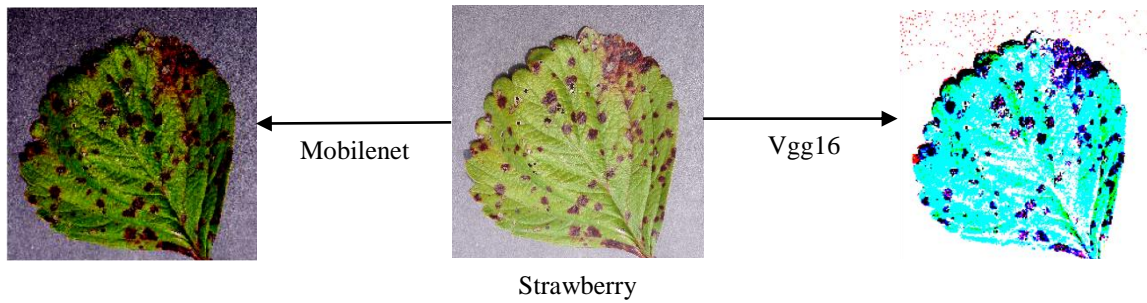
In the above two table we followed that the accuracy difference between Vgg16 model and Mobilenet model. After using Vgg16 model the average accuracy is 95.12% and the accuracy of after using Mobilenet is 98.52%. So we talk about that the Mobilenet model is much better than Vgg16 model.

### 4.3 Vgg16 and Mobilenet

**Vgg16:** Training is really sluggish. It has a large number of network architectural weights, which makes it rather hefty. A widely used Convolutional Neural Network (CNN) Architecture named Vgg16 that was developed for ImageNet, a big visual database project utilized in the development of visual object identification software. VGG stands for Visual Geometry Group, and it is a multiple-layer deep Convolutional Neural Network (CNN) architecture. It's a great learning tool because it's so simple to use. The VGG architecture serves as the foundation for cutting-edge object recognition models. It has a amount of 16 layers.

**Mobilenet:** Training is really quick. It is a low-weight structure. MobileNets are small deep neural networks that are well-suited to mobile and embedded vision applications. MobileNets are built using depthwise separable convolutions and a simplified design.

MobileNet makes use of two basic global hyperparameters to effectively balance accuracy and latency. Object identification, fine-grain categorization, facial recognition, large-scale geo localisation, and other applications might all benefit from MobileNet. It has amount of almost 28 layers.



**Figure 4.3:** Vgg16 and Mobilenet.

#### 4.4 Discussion

Our dataset and mode have been changed. We modified our every image folder like the amount of every classes image we stored there same amount so that we can solve the problem and can get much better accuracy. These two models make it easier to think about as well as obtain the right solution. But the mobilenet gave the good accuracy.

## **CHAPTER 5**

### **SUMMARY, CONCLUSION, RECOMMENDATION, IMPLICATION FOR FUTURE RESEARCH**

#### **5.1 Summary of the Study**

We reasoned that by using a deep convolutional neural network (CNN) we might identify actions. As a result, we propose an unique technique that uses a Convolutional Neural Network and a Deep Learning algorithm to categorize various types of crop illnesses. We suggested a CNN-based model with two convolution layers and two max pooling layers as inputs. The data from the tests is sent into the trained system. The outcome is determined on how well the system has been educated. When the system receives images as input, image processing techniques must be used to process the images. Crop disease diagnosis necessitates the use of real-time photographs of the plants. Finally, we wanted to identify how crop illnesses and healthy plants were detected. Our CNN model recognizes the activity of healthy and disease-affected leafs based on our own generated and modified data set.

#### **5.2 Conclusion**

We suggested detecting crop disease using a CNN system based on Deep Learning Image Processing and other techniques. Farmers can benefit from the proposed method since it provides real-time information regarding crop disease. It also minimizes outbreaks and upsurges that cause massive losses to crops and pastures, putting vulnerable farmers' livelihoods in jeopardy. When compared to standard crop disease detection systems, the disclosed approach has a 98.52% accuracy rate.

#### **5.3 Recommendations**

All above the things we have a discussion that in our modern time we need to use the any system automatically. Because in this time all of our daily do not possible to do manually. We need a system which is automatic. The manual takes a long time process but they do



not have enough time. As a result, we require current technologies such as Artificial Intelligence, Machine Learning, and Deep Learning among others. We employed a deep learning method called Convolutional Neural Network (CNN) in our research, which is highly important in today's world for further progress.

#### **5.4 Implication for Further Study**

To detect a crop disease, this system only looks at the leaf of the plant. Other sections of the crop, such as roots, stems, and branches, would be more handy if they increased detection accuracy over the existing one. In future we will try to use another parts of crop like roots, stem, branches etc. We also try to increase different types crops to detect the diseases of them. Finally, here we have a plan to create an Android or Web application so that people can use and detect the diseases easily

## **APPENDIX RESEARCH REFLECTION**

Several issues arose throughout the project's activity. However, there were three significant issues. One involves choosing the optimal algorithm and model, as well as posing several issues such as if our model provides improved accuracy, and the other is data collecting. Firstly if could not choose a best algorithm, model then we don't have expected a better performance. Then we created a lot of questions that how to solve this real life problem. After that finally to collect data, we faced too much difficulty. Because, in Covid-19 pandemic situation, data collecting is time intensive and challenging for students on a local level. As a result, we'll need to get some information from web sources. And after a long period, many efforts, and a lot of hard work, we succeeded.

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