ROSE PLANT DISEASE DETECTION USING DEEP LEARNING

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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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DHAKA, BANGLADESH

JANUARY 2023

APPROVAL

This Project titled **"Rose Plant Disease Detection using Deep Learning**, submitted by Md. Ali - Al - Alvy, ID :191-15-2490 and Golam Kibria Khan, ID :191-15-2368 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment 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 *04/02/2023*.

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We hereby declare that, this project has been done by us under the supervision of **Mohammad Jahangir Alam, Senior Lecturer, 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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ACKNOWLEDGEMENT

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

We are really grateful and wish our profound indebtedness to **Mohammad Jahangir Alam, Senior Lecturer**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Deep Learning*" 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 **Dr. Touhid Bhuiyan**, Professor & 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

This work is about the detection and identification of rose plant disease. Detection and Identification are part and parcel of modern agro-technology. Here we just used AI technology to detect rose plant disease but disease detection on plants is not easy for sustainable agriculture. Disease detection is challenging because of the infected leaf's availability. To see much enhancement in our work, we must analyze the agriculture field properly. Deep Learning technology is the most helpful tool for building this kind of disease detection model. Disease detection building involves the steps like image pre-processing and model analysis. In this paper, the algorithms used are ResNet50, (Visual Geometry Group) VGG-16, MobileNetV2, and Inception Version 3. There are four disease detections from the rose plant leaves. We researched image processing here with a detected method and achieved a successful accuracy of 96.11% with the MobileNetV2 model.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

The rose is the favorite ornamental plant for indoor gardening, outdoor landscaping, and industrial expansion. Maximum, people like to plant a rose flower for different occasions such as any wedding management time first choose is rose after that choose different types of flowers. The rose flower has been classified as the king of flowers as well as the rose is a delightful property in the world. Rose is the sign of love. Many types of roses are growing in our country. Without Rose, we can't even think about any wedding programs. So the rose is a very essential fascinating component of an important program. A huge Number of people have used rose flowers for various purposes. In this research rose plants were affected by lots of diseases as a result rose flowers don't stay long-lasting. If a rose plant is affected by any disease, slowly fall the flower from the rose plant. Rose plant disease starts from the rose leaf head point. Nowadays the Agriculture Institute and farmers are both growing more rose flowers in our country. Many types of rose disease. In this paper, we used an exceptional process by using transfer learning to create a new detection model. Here We used an algorithm is Convolutional Neural Network (CNN) as well as which has lots of layers of deep Learning. The algorithms CNN based have some models used here, There are Resnet50, MobileNet Version2, Inception Version3, Visual Geometry Group (VGG-16), and VGG-19. The model Accuracy is 95.76%, 99.15%, 98.30%, 98.30%, and 97.45%. In this paper, the average result is 96.11%. According to the successful result, we got 99.15% from MobileNet version 2.

1.2 Motivation

Flowers are a unique symbol of beauty in today's world. Flowers are loved by almost everyone, from any occasion to various functions, the use of flowers is desirable. Similarly in one of our university programs one day we went to the rose village to fetch flowers.. while picking flowers when we entered the garden one thing we noticed that some people in the garden were giving different medicines to flower leaves, then after asking them who told us who they are. Flowers have different diseases on their leaves, so they always have to take care of the issues and spray them to cure them.

That's when we think it's really actionable because if we can show in our research how to scan people to know what kind of disease a leaf has, we're working on 4 types of leaf disease diagnosis and using that for gardeners. By doing this they can also detect foliar diseases and maintain them accordingly.

1.3 Rationale of the Study

Our main reason for this study was that we wanted to do research on something that would help other people in real life. What we originally wanted was to project that someone else would be able to detect a leaf disease by scanning a photo of the leaves of a rose plant in their garden.

1.4 Research Questions

1. **Why we used Deep Learning on this project?**

We have to analyze the data that we have collected from the rose leaves. Also, Deep Learning allows us to identify & extra features from images. So in this way, we can analyze lots of pictures from the features to look for in images. And also it can create complex statistical models from unstructured data. So it definitely helps us to identify & analyzing the whole research phase.

2. **Why do we use mobilenetv2 in image detection?**

Basically, Mobilenetv2 is a pre-trained model for image classification with significantly fewer parameters and smaller computational complexity. In this version of the network inference time is faster than is trained using a large images dataset.

1.5 Expected Output

From the beginning our expected output was only one our expected output was to be able to diagnose rose flower leaf disease. In this case, we worked on 3 types of diagnosis such as Esca (Black Measles), Leaf blight, and Black Rot.

1.6 Report Layout

In this report, six individual chapters are discussed to make this research report more compact and efficient for any readers or researchers.

Chapter 1 gives an important introduction to this research work. This is related to Depression Detection and its details briefly. This chapter, shows the research motivation, rationale of this study, relevant research questions, expected outcome, and total management information along with financial aspects.

Chapter 2 gives a detailed report about the background of this study. Such as machine learning systems, classification information, and related work based on this research study. Comparative analysis, the scope of this problem statement is also described in this chapter with perceived challenges.

Chapter 3 gives descriptive information about the methodology. Structural information regarding this research work is given in this chapter.

Chapter 4 gives the complete result analysis for the result of each step. All of the results shown in this chapter were found in the experiments.

Chapter 5 describes this research's impact on society, the environment, and sustainability.

Chapter 6 shows the future scope of this research work where it is briefly described as the extension of this research study. This chapter concludes the entire research report with a useful conclusion where the core findings of this research are briefly discussed.

CHAPTER 2
BACKGROUND STUDY

2.1 Preliminaries/Terminologies

Rose is the king flower into the whole flower. Roses are one of the most common and favorite flowers in Bangladesh. One of the most general causes of crop failure is very poor disease control in our country. Many types of rose plant disease are affected in our country. In this paper, we are researching rose plant disease detection by using algorithms as well as we got the final output from this testing. We have to gain knowledge about flowers that can be kept neat and disease free from disease. As a result, flowers without we can't get a fascinating moment.

2.2 Related Works

According to the study, using Image Feature extraction is an essential successful key to a Content-Based Image Retrieval System (CBIR). The Image can extract low-level features from color. This paper described the method for the texture feature of diseased leaves and the extraction colors of the maze. Here they are working to detect the color of the leaf as well as detecting leaf spots from the image. They ensured here the Texture Feature, Image Feature, and Color features by PATIL J.K AND RAJ KUMAR et al (2012) [1]

Piyush Chaudhary, Anand Chaudhari, Dr.A.N Cheeran and Sharda Godara et al (2012) [2] show beyond doubt in their research paper that image detection by the algorithms. Here they used some algorithms for detecting leaf disease spot segmentation as well as image processing techniques and automatic detection with the classification of plant leaf diseases. In this research, they did a comparison of the effect of CIELAB, HSI, and YCbCr color space. The Algorithms Detected different colors from the leaf.

Erika Fujita, Yusuke Kawasaki, Hiroyuki Uga, Satoshi Kagiwada, and Hitoshi Iyatomi et al (2016) [3] Demonstrate in their paper they were researched by Convolutional Neural Networks (CNN) principal component of Deep Learning they have gathered datasets from the village. They gathered many types of the leaf then they completed the leaf testing. They worked here on image processing and detecting leaf disease. When Sharada et al trained the data with CNN that time they got a classified accuracy of 99.35% but they got accuracy from this research average accuracy of 82.3% with CNN.

Simranjeet Kaur, Geetanjali Babbar, Navneet Sandhu, and Dr. Gagan Jindal et al (2019) [4] proved here varieties of plant leaf disease detection and visualization into deep learning algorithms. Here the detection processing incorporates the phases such as image acquisition, feature extraction segmentation, and image pre-processing, from the algorithm segments after that classification depending on the result. In this paper, they discussed the elementary methods that are being used for plant leaf diseases for detection into image processing by plant leaf data. Here used algorithms are Support Vector Machine (SVM) classification, RELIEF-F, and K-Mean Clustering.

Varsha Sawarkar, Seema Kawathekar, et al (2018) [5] show beyond doubt in this research paper that they discussed the rose plant diseases leaf detected from the disease rose leaf-spot of the rose plant. They gathered data from agricultural rose gardens. After that, Here used image acquisition, image pre-processing, image segmentation, and feature extraction with classification as well as used algorithms Support Vector Machine (SVM), Fuzzy Classifier, Color Analysis, and KNN for finding diseases spot and detecting leaf diseases. Lastly, the spots of the plant and evaluated detected accuracy higher than 90%.

Ms. Kiran R. Gavhale, Prof. Ujwalla Gawande, et al (2014) [6] show doubt in their research paper as well as said that nowadays plant leaf diseases have received increasing attention in appearing and detecting diseases in a large field of crops. Here they used and followed some steps. There is RGB image acquisition, Converting the input image into the color space, segmenting the components, obtaining the useful segments, computing the texture features, and configuring the neural network for recognition. As well as used some algorithms such as K- nearest neighbor, Radial basis function, Artificial neural networks, and support vector machine. Here worked on image preprocessing and detecting leaf spots or leaf diseases.

Sharada p.Mohanty, David p. Hughes, and Marcel Salathe et al (2016) [7] show beyond doubt in their research paper Firstly here said that disease is a major threat to food security. After that, they gathered 38 types of leaves from a variety of plants. Then tested the real data and data-trained testing distribution five divided as the first train was from 20% to 40% than from 40% to 50% after that from 50% to 60% and from 60% to 80 %

data testing by GoogleNet and AlexNet. Again worked 38 types of data testing into the algorithms and output 38 types of leaves for the detection of plants.

Xiaoyue xie, Yuan Ma, Bin Liu, Jinrong He, Shuqin Li, and Hongyan Wang et al (2020) [8] show doubt in their research paper tested grape leaf diseases and detection diseases of a grape leaf. Many types of diseases are mentioned here as well as thought solutions for these diseases. Here classification of data accuracy is 91% and combined with the classification accuracy is 70%. Here used algorithms are Mobile net, ImageNet, and Retina Net and presented a new architecture named INAR-SSD based on VGGNet(Visual Geometry Group) Inception Construction another positive way was 13% greater than the best result on Faster R-CNN for detected grape leaf detection for finding the disease spot.

Amanda Ramcharan, Kelsee Baranowski, Peter McCloskey, Babuali Ahmed James Legg, and David p.Hughes et al (2017) [9] prove that cassava detection needs to be improved from diseases of cassava plant leaves. They took different types of leaves for testing by using some algorithms. They detected diseases of cassava plant variety types by using models. Convolution Neural Network (CNN), Support Vector Machine (SVM). Inception V3 currently Detected 78%. The Support Vectors Machine (SVM) model has the highest predictable accuracy for four out of six diseases. Here, using detection in image processing.

Peng Wang, Tong Niu, Yanru Nao, Zhang, Bin Liu, and Dongjian He et al (2021) [10] show doubt in their research paper that they worked for apple leaf disease detection. There are many types of diseases and as well as many types of disease detection in image processing. In this paper, the models are Artificial Neural Networks (ANN), and K-Nearest neighbors(KNN) used for classification. Here used algorithms are CA-Net, ResNet-101, DenseNet-152, and ResNet-152. These algorithms are used for detecting the disease's image spot and how it can improve the disease as well as declare the detected algorithm's accuracy. The Accuracy is 98.92%.

Sangyeon Lee, Amaepreet Singh Arora, and Choa Mun Yun et al (2022) [11] proved that infection of strawberry diseases with a stage ensemble. Many methods are used here to catch signs of diseases from plant images for detecting early. Strawberry leaf disease detection as well as Strawberry disease by using ResNet -50, (VGG) which means Visual

Geometry Group, and Mobile Net. In this Paper the Batter accuracy got 79.3% from using ResNet-50. In this Paper Image processing time, the algorithms detect the whole leaf as well as check one by one leaf and detect the diseases of the strawberry leaf of this plant.

Muhammad Shoaib , Babar Shah , Tariq Hussain , Akhtar Ali 4, Asad Ullah , Fayadh Alenezi , Tsanko Gechev, Farman Ali, and Ikram Syed et al (2022) [12] show doubt in their research paper that Firstly they are mentioned plants are the main source of food in the Earth. After that, the whole process is described as well as the model used and method used. Here applying the CNN model they proposed a context-aware 3D Convolution Neural Network(CNN). Here used algorithms are AlexNet, GoogleNet, VGG, and ResNet-50 and all Convolution Neural Network(CNN) models achieved greater than 97% accuracy. Secondly, this paper has included an image processing system and leaf disease detection testing model.

Huiru Zhou, Jie Deng, Dingzhou Cai, Xuan Lv, and Bo Ming Wu et al (2022) [13] demonstrate applied Deep learning algorithms, especially CNN for detecting disease diagnosis from plant leaves. In this paper, they have used here image processing classification of these images. The models used here are VGG-16 and Inception V3,

ResNet-50, MobileNet V2, and NasNetMobile. The achieved Validation accuracy is higher than 99% but The ResNet-50 gives the highest average validation accuracy is 98.51%. ResNet -50 excellent performance got from data training. Here mainly that worked paddy leaf spot detected with deep learning model. Disease detected in image processing.

Riyao Chen, Haixia Qi, Yu Liang, and Mingchao Yang et al (2022) [14] show doubt in their research paper that the Identification and diagnosis of plant disease in image processing got successful output accuracy using deep learning models. They gathered data from plant villages. The dataset has 54634 data. It had potato leaf, corn leaf, apple leaf, pepper leaf, orange leaf, etc. Here they used some algorithms model VGG-16, ResNet-50, ResNet-18, and DenseNet-121. The Disease Achieved Recognition accuracy came from VGG-16. The accuracy is 97.5% and the ResNet-50 accuracy is 95.5%. Here compare some models.

Pei Wang, Yin Tang, Fan Luo, Lihong Wang, Chengsong Li, Qi Niu, and Hui Li et al (2022) [15] Demonstrate in their paper weed identification by using deep learning as well as a comparison between algorithms models. In this paper, the most common detection models are YOLOv3 and YOLOv5 therefore Faster R-CNN. Algorithms accuracy is 91.8%, 92.4%, and 92.15% respectively. Here is just the identification of various types of weed plant detection using Deep learning.

Mingle Xu, Sook Yoon, Alvaro Fuentes, Jucheng Yang, and Dong sung park et al (2022) [16] research applied Deep Learning using algorithms and detection of disease spots from the plant leaf. They collected 1258 images from tomato leaves. After that this data increases by using segmentation annotation single image. Except for AP50 in YOLO-v3 and Faster R-CNN.This paper again mentioned the identification of many types of leaves of the tomato plant as well as the detection

of tomato leaf disease from a tomato plant. It has another part where they discussed disease solutions.

Yearning Hyeon Gu, Helin Yin, Dong Jin, Jong-Han park, and Seong Joon yoo et al (2021) [17] proved here the Diagnosis image of pepper and the detection of disease of the plant. They used a method for diagnosing plant damage and mentioning the disease point by using deep learning algorithms. Here used a model for data training VGG, ResNet-50 ImageNet as well as used for pre-training VGG-16, VGG19, and ResNet-50. In this paper, the algorithms can successfully detect the disease of the plant. The Disease accuracy is 96.2%, the Pest accuracy is 99.71%, and The average accuracy is 97.87%.

Chunshan Wang, Ji Zhou, Yan Zhang, Huarui Wu, Chunjiang Zhao Guifa Teng and Jiuxi Li et al (2022) [18] proved that they applied deep learning algorithms. In this paper, they detected diseases of cucumber and tomato leaves. Here for testing of data, the used models are DenseNet169, Resnet-18, AlexNet, MobileNet, and VGG-19. Moreover, the better performance achieved by DenseNet169 than Among Model. The accuracy achieved performance is 95.5%, 94.14%, 93.77%, 91.03%, and 89.74%. Lastly, average results or accuracy was 97.62%, 92.81%, 98.54%, and 93.57% got from Precision, sensitivity, Specificity, and respectively. The Best and average accuracy is 95.05% got from DenseNet169.

Yingshu Peng and Yi Wang et al (2022) [19] appear to prove in their paper that a new image using a retrieval system for automated detection, localization, and identification of single-leaf disease in this system provides a successful result. In this paper used models are MobileNet V3-Large, ResNet-101, ResNet-152, ResNet-50, EfficientNet-B0, Vit-Base-pach16, and Diet-Based-patch1-16. ResNet-152 provided better performance than among models. The best accuracy is 98.53%.

Itiar Egusquiza, Artzai Picon, unai Irusta, Aranta Bereciartua-Perez, Till Eggers, Christian Kiukas, Elisabete Aramendi and Ramon Navarra-Mestre et al (2022) [20] appear to provide in their paper applied deep learning using to models for detected and identification of disease leaf of the plant. Here used model is ResNet-50 for detecting disease spots from plant leaves as well as mentioned the prediction by CNN algorithms. They said their research paper analyzed wheat leaf. The Model detected the disease leaf of wheat. They gathered data from the plant village after prepossessing the data and got a successful result. wheat plant disease detection using ResNet-50.

2.3 Comparative Analysis and Summary

Rose plant disease is a common problem. Many types of rose plant diseases such as black spot, Esca black spot, Botrytis Blight, cankers, and crown Gall also. Unfortunately, many roses are susceptible to a number of diseases. Most of the rose disease can effectively be minimized through the combined use of culture casual and resistance. Many types of algorithms are used there and maximum people use CNN algorithms for getting and perfecting testing. This disease uses an integrated approach.

2.4 Scope of the Problem

Rose is a very delightful flower. The number of rose lovers increases day by day. Providing that rose is the most famous flower but we are not taking care of it properly. In this way, if rose plants continue to be careless then we will not see rose flowers in the future. That will be a very terrible moment. Some people researched rose plants and they gave an accuracy was 80% to 90% rose plant disease detection successful from the data testing. But in our research time, we got an accuracy of 96.11%. it is more than increasing. We got better results than them.

2.5 Challenges

From the beginning of the research we faced several challenges. Here the main challenge is getting the data, we need to collect proper high-quality images to build the models. And for the model building high configuration pc is needed. Also, when we went to the rose garden to collect data, the garden owner did not want to allow us to enter the garden, then we explained to them with great difficulty that we do not have permission to take pictures. Then again after taking pictures, the background of all these pictures has to be removed when it is convenient to do recognition and train data. Then we have to work on a very well-configured system for image processing.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Methodology

In this portion of the report, we will discuss the methodology used in our study as well as the procedures we took to conduct this research. First, we traveled to a rose village to gather real-time information on rose leaf disease. This specific dataset has four distinct classes, which are 'Esca (Black Measles)', 'Healthy', 'Leaf blight (Isariopsis Leaf Spot)', and 'Black rot'. Following the establishment of particular data preparation processes, the data was separated into test and train sets. We employed CNN-based architectures such as Inception V3, MobileNetV2, ResNet50, VGG16, and VGG19 to train our datasets.

3.2 Research Subject and Instrumentation

Here we are going to do building detection that is able to detect the disease of rose plants. Python, a computer programming language, and the Windows operating system were both used in the successful completion of our mission. In addition, a variety of packages, including Keras, Tensorflow, NumPy, and others, are employed in this process. All of the programming assignments were successfully completed with the help of Google Colaboratory, an online platform that runs in the cloud. In order to construct the categorization model, we used a Tesla T4 GPU.

3.3 Data Collection Procedure/Dataset Utilized

We have put together a picture album that demonstrates four distinguishing qualities that are associated with the rose-leaf disease. The vast bulk of the pictures was taken in the rose field. This collection has a total of 1443 photographic images in its entirety. Pictures numbered 339 for 'Esca (Black Measles),' 290 for 'Healthy,' 383 for 'Leaf Blight,' and 427 for 'Black Rot.' Seventy-five percent of the pictures from each category were utilized for the training process, fifteen percent of the photographs were used for the validation process, and ten percent of the photos were used for the testing process.

An instance of the sample data set of rose leaves is shown in the following picture:

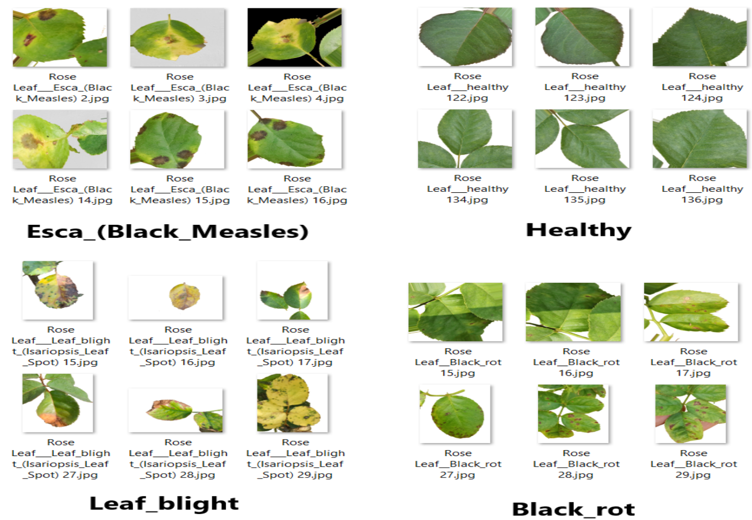

Figure (3.1) Sample Dataset of Rose Leaves

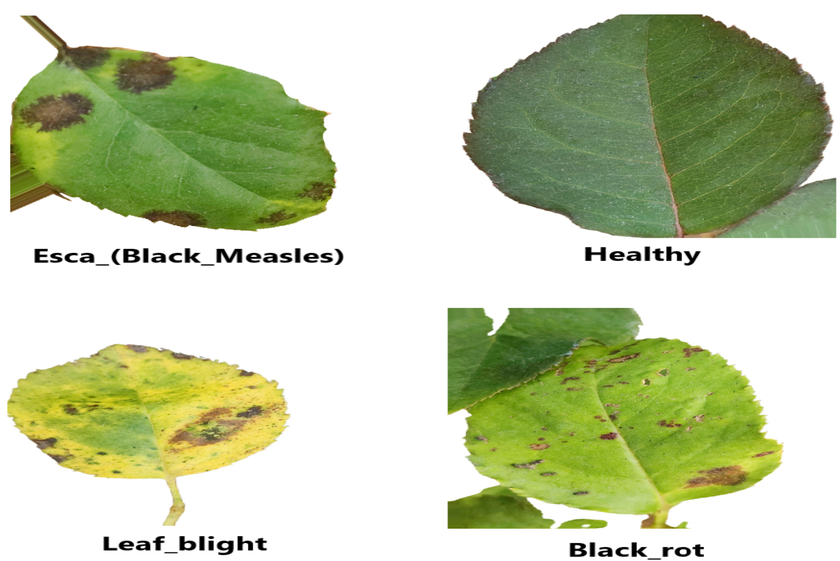

Figure: (3.2) Diseases Classes

3.4 Proposed Methodology/Applied Mechanism

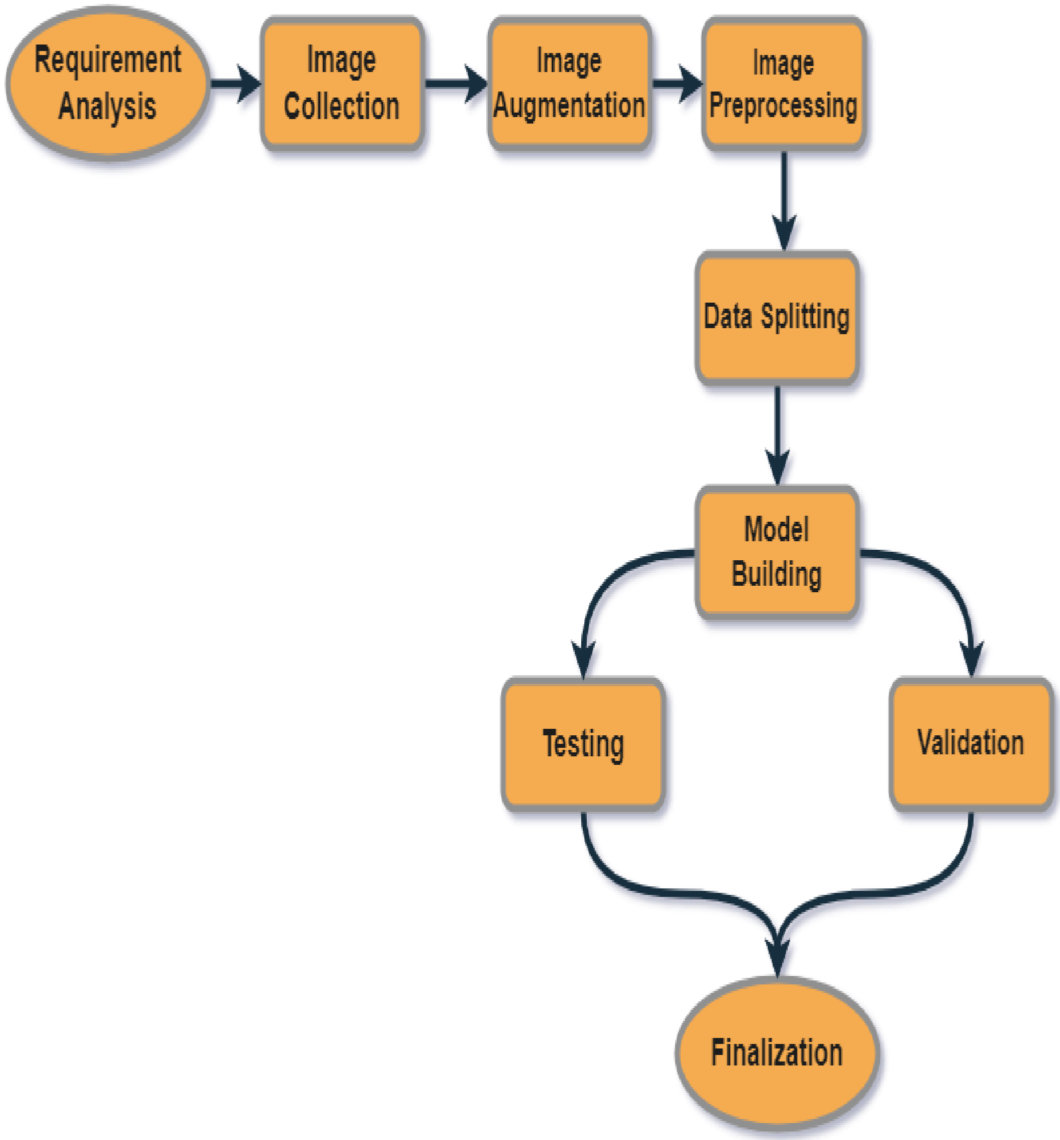

Figure (3.3) Proposed methodology

3.5 Data Augmentation

The images we get are not enough to make a good model. So we have done image augmentation; we have rotated, reduced, and enlarged our pictures. And the calculations of the images are presented in table (3.1).

Table (3.1) Dataset augmentation amount

Class	Real Image Amount	Augmented Amount
'Esca_(Black_Measles)'	92	247
'Healthy'	47	243
'Leaf_Blight'	117	266
'Black_Rot'	148	279

3.6 Data Preprocessing

Because the picture data resolutions in our collection are all different, we were forced to limit the size of the input photos to 224 by 224 pixels and make use of the 'Exception' preprocess input in order to generate the batches. After that, the images were processed using CNN structures that were developed mainly for this activity and made use of the RGB color space. Because of the part that this hue plays in the process of identifying characteristics, the accuracy of CNN may be improved by using it.

Figure: (3.4) Preprocessed images

3.7 Internal layers of the architecture

3.7.1 Pooling Layer

The impact of the pooling layer is one that reduces the overall amount of space that is shown in the image. It is placed in between two convolution layers, and maximum pooling is the only way that can be used to decrease the amount of space that is used up by the input picture. It is positioned in between the two convolution layers. It is conceivable to implement it in the center of two convolution layers, which is one of the available locations. It is common knowledge that the pooling layer does not have any parameters; however, it does have two hyperparameters that go by the titles filter and stride. These two hyperparameters may be found in the pooling layer.

3.7.2 Layer of Connected Components

The components that comprise the entirely connected layer are referred to as weight, bias, and neurons, respectively. Neurons on one layer and neuronal connections on another layer are connected to this layer via this layer. This layer is located between the two layers. On the other hand, it may be used in the process of taking training images in a broad variety of various ways, making it a more versatile tool.

3.7.3 SoftMax Layer

The last layer of the CNN algorithm is called either the Softmax layer or the logistic layer, depending on which name you choose. Binary logistic categorization and Softmax multi-classification are also applied in this investigation as additional methods of classification.

3.7.4 The Output Layer's Structure

The target 4 labels that were a part of the dataset that we were working with have been included in the output level.

3.8 Model Training

In the case of our own dataset, we made use of an architecture based on CNN. Imagenet was used to determine the weights to assign to each model. In addition, bogus information was added to pre-trained layers before training began. The following list contains the models that we have previously owned:

1)ResNet50

2) VGG 16

3)VGG 19

4) MobileNetV2

5) Inception Version 3

3.8.1 ResNet 50

The development of ResNet resulted in what is known as a Residual Network, which is a specific kind of neural network that was initially suggested by Microsoft in 2015. The ResNet50 network is shown here as an example of a possible element that may be included in the design of the ResNet network. The method that ResNet uses to combat the issue of degradation is called "residual mapping," and the company got its name from the phrase "residual mapping." It is made up of fifty layers and contains something in the neighborhood of twenty-three million trainable parameters. Instead of using layers that are eventually linked, as in the conventional approach to building a CNN, this one implements a technique called global average pooling, which is a more modern approach. Even though it is far more extensive than the other models employed in this inquiry, its weight is noticeably lower than that of the other designs.

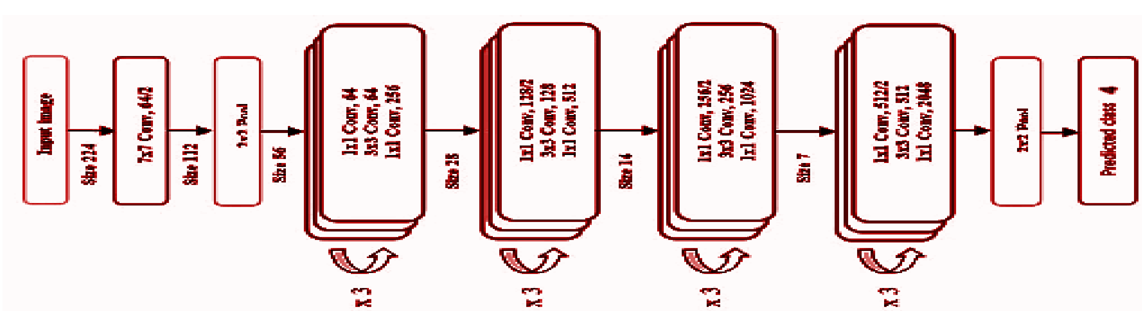

Figure (3.5) Architecture of ResNet50

3.8.2 VGG16

VGG16 is considered to be a part of the Visual Geometry Group (VGG) network as one of its nodes. A total of 17 layers make up the VGG16 network: 16 convolutional layers, 3 layers that are entirely linked, and 5 max-pooling layers. It finished in second place overall in the tournament that was hosted by the ILSVRC. More than 138 million different configurations may be made for each parameter with this tool. By making use of the dumping and ReLU activation functions, it is possible to cut down on the amount of generalization error that takes place over the whole of the fully connected layers. In addition to this, the output of the model makes use of the softmax function in a number of different contexts. Because it avoids the need for kernels or filters of a large size, this strategy makes use of a large number of 3*3 filters rather than those of a larger size. In addition to this, the diminutive size of these kernels makes it possible to do complex feature extraction at a cost that is far lower.

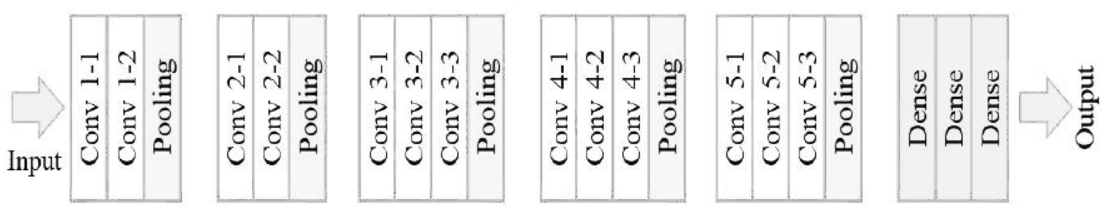

Figure (3.6) Architecture of VGG16

3.8.3 VGG19

There are several different variants of the VGG16 gene, and one of them is called VGG19. It has 19, which is an increase from the standard of 16 layers seen in similar products (One SoftMax layer, three fully connected layers, Sixteen convolution layers, and five MaxPool layers). This network's input was an RGB picture that had a fixed size of 224 pixels by 224 pixels. The size of the input image did not change. At the beginning of the preprocessing step, each pixel was first removed, and then the mean RGB value of each pixel was determined. Throughout the whole training period, this activity was carried out. It is possible to represent the general idea of the picture by using kernels that have a size of three pixels by three pixels and a stride size of one pixel. The purpose of the technique which is often referred to as "spatial padding" is to keep the image's spatial resolution as intact as possible. To a pixel window that was two by two in size, the max pooling technique was used, and the stride parameter was set to the value of 2. Following this stage, a Rectified linear unit, commonly referred to as a ReLu, was used on the model in order to include non-linearity into the structure of the thing being modeled. The computation process was sped up as a result of this, and the model was able to be classified with more accuracy. Implementation of three ultimately linked layers, the initial two of which had a size of 4096, a layer containing 1000 bands for 1000-way classification, and a layer with a softmax activation as the very last layer in the chain of development. Each of these layers had a size of 4096. Every one of the levels is intricately intertwined with the next one.

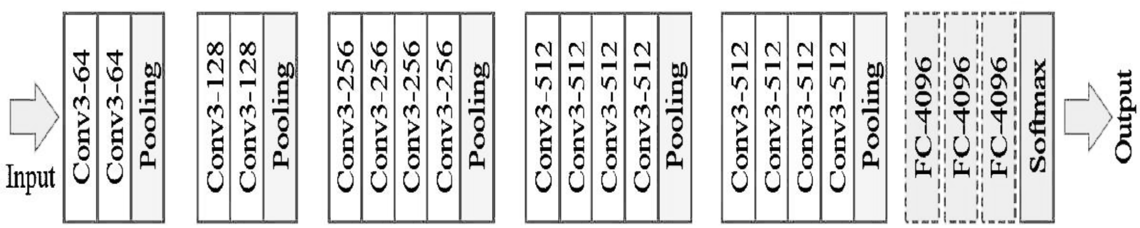

Figure: (3.7) Architecture of VGG19

3.8.4 MobileNetV2

The architecture of a neural network known as MobileNetV2 is one that is always being improved upon and is based on an inverted residual structure. Its major objective is to provide a satisfying experience for users on mobile devices. MobileNetV2's design has an initial complete convolution stage that has a total of 32 filters. This stage is then accompanied by 19 diffusion limits that are currently being used.

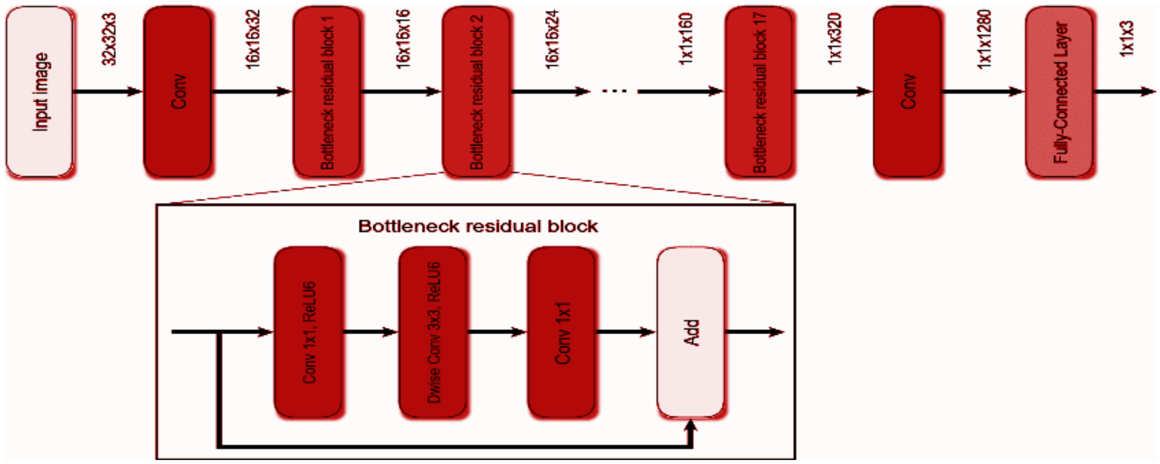

Figure: (3.8) Architecture of MobileNet V2

3.8.5 Inception v3

The coevolutionary algorithm known as Inception V23 was first designed as a module for Googlenet. The major objective of this tool is to provide assistance with the processes of image processing and object recognition. It is the third version of Google's Origin Convolutional Neural Network, which was initially exhibited during the ImageNet Evaluate Information competition. ICNN stands for "inception convolutional neural network." It was hypothesized that the design of Inceptionv3 would enable deeper networks while also limiting an excessive increase in the number of parameters: it has "under 25 million variables," while AlexNet has 60 million parameters.

Inception makes a contribution to the organization of things within the area of computer vision, much in the same way that ImageNet may be thought of as a database of visually ordered stuff. The architecture of Inceptionv3 has been reused for a broad range of applications, with "pre-trained" modeling most often coming from ImageNet. One of these uses is in the realm of biological sciences, where it is beneficial in the research of leukemia. This is only one of many potential applications.

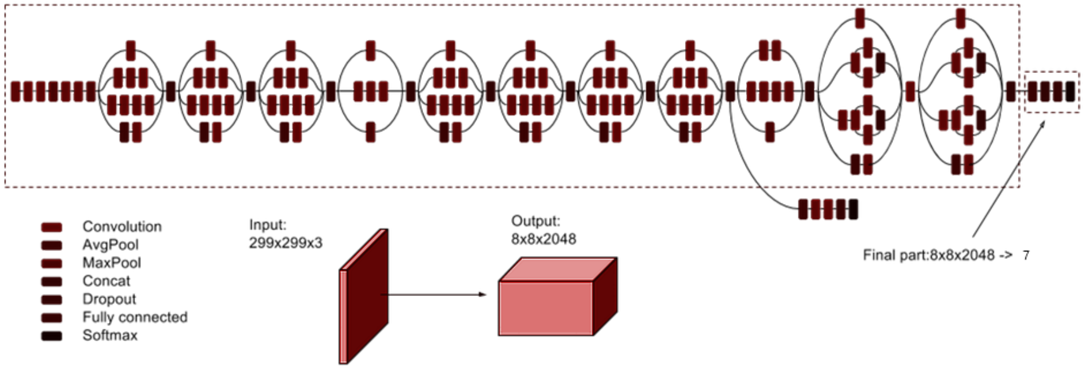

Figure: (3.9) Architecture of Inception V3

Every model has been used so that we may better understand how to impart knowledge. We utilized the weight assigned to each architecture in the 'imagenet' database, and the non pretrained parameters of our model were ultimately changed to false.

3.9 Implementation Requirements

In order to determine how accurate the models are, we have used a large number of different parameters in our analysis. Some examples are the accuracy score, the precision score, the recall score, and the F1 score.

Confusion Matrix A confusion matrix is a specific table arrangement that serves as the graphic user interface of the success of an algorithm, typically one that engages in supervised learning. Confusion matrices are used in the field of machine learning and, more significantly, the problem of statistical classification. In certain circles, it is also known as an error matrix. An error matrix is another term that may be used to refer to a confusion matrix.

Accuracy Examining the accuracy of a machine learning classification algorithm is one way to assess the percentage of times that the system correctly places a data point into one of the predetermined categories. The word "accuracy" is a measurement that may be used for accuracy. The term "accuracy" refers to the degree to which the actual quantity of data points matches the percentage of correctly expected data points.

Precision The amount of precision that a machine learning model has is one of the metrics that is used to measure how successful the model is. Precision refers to the quality of an optimistic prediction that the model has made. The ratio of the number of actual positive outcomes to the total number of successful predictions is the concept that is meant to be referred to when using the word "precision" (the numeral of true positives in addition to the numeral of false positives).

Recall The recall is determined by taking the ratio of the number of positive samples that were accurately categorized as favorable to the total number of positive samples. This ratio is then multiplied by 100.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

For the experiment we used Python, a computer programming language. The Windows operating system was used in the successful completion of our mission. In addition, a variety of packages, including Keras, Tensorflow, NumPy, and others, are employed in this process. All of the programming assignments were successfully completed with the help of Google Colaboratory, an online platform that runs in the cloud. In order to construct the categorization model, we used a Tesla T4 GPU.

4.2 Experimental Results & Analysis

At this point, we have covered the evaluation of the efficiency of our models, as well as a range of factors and the level of accuracy; in addition, we have demonstrated graph diagrams for each model. Using the necessary settings using Inception v3, ResNet50, MobileNetV2, VGG19, and VGG16 accordingly allowed for the findings to be validated and verified. We have put every model through its paces in order to determine which of the models is the most efficient both during the training stage and the testing stage. In order to do this, we have provided every model with its own individual set of hurdles to go through.

4.2.1 ResNet50

In this model, we accomplished a perfect score of 96.11% accuracy on the validation for the conventional architecture up to 35 epochs Figure(4.1), and we also accomplished a perfect score on the train dataset. In addition, the outcomes of the tests demonstrated an accuracy of 95.76%. Inaccurate predictions have been discovered in the confusion matrix. The individual findings of each class using the ResNet50 model are included in the table, which can be seen here.

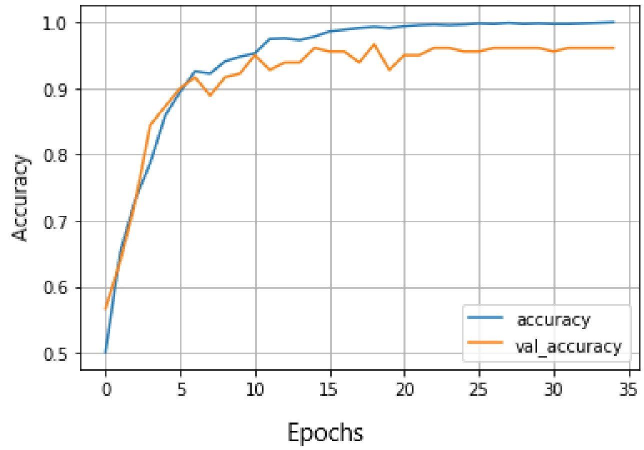

Figure: (4.1) Accuracy of Train and validation data (ResNet50)

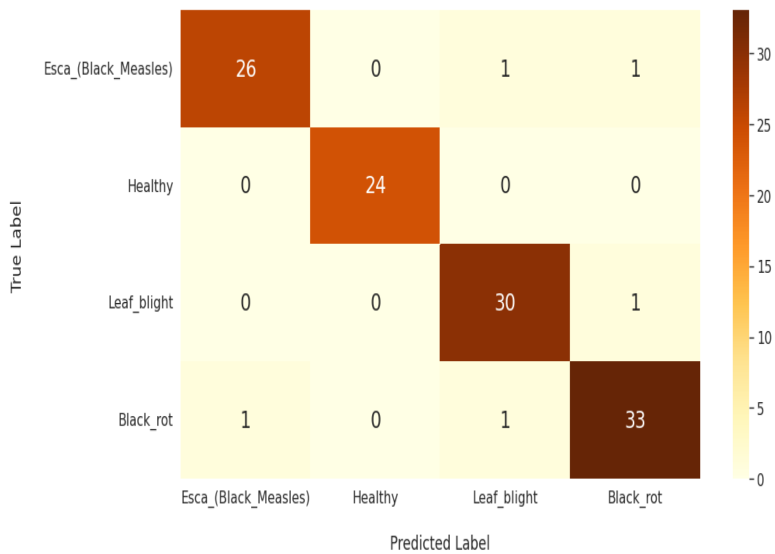

Figure: (4.2) Confusion Matrix of ResNet50

Tabel (4.1) Classification Report ResNet50

Class	Precision	Recall	F1 Score
'Esca_(Black_Measles)'	0.96	0.93	0.95
'Healthy'	1	1	1
'Leaf_Blight'	0.94	0.97	0.95
'Black_Rot'	0.94	0.94	0.94

4.2.2 VGG19

When we used VGG19, we were able to get an accuracy of 98.33% on the validation data and an accuracy of 100% on the train dataset. A total of 15 epochs were used throughout the process in order to get the findings. In addition, the overall accuracy of the test findings was determined to be 97.45%. Predictions have been shown to have improved in the confusion matrix. You can see that the individual results of each class have improved thanks to the VGG19 model in Table as well.

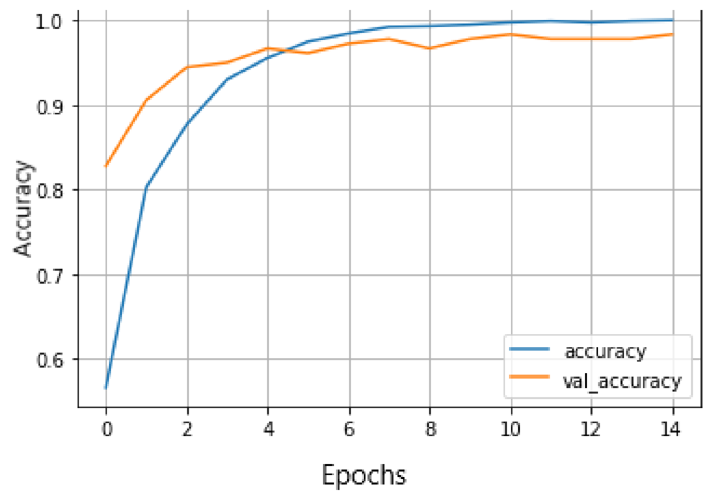

Figure: (4.3) Accuracy of Train and validation data (VGG19)

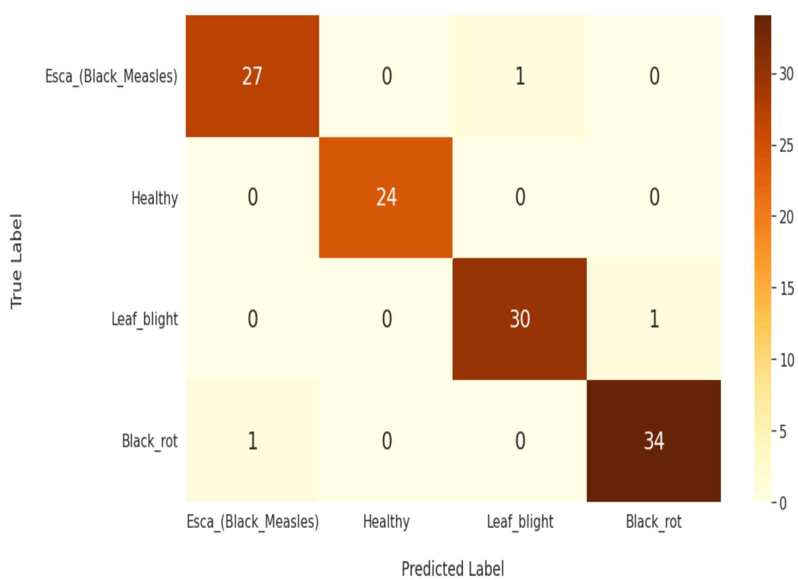

Figure: (4.4) Confusion Matrix of VGG19

Tabel (4.2) Classification Report VGG19

Class	Precision	Recall	F1 Score
'Esca_(Black_Measles)'	0.96	0.96	0.96
'Healthy'	1	1	1
'Leaf_Blight'	0.97	0.97	0.97
'Black_Rot'	0.97	0.97	0.97

4.2.3 VGG16

In comparison to earlier models, VGG16 did not provide any significantly better outcomes. Accuracy of 67.78% based on the validation data and accuracy of 100% based on the train dataset. In order to accomplish these outcomes, it required a total of thirteen epochs. In addition, the accuracy of the test findings was determined to be 98.30 percent. However, we can see that the outcome is becoming worse when we look at the validation data here. In addition, there is a significant gap between the validation accuracy and the test accuracy, which suggests that the model is overfitted.

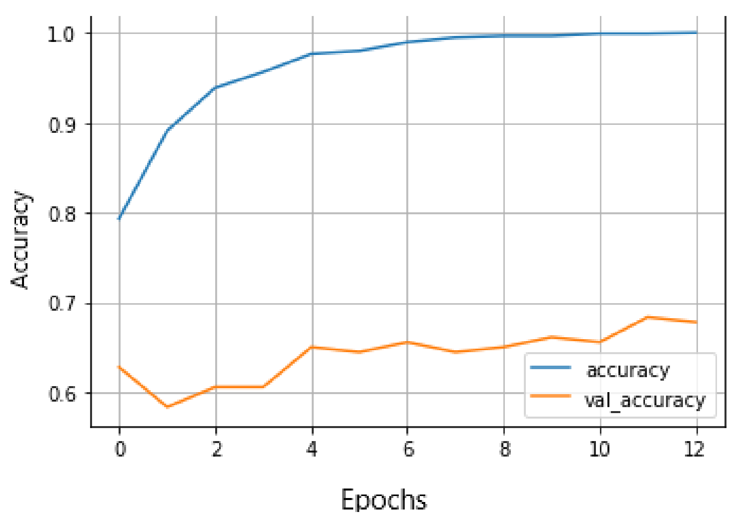

Figure: (4.5) Accuracy of Train and validation data (VGG16)

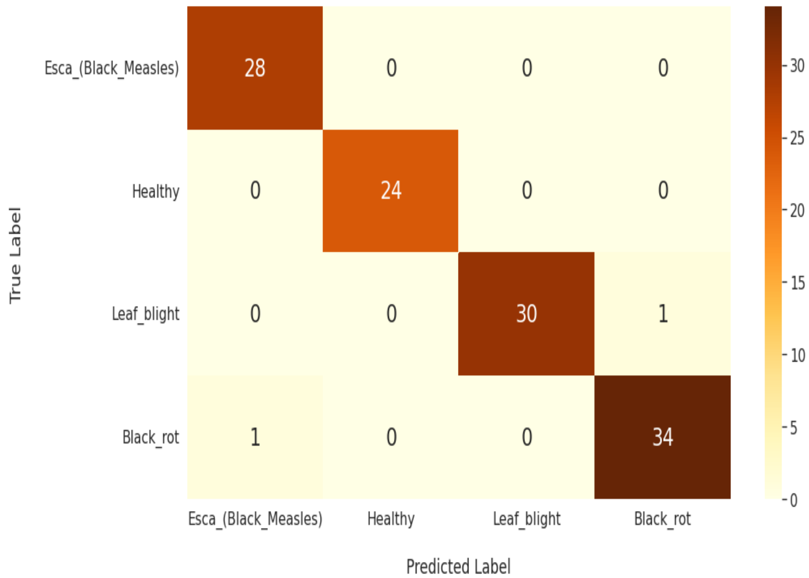

Figure: (4.6) Confusion Matrix of VGG16

Tabel (4.3) Classification Report VGG16

Class	Precision	Recall	F1 Score
'Esca_(Black_Measles)'	0.97	1	0.98
'Healthy'	1	1	1
'Leaf_Blight'	1	0.97	0.98
'Black_Rot'	0.97	0.97	0.97

4.2.4 Inception V3

In Inception V3, for standalone systems, up to 6 epochs, we were only able to achieve 99.44% accuracy on the validation dataset. However, we were able to get 100% accuracy on the train dataset. In addition, the results of the tests indicated a level of accuracy that was 98.30%. According to the confusion matrix, the baseline model had two incorrect predictions for the photos in Figure (4.7). The specific findings of each class are shown in the table, along with the Inception V3 model, which demonstrates that each class was correctly recognized.

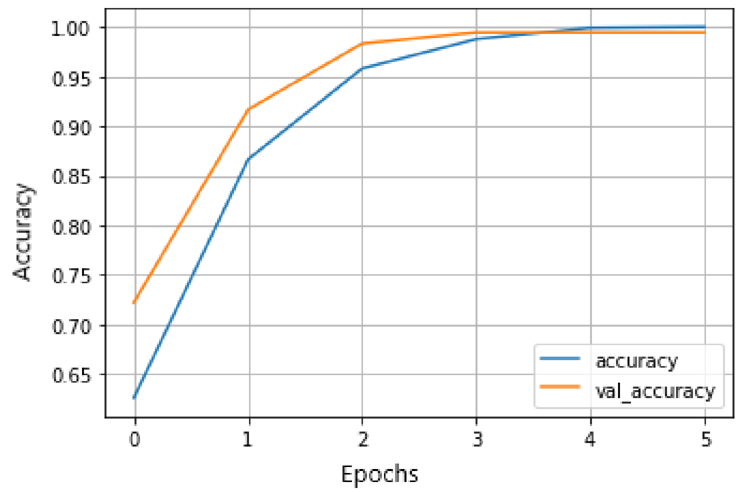

Figure: (4.7) Accuracy of Train and validation data(InceptionV3)

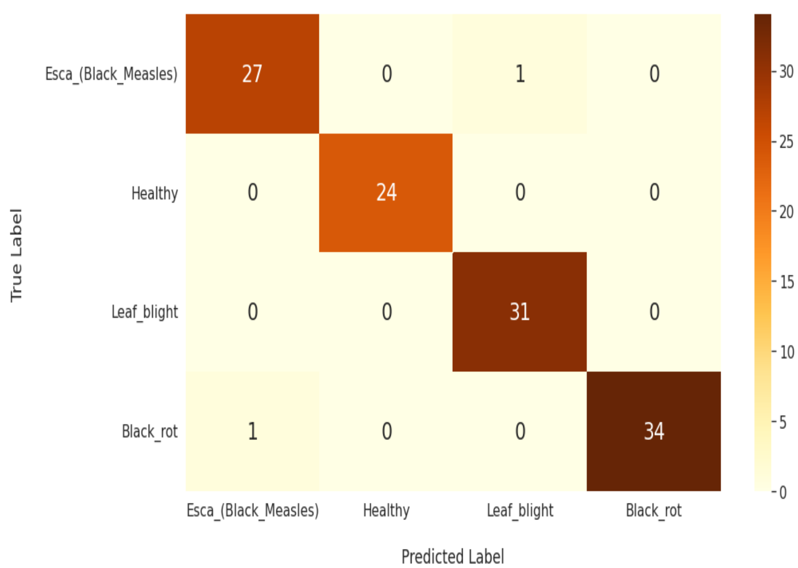

Figure: (4.8) Confusion Matrix of InceptionV3

Tabel (4.4) Classification Report Inception V3

Class	Precision	Recall	F1 Score
'Esca_(Black_Measles)'	0.96	0.96	0.96
'Healthy'	1	1	1
'Leaf_Blight'	0.97	1	0.98
'Black_Rot'	1	0.97	0.99

4.2.5 MobileNetV2

In this model, we accomplished a perfect score of one hundred percent accuracy on the validation for the conventional architecture up to four epochs Figure (4.9), and we also accomplished a perfect score on the train dataset. In addition, the outcomes of the tests demonstrated an accuracy of 99.15%. One inaccurate prediction has been discovered in the confusion matrix.

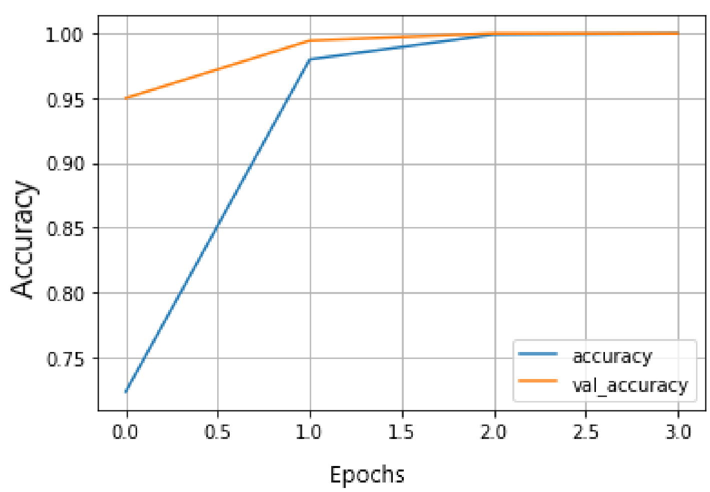

Figure: (4.9) Accuracy of Train and validation data (MobileNetV2)

Figure: (4.10) Confusion Matrix of MobileNetV2

Tabel (4.5) Classification Report MobileNetV2

Class	Precision	Recall	F1 Score
'Esca_(Black_Measles)'	0.97	1	0.98
'Healthy'	1	1	1
'Leaf_Blight'	1	1	1
'Black_Rot'	1	0.97	0.99

The individual findings of each class using the MobileNetV2 model are included in the table which is nearly 100% accurate in the three classes. So we can say this model outperformed all other models.

4.3 Performance comparisons

Tabel (4.6) Result Comparison of Architectures

Architecture	Accuracy	Validation accuracy	F1 score	Precision	Recall
MobileNetV2	0.99	1	0.99	0.99	0.99
InceptionV3	0.98	0.99	0.98	0.98	0.98
VGG16	0.98	0.67	0.98	0.98	0.98
VGG19	0.97	0.98	0.97	0.97	0.97
ResNet50	0.95	0.96	0.96	0.96	0.95

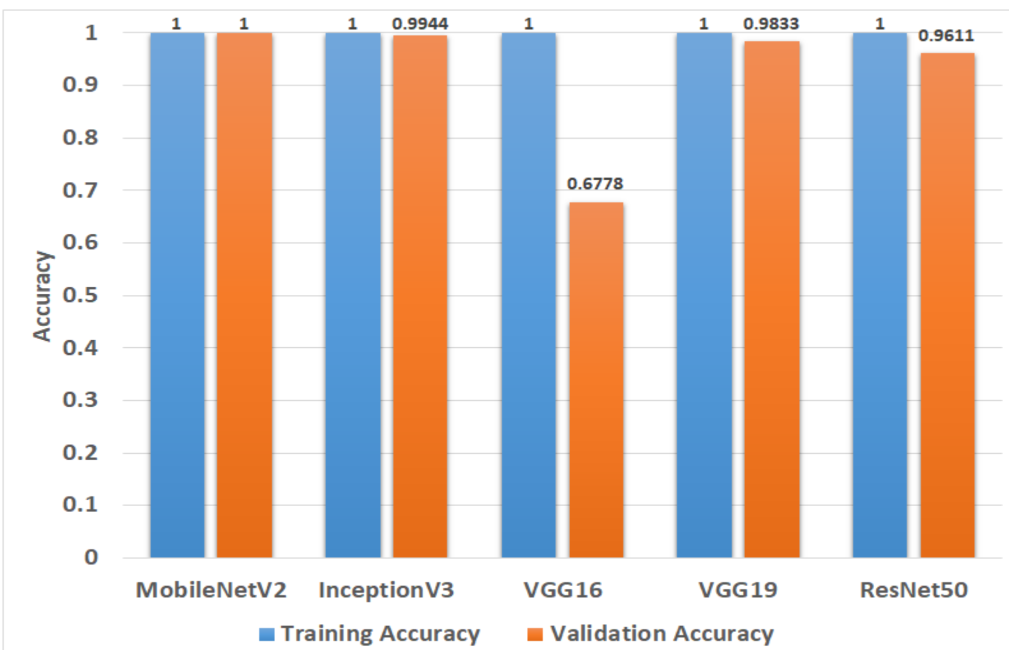

Figure: (4.11) Accuracy visualization

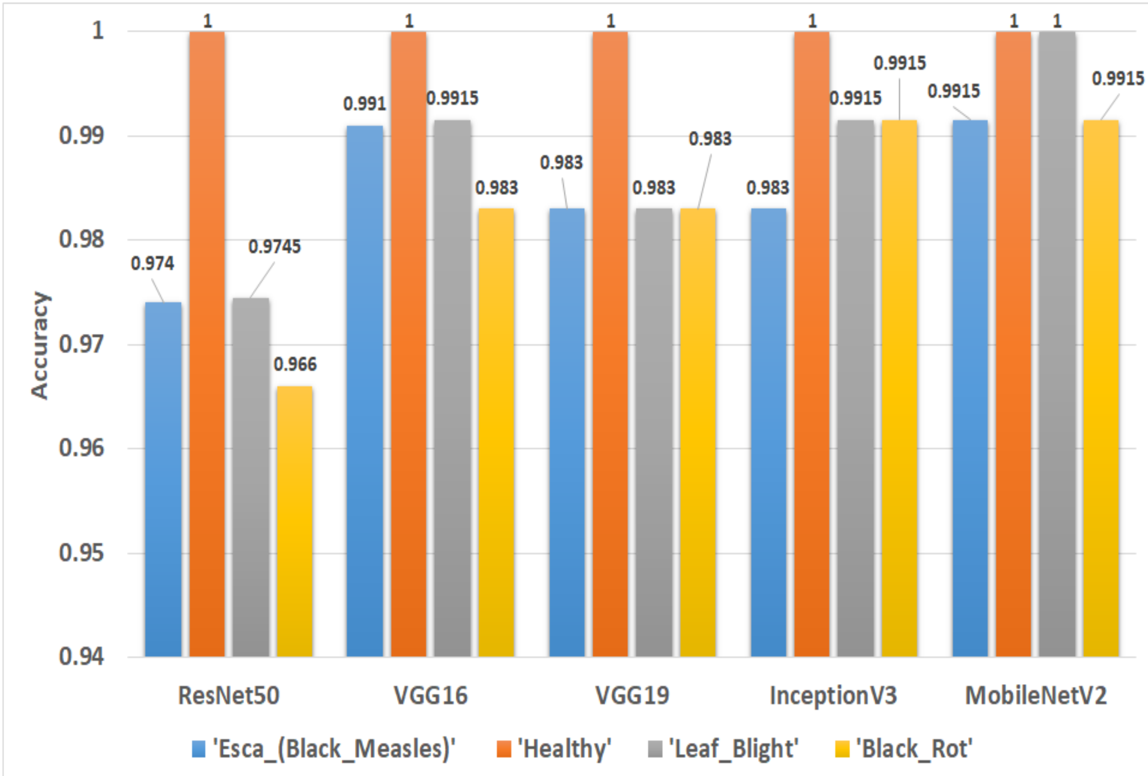

Figure: (4.12) Individual Class Results Visualization

When we look at the data in the table, we can see that the MobileNetv2 detection model has the best performance of all of the models. The performance of ReNet50 and VGG19 was subpar in comparison to that of the other models. In terms of validation accuracy, VGG16 accomplished overfitting of the observations. Despite the fact that MobileNetV2 and Inception V3 data are the most comparable to one another in terms of parameter, F1 score, precision, and recall. MobileNetV2 achieved a perfect score of 100 percent on the validation, but InceptionV3 earned a little lower result. And as we can see from Figure(4.12), the MobileNetV2 model was the one that recognized individual classes with the highest degree of precision compared to the other models. And the healthy class was correctly categorized across all of the models. As a result, we suggest using our ResNet50 model in order to diagnose the sickness affecting Roses.

4.4 Discussion

In our whole research we have used a number of models such as MobileNetV2, InceptionV3, VCG16, VCG19, and ResNet50. And we have got the best accuracy with MobileNetV2 with a percentage of 99.15%, although we have got almost the same accuracy level with InceptionV3 too. As a result, we can say that our models can detect diseases that they are meant to.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

A lot can be said about the social impact of our project. As we know, flowers are used in almost all places, and when you say flowers, the first name that comes to you is rose. Due to our research, if the leaf disease of rose flowers is diagnosed, those who cultivate flowers can detect the disease in advance, then they can take care of it at the right time, as a result, many plants will survive or regain health. In general, it will have a very good and effective impact on society.

5.2 Impact on Environment

As we've already discussed our project is based on machine learning principles. Machine learning works by a predetermined model which is in our case on a cloud server. Our direct carbon footprint on the environment is minuscule compared to even eating beef and burning coal. So, I can confidently say that our project will not harm the environment in any lasting way.

5.3 Ethical Aspects

As we're working with plants which are mostly considered inanimate objects that don't have feelings for humiliation or privacy we can be assured that no ethical dilemma has come up during our research.

5.4 Sustainability Plan

In terms of suitability there are many criteria in this arena. The main goal of our research is to reduce the economic and aesthetic damage caused by rose plant diseases. So throughout our research, we have developed a way so that people can detect the diseases and start working to cure them. Through it, the risk of disease spreading possibility can decrease, and also people can follow the right approaches at the right time. And it is very important for good and healthy monitoring in order to manage disease infections.

CHAPTER 6
SUMMARY, CONCLUSION, RECOMMENDATION, AND IMPLICATION FOR FUTURE

6.1 Summary of Study

The Rose Plant is a very essential tree for our fantastic enjoyment of daily life to fill up human requirements. The rose is the most popular garden plant in the world. Unfortunately, many roses are also susceptible to a number of diseases that lessen their value in human life. The rose may survive without a basic program to standard program and control the program. Another interesting fact about the disease is that plants grow. The disease we have to find out the way we used algorithms for detecting the disease. After that, we are trying to recover our rose plant disease gap. We will be able to free rose plant disease in the future.

6.2 Conclusions

The MobileNetV2 model, which obtained a testing accuracy of 99.3 percent, was a significant help in rose disease identification. We relied on a significant number of original sources, which enabled us to ensure the greatest possible degree of accuracy in our prediction. There is hope that a project of this kind would be beneficial to the agricultural industry as well as the farmers of Bangladesh. Due to the fact that the great majority of Bangladesh's farmers lack formal education, it is common for them to incorrectly diagnose ailments or fail to notice symptoms. As a direct consequence of this, they are unable to bring in prosperous crops. We have reason to assume that our models might be of assistance to farmers in identifying the true state of their health. In addition, engineers may develop Internet of Things (IoT) devices that may autonomously remove harmful plants from agricultural regions. The Internet of Things devices will have their conceptual foundation built by the model that we have designed. In the future, our data and model will be used in the development of an application that can evaluate the overall health of a Rose plant.

6.3 Implication for Further Study

In the future, we want to work with the flower petals of a Rose. In petals, there might be a lot of diseases so if we do the proper research on it then we can also detect the disease of rose petals.

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