A DEEP COMPUTER VISION APPROACH TO DETECT EGGPLANT DISEASES

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

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APPROVAL

This project titled "**A DEEP COMPUTER VISION APPROACH TO DETECT EGGPLANT DISEASES**", submitted by, **Raja Tariqul Hasan Tusher** and **Mr. Gazi Zahirul Islam** 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 (BSc) and approved as to its style and contents. The presentation has been held in September 2021.

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DECLARATION

We hereby declare that this thesis has been done by us under the supervision of Raja Tariqul Hasan Tushe, Senior Lecturer, Department of CSE, and co-supervision of Mr. Gazi Zahirul Islam, Assistant professor Lecturer, and Department of CSE Daffodil International University. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Farming inputs are very vital, yet they are not always available to farmers. The goal of this research was to construct an intelligence system utilizing the recognition of eggplant diseases utilizing picture treatment techniques in order to educate farmers about eggplant sickness. The lack of data for both disorders encouraged us to develop a standard dataset for two prominent diseases in the laboratory. Pre-trained Eggplant-disease classification Visual Geometry Group 16 (VGG16) resnet50 and inceptionV3 architectures are used in our work. Further, VGG16 was utilized as the 8th convolution layer feature extractor and these features were used to graduate illnesses. An equivalent or in some cases a greater accuracy was shown in the analysis. There have been proposed possible causes for variations in interclass precision and future direction. Our highest accuracy is achieved by VGG16 the accuracy rate is 99.55%.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

The contemporary innovation transformation in the new occasions has assisted with improving usefulness in horticulture. The identification of plant infections by a computerized camera picture, which thusly assists ranchers with dealing with their predominance in the fields, will be one of the employments. The availability of modest cameras and the remarkable improvement of the Internet have made the on-line recognition of the condition extensively less troublesome. [1] However, human diagnosis is still prone to mistakes. [2] Due to the achievement in machine training technologies, the extension for the programmed categorization of diseases has updated. Traditionally shallow machine learning methods like neural network, SVM, or other algorithms have been employed. These algorithms are time-consuming, since they need the extraction of the pictures manually and are fed in for the classification procedure. However, the techniques to deep learning include several layers of processing components that automatically analyses pictures and estimate characteristics for categorization. According to Guo et al. [3], There is one of four main types of profound learning algorithms: Convolutional Neural Networks (CNN), auto encoders, Boltzmann machines restricted and scarce encoding. Of them, architectures based on CNN are most commonly employed for issues related to picture classification. Recent developments in the categorization of diseases using CNN are increasing and several research have shown promising results. Deep learning models built on CNN from scratch are time-consuming and require a big database. Even with an expert judgment, it's also difficult to identify each picture into a crop disease. In our work we used image processing technique to identify eggplant diseases. For this purpose, we used 5017 images. We trained our total image by google collaborate. We used most usable architecture vgg16 and resnet50. Vgg16 produced best accuracy about 99.54%.

1.2 Motivation

Brinjal, otherwise called eggplant, is quite possibly the main, economical, and famous vegetable crop filled in Bangladesh. In a thickly populated region, the development and creation of brinjal are vital for the district and is an essential kind of revenue for helpless ranchers. Given its significance, researchers and ranchers have upset to foster both financially feasible and biologically harmless answers for overseeing crop misfortunes and lift ranchers' profit. Brinjal is the second biggest vegetable developed in Bangladesh, with around 150,000 helpless ranchers in assets and complete creation of 507,000 metric tons, more than 500,955 hectares in 2018 (Bangladesh Bureau of factual data (BBS), 2018), and Brinjal is the second biggest plant developed in Bangladesh. Brinjal is cultivated in nearly all agro climate areas, with more than 100 kinds, and offers fruits of all types of color, size, shape and flavor. Insect infestations, mainly eggplants and shoot borers, badly impacted Brinjal. EFSB causes loss of output between 30 and 60% even if the crop is often insecticide In Bangladesh there are two types eggplant disease happed more. One is Borer another is Choanephora. Lots of eggplant rotten every year for these two types of disease.

This problem motivated us to do our work. In our work we will try to early detect eggplant disease as a result farmer can provide medicine to prevent specific diseases.

1.3 Problem Definition

Choanephora and EFSB larvae are damaging to eggplant footsteps and flower, while boring the fruit and making it unmarketable are causing the worst damage. In all main growing locations in Bangladesh, Eggplant crops are usually sprayed more than 80 times in a 4-5 months’ period.

To prevent this problem we tried to developed an intelligence system based on deep learning technology. Our system can detect eggplant disease based on fruit condition. And it can detect disease 99.55% accurately.

1.4 Research Questions

- How is the dataset going to be assembled and produced?
- Can be specifically characterized by the conduct of the disease?
- How to categorize the disease and dissatisfaction?
- How may the illness and defected can be categorized?
- Are defective eggplant correctly predicted by the learning process?
- How does this work assist people?

1.5 Expected Outcome

Choanephora and EFSB larvae harm the development and flowering of eggplants while they grow and do the most damage to the fruit. Eggplant crops are often sprayed more than 80 times over 4-5 months in all key cultivation areas in Bangladesh.

We have tried to create a deep learning technology intelligence system in order to avert this problem. Our method is able to identify fruit-based eggplant illness. 99.54 percent of illness can be properly detected.

1.6 Report Layout

The contents of our report will have appeared as regards:

Chapter 1 Give this research an overview. In this first portion, the initial analysis is a crucial step. We also describe what prompted us to undertake this research in this chapter. The most important part of this chapter is the problem description. This portion of the research inquiry also includes the challenge.

Chapter 2 consists of the analysis of the context and includes a short overview of the relevant work. Notable work related to deep learning is described here, primarily predictive work.

Chapter 3 Provides a brief definition of the methodology or procedure. How the study was carried out in this part.

Chapter 4 Includes the evaluation of the findings. The analytical results are given in the graph.

Chapter 5 It is part of the study to demonstrate the conclusion. This section shows the efficiency of the model. This section also shows the comparison. This part also includes the component of the web implementation of the model and performance. The chapter ends with a discussion of the boundaries of the work. The next task is encoded as well.

1.7 Research Objectives

- To anatomize how to classify or categorize eggplant disease using classifier algorithm.
- To foster a model that will actually want to gauge the eggplant infection.
- To increase the consciousness about different eggplant disease.
- To develop an android application that can predict of detect eggplant disease and provided proper suggestions.

CHAPTER 2

BACKGROUND STUDY

2.1 Introduction

Several deep learning experiments have been performed to predict and detect various plant diseases. Prediction is one of the most often utilized machine learning and deep learning applications. There have been a large number of studies in which different plant diseases are predicted or detected. These research focused on issues and employed various machine learning methods to resolve the problem. This chapter provides an overview of the essential work carried out efficiently by certain specialists in the aforesaid field.

2.2 Related Works

Our paper name is a deep computer vision approach to detect eggplant disease. Our main purpose is to detect different eggplant diseases. What's more, we got a few papers from which we got the thought from some of late examination. The entirety of this is given bellow:

Mohanty et al. [1] describe The combination of expanding worldwide perception of the smartphone and the progress achieved by deep education in the field of computer vision has opened the door to diagnosis of smartphone-supported diseases. We create a deep convolutionary neural network for 14 crop species and 26 illnesses with the use of a public dataset of 54,306 pictures of sick and healthy plant leaves gathered under controlled conditions (or absence thereof). The model is trained to achieve 99,35 percent accuracy in a completed test set which shows the feasibility of this approach. They used ransfer learning & training from scratch. And for deep learning model they used AlexNet, GoogLeNet.

A deep CNNs were designed by Chen et al. [4] for the identification of kinds of tea plant diseases from leaf pictures. Materials: a CNNs model called LeafNet has been created with several extractor filters that automatically extract pictures from the characteristics of tea plant illnesses. DSIFT features are also retrieved from the BOVW model which is then utilized for classifying illnesses using support vector machine(SVMs) and multi-layer percepttron(MLP's) classifications to build a bag of visual word (BOVWs). DSIFT is also employed. The results of the three disease-recognition classifiers were then examined separately. The LeafNet algorithm most accurately diagnosed tea leaf illnesses with an average rating accuracy of 90.16%, with an average SVM algorithm of 60.62% and MLP rating of 70.77%.

Liu et al. [5] Introduced an article that gives an exact distinguishing proof strategy to apple leaf illnesses dependent on profound seizure organizations. The program comprises of delivering enough unhealthy pictures and another engineering for the recognition of apple leaf sicknesses dependent on a profound convolutional neural organization. The proposed profound convolutional network model is prepared utilizing an informational collection of 13,689 pictures of debilitated apple leaves to distinguish the four common apple leaf conditions. Under the hold-out test set, the trial discoveries show that the proposed technique to disease identification dependent on the counterfeit neural organization has an all out precision of 97,62%, the boundaries for the model must be brought by 51,206,928 contrasted down with the ordinary AlexNet model. This examination shows that the profound learning model introduced gives a better arrangement than infection the board for high-exactitude and speedier intermingling sicknesses in apple leaf illnesses and that the imaging approach recommended in this record might work on the power of the CNN model.

Ma et al. [6] Introduced A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. The showed that manually, time consuming, tedious and subjective ways to recognizing Cucumber illnesses. The proposal is for the symptomatic identification of four cucumber diseases, namely anthracnose, drowned mildew, powdery mildew, and the target leaf spots, via a deep convolutional neural network (DCNN). The pictures of symptoms were split from pictures taken in the field of cucumber leaves. Data increase techniques have been used to increase the data sets generated by the segmented symptom pictures to minimize the chances of overlaying. The DCNN obtained strong recognition results with an increase of 14,208 symptom pictures with 93,4 percent accuracy. Comparative tests with classical classificators (Random Forest and Support Vector Machines), as well as AlexNet, were done in order to compare the DCNN findings. Results indicated that the DCNN is a strong tool in field circumstances for the detection of cucumber illnesses.

Ferentinos [7] presented neural network modeling to detect and diagnose plants with basic pictures of healthy and sick plants utilizing in-depth methods of learning. Model training was carried out using an open collection of 87,848 pictures, including 25 plants in 58 unique classes of pairings, including healthy crops, of [plant, illness] plants. Several models were trained with the best performance achieving a success rate of 99.53 percent to find the appropriate combination [plant, illness] (or healthy plant). The very high success rate makes the model a highly valuable early warning tool and method to support an integrated system of detection of plant diseases for operation in real cultivation circumstances.

Liang et al. [8] are proposing a new CNN-based technique of rice blast identification. For the training and testing of the CNN model, a data set of 2906 positive and 2902 negative samples is set. Moreover, in our assessment of the successful use of the proposed approach, they carried out comparison tests for qualitative and quantitative analysis. The findings of the study demonstrate that CNN derived high-level features more discriminatory and more effective than typical handcrafted features, such as local histogram binary patterns (LBPH and Haar WT) (Wavelet Transform). The quantitative assessment findings also show that CNN with Softmax and CNN with SUVMs perform similarly, with higher accuracy, a wider AUC and better ROC curves than both the LBPH plus an SVM and Haar-WT plus an SVM as classification method. CNN with the softmax and ROC have a comparable performance. Their CNN model is therefore a high performer approach for recognizing rice blast illness and may be used in practice.

In comparison to the state of the art technique, Brahimi et al [9] employed a huge dataset. Here, 14828 tomato leaves afflicted by nine illnesses are presented in the dataset. They introduced the convolutional neural network (CNN) for the training of their classification as a learning method that directly uses pictures and prevents handmade features. We have utilized methods of visualization to identify symptoms and to track illness areas in the leaf in order to assess the deep model presented. The results achieved are encouraging, achieving 99.18 percent accuracy, performing dramatically shallow models and can be used as practical tools to protect farmers from tomatoes.

Table 2.1 Related work comparison table

Authors	Area of study	Deep Learning models	Accuracy
Mohanty et al.	14 different crops species	Alexnet and googlenet	99%
Chen et al.	Tea leaf disease	Custom CNN	90.16%
Lu et al.	Rice blast disease	Custom CNN	95.48%
Ma et al.	Cucumber disease detection	Custom CNN	94.4%
Ferentinos	25 different crop species	AlexNet, GoogleNet, overfeat, vGG	98%
Picon et al.	Wheat disease detection	ResNet50	96%

2.4 Research Summary

This analysis is carried out in multiple diverse research teams and shows the sort of study that was done in the image classification sector. The research is carried out in various research teams. By analysis, we have successful findings. Although there are not enough resources available, it is hoped that this field will increase resources every single day, by adding purchase information from various items.

2.5 Challenges

During our work, the major problem is to prepare the data sets for future handling. We have utilized powerful ML and image processing technologies to accurately specify the dataset for our work or subsequent alteration. Another difficulty we encounter in Bangladesh is inability to locate sufficient resources or job.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

We have five stages in the strategy of our work which are the information assortment, information preprocessing, dataset, calculation execution, assessment. Figure 3.1 shows the chart of our work:

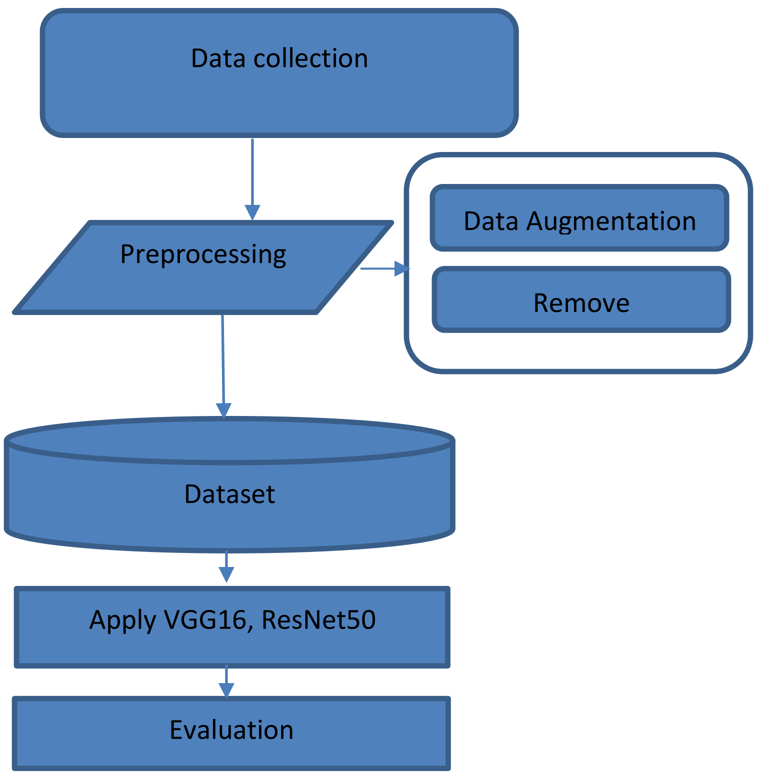


Figure 3.1: Methodology diagram

3.2 Data Collection

We collected our required data from field. For data collection we used mobile camera and DSLR camera. We collected eggplant image from different eggplant field from location in Bangladesh. About 510 image is collected from Sirajganj district and about 470 images are collected from Bhola district.

3.3 Data Pre-Processing

We processed the data two ways before using the algorithm after the data collection, that is. Increased data and backdrop removal. In most situations, pre-processing may minimize the categorization error, according to authors [10].

Data augmentation:

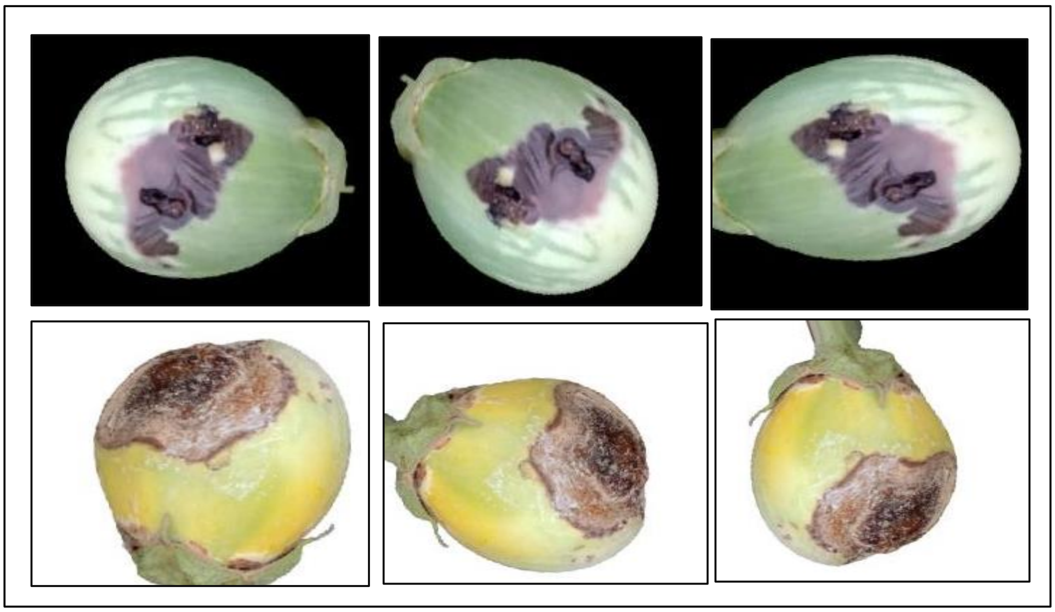


Figure 3.2: Data augmentation and background removal

Figure 3.1 represents the data augmenting and background removal process. For data augmentation we used zoom, shree, rotation, horizontal flip, vertical flip etc. and we removed background of a image by using different website.

3.4 Dataset

After image augmentation our total dataset was 5017 images. These image dataset contains preprocessed, augmented and background removed images. Some of raw data also included in this dataset. The graphical representation of our dataset is given bellow:

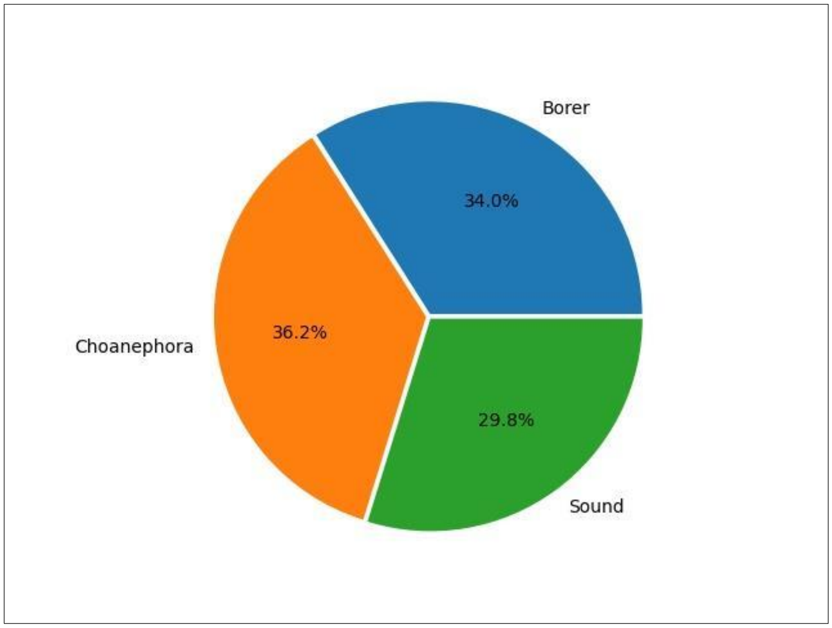


Figure 3.3: Dataset representations

We classified our total 5017 images into 3 classes. Borer , Choanephora, and sound. 34.0% of 5017 images are assigned as borer, 36.2% images assigned as choanephora. And 29.8% images assigned as sound images.

3.5 Apply VGG16, ResNet50

In our work we used most usable CNN architecture VGG16 and ResNet50. The basic structure of these two architecture is given bellow:

3.5.1 ResNet50 architecture:

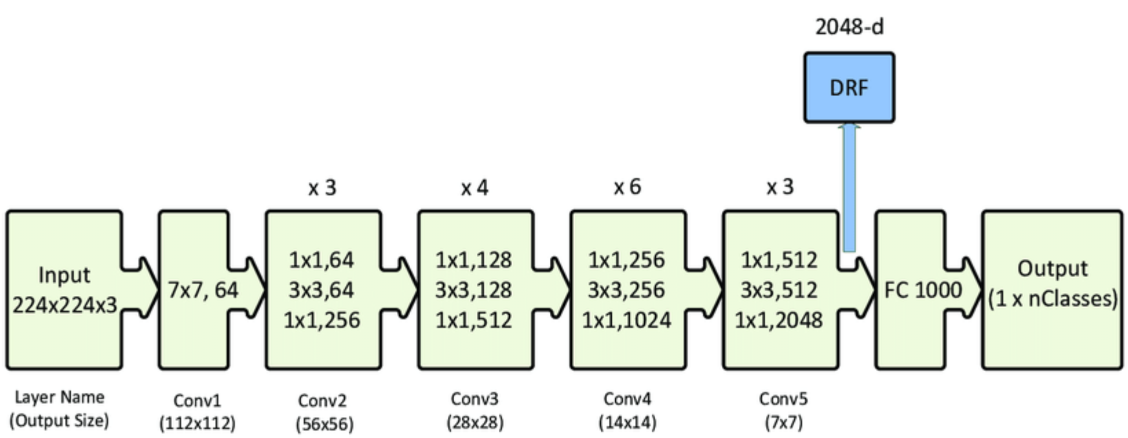


Figure 3.4: Basic ResNet50 architecture.

A residual neural network (ResNet) is a type of artificial neural system (ANN), building on buildings in the cerebral cortex known from pyramidal cells. This is done by residual neural networks using skip connections or shortcuts to hop over certain levels. The ResNet-50 comprises of five phases with an identity block and a convolution. Each block of convolution has three layers and each block of identity has three levels.

3.5.2 InceptionV3 architecture

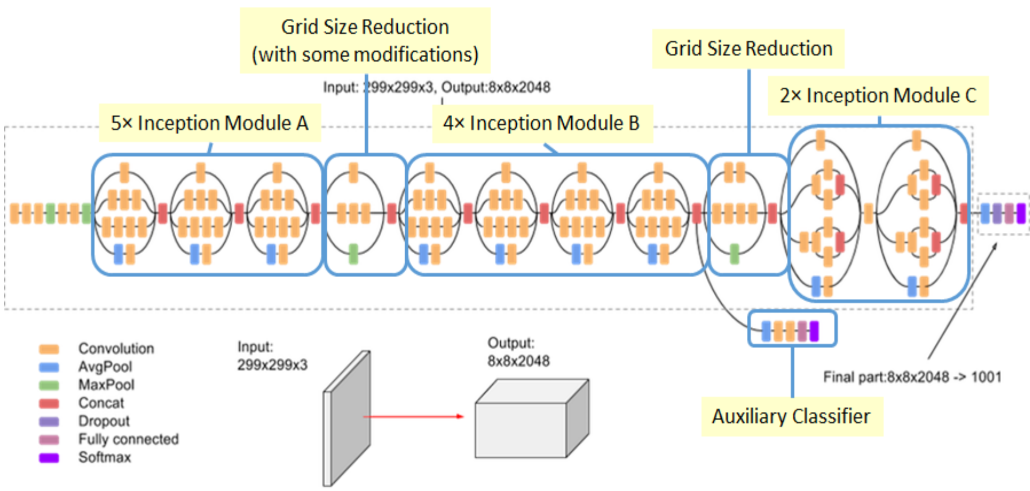


Figure 3.5: Inception V3 architecture.

Inception-v3 v3 is a convolutional group of neural organization designs that works on a few things, including using Label Smoothing, factorized 7*7 convolutions and the utilization of an assistant classifier to spread marking data beneath the organization. This model comprises of symmetric and uneven underlying squares including convolutions, normal packaging, max groups, concats, dropouts, and completely connected layers.Batchnorm is widely utilized and applied to activation inputs throughout the model. Losses are calculated using Softmax. Initiation v3's present implementation is at the very edge of the input bound. Images must be recovered, encoded and preprocessed from the file system. Various sorts of preprocessing phases, from mild to sophisticated, are available. If you employ the most complicated preprocessing steps, the huge number of expensive operations performed via the preprocessing stage pushes the system across the edge and you have to prepare the training pipeline.

3.5.3 VGG16 architecture

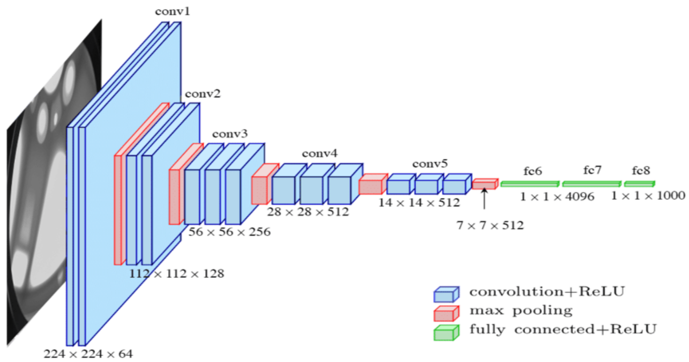


Figure 3.6: VGG16 architecture.

VGG16 was utilized during the 2014 ILSVR(Imagenet) competitions, and is a CNN architecture for neural network (CNN). It has been regarded as one of the best architecture models until now. The most distinctive feature about VGG16 is that they concentrated on having 3x3 filter layers with step 1 and utilized always the same padding and maxpool layer 2x2 stride 2 filter instead of having a huge numbers of hyper-parameters. It is constant across the whole design with this combination of convolution and maximum pool layers. Finally, it has 2 FCs followed by a softmax for output. The layers are linked completely. The 16th layer of VGG16 has a weight of 16 layers.

In our dataset VGG16 generates highest accuracy about 99.54%. The basic model implementation of vgg16 is given bellow:

```
=================================================================
input_1 (InputLayer)         [(None, 224, 224, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 3)                 75267
=================================================================
Total params: 14,789,955
Trainable params: 75,267
Non-trainable params: 14,714,688
```

Figure 3.7: Model design of VGG16.

Figure 3.3 represents the total structure of vgg16.

CHAPTER 4

RESULT ANALYSIS

4.1 Introduction

This chapter focuses mostly on the empirical evidence and test findings descriptive research. When we analyze it, we first think about what is the analysis of results? The Implications section should be structured to communicate the findings without knowing or examining them. Includes suggestions in the section on research papers. The results are recorded and the test shown.

4.2 Experimental Result

CNN structure	Image size	Epochs	Parameter usages	Highest Accuracy
VGG16	224*224	50	activation = 'softmax' loss ='categorical_crossentropy'	99.55%
InceptionV3	224*224	50	activation = 'softmax' loss ='categorical_crossentropy'	98.40%
ResNet50	224*224	50	activation = 'softmax' loss ='categorical_crossentropy'	87.72%

As usual, an experiment consists of the systematic modification of one or more independent variables and their influence on certain dependent variables. Therefore, a machine learning experiment requires a lot of runs under various conditions than a single learning run.

Table 4.1 Algorithms implementation

4.3 Inception V3

Inception v3 is an image recognition algorithm commonly used that has demonstrated an accuracy of over 78.1% using dataset of ImageNet. The model culminates in numerous concepts that have been developed over the years by several scholars. In our work inception v3 produced 98.40% accuracy. It is the 2nd highest accuracy. The summary of inception vs is given bellow.

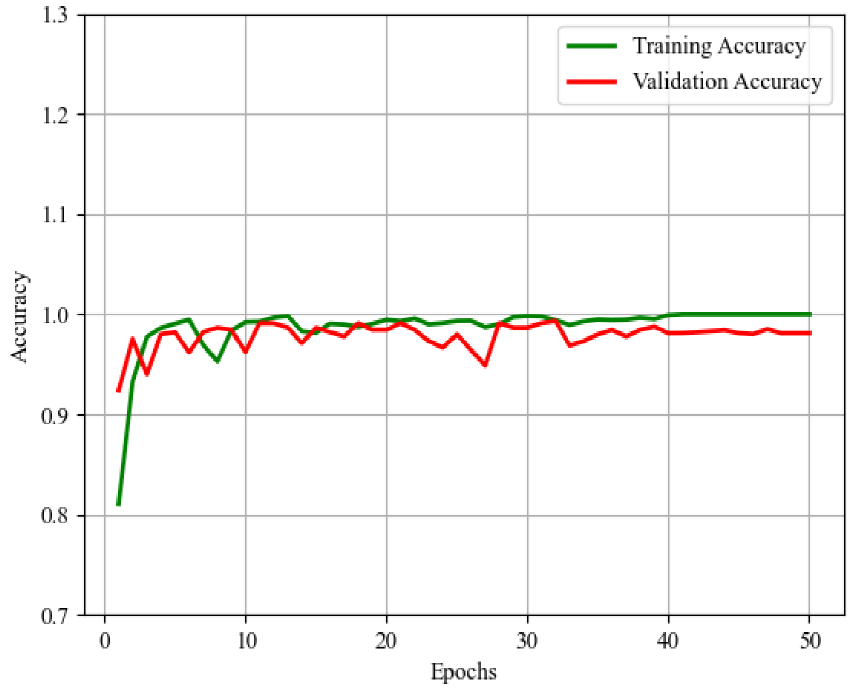


Figure 4.1: Training accuracy vs validation accuracy of inception v3

Figure 4.1 represents training vs validation accuracy of inception algorithms. Green color represents training accuracy and red color represents validation accuracy. We compiled our model over 50 epochs. For inception v3 algorithm the training accuracy is about 100%. That means our dataset is good fit for inception v3 model. The validation accuracy is so good is about 98.40%. but for validation accuracy inception v3 produced zigzag line. That means the up down rate is very high.

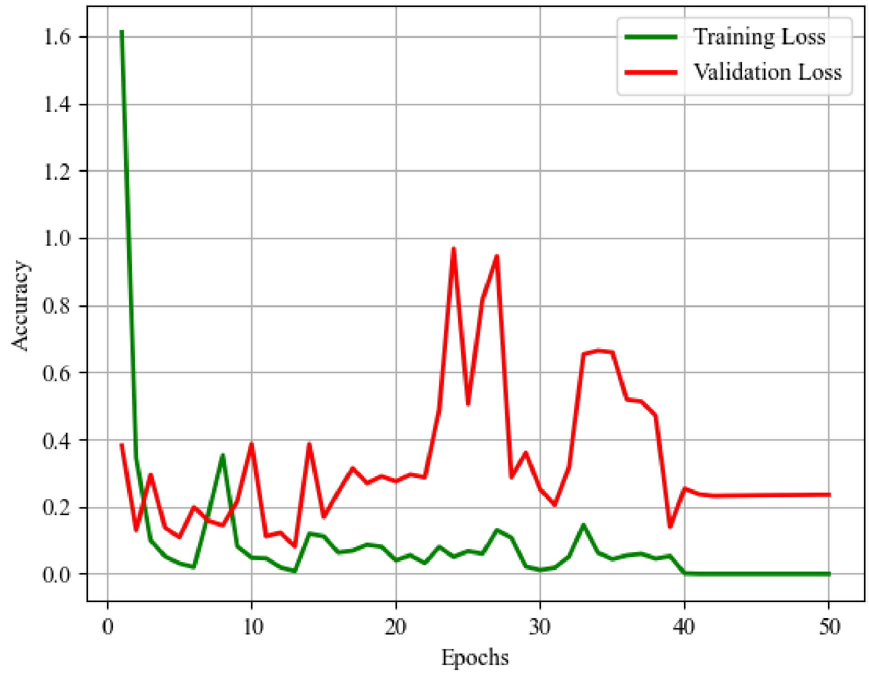


Figure 4.2: Training loss vs validation loss of inception v3

Figure 4.2 addresses preparing versus approval loss of initiation v3 model. Green tone addresses training misfortune and red tone addresses validation misfortune. For training loss our model shows that loss is gradually decreasing when increasing epochs. This incident represents good learning rate of inception vs. But for validation loss inception v3 produced very zigzag line. And sometime it very less and sometime is very high. This overfitting occurrence represents an increase in our loss, more accurately recorded losses, more sensitive to the noisy forecast if the signs/thresholds are not crushed. We can intuitively envisage a situation when the network is overly convinced about output, such that in event of random misclassification it provides a value far from the threshold.

4.4 VGG16

VGG16 was utilized to win the ILSVR(Imagenet) competition in 2014 as a CNN architecture. It is regarded one of the best architecture of the vision model until now. The distinctive feature about VGG16 is to focus on having 3x3 filter convolution layers with step 1 in place of having a large number of hyperparameters and always having the same 2x2 stride 2 filter padding layer. The entire architecture is consistently followed by this arrangement of convolution and Max Pool Layers. Finally, the softmax for exit contains 2 FC(fully connected layers). The 16 in VGG16 refers to a weight of 16 layers.

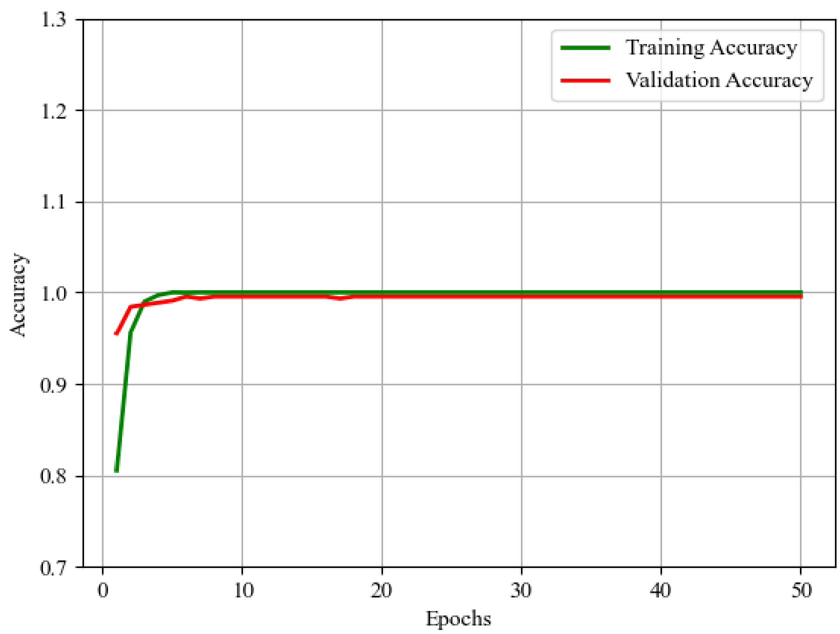
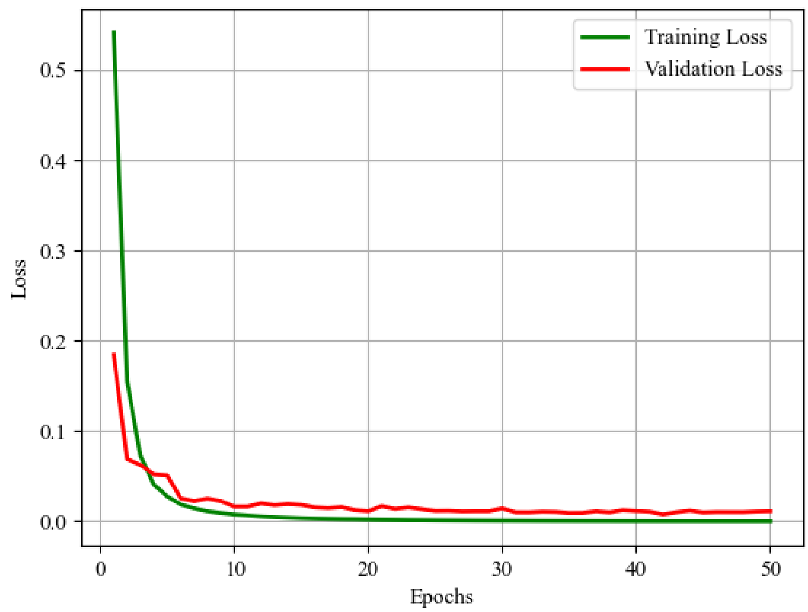


Figure 4.3: Training accuracy vs validation accuracy of vgg16

The precise training vs validation of the initial algorithms is shown in Figure 4.1. Green line indicates the accuracy of training, while the red line reflects the accuracy of validation. Over 50 epochs, we constructed our vgg16. For this model when epochs is increasing the training and validation accuracy gradually increasing. Like inception v3 this model did not produced zigzag line. Both training and validation line are very smooth. And there is very less difference between two line. This incident represents good learning rate of our dataset. The highest training accuracy of this model is 100% and validation accuracy is 99.55% which is best accuracy among our used three architectures.

Figure 4.4: Training loss vs validation loss of vgg16

The training loss + validation loss over time is one of the most commonly utilized measuring



combinations. The loss of training shows well the model fits the training data, whereas the loss of validation shows how well the model fits fresh data. Figure 4.4 represents training vs validation loss of vgg16. Inception v3 produced very zigzag line for this measurements. But in vgg16 produced very smooth line for both training loss and validation loss. And when epochs are increasing validation loss and training loss decreasing gradually. This incident represents very good learning rate and no overfitting of vgg16 model.

4.5 ResNet50

ResNet-50 contains 50-layer deep neural network(DNN). In more than one millions of photos from the ImageNet database, you can load an advanced version of the network. The network can group pictures into 1000 types of objects, such as keys, mouse, pencils and numerous animals.

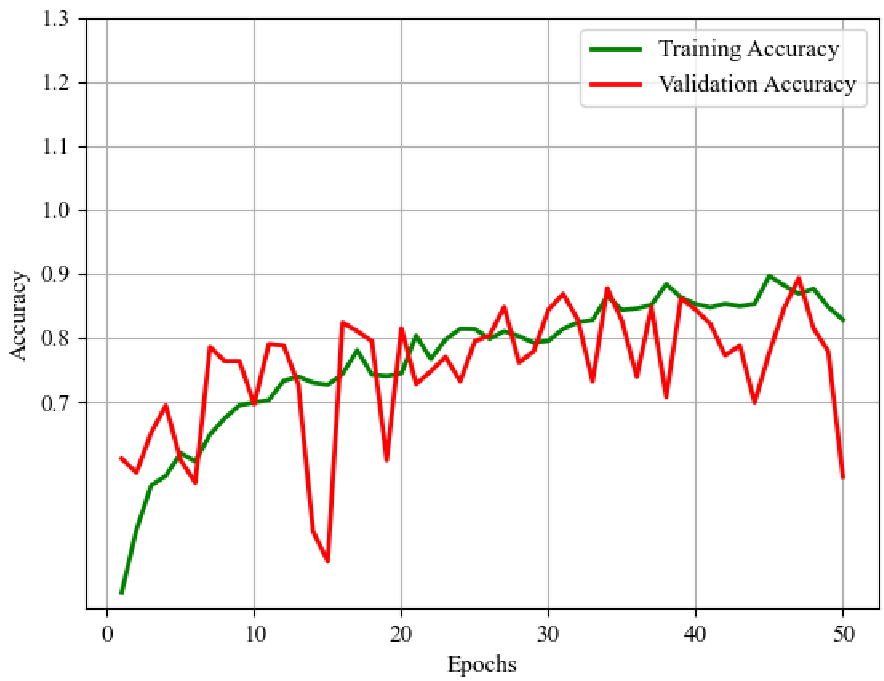


Figure 4.5: Training accuracy vs validation accuracy of ResNet 50

Figure 4.5 represents training vs validation accuracy of resnet50 architecture. For this model when epochs is increasing training accuracy is also increasing but for validation accuracy it produced very zigzag line. That means this model is not fit for our dataset. The highest accuracy of resnet50 model is about 87%. Which is less than other 2 models.

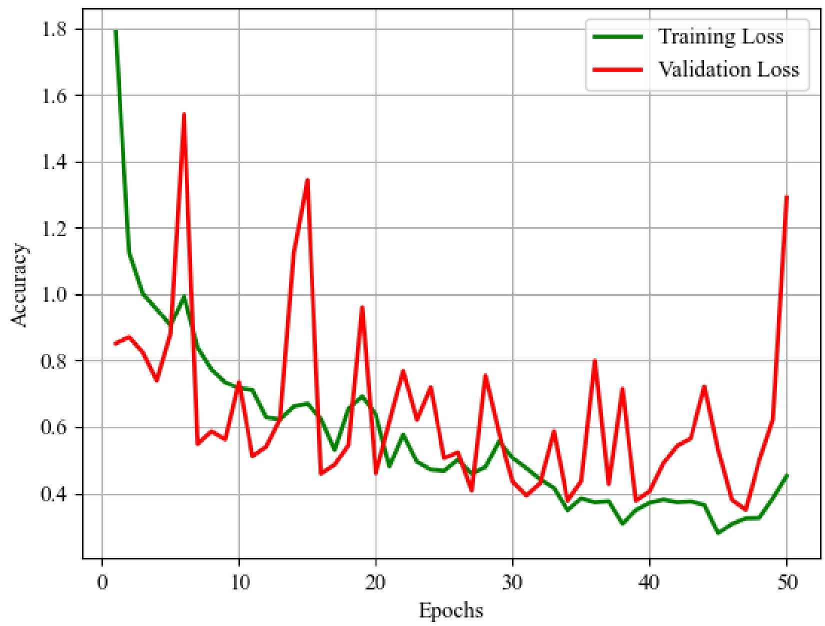


Figure 4.6: Training loss vs validation loss of ResNet 50

Figure 4.6 represents the training vs validation loss of ResNet50 architecture. Resnet50 perform very bad rather than other two models. for loss comparison of resnet50 training loss gradually decreasing while epochs are increasing but for validation loss it produced vey zigzag line that means for some epochs loss is very high and for some epochs loss is very low.

4.6 Three models comparison

In this section we will graphically compare our used three architectures in terms of accuracy to find which architecture produced best accuracy.

Figure 4.7 represents comparison of three based on accuracy. Green color represents resnet50 accuracy. Red color represents inception v3 accuracy. And blue color represents vgg16 accuracy. By this graph we can see that vgg16 produced highest accuracy among 3 architectures. And the accuracy rate is very stable than other two architectures. And the highest accuracy of vgg16 is 99.54%. So we have decided to use vgg16 for prediction and evaluation.

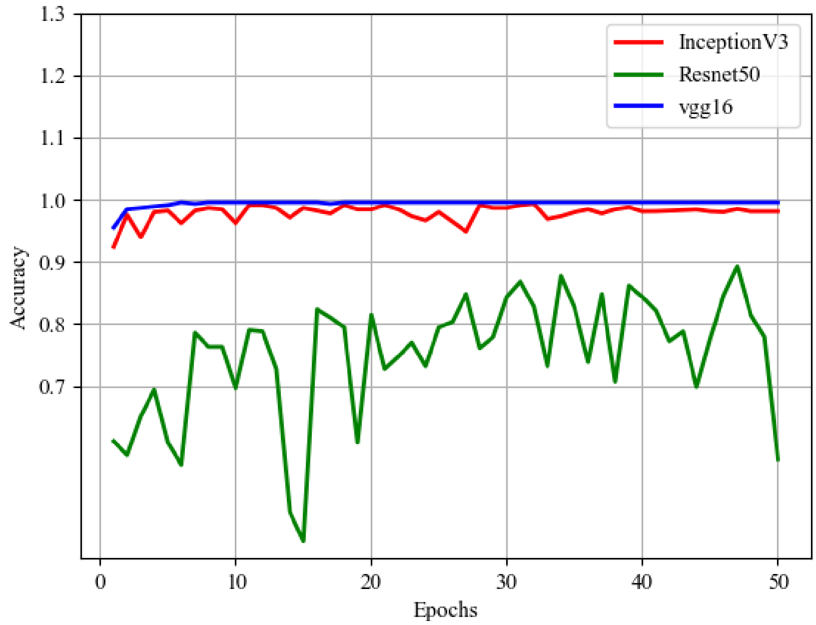


Figure 4.7 Three models comparison

4.7 Evaluation

Assessment research is described as a disciplined and methodical study to assess or appraise an object, program, practice, activity or system for the sake of producing knowledge that is used in decision-making.

For evaluation of our model we used real and predicted comparison method. Figure 4.8 represents the real and prediction comparison bar graph. For evaluation of our model we used 26 images that are never seen by our model. This 26 images are divided into three classes. Borer contains 11 images choanephora contains 10 images and sound class contains 5 images. We predicted each and every images by vgg16. For borer detection our model detects 11 borer disease correctly. And for choanephora disease our model also accurately detected all images. For sound detection our model detected 4 sound eggplant correctly out of 5 images this is only one error produced by our model among 16 unseen images data. This incident represents our model is also better for unseen real life data.

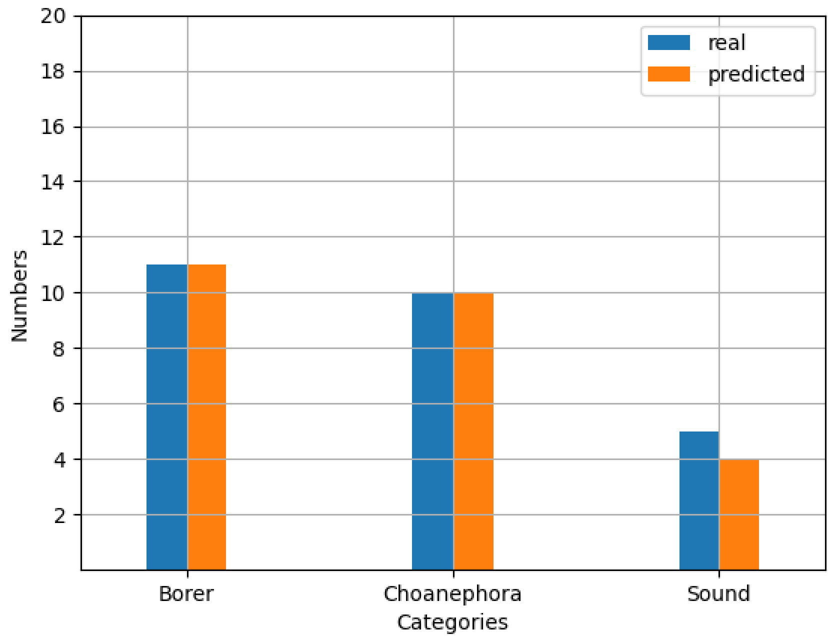


Figure 4.8: Evaluation of vgg16.

4.8 Implementation by opencv method

We tried to implemented our model by opencv framework. The sample is given bellow.

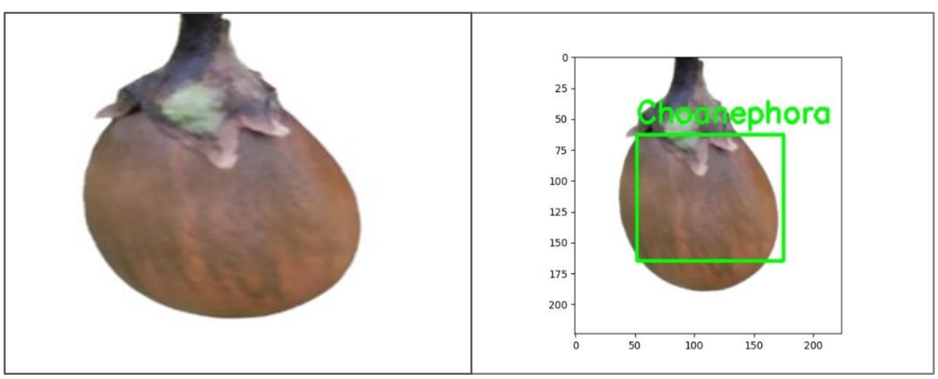


Figure 4.9: Choanephora detection

Figure 4.9 represents choanephora detection. In this figure left side image represents choanephora disease. By open cv framework we are able to detected this disease accurately using vgg16 model.

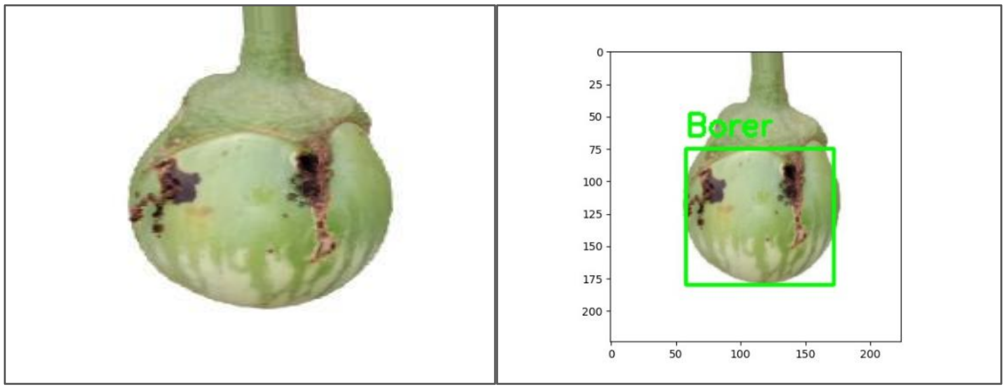


Figure 4.10: Borer detection

The initial detection of the illness is shown in Figure 4.10. Borer sickness occurs in this figure on the left side. We can identify this sickness with precise use of vgg16 model.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Summary of the Study

Many automation studies have been carried out, however the number of such studies in Bangladesh is quite small. Predictive work is a common phrase for machine learning and deep learning, however in Bangladeshi products it is not yet acknowledged. This kind of study was launched recently as to whether the impact of such a challenge will drastically enhance our lives. We get some intriguing implementations for this kind of investigation. In Bangladesh's economy, however, several research initiatives are being launched. However, other researchers from different nations are predicted in this field.

5.2 Conclusion

Each calculation performs mindfully in our work. We investigated three cnn architecture exhibition and tracked down the best calculation to recognize eggplant illness precisely.

Finally, we have a model from which we can detect eggplant diseases accurately. We work with about 5017 images. And 5017 images are divided into 3 classes. The class name are Borer, Choanephora, and Sound. That means our problem is multiclass classification problem. In this work we used pre trained deep learning model. The model name are VGG16 and ResNet50. Our dataset is best fit for vgg16 and by this model we found highest accuracy about 99.55%. As vgg16 provided best accuracy, so we have decided to used vgg16 as prediction model. And for real life prediction our selected model produced better performance.

In our work there are some minor limitation exist. The mail limitation of this work is low number of dataset. In deep learning model the minimum number of data should be 1 million instead of this we used only 5017 number of images. Actually during corona pandemic we could not collect more data from field.

5.3 Recommendations

There are a few remarkable suggestions for this is given bellow:

• to improve the performance of data processing and deliver better outcomes.

• Improved processing of data would also improve performance.

• Make our algorithm more complex or advanced deep learning framework more accurate.

• Consistency works well in your field of application and data collection.

• It is preferable if research is utilized for the detection and correct detection of eggplant disease by farmers.

5.4 Future Work

In not so distant future we will assemble an android application that can direct the rancher to identify eggplant illness all the more precisely.

The instructions for the further production of the work are given below:

- In future work on our dataset, we will utilize advanced algorithms.
- Increasing the amount of data by adding additional Bangladeshi region or division. If we add all other cities and countryside, our model can be more precisely analyzed.
- If we can collect large amounts of data, then we utilize profound knowledge technology in our data.
- In the end we'll strive to construct an intelligence system that can guide farmers in the detection of eggplant diseases and offer them the right advice or treatment for the recovery of sickness.

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APPENDIX

One was to describe the analytical procedures that we faced in our analysis with too many obstacles. Moreover, hardly much has been done before in this field. We received much support from our supervisor. Another difficulty was the collection of data, which for us was a huge task. We started manually collecting data. In contrast, the categories of the various posts face another problem. We could achieve that after a long time of hard work.

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