LOCAL FRUIT CLASSIFICATION AND RECOGNITION USING CNN

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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 "**Local Fruit Classification and Recognition Using CNN**", submitted by Udoy Chandra Dey, ID No: 171-15-9091, Rajesh Kumar Pal, ID No: 171-15-9272, and Toufiq Hasan Turza, ID No: 171-15-8725, 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 3 June 2021.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Rubaiya Hafiz, Sr. 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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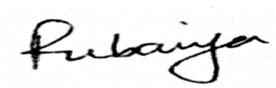

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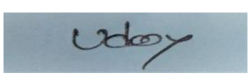

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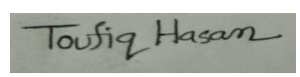

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Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

Automatic fruits classification is becoming more popular day by day. Many of us have very few idea about local fruits so we can attest to them even if we don't know about the local fruits. In our thesis, we will describes about a system that can automatically recognize local fruits using computer vision approach. It is very common process to identifying fruit however automatic fruit classification is not easy task depending on their object's positions, shape, colors, etc. In our project, we have collected the samples from different local area and then we applied different deep learning models like Resnet-50, VGG-19, Inception-v3, MobileNet, etc. that used Convolutional Neural Network (CNN) techniques to detect local fruits and classify in different classes. Among them MobileNet, VGG-19 given us higher accuracy of 99% and 98%. We also proposed a best model based on our training accuracy.

We have collected eight different types of local fruits to done the project. We have total 3240 samples among them for training purpose we used 60 percentage of image data, 20 percentage of image for validation and 20 percent of total image used for testing purpose. To get better result, we removed image background and then augmented them in various way. After training and testing we got satisfied result. As the result of this research model local fruits detection are classified, which can help in our daily life to identify local fruits.

Keywords: CNN, Resnet-50, VGG-19, Augmentation, Inception-v3, Mobilenet.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

1.1 Introduction

The computer vision system is powerful tool for the automatic inspection of fruit. At present time Convolutional Neural Network is one of the best for identification and classification of fruits outperform between all other algorithms. Nowadays, it is a very popular conventional scientific medium where we are able to solve classification problems. By using classification system we can able to identify the desired local fruit. However, automatic fruits classification still a risk to detect the different types of local fruits by their color, shape and size. We have very few ideas about local fruits so we can attest to them even if we don’t know the local fruits by using classification models. In any case, the recognizable proof is still a challenging assignment due to assortments of picture shape, skin color in fruits, changeability of deformity sorts, and nearness of stem and so on. Here, we propose a programmed strategy to solve the problem. In our project, we will explain a desired result based on our dataset using Convolutional Neural Network.

1.2 Motivation of the research

Most of the city people especially our young generation doesn’t have any idea about local fruits. Even we can’t find most of the local fruits because only the common fruits are available in our local market. As a result these local fruit are now extinct and also people have some common confusion to recognize between Sofeda and Gab. Besides that most of the people even don’t know about chalta, bilimbi.

Here is a list of some local fruits.

- Bel
- Carambola
- Lotkon
- Amoloki

- Sofeda
- Tetul

We are trying to build a system that can recognize and classify local fruits. In this way people can recognize and classify local fruits easily. Especially it will be helpful for our young generation to identify these types of fruits.

1.3 Research Questions

- What is the role of fruit recognition in our daily life?
- How and what kind of people will be able to take advantage of it?
- What percentage of accuracy we can get from our dataset?
- Which architecture is best for our fruit recognition system?
- Why we choose this research topic?

1.4 Objective

Following are the objective of our project:

- The objective of this project to find out and analysis a technique by which people can recognize about the local fruit.
- To find the best algorithm which gives us the highest accuracy among the four algorithm which are used in our project.
- It helps to recognize local fruits through more than three thousands of data.

1.5 Expected Outcome

Main purpose of this research is to increase the accuracy rate than the previous fruits classification and recognition of other research and we want to complete our work perfectly with high accuracy. That is why we apply CNN algorithm. By this project we are trying to reach people especially our new generation to introduce them with the local fruits.

CHAPTER 2

Background

2.1 Introduction

A Convolutional Neural Network (CNN) is a very popular and powerful Deep Learning algorithm. Which can take input as an image directly, assign consideration to various aspects in the image and it will be able to differentiate one from the others. The image pre-processing required in a CNN is much lower as compared to other classification algorithms in deep learning. While in primitive methods filters are hand-engineered, with enough training, Convolutional Neural Network or ConvNet have the ability to learn these filters very smartly. The architecture of a Convolutional Neural Network is very similar pattern of neurons in the human brain and was inspired by the organization of the cerebral cortex. Each and every Neurons respond to incentive only in a restricted region of the visual field. A collection of such fields overlap to cover the entire visual area. A ConvNet is able to successfully capture all the dependencies in an image through the application of exact filters. The ConvNet architecture performs a better fitting to the image dataset due to the retrenchment in the number of parameters involved and reusability of weights. The first layer in a Convolutional neural networks is the 'convolutional layer' then 'pooling layer' and finally 'fully connected layer'. At the pooling layer, forward propagation results in the n*n pooling block being reduced to a single value - the value of the "winning unit". Backpropagation of the pooling layer then computes the error which is acquired by this single value "winning unit".

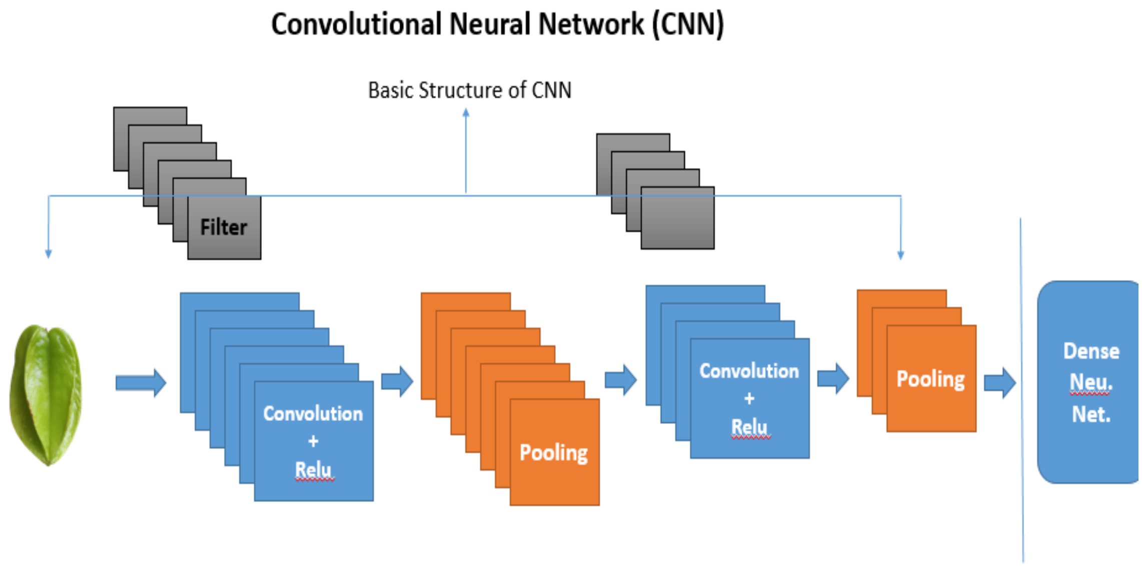


FIGURE 2.1.1: STRUCTURE OF CNN

2.2 Related works:

A research project done by Jose Luis Rojas-Aranda [1] they proposes an algorithms CNN architecture based on MobileNetV2. They used single RGB color, the RGB histogram, and the RGB centroid obtained from K-means clustering. According to the research, database contained 1067 images along with 3 different classes of fruits. Except for the use of plastic bag they got classification accuracy rate 95% whereas using transparent plastic bag accuracy was 93%. They used total 1067 fruit images, 725 images used for training purpose and 342 used for testing purpose.

Asia Kausar 2018 [2] proposed an approach to correctly identify different kind of fruits using a (PCNN) with minimum number of parameters. In their experimental results the classification accuracy rate was 98.88% among 55244 fruit images where it contain 81 different category.

Inkyu Sa 2016 [3] proposed a novel approach using deep convolutional neural networks (DCNN) for fruit detection. They used a Region-based CNN because they mainly focused to create a neural network which would able to harvest fruits by the help of autonomous robots. From two modalities: color (RGB) and Near-Infrared (NIR) they used imagery obtained to achieved better result.

Xiang [4] proposed an approach to classification fruit image based on a lightweight neural network MobileNetV2. After comparing between MobileNetV1, InceptionV3 and DenseNet121 they got the best classification accuracy rate 85.12% using MobileNetV2.They used total 3670 fruit images with 5 different classes.

Another related work done by Siddiqi [5] they used Inception v3 and VGG16 with fine tuning can significantly improve fruit image classification accuracy. Achieved the classification accuracy of 99.27% using VGG16. They used 48,249 fruit images with 72 classes.

Palakodati [6] proposed classification the fresh fruits and rotten fruits. They used apple, banana, and oranges for their dataset. In their research for image classification into fresh and rotten fruits they used CNN and Softmax. They achieved 97.82% accuracy.

Hetal N. Patel [7] proposed a novel approach which can be applied for harvesting targeted fruits using robot. Improved multiple features based algorithm develop for detection fruit on the tree. The fruit on the tree and the images taken in different positions were up to 90% detection accuracy.

Dubey SR. [8] proposed an efficient improved sum and difference histogram (ISADH) texture feature which help to get high accuracy and outperform other color and texture feature and to identify the infected area from the fruit image for fruit disease recognition they used Precise defect segmentation. Their proposed technique can recognize those infections which are practically similar in color and texture.

Woo Chaw Seng [9] proposed a novel approach to use nearest neighbours classification to classification and recognize fruit images based on selected feature values. For better accuracy of recognition they mainly focused on color, shape and size where they successfully achieve up to 90% accuracy.

2.3 Challenges

1) Data Collection

First of all, we know that millions of image data available on online. Data collection is easy task according to this type of research based project. We can’t find huge amount of qualityful image data in online, because most of the image was low resolution. So that we work with real dataset. When we started to collect image data, we have faced various types of challenges. We can’t find huge amount of qualityful image data in online, because most of the image was low resolution.

Secondly due to this pandemic situation we have to stay home most of time. The local fruits we are searching for research purpose are not available in all areas. Most of the fruits are area based but for this pandemic situation all area was under lockdown. so it is quite difficult for us to find local fruits which are not available in markets. But, after trying one month finally we were able to collect our desired dataset.

2) Model Selection:

For every researcher Model selection is a quiet tough job, because model selection and dataset will help researcher to achieve best accuracy. I choose a Convolution neural network (CNN) algorithm. To find the best model, firstly I tried different types of model with our own dataset. But after trying so many algorithms, I realized that CNN algorithms is one of best. Because Convolution neural network is most popular algorithm model for image classification. I also recognize that google did somethings exceptional to make our job easy. Google has a library called Tensor flow which help easily images classification, I am working with Google Colaboratory because using only 50 percentage of GPU, I can do my work with dataset.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

We will describe research methodology and how it implemented. To complete any project, research methodology is the major part because though this part we can move our work forward successfully. We have done our fruits classification project by various step like image acquisition, Image preprocessing, Data augmentation and Train model, Model evaluate, etc. We used Convolutional Neural Network to implement out project and mainly we used various models like Inception v3, VGG19, MobileNet, ResNet50, etc.

We have proposed a research methodology for our project given below:-

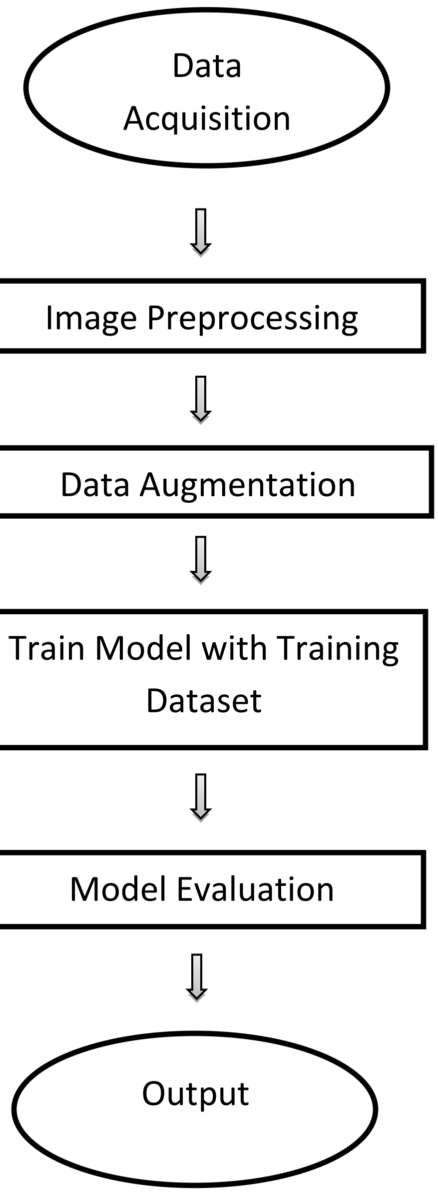


FIGURE 3.1.1: PROPOSED METHODOLOGY TO CLASSIFY LOCAL FRUITS

3.2 Image Acquisition Procedure

In experiment, we classified some local fruits where there were eight categories Bangladeshi local fruits such as amoloki, bel, carambola, sofeda, bilimbi, tetol, lotkon, chalta. We used total 1960 images for training dataset, 640 images for validation dataset and 640 image used for testing dataset under eight classes of local fruits. The statistical analysis for each category are given below-

TABLE 3.2.1: TRAINING DATASET

Fruit Name	**Quantity**
Camranga	245
Bilimbi	245
Chalta	245
Amoloki	245
Lotkon	245
Sofeda	245
Tetul	245
Bel	245

TABLE 3.2.2: VALIDATION DATASET

Fruit Name	**Quantity**
Camranga	80
Bilimbi	80
Chalta	80
Amoloki	80
Lotkon	80
Sofeda	80
Tetul	80
Bel	80

TABLE 3.2.3: TESTING DATASET

Fruit Name	**Quantity**
Camranga	80
Bilimbi	80
Chalta	80
Amoloki	80
Lotkon	80
Sofeda	80
Tetul	80
Bel	80

3.3 Image Preprocessing:

Most of the time we didn’t get expected outcome from raw dataset and also get low accuracy. Because raw data have some unnecessary or noisy data. So, to get proper outcome and best accuracy result we need image pre-processing. That’s why image pre-processing is one of the most important part of research.

3.4 Data Augmentation:

Basically to train a model we need huge amount of dataset, but practically it’s not possible to collect huge amount of data. So we used augmentation to increase our dataset for training model and to get better outcomes. For data incensement we use some data augmentation procedures, as like: zooming, shear, flipping, rotating to train our models.

3.5 Train model with training dataset:

To train our models with training dataset we used 3240 fruits image. For training purpose, we choosed four types of convolution neural networks model.

Chosen models are:

- Inception-v3

- VGG-19
- MobileNet
- ResNet-50

3.6 Model evaluation:

Model Evaluation is an integral part to create a proper convolutional neural network model. It’s a way which helps us to find out the best model for our dataset and also help us to understand how accurately it will work in future.

3.7 Implementation Requirements

Google CoLab

Google colab is free platform where anybody can write and execute python programming language using the browser.it is especially appropriate to machine learning, deep learning and data analysis. Google colab given us Free GPU access, which is main benefit of this platform.

Basic Requirements

- Web Browser (Chrome, Opera mini, Brave, Mozilla).

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction:

Here we will demonstrates classification result using the four CNN models (Inception-v3, ResNet-50, VGG-19, MobileNet). To get best model for our Dataset, we have tested each model separately and we also determined confusion matrix, plot diagram for each model.

Plot diagram: A plot diagram is a tool which show us relationship between two or more variables.

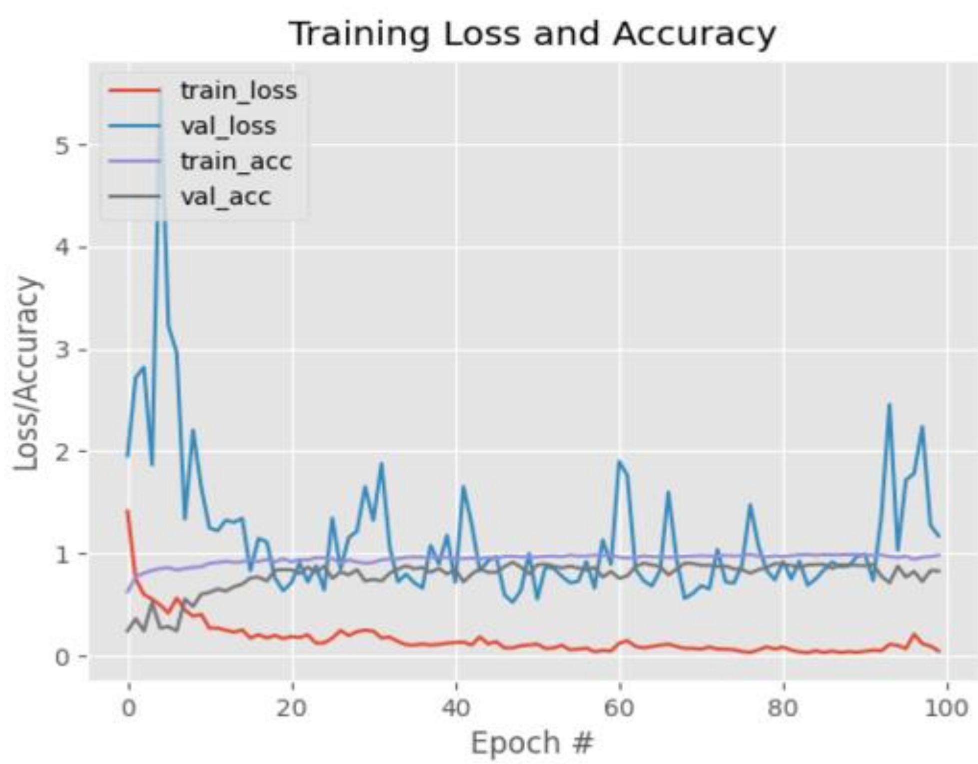


FIGURE 4.1.1: ACCURACY AND LOSS GRAPH

Confusion Matrix: It measure performance for deep learning classification model on a test dataset.

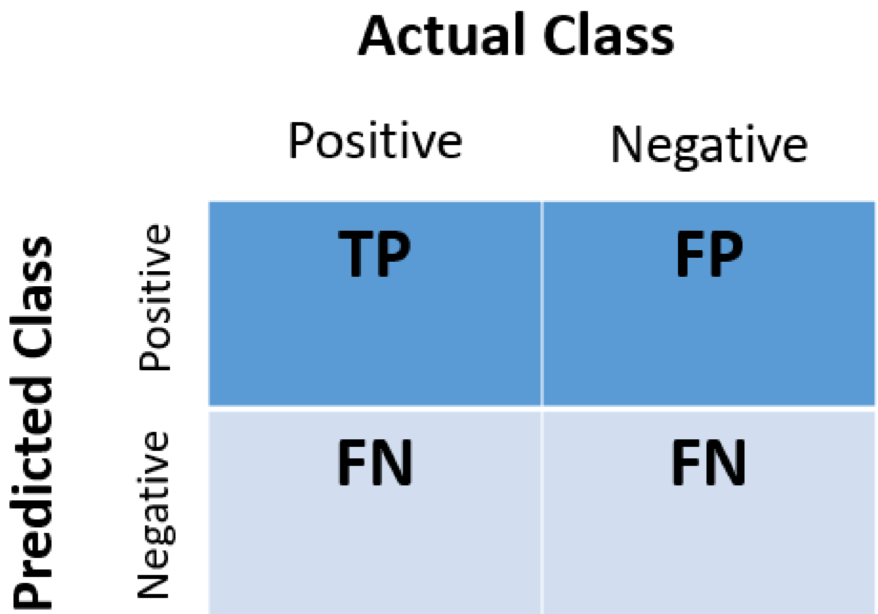


FIGURE 4.1.2: CONFUSION MATRIX

In this paper to demonstrate the detection of local fruits the used fruits are Camranga, Bilimbi, Chalta, Amoloki, Lotkon, Sofeda, Tetul, and Bel. Out of total 3240 local fruits images, we used 1960 images for training purpose, 640 fruits image for validation and 640 using for testing.

Data samples

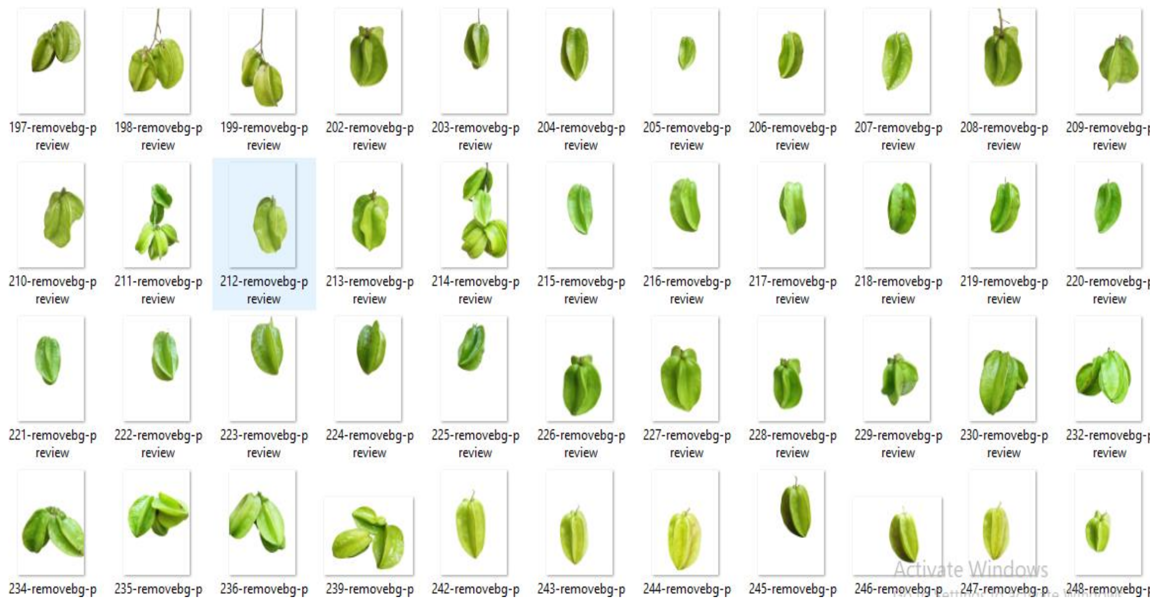


FIGURE 4.1.3: IMAGES OF DATASET CAMRANGA

FIGURE 4.1.4: IMAGES OF DATASET CHALTA

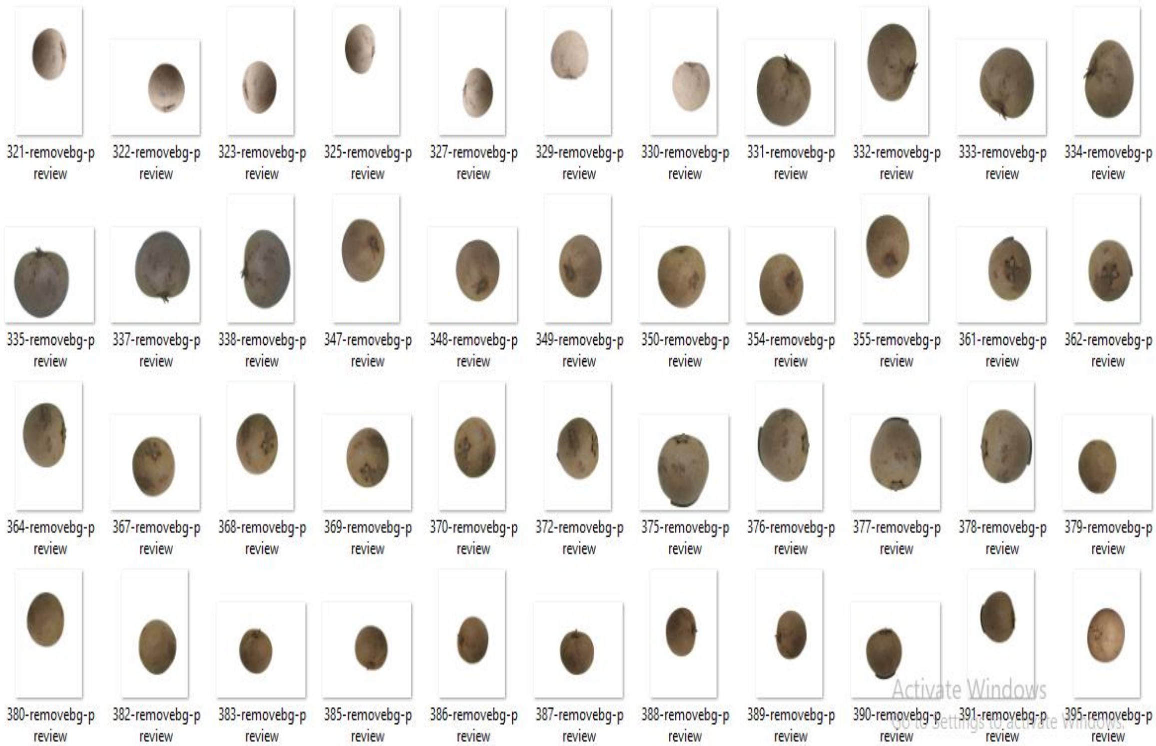


FIGURE 4.1.5: IMAGES OF DATASET SOFEDA

4.2 Experimental Result for MobileNet:

Accuracy depend on number of epoch. Here we used 15 epoch and from 11 to 15 epoch got the best accuracy.

```
Epoch 1/15
62/62 [==============================] - 1340s 22s/step - loss: 19.9674 - accuracy: 0.6451 - val_loss: 0.6459 - val_accuracy: 0.9375
Epoch 2/15
62/62 [==============================] - 154s 2s/step - loss: 0.1850 - accuracy: 0.9764 - val_loss: 0.3008 - val_accuracy: 0.9703
Epoch 3/15
62/62 [==============================] - 152s 2s/step - loss: 0.0766 - accuracy: 0.9895 - val_loss: 0.3834 - val_accuracy: 0.9594
Epoch 4/15
62/62 [==============================] - 152s 2s/step - loss: 0.0653 - accuracy: 0.9886 - val_loss: 0.2633 - val_accuracy: 0.9703
Epoch 5/15
62/62 [==============================] - 152s 2s/step - loss: 0.0766 - accuracy: 0.9867 - val_loss: 0.6686 - val_accuracy: 0.9406
Epoch 6/15
62/62 [==============================] - 153s 2s/step - loss: 0.1247 - accuracy: 0.9849 - val_loss: 0.8286 - val_accuracy: 0.9297
Epoch 7/15
62/62 [==============================] - 153s 2s/step - loss: 0.1775 - accuracy: 0.9774 - val_loss: 0.4513 - val_accuracy: 0.9688
Epoch 8/15
62/62 [==============================] - 153s 2s/step - loss: 0.2610 - accuracy: 0.9814 - val_loss: 0.3937 - val_accuracy: 0.9750
Epoch 9/15
62/62 [==============================] - 154s 2s/step - loss: 0.0937 - accuracy: 0.9849 - val_loss: 0.8650 - val_accuracy: 0.9500
Epoch 10/15
62/62 [==============================] - 155s 2s/step - loss: 0.1777 - accuracy: 0.9847 - val_loss: 0.7480 - val_accuracy: 0.9578
Epoch 11/15
62/62 [==============================] - 155s 3s/step - loss: 0.0471 - accuracy: 0.9956 - val_loss: 0.5245 - val_accuracy: 0.9719
Epoch 12/15
62/62 [==============================] - 155s 2s/step - loss: 0.0156 - accuracy: 0.9962 - val_loss: 0.2804 - val_accuracy: 0.9828
Epoch 13/15
62/62 [==============================] - 155s 2s/step - loss: 0.0885 - accuracy: 0.9932 - val_loss: 0.2747 - val_accuracy: 0.9891
Epoch 14/15
62/62 [==============================] - 155s 3s/step - loss: 0.0072 - accuracy: 0.9979 - val_loss: 0.2386 - val_accuracy: 0.9891
Epoch 15/15
62/62 [==============================] - 155s 2s/step - loss: 0.0035 - accuracy: 0.9988 - val_loss: 0.1401 - val_accuracy: 0.9875
```

FIGURE 4.2.1: ACCURACY FOR MOBILENET.

Higher difference in the beginning and train accuracy curve increased dramatically whereas a lower difference in final progression.

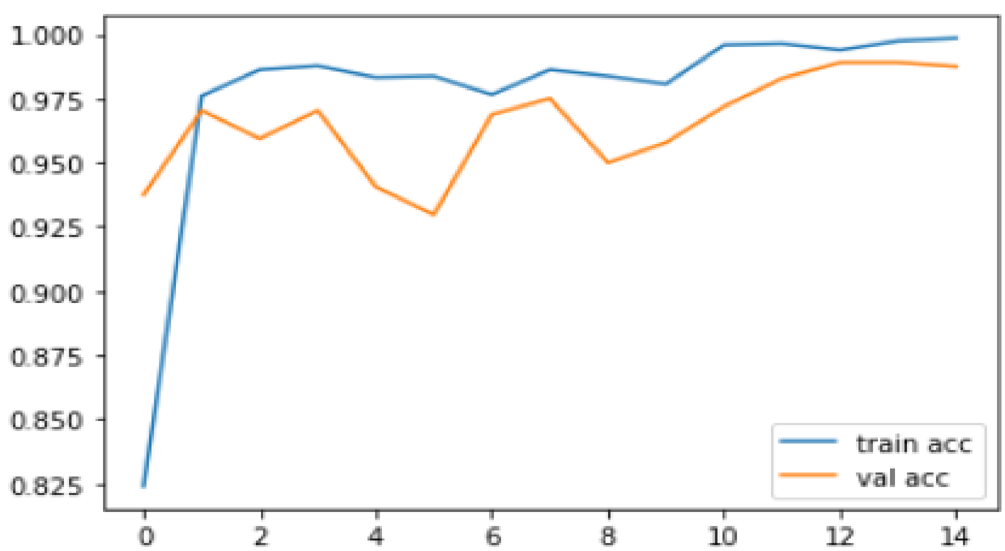


FIGURE 4.2.2: TRAIN VS VALIDATION ACCURACY PLOT FOR MOBILENET

We notice a higher difference in the beginning and train loss curve decreased whereas the final progression remains almost same.

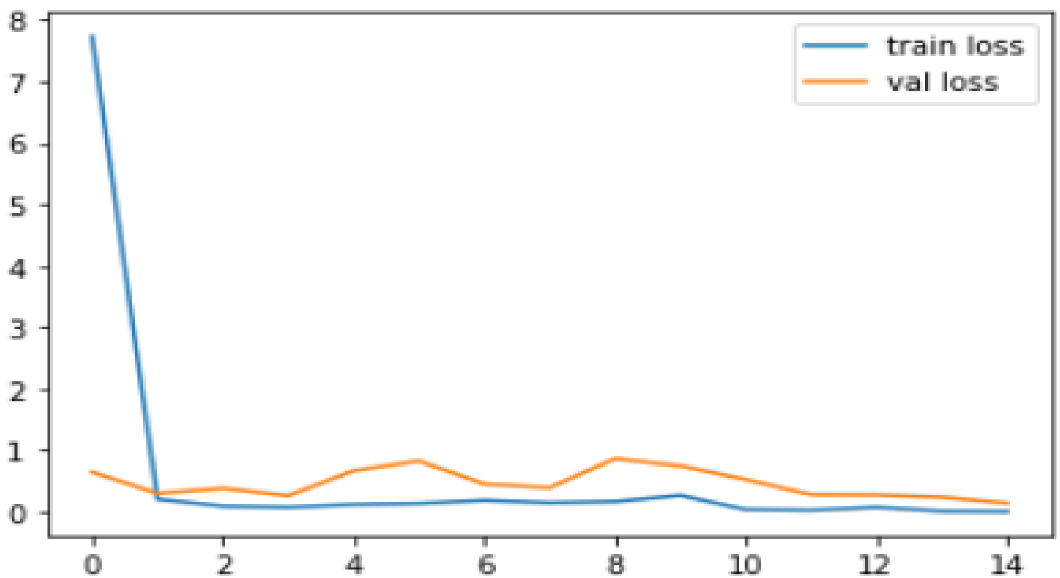
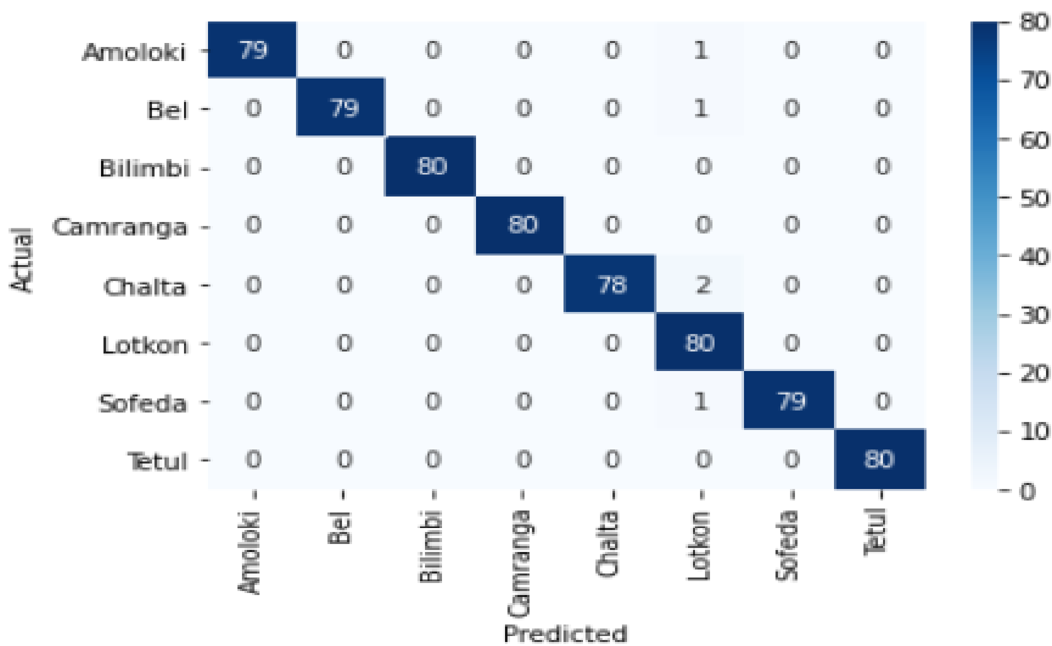


FIGURE 4.2.3: TRAIN VS VALIDATION LOSS PLOT FOR MOBILENET

Confusion Matrix:




```
test accuracy : 99.21875
```

FIGURE 4.2.4: CONFUSION MATRIX FOR MOBILENET

4.3 Experimental Result for VGG-19 Model:

Accuracy depend on number of epoch. Here we used 10 epoch and got the best accuracy.

```
Epoch 1/10
62/62 [==============================] - 1543s 25s/step - loss: 5.3054 - accuracy: 0.4510 - val_loss: 0.3544 - val_accuracy: 0.8781
Epoch 2/10
62/62 [==============================] - 1500s 24s/step - loss: 0.3415 - accuracy: 0.8841 - val_loss: 0.3532 - val_accuracy: 0.8797
Epoch 3/10
62/62 [==============================] - 1502s 24s/step - loss: 0.2464 - accuracy: 0.9143 - val_loss: 0.1926 - val_accuracy: 0.9344
Epoch 4/10
62/62 [==============================] - 1506s 24s/step - loss: 0.1257 - accuracy: 0.9618 - val_loss: 0.1774 - val_accuracy: 0.9516
Epoch 5/10
62/62 [==============================] - 1498s 24s/step - loss: 0.0912 - accuracy: 0.9723 - val_loss: 0.2541 - val_accuracy: 0.9156
Epoch 6/10
62/62 [==============================] - 1496s 24s/step - loss: 0.0841 - accuracy: 0.9729 - val_loss: 0.1621 - val_accuracy: 0.9453
Epoch 7/10
62/62 [==============================] - 1497s 24s/step - loss: 0.1109 - accuracy: 0.9604 - val_loss: 0.4608 - val_accuracy: 0.8484
Epoch 8/10
62/62 [==============================] - 1486s 24s/step - loss: 0.1672 - accuracy: 0.9403 - val_loss: 0.1697 - val_accuracy: 0.9484
Epoch 9/10
62/62 [==============================] - 1479s 24s/step - loss: 0.0993 - accuracy: 0.9691 - val_loss: 0.2684 - val_accuracy: 0.9406
Epoch 10/10
62/62 [==============================] - 1479s 24s/step - loss: 0.1118 - accuracy: 0.9664 - val_loss: 0.1259 - val_accuracy: 0.9563
```

FIGURE 4.3.1: ACCURACY FOR VGG-19.

In the beginning we can see that higher difference between the curves, after that train accuracy curve increased and it remains sustainable whereas validation accuracy curve fluctuated immensely.

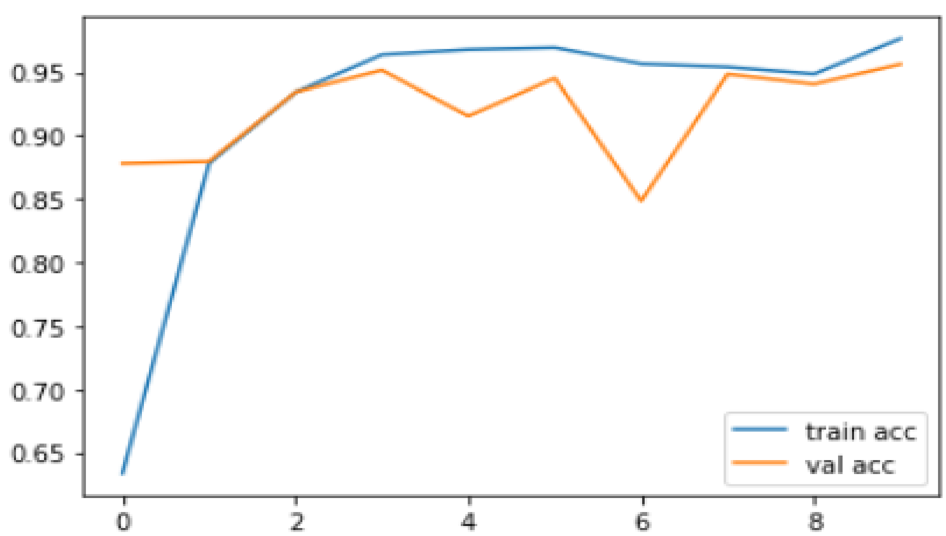


FIGURE 4.3.2: TRAIN VS VALIDATION ACCURACY PLOT FOR VGG-19

Validation loss curve fluctuated initially but in final progression the difference was almost same.

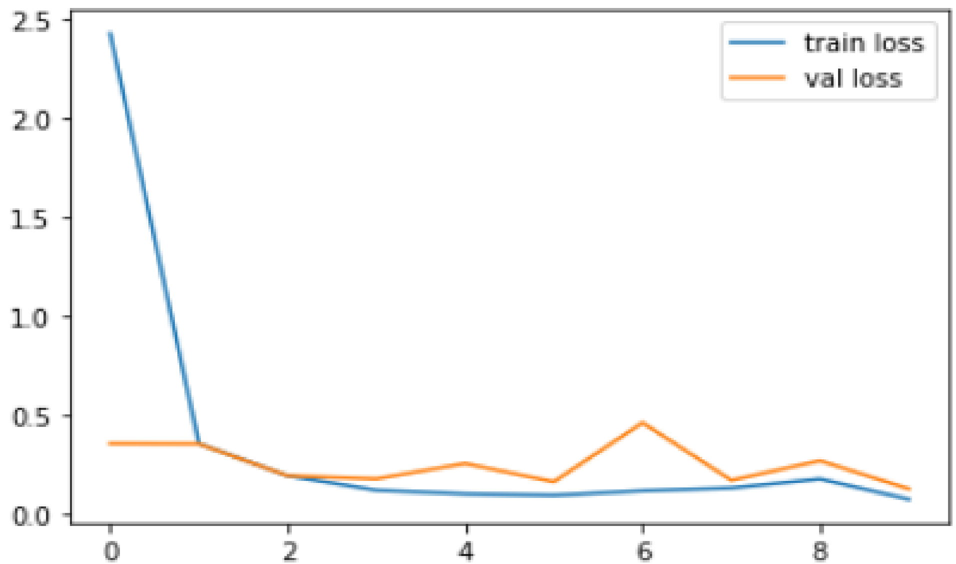
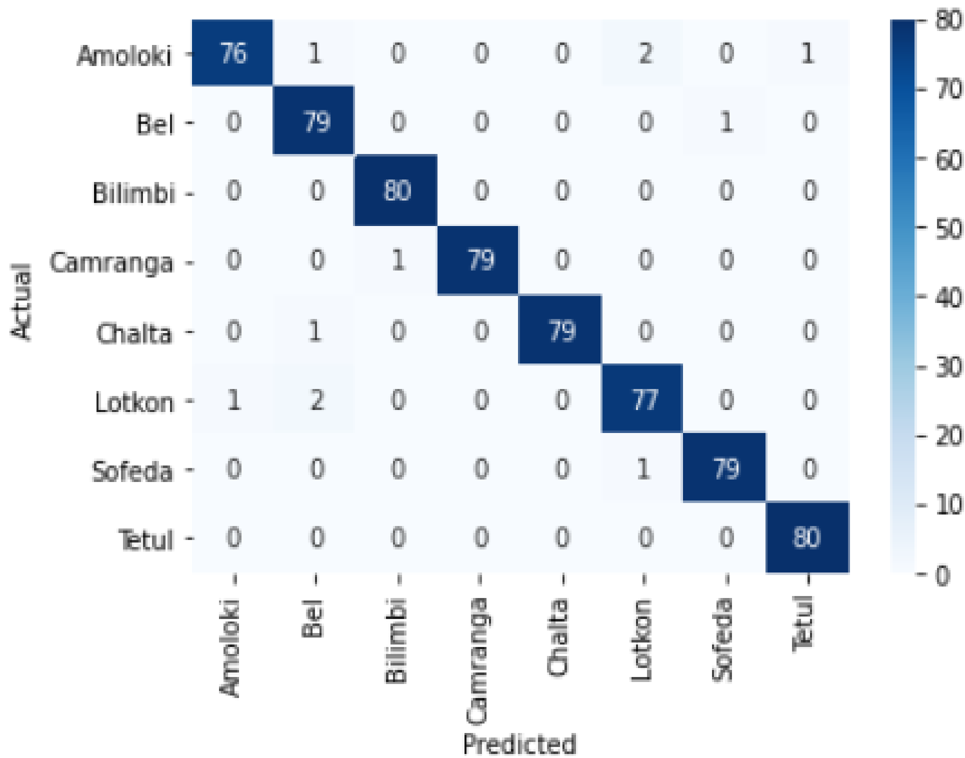


FIGURE 4.3.3: TRAIN LOSS VS VALIDATION LOSS PLOT FOR VGG-19

Confusion Matrix:




```
test accuracy : 98.28125
```

FIGURE 4.3.4: CONFUSION MATRIX FOR VGG-19

4.4 Experimental Result for Inception-v3 Model:

Accuracy depend on number of epoch. Here we used 15 epoch and from 12 to 15 epoch got the best accuracy.

```
Epoch 1/15
62/62 [==============================] - 892s 14s/step - loss: 26.9105 - accuracy: 0.5745 - val_loss: 0.3644 - val_accuracy: 0.9688
Epoch 2/15
62/62 [==============================] - 311s 5s/step - loss: 0.5232 - accuracy: 0.9537 - val_loss: 0.6792 - val_accuracy: 0.9453
Epoch 3/15
62/62 [==============================] - 311s 5s/step - loss: 0.3970 - accuracy: 0.9596 - val_loss: 0.4591 - val_accuracy: 0.9594
Epoch 4/15
62/62 [==============================] - 309s 5s/step - loss: 0.3914 - accuracy: 0.9708 - val_loss: 0.9174 - val_accuracy: 0.9297
Epoch 5/15
62/62 [==============================] - 309s 5s/step - loss: 0.2117 - accuracy: 0.9796 - val_loss: 0.6863 - val_accuracy: 0.9563
Epoch 6/15
62/62 [==============================] - 310s 5s/step - loss: 0.2384 - accuracy: 0.9704 - val_loss: 0.7307 - val_accuracy: 0.9484
Epoch 7/15
62/62 [==============================] - 310s 5s/step - loss: 0.3361 - accuracy: 0.9718 - val_loss: 0.3096 - val_accuracy: 0.9672
Epoch 8/15
62/62 [==============================] - 309s 5s/step - loss: 0.1038 - accuracy: 0.9898 - val_loss: 0.3773 - val_accuracy: 0.9672
Epoch 9/15
62/62 [==============================] - 309s 5s/step - loss: 0.1873 - accuracy: 0.9808 - val_loss: 0.4297 - val_accuracy: 0.9563
Epoch 10/15
62/62 [==============================] - 309s 5s/step - loss: 0.1843 - accuracy: 0.9771 - val_loss: 0.8394 - val_accuracy: 0.9375
Epoch 11/15
62/62 [==============================] - 310s 5s/step - loss: 0.2325 - accuracy: 0.9787 - val_loss: 0.3915 - val_accuracy: 0.9719
Epoch 12/15
62/62 [==============================] - 309s 5s/step - loss: 0.0388 - accuracy: 0.9951 - val_loss: 0.1391 - val_accuracy: 0.9828
Epoch 13/15
62/62 [==============================] - 309s 5s/step - loss: 0.0481 - accuracy: 0.9950 - val_loss: 0.5262 - val_accuracy: 0.9719
Epoch 14/15
62/62 [==============================] - 309s 5s/step - loss: 0.1052 - accuracy: 0.9874 - val_loss: 0.5439 - val_accuracy: 0.9625
Epoch 15/15
62/62 [==============================] - 309s 5s/step - loss: 0.0972 - accuracy: 0.9897 - val_loss: 1.1640 - val_accuracy: 0.9422
```

FIGURE 4.4.1: ACCURACY FOR INCEPTION-V3.

We noticed higher difference between the curves in the beginning and train accuracy curve increased dramatically whereas a lower difference in final progression.

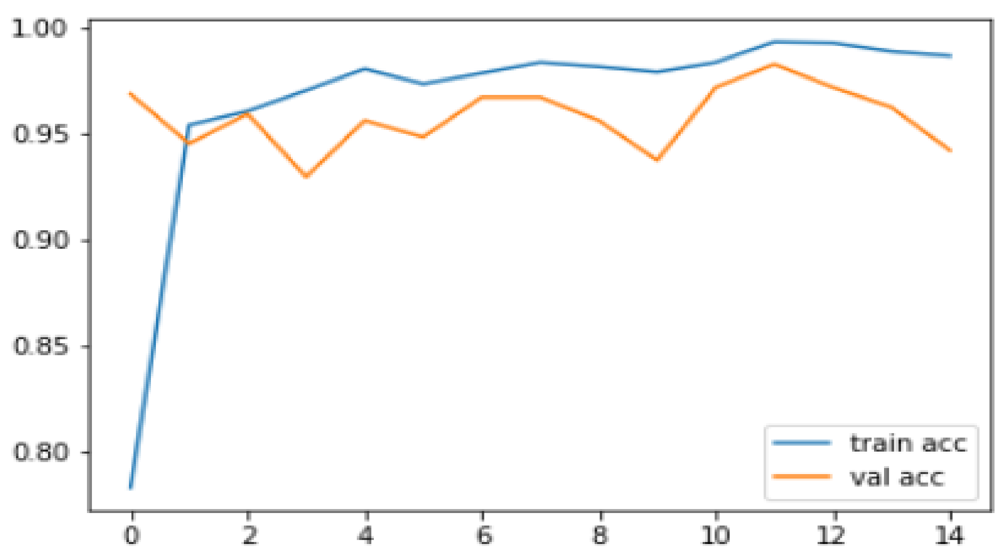


FIGURE 4.4.2: TRAIN VS VALIDATION ACCURACY PLOT FOR INCEPTION-V3

Train loss decreased dramatically after that there is no noticeable train loss however validation loss curve fluctuated immensely.

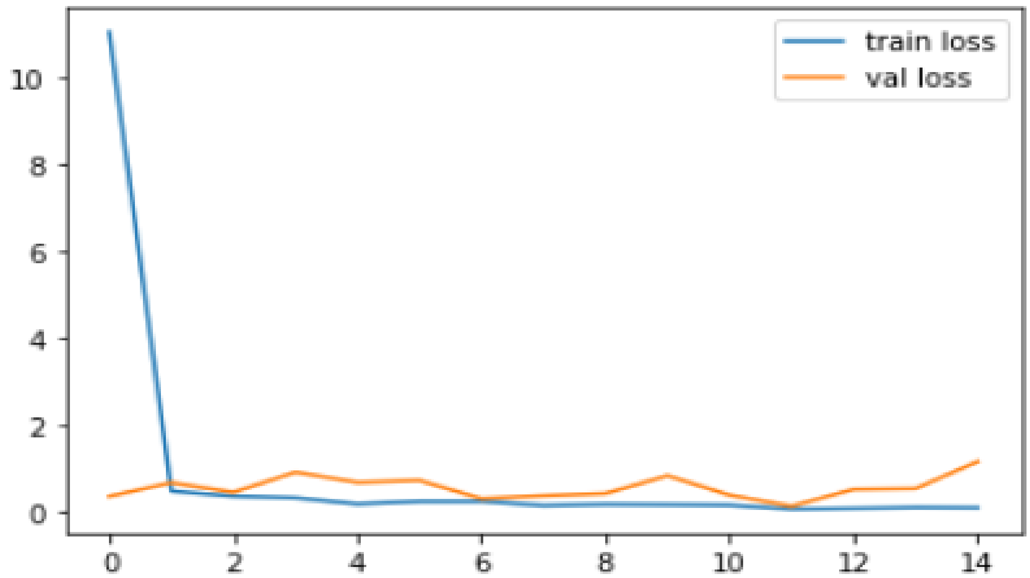
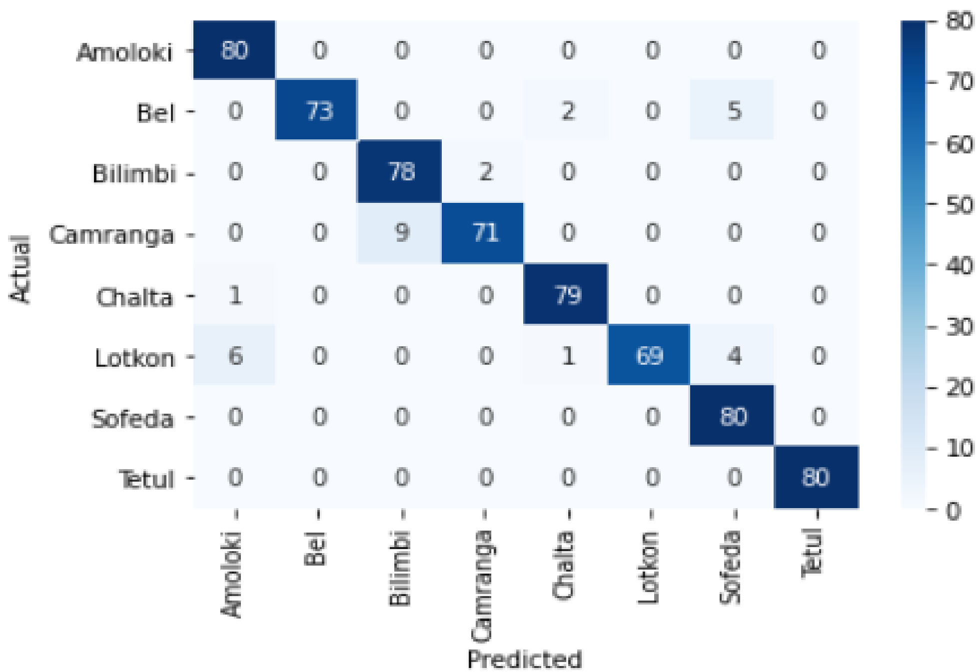


FIGURE 4.4.3: TRAIN VS VALIDATION LOSS PLOT FOR INCEPTION-V3

Confusion Matrix:




```
test accuracy : 95.3125
```

FIGURE 4.4.4: CONFUSION MATRIX FOR INCEPTION-V3

4.5 Experimental Result and Analysis for ResNet-50 Model:

Accuracy depend on number of epoch. Here we used 10 epoch and got training and validation accuracy.

```
Epoch 1/10
62/62 [==============================] - 928s 15s/step - loss: 20.3468 - accuracy: 0.1374 - val_loss: 2.0865 - val_accuracy: 0.3578
Epoch 2/10
62/62 [==============================] - 468s 8s/step - loss: 2.1877 - accuracy: 0.2422 - val_loss: 1.9404 - val_accuracy: 0.3484
Epoch 3/10
62/62 [==============================] - 468s 8s/step - loss: 1.7685 - accuracy: 0.3797 - val_loss: 1.5270 - val_accuracy: 0.4625
Epoch 4/10
62/62 [==============================] - 467s 8s/step - loss: 1.6642 - accuracy: 0.4090 - val_loss: 1.6069 - val_accuracy: 0.4500
Epoch 5/10
62/62 [==============================] - 467s 8s/step - loss: 1.8278 - accuracy: 0.3985 - val_loss: 1.5120 - val_accuracy: 0.4359
Epoch 6/10
62/62 [==============================] - 467s 8s/step - loss: 1.5108 - accuracy: 0.4657 - val_loss: 1.5906 - val_accuracy: 0.4531
Epoch 7/10
62/62 [==============================] - 475s 8s/step - loss: 1.5274 - accuracy: 0.4452 - val_loss: 1.4250 - val_accuracy: 0.5219
Epoch 8/10
62/62 [==============================] - 470s 8s/step - loss: 1.3609 - accuracy: 0.4917 - val_loss: 1.7392 - val_accuracy: 0.4359
Epoch 9/10
62/62 [==============================] - 471s 8s/step - loss: 1.3924 - accuracy: 0.4791 - val_loss: 1.5491 - val_accuracy: 0.4453
Epoch 10/10
62/62 [==============================] - 471s 8s/step - loss: 1.2799 - accuracy: 0.5205 - val_loss: 1.4128 - val_accuracy: 0.5016
```

FIGURE 4.5.1: ACCURACY FOR RESNET-50.

Noticeable difference between two curves whereas validation accuracy fluctuated immensely and train accuracy increased gradually.

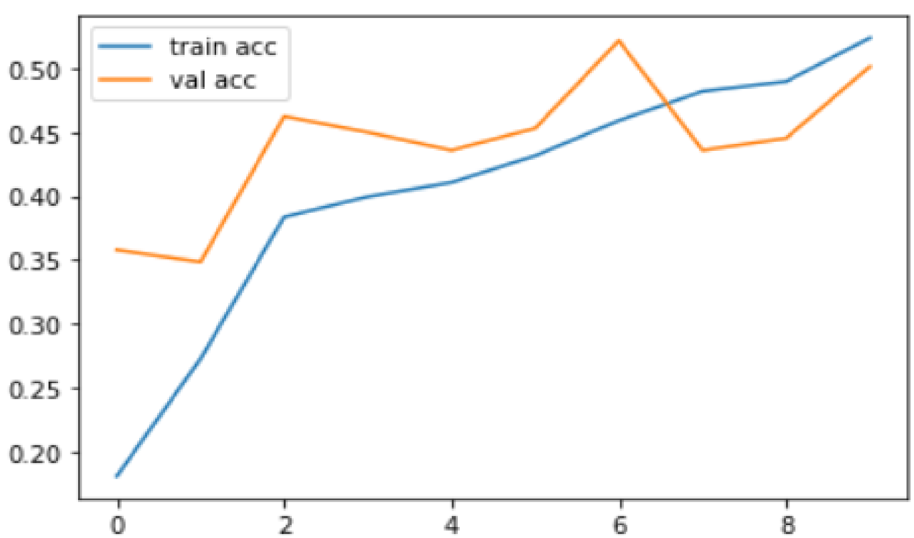


FIGURE 4.5.2: TRAIN VS VALIDATION ACCURACY PLOT FOR RESNET-50

Train loss decreased in the beginning after that in final progression train loss and validation loss remains same.

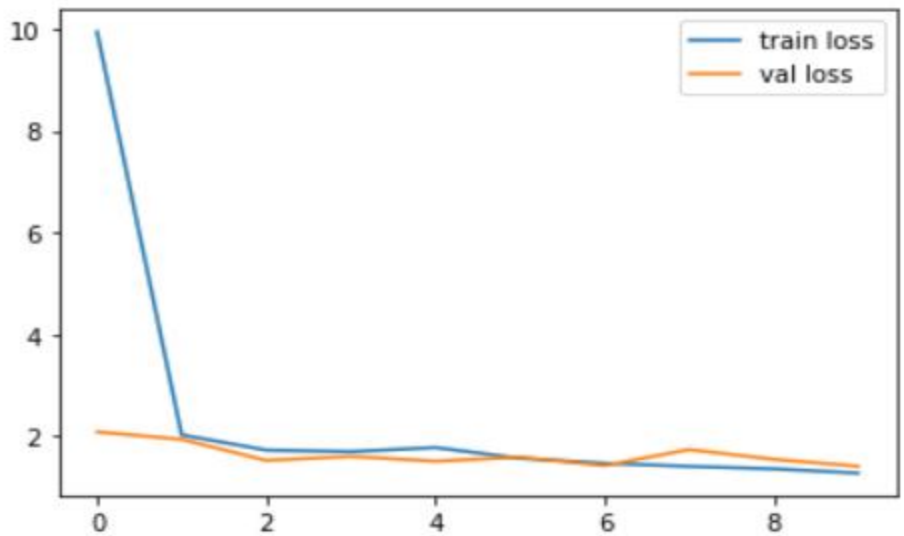
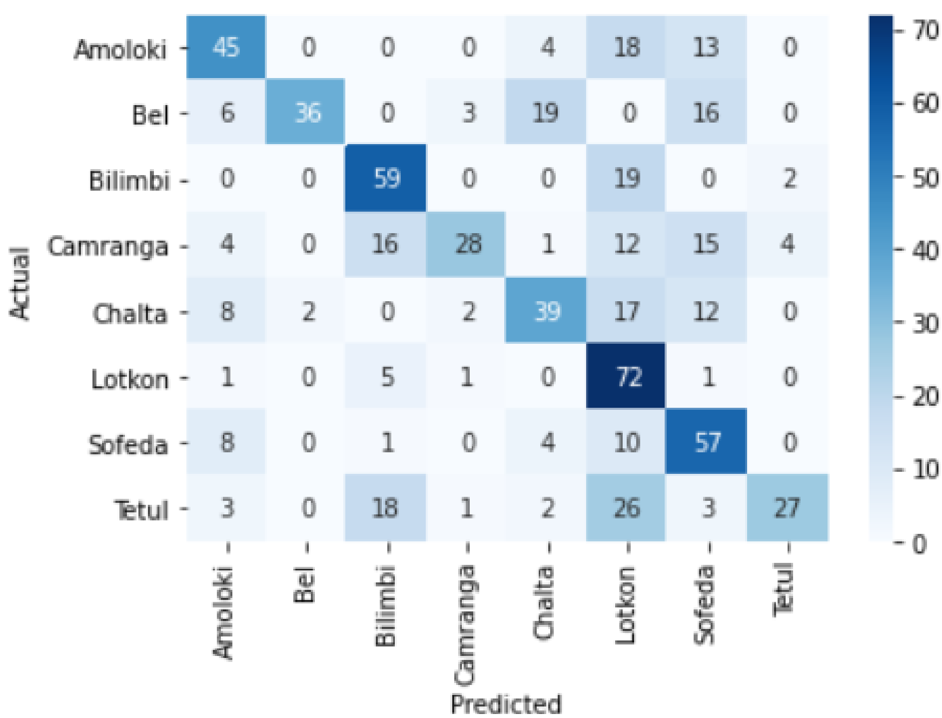


FIGURE 4.5.3: TRAIN LOSS VS VALIDATION LOSS PLOT FOR RESNET-50

Confusion Matrix:



test accuracy : 56.71874999999999

FIGURE 4.5.4: CONFUSION MATRIX FOR RESNET-50

4.6 Discussion:

After completing our research we can say that, to fruit classification we used four popular models on our dataset and came up with a solution that MobileNet has the best accuracy between those four models.

For MobileNet, evaluating the confusion matrix we identified Bilimbi, Camranga, Lotkon, Tetul accurately. We can see it falsely predicted 1 out of 80 Amaloki for Lotkon, 1 out of 80 Bel for Lotkon, 2 out of 80 Chalta for Lotkon and 1 out of sofeda for Lotkon. From this model we got accuracy rate of 99.22% for our dataset.

For VGG-19, evaluating confusion matrix we accurately identified Bilimbi and Tetul but falsely predicted 4 out of 80 Amaloki for 1 bel, 2 Lotkon and 1 Tetul, 1 out of 80 Bel for Sofeda, 1 out of 80 Camranga for Bilimbi, 1 out of 80 chalta for Bel, 3 out of 80 Lotkon for 1 Amoloki and 2 Bel, 1 out of 80 Sofeda for Lotkon. From this model we got accuracy rate of 98.28% for our dataset.

For Inception-v3, the model accurately identified Amoloki, Sofeda and Tetul but falsely predicted 7 out of 80 Bel for 2 Chalta and 5 Sofeda, 2 out of 80 Bilimbi for Camranga, 9 out of 80 Camranga for Bilimbi, 1 out of 80 chalta for Amoloki, 11 out of 80 Lotkon for 6 Amoloki, 1 Chalta and 4 Sofeda. From this model we got accuracy rate of 95.31% for our dataset.

For ResNet-50, this model is not perfect for our dataset, because it was unable to find any the local fruit from our dataset accurately.it falsely predicted 35 out of 80 Amoloki for 4 Chalta, 18 Lotkon and 17 Sofeda, 44 out of 80 Bel for 6 Amoloki, 3 Camranga, 19 Chalta and 16 Sofeda, 21 out of 80 Bilimbi for 19 Lotkon and 2 Tetul, 52 out of 80 Camranga for 4 Amoloki, 16 Bilimbi, 1 Chalta, 12 Lotkon, 15 Sofeda and 4 Tetul, 41 out of 80 chalta for 8 Amoloki, 2 Bel, 2 Camranga, 17 Lotkon and 12 Sofeda, 8 out of 80 Lotkon for 1 Amoloki, 5 Bilimbi, 1 Camranga and 1 Sofeda. 23 out of 80 Sofeda for 8 Amoloki, 1 Bilimbi, 4 Chalta and 10 Lotkon, 53 out of 80 Tetul for 3 Amoloki, 18 Bilimbi, 1

Camranga, 2 Chalta, 26 Lotkon and 3 Sofeda. From this model we got poor accuracy rate of 56.72% for our dataset.

At the end we came to conclusion that, with 99.22% accuracy rate MobileNet model work better than other models for our dataset.

CHAPTER 5
CONCLUSIONS, LIMITATIONS AND FUTERE WORKS

Conclusion: Nowadays deep learning is one of the most popular process for image classification and recognition because without any human supervision it automatically detects the important features. In our research we used some deep learning model as like MobileNet, VGG-19, Inception-v3 and ResNet-50 for Local fruits classification and recognition. Among all those models three of them achieved very impressive test accuracy rate of above 95%. Comparing those models MobileNet achieved the best test accuracy rate of 99.22%. In fruits classification and recognition this type of higher accuracy will help to stimulate the overall performance of the machine more adequately.

Limitations:

1. Due to this covid-19 pandemic situation we could not enough data for our project.
2. We work with only four algorithms but there are so many algorithms that can be used for our project.

Future works: Due to this Pandemic we only able use eight different type of local fruits for our research but in future we want to do our research with more local fruits. In our research we only used four model and 3240 local fruit images but we can achieve better result if we use more data and models in future. Based on our research we wanted to make a mobile application for local fruits detection but we were able complete only research based project because due to this pandemic we were unable to collect sufficient data and resource to make a mobile application. So in future our goal is to make a mobile application which can detect different kind of local fruits.

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