AN EFFICIENT FRUIT RECOGNITION APPROACH FOR PREGNANT WOMEN USING DEEP CONVOLUTIONAL NEURAL NETWORKS

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APPROVAL

This Project titled "**An Efficient Fruit Recognition Approach for Pregnant Women using Deep Convolutional Neural Networks**", submitted by Md. Jannat UL Naim, Shahed Mahamud Lemon and Md. Abdur Rahman Shuvo 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 4 January 2022.

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We hereby declare that, this project has been done by us under the supervision of **Aniruddha Rakshit, 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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ABSTRACT

Pregnancy is a period when women require extra care. It is necessary to make sure optimal nutritional level and a well-balanced diet. However, it is regrettable that a huge percentage of the Bangladeshi population is unaware of this issue. New mothers, in particular, who have no prior experience with this situation, suffer the most. During this time, an imbalance of nutrition and inappropriate fruit consumption might lead to major pregnancy complications. We used a deep learning approach called Convolutional neural network (CNN) to classify and recognize different types of fruit to solve this problem. Our eight fruit classes have been divided into two primary categories based on whether they are beneficial or avoidable. We gathered information about fruit consumption during pregnancy from gynecologists and various health articles and journals on the internet. People will learn what fruits they should eat and what fruits they should avoid from our eight fruit classes by reading our paper. We deployed two pre-trained CNN models, VGG19 and MobileNetV2, to complete this task. We received our result after running these two models on our collect dataset. We achieved a training accuracy of 94.06 % and a testing accuracy of 93.43 % for VGG19. In MobileNetV2, on the other hand, we achieved accuracy of 90.12 % for training and 89.05 % for testing. VGG19 requires less time than MobileNetV2 during the training phase.

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Introduction

1.1 Introduction

In the deep learning field, Convolutional neural network (CNN) has become the most used image recognition and classification approach. This approach is capable of handling large amounts of data with higher efficiency. We may train our system using a deep learning technique by extracting visual imagery data. There are numerous deep learning algorithms that may be utilized to handle various image classification problems. To achieve a better accuracy, deep learning algorithms must be properly trained and tested.

Pregnancy is a period when a woman's health needs to be prioritized. Being irresponsible might have negative consequences for both the mother and the baby. Women in Bangladesh are unaware of the importance of nutrition during pregnancy. Because of their illiteracy and poverty, a large portion of the country's population is affected. The majority of women are unconscious of their eating habits. In reality, they have no idea what to consume or avoid during this time. Fresh fruits contain a variety of nutrients that pregnant women should take to avoid malnutrition. Around 75% of mothers believe that malnutrition in the mother is the primary cause of malnutrition in children [1]. Aside from that, several fruits have a negative impact during this time. This type of fruit is harmful to a baby's growth and development. This can sometimes result in a miscarriage [2].

TABLE 1: FRUIT CHART FOR CLASSIFICATION

Fruit to eat	**Fruit to avoid**
Orange	Pineapple
Mango	Papaya
Apple	Grapes
Banana	Tamarind

We applied two different Convolutional neural network architectures to classify and recognize two different fruit categories in this paper. When compared to other methodologies, CNN generates significantly higher accuracy in terms of visual imaging data.

1.2 Motivation

As we all know, women require special attention during pregnancy. Women need to know if the food they consume is healthy or not in order to maintain a nutritional balance. It is essential at this time to ensure that they are receiving a nutritious food chart. They can include some foods, fruits, or vegetables in this chart for nutritional balance. There are a plenty of affordable fruits all around us. However, very few of these fruits are safe for a pregnant woman or her unborn child. Fruits which are high in calcium, iron, Vitamin A, C, D, B12, and folic acid are wise choices for women during this time [3]. Apart from latex-containing fruits, enzymes and fruits which generate heat in the mother's body must be avoided [4]. Therefore, in this study, we're trying to solve this difficulty by categorizing various fruits into two groups. This paper will show whether some fruits are healthy or harmful to pregnant women. As a result, we've decided to use a deep learning approach to solve this problem by classifying and recognizing fruits for pregnant women.

1.3 Objective

We will use a Convolutional Neural Network in our research to classify and recognize different type of fruit classes from two main categories. There is a lot of research on fruit or food classification in this sector, but there is relatively little work on this. CNN is more optimized than other image classification methods due to automatic learning with relatively less pre-processing. Large-scale imagery data can be distinguished from one another using this deep learning approach.

Because of its simple architecture and high efficiency rate, CNN is now playing a major role in the field of image classification. On our collected dataset, we are using two models based on CNN architecture: VGG19 and MobileNetV2. VGG19 which is a VGG model variation of 16 convolution layers and 3 fully connected layers, as well as it has many other variant. On the other side, we used MobileNetV2 to adapt the architecture to mobile devices, which includes a fully convolutional layer. Additionally, this model is compatible with nearly every platform. We have choose to work with this deep learning model after analyzing these perspectives.

1.4 Expected Outcome

We worked on this research paper to classify various fruits and separate them into two categories, which will guide pregnant ladies in making the best fruit consumption choices possible. They will be able to keep a healthy nutrition practice as a result of this, which will benefit the baby's growth and development. Our research will also assist them in avoiding fruits that are harmful to the nutrition and health of mothers and babies. This research will also assist people in understanding more about deep learning techniques for image classification and recognition. Especially for new mothers who have no prior knowledge of pregnancy nutrition. The fruits we mentioned in our paper were from the perspective of Bangladesh, however there are many regional fruits all across the world.

1.5 Report Layout

Here in this report, we proposed CNN models for fruit image recognition and classification, this contains 6 parts which are given below:

Chapter 1: Introduction

In this chapter, we briefly explain the introduction part of the research work of its motivation, objectives, and expected outcome.

Chapter 2: Background Study

In this part we discussed about the literature review, research summary, the scope of the problem, and challenges for this paper.

Chapter 3: Research Methodology

Here we explained about the workflow of the research, Data collection procedure and implementation part.

Chapter 4: Experimental Results and Discussion

In this part we discussed about the result and outcome along with graphical representation.

Chapter 5: Impact on Society, Environment, and Sustainability

We covered the impact of our research on our society in this chapter.

Chapter 6: Conclusion

In this chapter we summarized our whole research work and future work as well.

CHAPTER 2

Background Study

2.1 Introduction

This chapter will cover the literature review, research summary, scope of the problem, and all of the obstacles we experienced during our study. We discussed the methodologies, classifiers, and accuracies of their work in the literature review chapter by summarizing some research publications relevant to our work. We covered other related paper works and their drawbacks in the research summary section. In the scope of the problem chapter, we explained how we can figure out the problem utilizing our CNN approach. We also mentioned the obstacles we met during our research work in the challenges chapter.

2.2 Literature Review

Many studies have been conducted using a deep learning approach to classify and recognize images. Many researchers use Convolutional Neural Network to explain their work in object recognition.

RP Prasetya et al. [5] introduced a Convolutional neural network using InceptionV3 architecture to recognize and classify several type of Indonesian food. The proposed CNN method produce an accuracy of 70% by using 500 times iteration process. For future work, increasing the number of iteration and learning rate as well as computational process can be run longer. And also using other recognition methods may decrease error level of recognition.

Ke Dong et al. [6] proposed a image classification model where they compared MobileNetV2 model with MobileNetV1 with respect to a variety of datasets extracted from TensorFlow. Here they implementing MobileNetV2 and MobileNetV1 with multiple datasets for image classification where they got 88.60% accuracy of MobileNetV1 and 89.00% accuracy of MobileNetV2 model. MobileNetV2 model achieves better accuracy. In future by expending datasets, image classification can be improved.

Md Tohidul Islam et al. [7] proposed a Convolutional neural network to classify food images by extracting spatial characteristics from image. To analyze any visual imagery CNN works very efficiently. Comparing all the model Inception V3 performed better and get the higher accuracy of 92.86% because of it's because of the pre-training on the imagenet. In future this can be collaborate with mobile application. Training with more category of food will get more accurate result also help us to classify food even if the food name is not captioned.

Keiji Yanai et al. [8] proposed a deep convolutional neural network (DCNN) to examine the effectiveness for food recognition with the help of Pre-training and Fine-Tuning on twitter photo data. They have applied pre-training with a large-scale of ImageNet data and pre-trained with Fine-tuning as well. By this model they got highest accuracy of 78.77% and 67.57%, it was time efficient as well. They have found that DCNN provide better accuracy for large scale image data. For future work bringing this into mobile device based on the proposed framework.

Narit Hnoohom et al. [9] proposed a model using deep learning process that was trained on natural images to predict Thai fast food (TFF). They used the dataset with eleven groups of food images where they deep learning algorithms in order to address the problem of TFF classification in differing dishes, backgrounds, and locations. They got 88.33% classification average accuracy on the TFF dataset. For future work more real-time classification should include with mobile application.

David J. Attokaren et al. [10] proposed an approach using convolutional neural networks to classify images of food .They used Max-Pooling function to reduces variance and computational complexity. They got the accuracy of 86.97%. In future using prominent features the task of image classification can be extended where feature-based approach is highly appreciable.

Takumi Ege et al. [11] proposed a multi-task CNN to categorized food and ingredients based on calorie by using two kind of dataset of Japanese and American recipe. The proposed model is based on VGG-16 architecture which used for solving image classification problem. They have compared between single-task and multi-task CNN, they have got better accuracy of 80% on multi-task CNN. In future work, more accurate calorie estimation is needed and high quality dataset may also produce better accuracy.

Rajesh Yamparala et al. [12] introduce a convolutional neural network (CNN) to classify various kind of fruits and applied Segmentation, Classification, Filtering to detect the specific fruit. They have compared CNN with PNN and BPNN then got the outcome. By applying this method they got highest accuracy of 90% which is better comparing other methodologies till that time. Extending the number of varieties of fruits can be a wise choice to increase the accuracy for proposed methodology.

Qian Xiang et al. [13] proposed a classification method to recognize fruit images based on a lightweight neural network MobileNetV2 pre-trained by ImageNet dataset where they replace the top layer of the base network with a conv2d layer and a Softmax classifier. They got accuracy of 85.12% in their dataset. To get more accuracy there can be added more data in future.

Sapna Yadav et al. [14] proposed an automated food image classification techniques based on two deep learning approach SqueezeNet and VGG-16 Convolutional Neural Networks for food image classification. They used the dataset Food-101 and choose 10 category of Indian food. After implementation they have got better accuracy of 85.07% in VGG-16 which is better than SqueezeNet because of the network depth. If we increase the depth of the network or layer then it will generate greater accuracy than the proposed model. Increasing the number of iteration may affect the accuracy as well.

MA Subhi et al. [15] proposed a modified Convolutional neural network(CNN) approach which has 24 layers to detect and recognize image using a dataset of local Malaysian food items. This model has 21 convolutional layers and 3 fully connected layers. By using the proposed model they have got better output. In future work, using more layer may provide better output.

Duc Thanh Nguyen et al. [16] proposed food image classification methods where they used both non-redundant local binary pattern (NRLBP) and global structural information of food objects. In three steps, they used integrating appearance and structural information to describe and classify the food images. They got 68% and 69% of accuracy respectively for

NRLBP and global structural information. This combine model improve the food image classification. For future work food images from different viewpoints, developing view invariant texture features would give better output.

Thuan Trong Nguyen et al. [17] introduced a modified CNN model called EfficientNet-B0 to classify differ kind of food from a dataset named VinaFood21. In this paper they work on some pre-trained CNN model and their proposed model. They have observed that their proposed EfficientNet-B0 model outperformed than other model with accuracy of 74.81%. In future extending more data and improving model may generate better output.

S Christodoulidis et al. [18] proposed a modified CNN architecture to classify and recognize food over a dataset which was collected from Inselspital at Switzerland. The proposed model based on 6-layer deep convolutional neural network. They have got 84.9% accuracy on their proposed model. For future study purpose, one should go through with optimal architecture and parameter with the network.

José Naranjo-Torres et al. [20] proposed a CNN-based approaches for fruit classification, fruit quality control and fruit detection. Where they used some pre-trained model and the proposed example and got accuracy of an average accuracy of 81.25% with an average F1-score of 0.87. By increasing the amount of data using more complex models more accuracy can be achieved in future.

Tao Zhao et al. [21] proposed a deep learning techniques using convolutional neural networks (CNNs) to fault detection problems on seismic data in Great South Basin, offshore New Zealand. They worked on a fault detection workflow using both CNN and directional smoothing/sharpening based on the SEAM (SEG Advanced Modeling) model. Here the results of CNN and regularization provide clean fault planes with very little noise.

Amir Alipasandi et al. [22] proposed a system to classify three varieties of peach fruit using machine vision algorithms and Neural Network classifier. Where they classify them based on mature and immature fruits. They collected data at the Miandoab, west Azerbaijan, Iran, and for three peach cultivar and stage of growth 45 fruits which were randomly selected and processed using MATLAB.. They got the classification accuracy was 98.5% and 99.3% for mature and immature fruits respectively.

Monika Jhuria et al. [23] proposed a Image processing model using Artificial Neural Network to monitor the diseases on fruits during plantation to harvesting. They used two database where they kept one for training of already stored disease images band one for implementation of query images. They got 90% accuracy in their work. In future different metrics can be used to get better performance.

Xu Liming et al. [24] proposed a machine-vision technology where automated strawberry grading system can grade strawberries which can increase the commercial value based on three characteristics: shape, size and color. They have used K-means clustering method for the strawberry image and to sort the strawberry color they have used a* channel. They got the accuracy of color grading and shape classification is 88.8%and 90%. In future to get more accuracy more data with less error size can be implemented.

Hongshe Dang et al. [25] proposed a fruit size detecting and grading system based on image processing Here they have used the capture of a fruit side view image, several fruit characteristics are retrieved utilizing detecting algorithms.. Experiments reveal that this embedded grading system offers the benefits of high grading accuracy, fast speed, and cheap cost. In Future, it will have promising fields of fruit quality detection and grading.

2.3 Research Summary

Many image detection and classification works have been done earlier utilizing various data mining and deep learning methodologies. Convolutional neural network and their various types of models have previously demonstrated that they can perform tasks with higher accuracy and efficiency. We reviewed many types of image classification and detection using various types of visual imagery datasets in the literature review chapter. We have yet to come across any research work on our chosen topic. There are numerous studies on fruit classification and disease detection, but none on pregnant women's fruit preferences using deep learning during pregnancy. As a result of this observation, we can assume that there is no paper work that is directly compatible with this topic. According to the literature review, CNN outperforms and provides superior accuracy on several types of visual imagery data.

2.4 Scope of the Problem

After studying on many image recognition and classification related paper, we have discovered that their dataset wasn't compatible with their proposed model. The majority of the dataset has a lower rate of data. Aside from that, the amount of classes they used in their work wasn't enough to properly train their model. The majority of the work is based on the VGG-16 structure, which produces lower accuracy due to the usage of fewer layers. However, in order to solve these types of problems, researchers have developed some modified model that performs better than the prior model by adding more layers. These improved models are also capable of detecting images with greater accuracy than previous models. As a result, we've decided to develop on a deep learning model with more layers and that is more updated. We also have high hopes for this model's compatibility with modern technology.

2.5 Challenges

We were confused about choosing two different categories of fruits during data collection because we were working on fruit classification for pregnant women. Then we speak with a gynecologist to have a better understanding of the situation. When obtaining data from the internet, we ran into certain issues. Some of the images had poor resolution. There were also much too many duplicate and blurred image data on the internet. In order to improve accuracy, we also modified the traditional CNN architecture. But, in the end, we were able to overcome all obstacles and reach great accuracy. With new images, our Convolutional neural network models have also performed well.

CHAPTER 3

Research Methodology

3.1 Introduction

To detect and classify fruits for pregnant women, we developed a model that can detect and classify fruits in less time. We hope that it will assist all pregnant women in making fruit choices during their pregnancy. In our research, we used Convolutional Neural Network (CNN) model for this purpose. In addition, we used two pre-trained models in our research. Our working procedure is shown in the figure below (Fig. 3.1).

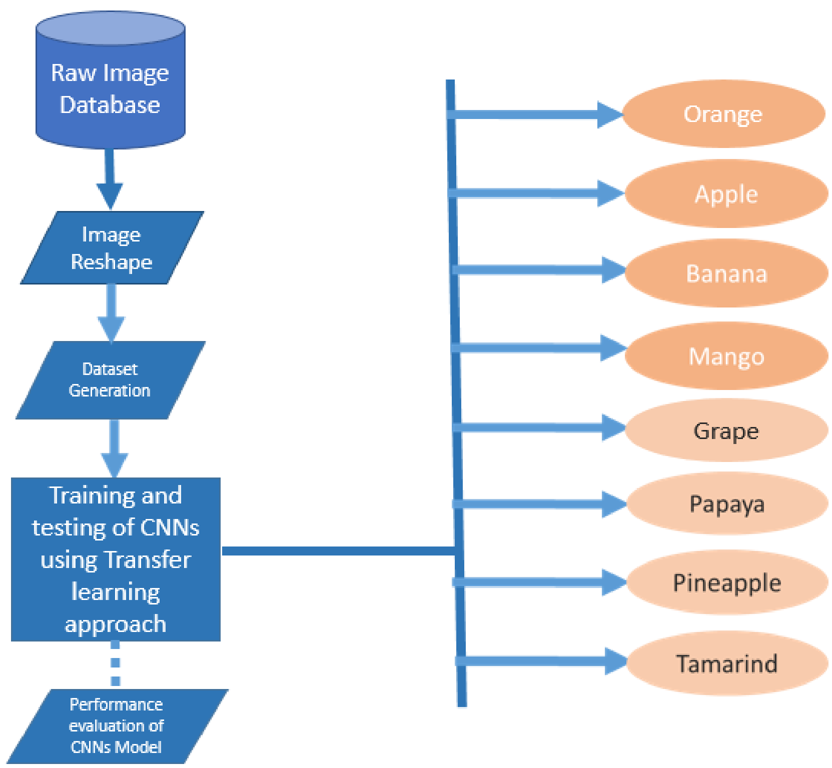

Fig. 3.1: Block diagram of this research methodology

The workflow of our entire project is represented in this diagram. The dataset is the most important part of any research project. Before we started collecting pictures, we did a lot of research on fruit nutrition for pregnant women. Following that, we gather images from the internet. In this chapter, we go over the various fruits that were mentioned previously, as well as a quick discussion of the data collection technique. In this chapter, we'll go through all of the theoretical information relevant to our research topic.

3.2 Fruit description

This was the most significant part of our research. It guides us on which fruits a pregnant woman should eat and which fruits she should avoid. Fruit contains a variety of vitamins, minerals, fiber, antioxidants, and other nutrients that benefit our bodies. However, during pregnancy, some of these fruits are harmful to both the mother and the baby.

We include four specific fruits in our list of beneficial fruits: oranges, apples, bananas, and mangos. These fruits are highly beneficial to a mother's health when she is pregnant, as they help in the development of the baby's growth. Because these fruits are high in calcium, iron, Vitamin A, C, D, B12, and folic acid, they meet the nutritional needs of the body.

Besides Papaya, Pineapple, Grape, and Tamarind were some of the fruits to avoid during pregnancy due to their negative effects. These fruits contain latex and enzymes, as well as generating heat in our bodies. Pregnancy-related problems can be caused by eating these fruits during pregnancy. Even consuming too much of these fruits can cause problems such as miscarriage.

Now the image of each of the eight classes is shown in the Fig. 3.2

Fruits to eat

Fruits to avoid

Fig. 3.2: Fruits to eat (Orange, Banana, Apple, Mango) and Fruits to avoid (Pineapple, Papaya, Grape, Tamarind)

3.3 Data Collection

We used a variety of internet source to get image data for eight different types of fruit. We had to choose images that were both fresh and clear while still maintaining good resolution. We gathered 2549 image data from eight different types of fruit, which were then categorized into two main categories.

3.4 Dataset Description

We used a total of 2549 images of various fruits in our research, which were classified into eight categories. Orange, Apple, Banana, Mango, Grape, Papaya, Pineapple, and Tamarind are the different classes. We used color images during the implementation process. In our research, we used images with a resolution of 224 x 224 pixels. In Table 3.1, list of distributions for each class of the collected dataset is given.

Table 3.1: The class-wise distribution of the collected images

Class Name	Frequency
Orange	472
Apple	319
Banana	211
Mango	266
Grape	404
Papaya	217
Pineapple	343
Tamarind	317
Total	2549

We used Pillow to resize all images to 224 × 224 pixels and reduces the resolution of all images. Pillow is a Python programming language library which can access, manipulate, and save a variety of image file formats with free access.

3.5 Statistical Analysis

We have a total of 2549 fruit images in our database. The number of fruits to consume was 1268, while the number of fruits to avoid was 1281, as shown as statistical representation at Fig. 3.3. The statistical value of each class for specific numbers of fruit is shown in Fig. 3.4.

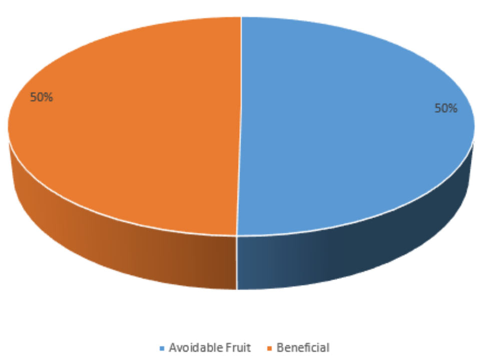

Fig. 3.3: Percentage of beneficial and avoidable images.

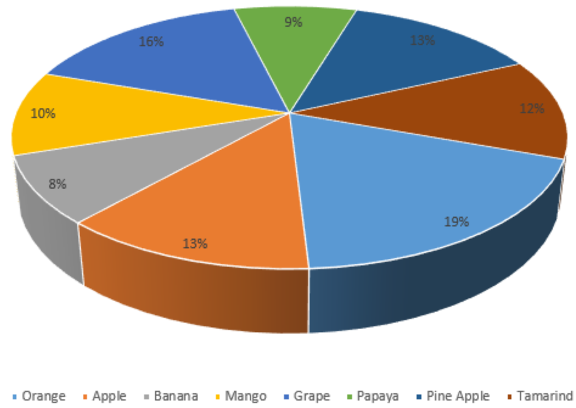

Fig. 3.4: Percentage of beneficial (Orange, Apple, Banana, Mango) and avoidable (Grape, Papaya, Pineapple, Tamarind) images.

3.6 CNN Model for Fruit Recognition

Because of its high efficiency rate, CNN is now the most widely used approach in the field of image recognition. Convolutional neural network (CNN) is a type of deep neural network that gained prominence after AlexNet was introduced in 2012. It was created with the goal of detecting and classifying visual imagery data with greater accuracy. The input layer, hidden layer, and output layer are the three layers that make up this system. Convolution and pooling are the two most important operations in CNN. It performs well in terms of designing on the input image, such as lines, gradients, and circles. This model can be used on any platform. With CNN's help, researchers are currently working on a variety of problems. CNN may decrease image dimension during image extraction without losing any features.

Feature extraction and classification are two key components of CNN. Images are sent into the convolutional layer, which extracts features from the image. For multiclass classification problems, softmax is employed to normalize the output of the neural network.

The convolutional operation helps with multiple filters to extract features from dataset. The number of kernels and their size are critical parameters in the convolution layer. It compresses the image in order to reduce the network's parameters. Pooling layers come after the convolution layer, which operates separately in each feature map

3.6.1 VGG19

VGG19 is a 16 convolutional layer and 3 fully connected layer convolutional neural network. We can load a pre-trained version of the network trained on over a million images from the ImageNet database using this architecture. This network has been pre-trained to classify images into 1000 different object categories. For instance, animals, meals, and vehicles. It has the ability to work with a large number of images while maintaining higher efficiency. This network use a 224 x 224 image size. This has a 3 x 3 kernel size and a 2 x 2 Max-Pooling size.

VGG19 is the most recent version of the VGG models. It has three more layers than the previous edition, allowing it to perform better. It also requires more memory than the previous. It allows CNN to perform a variety of complex tasks and to train machines more effectively. Comparing different CNN models VGG19 also requires less time.

3.6.2 MobileNetV2

MobileNetV2 is a convolutional neural network architecture that works well on mobile devices and other low-power computing systems. With the introduction of inverted residual structure, MobileNetV2 conquered. It maintains the parameters and mathematical operations while trying to keep them as minimal as possible. This condition provides us with the best amount of accuracy. MobileNetV2 is made up of two types of residual blocks: one with a stride of 1 and the other with a stride of 2. Both blocks have three levels. The first layer is a 1 x 1 convolution with ReLU6, the second is a depth wise convolution, and the third layer is a 1 x 1 convolution with no non-linearity [19].

MobileNetV2 provides a very efficient mobile-oriented model for object detection that can be used to detect and recognize various visual data. It provides a memory-friendly interface and simple operations which are more efficient.

3.6.3 Transfer learning

Transfer learning is a deep learning technique that involves training a neural network model on a problem that has previously been solved on a similar problem. We can utilize one or more layers to train new models to solve our desired problem using the train model. We can decrease the rate of error and training times by implementing transfer learning. Because they already know how to understand the features of the targeted problem, transfer learning delivers a more optimal solution than typical machine learning models.

3.7 Implementation Requirements

Images of fruits were gathered from the internet. After that, we utilized Jupyter Notebook to resize and lower the quality of the images. The quality of the images has been reduced due to RAM limitations. Our image dataset is stored in Google Drive. We use Google Colab to train our CNN models. We executed our research using Python 3.8.

3.8 Performance Metrics

We have used a confusion matrix and accuracy in our model for detection and recognition.

Now, to find the average recognition performance for our model,

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of prediction}}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$F1 - Score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

TP = True positive, TN = True negative, FP = False positive, FN = False negative

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction

For our project, we collected various types of fruit images from the internet and stored our dataset and models in a cloud storage. In order to train our model, we deployed a cloud-based notebook. We applied CNN techniques in our research to recognize and classify the fruits we discussed before. Using our VGG19 and MobileNetV2 models, we were able to achieve a good accuracy after implementation. Our pre-trained models can easily and quickly recognize fruits. We'll briefly discuss our experimental results in this chapter.

4.2 Experimental Results & Analysis

For this study, we used a dataset of 2549 images divided into eight class. We have trained our models using Google Colab. We used a transfer learning strategy to train two pre-trained models named VGG19 and MobileNetV2. We'll talk about our models and relevant information in the next few steps.

4.2.1 VGG19

The VGG19 architecture is based on deep learning. For our work, we applied a transfer learning approach. After 50 epochs of implementation, the VGG19 model obtained a training accuracy of 94.06 % and a test accuracy of 93.43 %. We utilized a 224 × 224 pixel input image size for the VGG19 model. For VGG19, we used Categorical Crossentropy as the loss function and Adam as the optimizer. Using scikit-learn's confusion matrix module, we created a confusion matrix. Fig 4.1 shows the VGG19 confusion matrix.

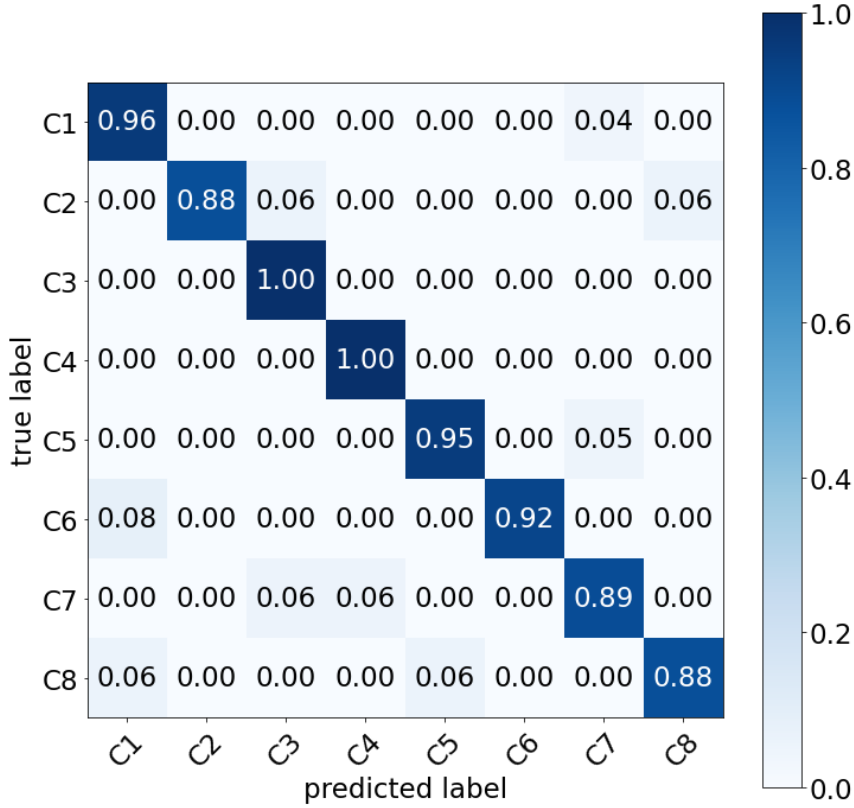

Fig. 4.1: Confusion Matrix of VGG19 model.

The confusion matrix reflects the effectiveness of our VGG19 model when applied to our new dataset. The performance of the VGG19 model is presented in Table 4.1 based on class-wise classification.

TABLE 4.1: CLASS-WISE CLASSIFICATION PERFORMANCE OF VGG19

Class	**Sensitivity**	**Specificity**	**Accuracy**	**Precision**
Orange	92.31%	99.10	97.81	96.00
Apple	100.0	98.36	98.54	88.24
Banana	85.71	100.0	98.54	100.0
Mango	93.75	100.0	99.27	100.0
Grape	95.24	99.14	98.54	95.24
Papaya	100.00%	99.21	99.27	91.67
Pineapple	88.89	98.32	97.08	88.89
Tamarind	93.75	98.35	97.81	88.24

The plot graph of the VGG19 is shown below in Fig. 4.2.

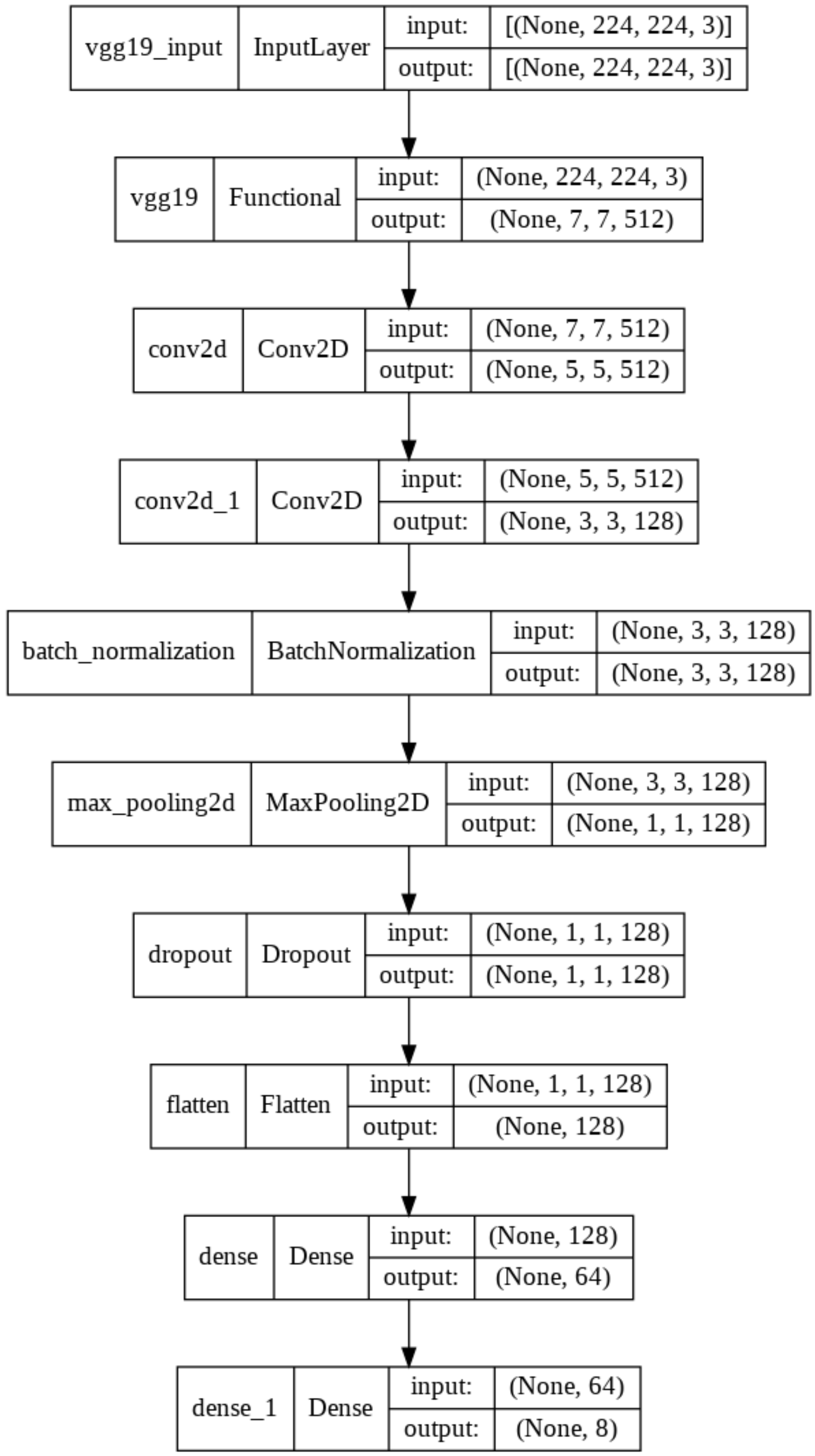

Fig. 4.2: Plot of VGG19 model.

There are 22,983,432 params with non-trainable params in VGG19. Model summary of VGG19 is given in Fig 4.3.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg19 (Functional)          (None, 7, 7, 512)         20024384

 conv2d (Conv2D)             (None, 5, 5, 512)         2359808

 conv2d_1 (Conv2D)           (None, 3, 3, 128)         589952

 batch_normalization (BatchN  (None, 3, 3, 128)        512
 ormalization)

 max_pooling2d (MaxPooling2D  (None, 1, 1, 128)        0
 )

 dropout (Dropout)           (None, 1, 1, 128)         0

 flatten (Flatten)           (None, 128)               0

 dense (Dense)               (None, 64)                8256

 dense_1 (Dense)             (None, 8)                 520

=================================================================
Total params: 22,983,432
Trainable params: 7,678,408
Non-trainable params: 15,305,024
_________________________________________________________________
```

Fig. 4.3: Model Summary of VGG19.

Fig 4.4 and Fig 4.5 represents the accuracy and loss of training and validation for VGG19.

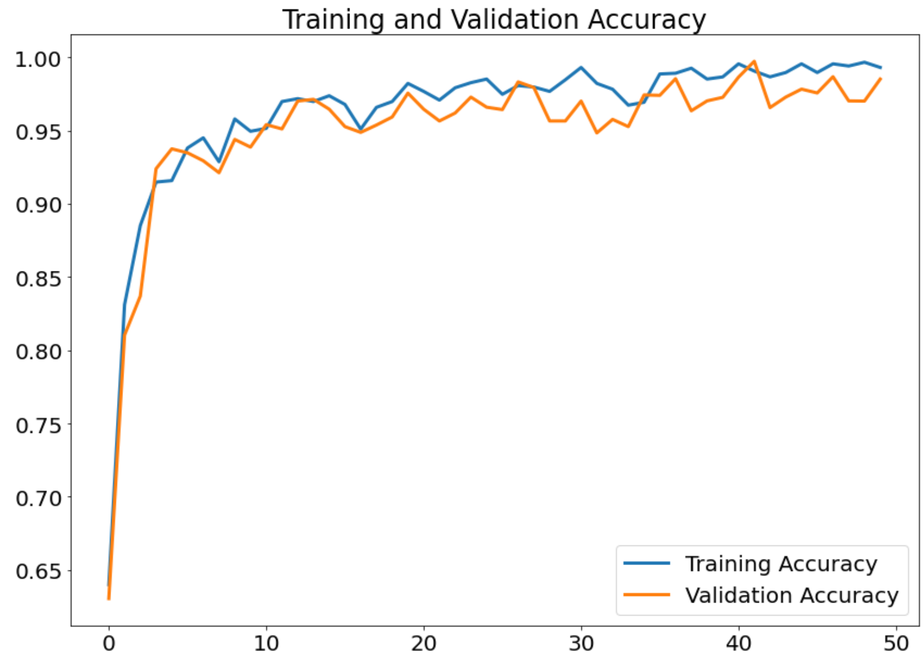

Fig. 4.4: Training accuracy vs. validation accuracy of VGG19.

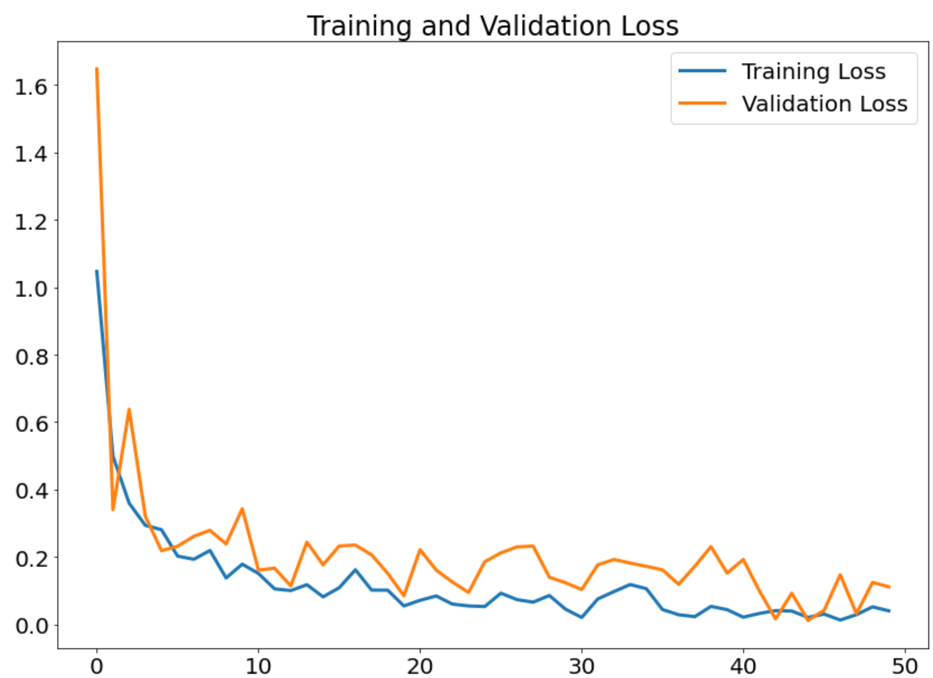

Fig. 4.5: Training loss vs. validation loss of VGG19.

4.2.2 MobileNetV2

MobileNetV2 is a mobile-friendly convolutional neural network model. In this model, we've used the transfer learning method. We used a 224 × 224 pixel input size for our images. We have gained training and testing accuracy of 90.12% and 89.05% respectively after 50 epochs. Adam was our optimizer during implementation, and the loss function was Categorical Crossentropy. A confusion matrix was created using scikit-learn's confusion matrix module. In Figure 4.6, you can see the confusion matrix for MobileNetV2.

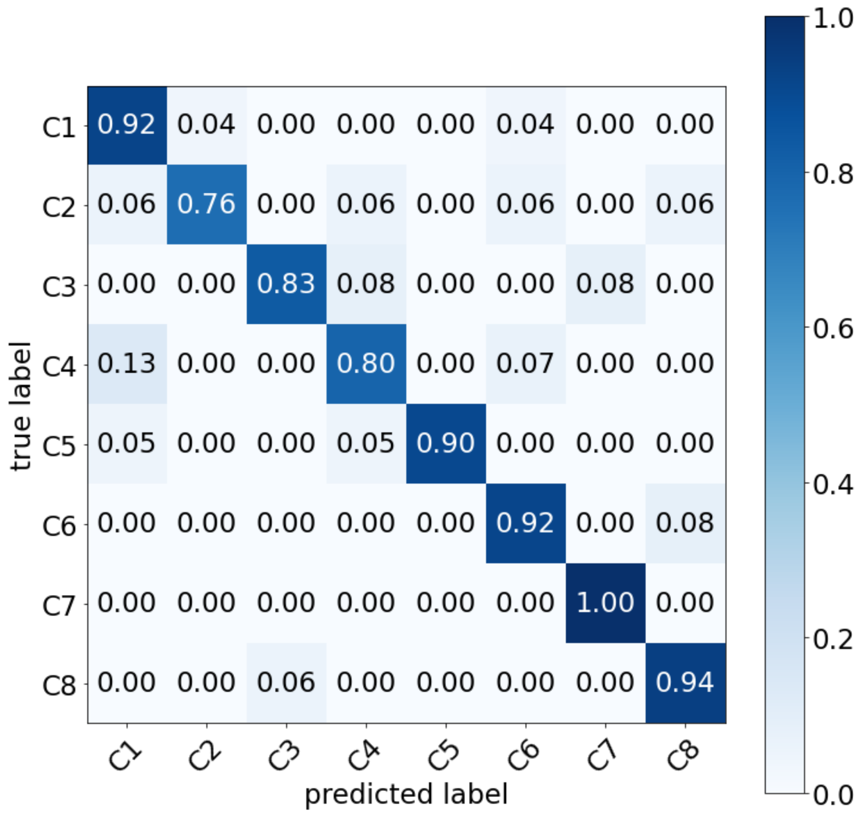

Fig. 4.6: Confusion Matrix of MobileNetV2 model

Our MobileNetV2 model's performance is reflected in the confusion matrix. Table 4.2 shows the performance of the MobileNetV2 model based on class-wise classification.

TABLE 4.2: CLASS-WISE CLASSIFICATION PERFORMANCE OF MOBILENETV2

Class	**Sensitivity**	***Specificity***	**Accuracy**	**Precision**
Orange	85.19	98.18	95.62	92.00
Apple	92.86	96.75	96.35	76.47
Banana	90.91	98.41	97.81	83.33
Mango	80.00	97.54	95.62	80.00
Grape	100.00	98.31	98.54	90.48
Papaya	78.57	99.19	97.08	91.67
Pineapple	94.74	100.00	99.27	100.00
Tamarind	88.89	99.16	97.81	94.12

The plot graph of the MobileNetV2 is shown in Fig 4.7

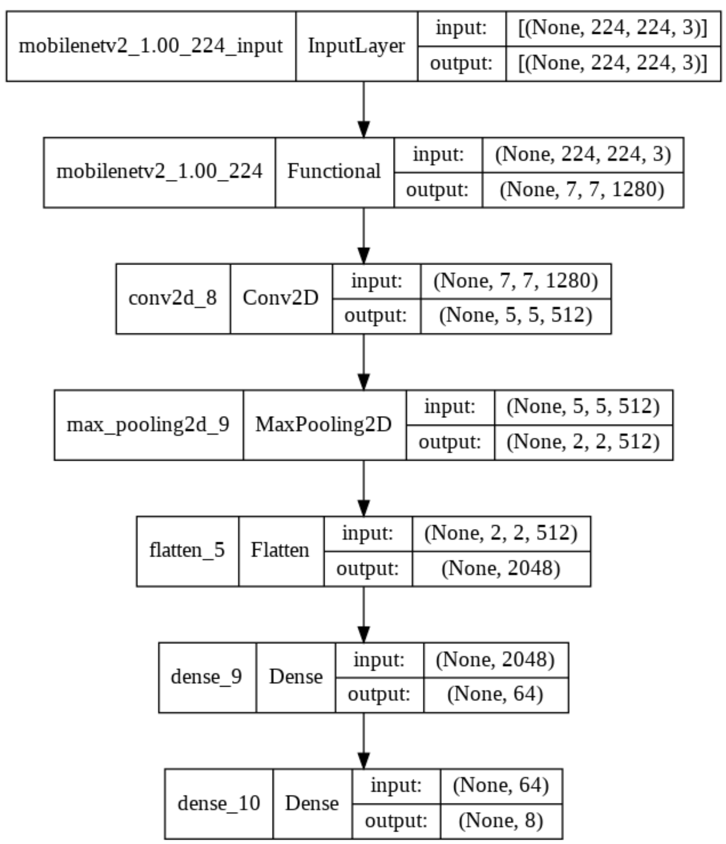

Fig. 4.7: Plot of MobileNetV2 model

MobileNetV2 has 8,288,392 params with non-trainable params. Model summary of MobileNetV2 is given in Fig 4.8

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 mobilenetv2_1.00_224 (Funct  (None, 7, 7, 1280)       2257984
 ional)

 conv2d_8 (Conv2D)           (None, 5, 5, 512)         5898752

 max_pooling2d_9 (MaxPooling  (None, 2, 2, 512)        0
 2D)

 flatten_5 (Flatten)         (None, 2048)              0

 dense_9 (Dense)             (None, 64)                131136

 dense_10 (Dense)            (None, 8)                 520

=================================================================
Total params: 8,288,392
Trainable params: 8,198,792
Non-trainable params: 89,600
_________________________________________________________________
```

Fig. 4.8: Model Summary of MobileNetV2

The accuracy and loss of training and validation for MobileNetV2 is shown in Fig 4.9 and Fig 4.10 respectively.

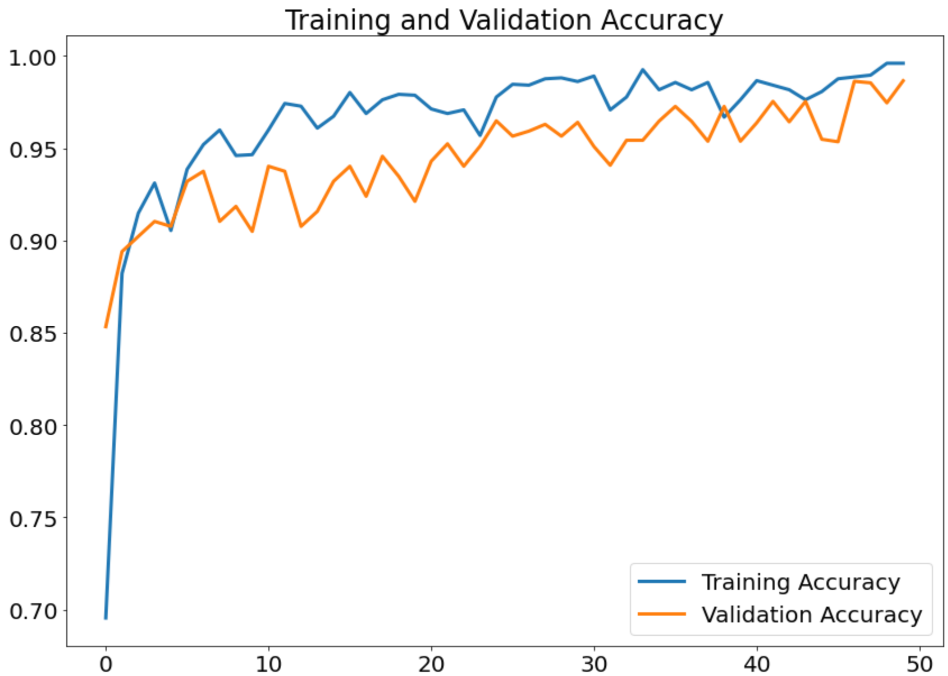

Fig. 4.9: Training accuracy vs. validation accuracy of MobileNetV2.

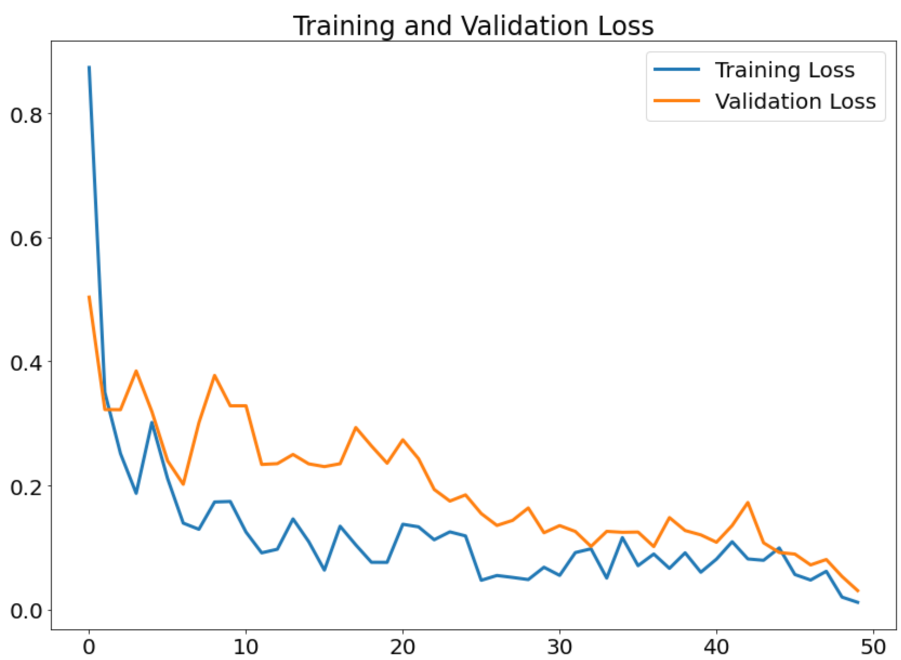

Fig. 4.10: Training loss vs. validation loss of MobileNetV2

4.3 Comparative Analysis

In our research work, we used images with a size of 224 × 224 in both of our models. Input image size and number of parameters for both MobileNerV2 and VGG19 is given in Table 4.3.

Table 4.3: The input image and number of parameter for VGG19 and MobileNetV2.

Model Name	**Image size**	**Number of total parameters**
MobileNetV2	224 × 224	8,288,392
VGG19	224 × 224	22,982,432

VGG19 performed better between two models in terms of training and testing accuracy. Table 4.4 shows them all.

Table 4.4: The performance of two different models.

Model name	**Number of epochs**	**Training accuracy (%)**	**Testing accuracy (%)**
MobileNetV2	50	90.12	89.05
VGG19	50	94.06	93.43

Two of our pre-trained models performed well enough during our research and managed to recognize each of the eight fruit classes. Table 4.5 shows the performance of each classes in terms of for both models.

Table 4.5: Class-wise performance of two model

Class names	Model	
	MobileNetV2 (%)	**VGG19 (%)**
Orange	95.62	97.81
Apple	96.35	98.54
Banana	97.81	98.54
Mango	95.62	99.27
Grape	98.54	98.54
Papaya	97.08	99.27
Pineapple	99.27	97.08
Tamarind	97.81	97.81

Before beginning this research plan, we reviewed related papers that dealt with several image classification methods and compared their comprehensive performance with our work in Table 4.6.

Table 4.6: Comparative performances among different work.

Work Done	**Mode of solution**	**Size of Dataset**	**Segmentation Algorithm**	**Classification Status**	**Classifier**	**Accuracy (%)**
MobileNetV(Our work)	Deep learning	2549	CNN	√	CNN	89.05
VGG19(Our work)	Deep learning	2549	CNN	√	CNN	93.43
RP Prasetya et al.[5]	Deep learning	400	CNN	√	CNN	70
Sapna Yadav et al.[14]	Deep learning	101000	CNN	√	CNN	85.07

Thuan Trong Nguyen et al.[17]	Deep learning	13950	CNN	√	CNN	74.81
Qian Xiang et al.[13]	Deep learning	10000	CNN	√	CNN	85.12

4.4 Discussion

In this chapter, we briefly described two of our pre-trained models and their accuracy, as well as model summary, plot diagram, and confusion matrix. We explained the main purpose and process of MoboleNetV2 and VGG19 model which are based on transfer learning approach via our summary and graphs. We can check the recognition accuracy of each of our classes individually in the section of the Confusion matrix. The training and validation accuracy, as well as the loss, of each of our models are given in the accuracy graph. MobileNetV2 had spends more time in training than VGG19. On the other hand, VGG19 was more accurate than MobileNetV2. During training phase, MobileNetV2 achieved the best of 90.12 %, while during testing, it achieved an accuracy of 89.05 %. Apart from that, VGG19 achieved a training accuracy of 94.06 % and a testing accuracy of 93.46 % while requiring less time.

CHAPTER 5

Impact on Society, Environment, and Sustainability

5.1 Impact on Society, Environment, and Sustainability

Our primary goal in our research is to raise public awareness about the need of proper nutrition during pregnancy. The most crucial time in a woman's life is during her pregnancy. They must look after their physical and mental health by ensuring that they get the nutrition they require during this phase. Fruit, in general, contains a variety of vitamins and carbohydrates in the development of both mothers and babies. Many people in our society are unaware of the fruit they should choose for pregnant women for a variety of reasons. Some fruits, such as those that contain latex, enzymes, or generate heat in the body, should be avoided. Our research will assist people in learning about useful and harmful fruits, especially for new mothers who are unfamiliar with nutrition and healthy fruits. This will help a mother in caring for her unborn child. When they learn about dangerous fruits, they will be able to avoid them simply. We improved the accuracy of our Convolutional neural network model by training it with the data we acquired. Our model is also compatible with modern platforms. Those who are unaware of the benefits of eating fruit while pregnant will be able to learn about the food habits they should adopt. As a result, our research has a significant social impact.

5.2 Impact on Environment

Fruit demand is continuously increasing. People are consuming more fruits than other foods, which has an impact on our bodies and the environment. As we all know, the world's population is continually growing, so fruit is always a better option for meeting their nutritional needs. More trees are being planted to meet the demand for fruit, which has a positive impact on our ecosystem. As a result, our work has a good impact on the environment.

5.3 Sustainability Plan

Our main goal in this study is to inform people about fruit choices during pregnancy. So that they can realize the importance of making the proper decision at an early stage. Our research work can help organizations which working on pregnancy can raise awareness. It will help in the reduction of many pregnancy-related disorders such as miscarriage and delivery complications.

CHAPTER 6

Summary, Conclusion, Recommendation, And Implication for Future Research

6.1 Summary of the Study

We used a deep learning approach to classify different types of fruit in our research. Study about Nutrition During Pregnancy, Data Collection, Methodologies Research, Implementation, Result, and Analysis are some of the steps in our research. We gathered image data from the internet and used Jupyter Notebook to resize and improve the quality of the images we gathered. We selected to use CNN for our implementation after conducting a background research and literature review, and we also divided our data into eight classes. CNN has excelled in the field of image classification and recognition in recent years. We used Google Colab to train the model. VGG19 and MobileNetV2 are two pre-trained models on which we have worked. The VGG19 model, in our opinion, has a higher accuracy. Based on our research, we discovered that our VGG19 model outperforms which is a satisfactory performance with new image.

6.2 Limitations and Conclusions

We used two Convolutional neural network (CNN) architectures in our research to classify and recognize eight different fruits. And our model is more accurate at performing this task. However, we do have certain limitations after all of this. We've worked with eight different fruit classes throughout our study. Except for those eight types of fruit, our models will be unable to identify any other fruit. Furthermore, using a larger dataset may result in improved performance. Aside from that, adding more layers to the network may improve accuracy. In the field of image recognition and classification, however, the CNN technique has a quite good reputation. Our experimental results show that our CNN models perform perfectly with our new image dataset, which is quite pleasing. Our research will assist people in making the best fruit choices for pregnant women. We believe that our work will help pregnant women maintain a healthy diet for themselves and their babies. Since we live in a technological age, health-related organizations can take our work one step further.

6.3 Implication for Further Study

We live in a digital age where everything is simpler than ever before. The majority of the systems that surround us nowadays are AI-based. Smart technologies, such as smartphones, have become closely linked to people. As a result, it would be more beneficial to individuals if we could deploy our CNN models using an Android application. Because smartphones have a user-friendly interface and may be carried wherever you want. So, if we can put our models on the Android platform, people will be able to take quick decision about the nutritional value of their fruits. Aside from that, in the future, we can add more fruit classes with more data to improve the performance of our models.

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