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A Comparative Study of Fruit Images Classification Using VGG16 and VGG19

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***Abstract* - Fruit classification is important topic, it is used in fruit industry and supermarket. It is reduced time and workers' effort in marketing. The results of previous studies explained that vgg16 and vgg19 models are outperform other CNNs models (Alexnet, resident50 and googlenet) in fruit classification. Fruit images dataset is used. It is contained 1000 images divided into five classes they are banana, grape, apple, mango and strawberry. Each class has 200 images. The study highlights how to modifying them by fine tuning their hyper parameters. The results showed that vgg16 is out performing than vgg19 after modified. Because it has accuracy of 0.92% and complexity of 122 million floating point operations (FLOP), where vgg19 has accuracy of 0.88% and complexity of 137 million million floating point operations (FLOP).**

Keywords: CNN, machine learning, deep learning, vgg16, vgg19, fruit classification Iraq.

I. INTRODUCTION

In this time, with the advancement of agriculture, the concept of fruit industries and fruit marketing emerged. Traditionally, this task has been carried out manually by humans, but it faces several challenges, such as the need for significant effort to distinguish between different fruits and the time-consuming nature of the process. This has led to the necessity of developing an automatic fruit classification system using deep learning, relying on features extracted from images of fruits. In addition to its applications in fruit industries and supermarkets, this system can also be used to enhance cognitive abilities in children [1]. This system is using convolutional neural networks (CNNs) for fruit classification. It has gained attention because it has the ability to classify any type of objects in high accuracy. Among the various convolutional neural networks architectures are VGG-16 and VGG-19are considered to be state-of-the-art models for image analysis. The VGG16 and VGG19 models, were proposed by the Visual Geometry Group at the University of Oxford [2], and are known for their use of deep architectures and small convolutional filters. In the previous work the authors after making a comparative study for fruit classification using pre-trained CNNs network [3]. The results are shown that are vgg16 and vgg19 are outperform the proposed work is used transfer learning process to enhance their performance, then make comparison between them. In spite of there is some complexity, such as few dataset utilized in experiment. The research was carried out using kaggle fruit images dataset. The dataset contained of five classes: banana, apple, mango, grape and strawberry, 1000 images in total. The results of our study indicate that the VGG16 model outperforms VGG19 and in terms of accuracy and complexity. In conclusion, our study demonstrates the effectiveness of the VGG16 model for fruit classification and its potential for use in real-world systems. Furthermore, the comparison of these two models provides insights into the strengths and weaknesses of these architectures for this specific task. Thus, the paper is organized as follows: The second section examines the related work. In the third section, the methodology related to proposed work is discussed. Section four and five present the results and conclusions for CNNs models in fruit images classification.

1.1 Motivation

Classifying fruit images serves a wide range of practical and scientific purposes across industries.

1. Agriculture & Farming

- Automated Sorting: Helps machines identify and sort fruits by type, size, ripeness, or quality.
- Yield Prediction: By analyzing images over time, farmers can estimate crop yields more accurately.

2. Retail & Supply Chain

- Inventory Management: Supermarkets use image classification to track stock and automate checkout systems.

3. Food Industry & Robotics

- Smart Packaging: Machines can pack fruits based on type and ripeness.
- Autonomous Harvesting: Robots use image classification to identify which fruits are ready to pick.

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1.2 Problem Statement

After evaluating CNN models for fruit classification, it was found that VGG16 and VGG19 achieved the highest accuracy. Therefore, we were compelled to optimize them and reduce their complexity. A comparison was conducted between the two models in terms of both accuracy and complexity.

II. METHODOLOGY

This section will discuss the Materials and methods used in the proposed work

2.1 Software and hardware resource

In the research the software was matlab program version 2024, the hardware was computer with specifications were processer cori5 and RAM size 16 Giga bytes.

2.2 VGG16

VGG16 is a convolutional neural network architecture that was introduced by the Visual Geometry Group (VGG) at the University of Oxford in 2014. This particular VGG network architecture version, which uses tiny 3x3 convolutional filters (CONV) and a deep architecture, is intended to carry out picture categorization tasks. Three fully connected layers(FC) and thirteen convolutional layers make up the 16 layers that make up VGG16, as shown in figure(1)[5]. It also uses a method known as "very deep supervision" that gives intermediary levels more oversight, leading to more precise and reliable optimization [4].

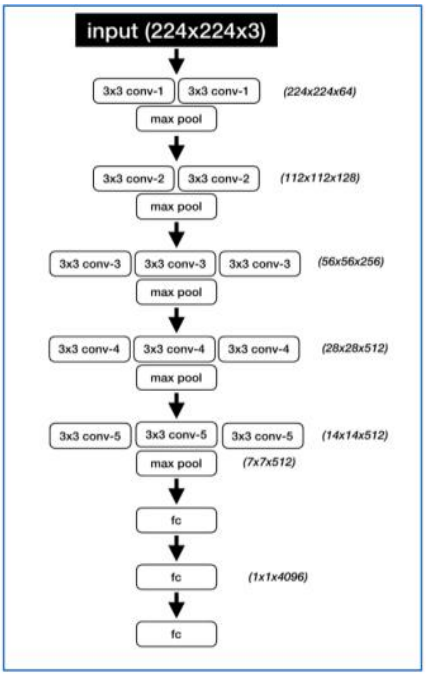

Figure 1: VGG-16 based Architecture [5]

2.3 VGG19

Similar to VGG16, VGG19 is a convolutional neural network design with 19 layers. The Visual Geometry Group (VGG) at the University of Oxford first used it in 2014.

This architecture's primary goal is to carry out picture categorization tasks. VGG19 makes use of deep network architecture and tiny 3x3 convolutional filters (CONV). Five convolutional blocks, each with several convolutional layers, make up therchitecture.

The subsequent three blocks each have four convolutional layers, whereas the first two blocks have two. Three fully connected layers (FC) follow the final blockis showed in figure(2)[6]. The "very deep supervision" method, which was previously utilized in VGG16, is also utilized in VGG19 [7].

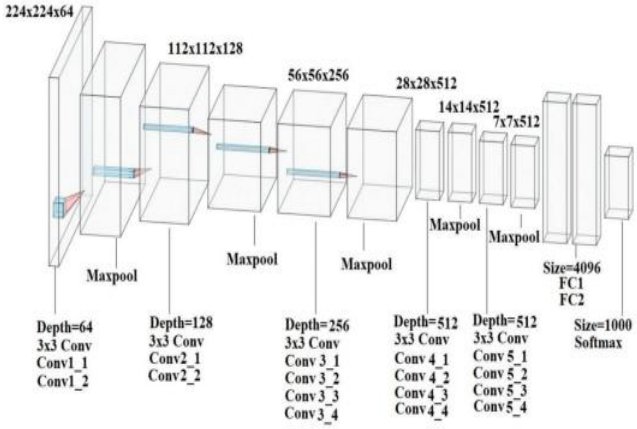

Figure 2: VGG19 based architecture [6]

2.4 The Training Phase

Training set [8] is an essential part of the model generation process in machine learning. To train a model and allow it to recognize the underlying patterns in the data, a representative sample of the data is utilized. As the model continues to learn the properties of the data, it is continuously exposed to the same training data across a number of repetitions known as epochs. A varied set of inputs in the training set is necessary to guarantee the model's generalization and to produce precise predictions on unobserved data.

2.5 The Test Phase

The usage of a test set is a crucial stage in the training of machine learning models [5] in order to assess the trained model's performance. The model's generalization performance on unseen data is estimated using the test set, which is distinct and independent from the training and validation sets. During

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the training phase, the model is trained using the training set, and its performance is assessed using the validation set. However, once the model has been fully trained, the test set is used to conduct the final performance evaluation. The test set is used to validate the model's performance and offers an objective assessment of the model's capacity to generalize to new data. It is crucial to remember that the test set should only be utilized as the last stage of evaluation following complete training of the model; any further modifications should be made to the model in response to test set performance. To sum up, using a test set is a crucial part of the model development process because it guarantees that the model can accurately predict data that hasn't been observed yet [10].

2.6 Epoch

In machine learning model training, an epoch denotes one complete pass through the entire training dataset. During this cycle, the model's parameters are refined using the training data in order to minimize error. The number of epochs is an important hyperparameter that specifies how many times the model is exposed to the training data before the training process concludes.

Determining the appropriate number of epochs requires consideration of the specific task, the size of the dataset, and the desired level of generalization. Although increasing the number of epochs can enhance the model's learning, it also raises the likelihood of overfitting. Therefore, identifying an optimal value that balances learning and generalization is essential [11].

2.7 Dataset

The dataset used in this study is taken from the Kaggle website. It is divided to five classes. They are: apple, banana, mango, grape and strawberry. It is contained 1000 images as total. They have different dimensions. There are divided to 200 images for every class. It is also spited to 120 images for training Phase and 40 images for validation and testing phases for each class.

2.8 Data Augmentation

It's a technique that artificially expands the training dataset by applying various transformations to input images. This includes scaling, cropping, rotation, and flipping. These transformations help the model learn to recognize patterns regardless of slight variations, improving its ability to generalize [12].

2.9 Hyperparameters Fine Tuning

Hyperparameter tuning plays a critical role in enhancing the performance of the proposed model. Techniques such as grid search or random search can be used to find the optimal combination of hyperparameters, including the learning rate, batch size, and number of epochs. This process is essential for achieving the best results in model optimization [13].

2.10 Dropout

Dropout is another effective regularization technique that helps mitigate overfitting. During training, dropout randomly sets a portion of the input units to zero at each update [14].

2.11 Batch Size

Is refers to the number of training examples utilized in one iteration. The choice of batch size can influence the training dynamics and the generalization ability of the model [15].

2.12 Learning Rate

Is a critical hyperparameter that determines the step size at each iteration while moving toward a minimum of the loss function.

A well tuned learning rate can significantly enhance the convergence speed and model accuracy [16].

2.13 Weight L2 Factor

By punishing large weights and introducing an L2 regularization term to the loss function, the Weight decay parameter in training avoids overfitting. By encouraging the VGG model to learn simpler decision boundaries, this regularization enhances the model's ability to generalize on unknown input [16].

2.14 Confusion matrix

To calculate a confusion matrix based on the results of fine tuning and used accuracy metrics for evaluating the performance of each model. The accuracy was calculated by using formulas (1). The Parameters Are: TP, TN, FP, FN. In other words TP (True Positive) the model correctly predicted the positive class. TN (True Negative) is a result where the model correctly anticipated the negative class. FP (False Positive) is an outcome where the model incorrectly predicted the positive class. FN (False Negative) is a result where the model incorrectly predicted the negative class [17].

Accuracy is a metric that describes the overall prediction accuracy of a model across all classes [18].

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad \text{---------- (1)}$$

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Calculating the number of FOLP for each layer is done by using the following equations:

Convolution' parameters are calculated as: [\text{FLOPs}=(\text{Output Height}\times \text{Output Width} \ times\text{Filter})\times(\text{Kernel Size}\times\text{input Channels}\times2)] ------ (2)

Fully connected parameters are calculated as: [(\text(Input Units)+1)\times\text{Output Units}]---------- (3)

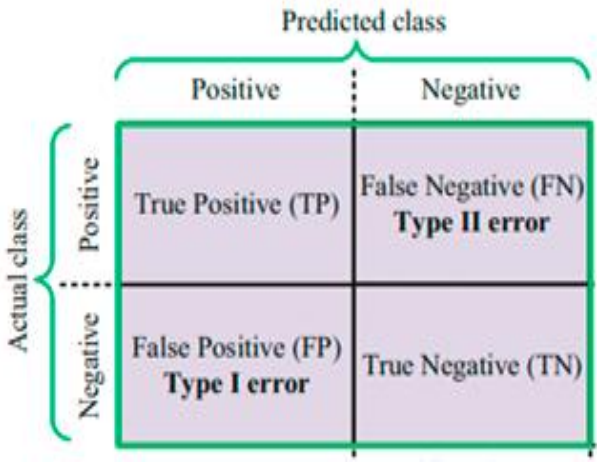

Figure 3: Actual class versus Predicted class at Confusion matrix [19]

III. PROPOSED WORK

In this paper, the proposed work is modified thevgg16 base model and vgg19 base model through the manipulation of hyperparameters for each of them. And determine which of them is the best after being modified, achieves the highest accuracy to classify a set of images consisting of five types of fruits: mango, banana, strawberry, and grape. The fruit images used are of the RGB type, with a total of 1,000 images, and each class has 200 images.

It was downloaded from the website www.kaggle.com. Where the images of each class are divided according to the following ratios: 60% for training, 20%validation and 20% for testing. Since the images downloaded from the website above vary in size, they were resized to the required dimensions before entering the input stage in the modified model. And this applies to both training and testing. Regarding VGG19, after removing the last three layers and replacing them with new three layers from types of fully connected layers with the size of five classes. And then the proposed model became as follow:

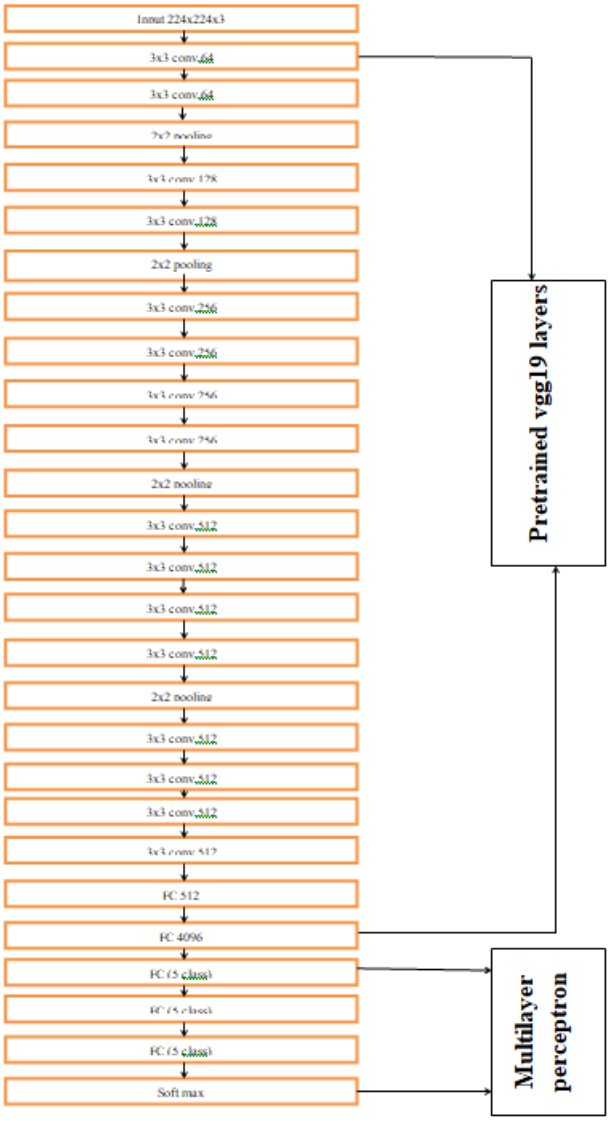

Figure 4: VGG19 modified model

3.1 Hyperparameters fine-tuning will be performed on the modified model, and the optimal value for each parameter will be selected. Through the following steps:

1) Changing the types of optimizers and selecting the best one among them for the dataset used. The purpose of this step is to improve the weights of the neural network. Through training, which reduces the loss function. Here, three types of optimizers were tested: They are SGDM, RMS, and Adam. To determine which of them achieves the highest accuracy in the shortest time.
2) After determining the optimal optimizer, the values of the learning rate parameters for the model were adjusted within the range (0.01, 0.001, ... 0.00001).After fixing the values of both epoch and MBS to determine which value achieves the highest accuracy in the shortest time.
3) After determining the optimal of both learning rate value and the type of optimizer. Those who achieve the highest

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accuracy in the shortest time. In addition, the MBS value will be fixed. Changing the value of the epoch parameter within the range (10, 20, 30). And then selecting the optimal value.

4) After fixing the values of epoch, learning rate, and the type of optimizer. The value of MBS for the neural network, which represents the number of training samples used within a single iteration, will be adjusted. The optimal MBS value will be selected from the range (16, 32, 128).
5) After fixing the optimal values for the parameters of the previous steps, the weight L2 factor (wL2F) will be adjusted within the values (0.0, 0.25, 0.5).
6) After selecting the optimal values for the previous variables. The number of dropout layers in the proposed model will be modified. To determine its effect on the performance of the proposed model.

3.2 VGG16 modified model

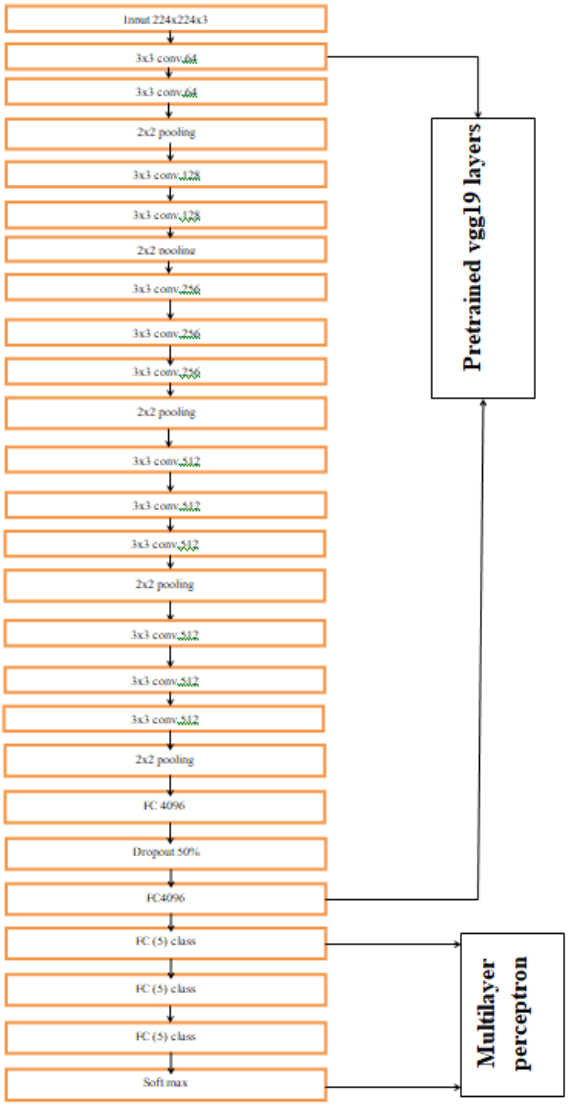

Figure 5: VGG16 modified model

At first, the last three layers will be deleted and are replaced with new three layers from types of fully connected layers with the size of five classes. And the proposed model became as shown in the figure (5). Hyperparameters fine-tuning was performed on the proposed model to achieve the highest accuracy in the shortest time. The same six previous steps are used with VGG19 were followed, in addition to the following steps:

3.2.1 Performing data augmentation through several activations, including Rotation, Scaling, and Cropping, for the dataset used to train the proposed model.

3.2.2 The architecture of the proposed model was modified by changing the number of the last removed layers. And determining its effect on performance.

IV. RESULTS AND DISCUSSION

Two kinds of machine learning classification models are used. The dataset is used in testing contains 200 images, where each class has 40images. The performance of each model is assessed using two metrics, are accuracy and complexity. The parameters are used in two models are (learning rate, epoch, number of epoch, min Batch size and other). Tables (1-8) they are accuracy results for vgg16 modified model. Tables (9-14) they are accuracy results for vgg19 modified model.

4.1 Results for vgg16 modified model

Table 1: The parameters are: MBS=128, LR=0.0001and Epoch=10are fixed, where optimizer type is varied at each time

Optimizer	Accuracy
Sgdm	0.79
Adam	0.589
RMSprop	0.208

From the table above showed that sgdm achieved highest accuracy

Table 2: The parameters are: MBS=128, optimizer type is sgdm and Epoch=10 are fixed, where optimizer type is varied at each time

Learning rate(LR)	Accuracy
0.01	0.19
0.001	0.723
0.0001	0.832
0.00001	0.594

From the table above showed that LR=0.0001 achieved highest accuracy.

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Table 3: The parameters are: MBS=128, optimizer type is sgdm and Learning rate =0.0001 are fixed, where Epoch value is varied at each time

Epoch	Accuracy
10	0.846
20	0.777
30	0.832

From the table above showed that Epoch=10 achieved highest accuracy.

Table 4: The parameters are: epoch=10, optimizer type is SGDM and Learning rate =0.0001 are fixed, whereas MBS value is varied at each time

MBS	Accuracy
16	0.846
32	0.767
64	0.69
128	0.633

From the table above showed that MBS value of 16 achieved highest accuracy.

Table 5: The parameters are: epoch =10, optimizer type is sgdm, MBS=16 and Learning rate =0.0001 are fixed, where L2Factor value is varied at each time

L2Factor	Accuracy
0.5	0.777
0.3	0.831
0.25	0.891
0.1	0.851

From the table above is explained that L2Factor value of 0.25is the best one.

Table 6: Change the number of dropout layer in the architecture of proposed model. The parameters are: epoch =10, optimizer type is sgdm, MBS=16 and Learning rate =0.0001 are fixed, where the number of dropout layer is varied at each time

Dropout layer	Accuracy
2layer included	0.797
1Layer remove	0.811
2layer remove	0.866

From the table above is explained that operation of removing 2dropout layer is the best one.

Table 7: Make data augmentation on the dataset which used by the proposed model. This includes some activation with fixing some parameters are: epoch =10, optimizer type is sgdm, MBS=16 and Learning rate =0.0001 at each time

Activation	Accuracy
Rotation	0.886
Scaling	0.871
Cropping	0.837

From the table above is explained that first active achieved highest accuracy, therefore it is the best one.

Table 8: Changing the number of deleted layers in the architecture of proposed model. Where other parameters are: epoch =10, optimizer type is SGDM, MBS=16, L2Factor =0.25 and Learning rate =0.0001 are fixed, where the number of deleted layers is varied at each trying

Number of deleted layers	Accuracy
Last 2 layers	0.851
Last 3 layers	0.886
Last 4 layers	0.891
Last 5 layers	0.92
Last 6 layers	0.841

From the table above noticed that fourth one is the best. So it is achieved highest accuracy among them.

4.2 Vgg16 modified model prediction

Five different fruit images were used to test the proposed model, and most of them were correctly predicted by the model. If there is any image in test set out of previous five classes the two proposed model will are assumed as one of the closest of these classes.

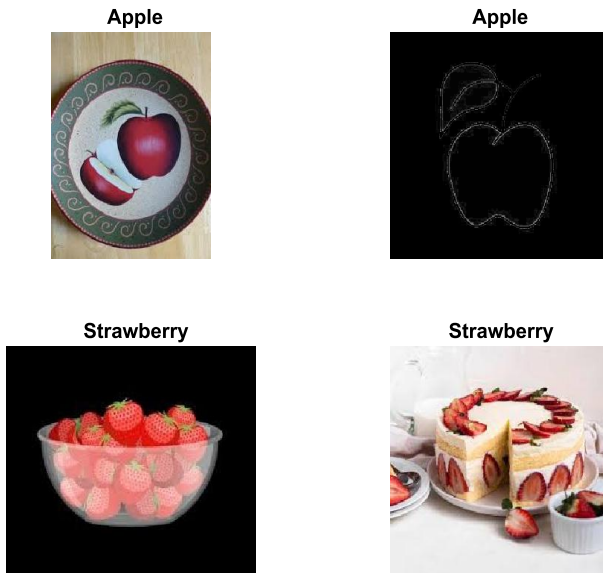

Figure 6: Prediction of vgg16 modified model

A confusion matrix was generated to evaluate the proposed model using the testing dataset, and the result was as follows.

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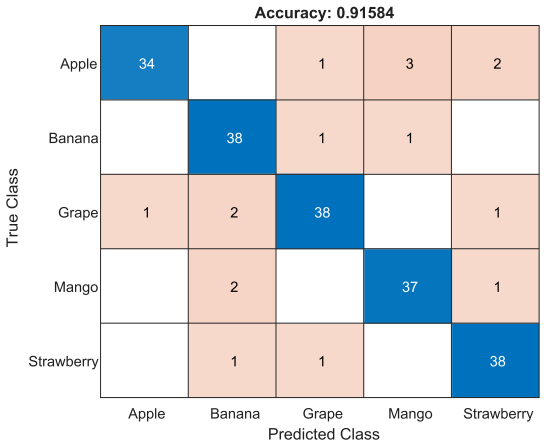

Figure 7: Vgg16 modified model confusion matrix

From figure (7) had stated that:

For apple class the parameters were TP=34, FP=1, FN=6, TN=161.

For banana class parameters were TP=38, FP=5, FN=2, TN=157.

For grape class the parameters were TP=38, FP=3, FN=4, TN=157.

For mango class the parameters were TP=37, FP=4, FN=3, TN=158.

For strawberry class the parameters were TP=38, FP=4, FN=2, TN=157.

4.3 Vgg19 modified model results

Table 9: The parameters of proposed model value are epoch=10, MBS=128 and LR=0.0001), whereas, optimizer types is varied at every time

Optimizer	Accuracy
SGDM	0.7624
RMS prop	0.3465
ADAM	0.7525

From the result in the table above can be concluding that SGDM is the best. So it is achieved highest accuracy.

Table 10: The parameters are: optimizer type is SGDM, epoch =10, MBS=128, whereas learning rate (LR) is changed at each time

Learning rate	Accuracy
0.01	0.198
0.001	0.8267
0.0001	0.7623
0.00001	0.3564

From the results in the table above. Can be conclude that learning rate value (0.001) achieved highest accuracy.

Table 11: Epoch parameter value is changed, whereas, other parameters (MBS =128, optimizer type is SGDM, LR=0.001) are fixed at every time

Epoch	Accuracy
10	0.8713
20	0.8663
30	0.8217

From the results in the table above, it is explained that epoch value of 10 achieved highest accuracy.

Table 12: MBS value is varied at every time, whereas, other parameters are remained fixed (epoch=10, optimizer: SGDM and LR=0.001)

MBS	Accuracy
32	0.7475
64	0.8514
128	0.8465

MBS value is 64 has been achieved highest accuracy

Table 13: Regularization parameter (WL2F) parameter is varied, but other parameters (with epoch=10, optimizer: SGDM, MBS=64 and LR=0.001.) are fixed at each time various

WL2F	Accuracy
0	0.8416
0.25	0.8861
0.5	0.817

(WL2F) value of 0.25 achieved highest accuracy, so it is best one.

Table 14: Various number of dropout layer with epoch=10, optimizer: SGDM, MBS=64 and LR=0.001 at each time

Dropout layer	Accuracy
2DL include	0.792
1DL removed	0.292
2DL removed	0.678

From the results in the table above, is explained that the case of adding extra two layers to the proposed, has been enhanced the accuracy.

4.4 Vgg19 modified model prediction

Five different fruit images were used to test the proposed model, and it predicted them accordingly. It turned out that three images were correctly classified, while the fourth image was misclassified—the model predicted it as a grape, whereas

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it was actually a mango as shown in figure. If there is image in test set out of previous five classes the two proposed model will are assumed as one of the closest of these classes.

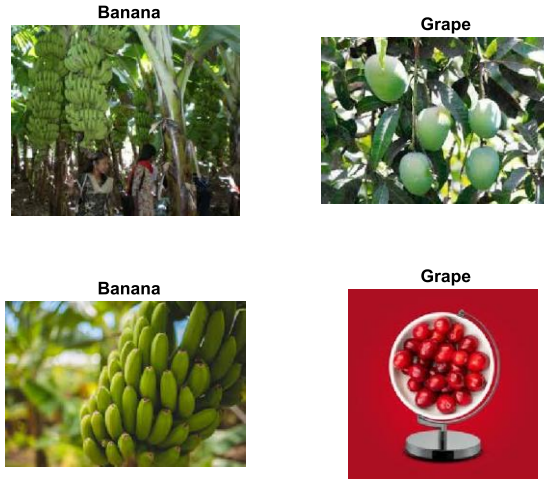

Figure 8: Prediction of vgg19 modified model

A confusion matrix was generated to evaluate the proposed model using the testing dataset, and the result was as follows.

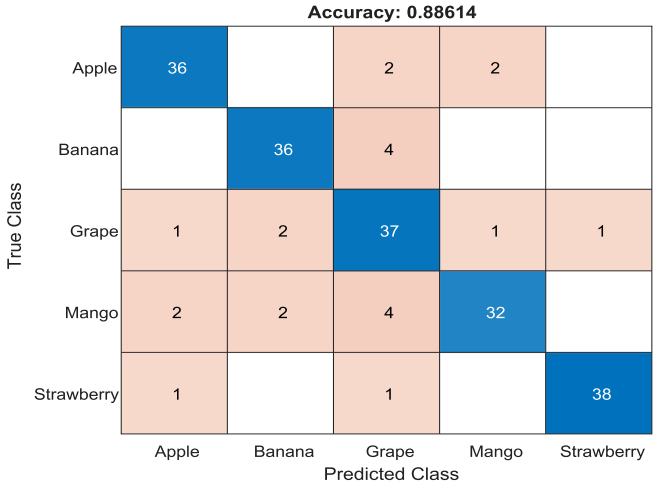

Figure 9: Vgg19 modified model confusion matrix

From figure (9) is stated that:

For apple class the parameters were TP=36, FP=4, FN=4, TN=158.

For banana class parameters were TP=36, FP=4, FN=4, TN=158.

For grape class the parameters were TP=37, FP=11, FN=5, TN=149.

For mango class the parameters were TP=32, FP=3, FN=8, TN=160.

For strawberry class the parameters were TP=38, FP=1, FN=2, TN=163.

Table 15: Compare between VGG16modified and VGG19 modified models

Making comparison between vgg16 and vgg19 model before and after modification. The two metrics are used, they are accuracy and complexity.

Modified model name	VGG16 modified model	VGG19 modified model	VGG16 based model [20]	VGG19 based model [20]
Accuracy	0.92	0.886	0.901	0.807
Complexity	approximately 122 million FLOPs	approximately 137 million FLOPs	15.3 Billion FLOPs	19.6 Billion FLOPs

The table (15) is shown that vgg16 modified model is higher accuracy and lower complexity than vgg19 modified model.

V. CONCLUSION AND DISCUSSION

The following points can be concluded from this work:

1) VGG16 modified model achieved accuracy better than vgg19 modified model
2) Vgg16 modified model's architecture is less complexity than vgg19 modified model
3) For the dataset are used was learning rate parameter value (0.0001) is suitable for vgg16 modified model , whereas (0.001) is suitable for vgg19 modified model.
4) SGDM optimizer is suitable for both modified models.
5) For the dataset are used was epoch parameter value (10) is suitable for both modified models.
6) For the dataset are used was MBS value (16) is suitable for vgg16 modified model, whereas (64) is suitable for vgg19 modified model.
7) At both modified models if the used image does not belong to any one of the five classes used in the research, the modified models will classify it to the closest class to it.

5.1 Future work

The other point can be considered as future works. It focus on enhancing the accuracy of the proposed model at preprocessing stage by doing some operations like average filtering or using Gabor filter.

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