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Comparison CNN and Mobilenet_v2 Model for Oil Palm FBB Ripeness Classification

Muhammad Hanafi Mohtar Luddin[1], Munirah Ab. Rahman[1]*

[1]Faculty of Electrical and Electronic Engineering,
Universiti Tun Hussein Onn Malaysia, 86400, Batu Pahat MALAYSIA

*Corresponding Author Designation

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Abstract: In 2021, the value of exports of palm oil and derivatives increased by 40% to RM91.4 billion. This makes the palm oil industry the fourth largest contributor to the national economy and palm oil as well as the largest contributor to Malaysia's commodity exports. The selection of the ripeness of fresh fruit bunches (FFB) of oil palm is very important to obtain the best quality palm oil. But the selection process is still carried out manually, while the selection process through machines is still poorly introduced in the palm oil industry. To overcome this problem, this study has produced a deep learning system using the CNN and Mobilenet_v2 model algorithms. The data set used consists of 1542 images of oil palm FFB for both the training and validation process. The CNN model was built as the primary model for this study, while the Mobilenet_v2 model was built to differentiate accuracy performance. Based on the experiments conducted in this study, the CNN Model managed to classify the new image of oil palm FFB with a percentage of 99.99% accuracy based on epoch = 30 compared to the Mobilenet_v2 model with a percentage of 14.89% accuracy. Finally, the study has proven that the CNN model successfully classifies the 10 categories of oil palm FFB ripeness using data set of 1542 images.

Keywords: Deep Learning, Classification, CNN, Mobilenet_v2

1. Introduction

Referring to an article from the Malaysian Palm Oil Council website, oil palm with its scientific name, Elaeis Guineensis Jacq, originated from West Africa, then brought into the British countryside to be used as an ornamental plant [1]. In the 1960s, the Malaysian Government introduced large-scale oil palm cultivation in Malaysia. This is because the Malaysian government wants to eradicate poverty and improve living standards among the rural population. Until now, oil palm has grown and developed throughout the country, from Perlis to Sabah.

In a statement from the Minister of Plantation Industries and Commodities (KPPK), Datuk Zuraida Kamaruddin, the export value of palm oil and derivatives increased by 40% to RM91.4 billion from January to November 2021, an increase of RM65.3 billion the previous year [2]. In addition, she also

*Corresponding author: munira@uthm.edu.my

noted that the palm oil industry is the fourth largest contributor to the national economy and palm oil is the largest contributor to Malaysia's commodity exports. In addition, He also stated that in 2021, India is a major exporter of Malaysian palm oil, accounting for over 3.2 million tons and in 2022, Malaysia will explore new export markets to consumer countries such as Sri Lanka, West Asia, Iran, Turkey, and Bangladesh.

In 2019, the palm oil industry was affected due to the shortage of plantation workers due to the COVID-19 outbreak. The incident caused the country's palm oil production to decrease by 1.3 million tons, or eight percent (8%), to 15.033 million tons. To address the problem, the government agreed to hire 32,000 foreign workers with strict compliance and established standard operating procedures (SOPs). In addition, MPOB (Malaysian Palm Oil Board) has proposed four innovative technologies to help improve national palm oil production i.e., fertilizer formulation, plantation mechanization, and palm -based polyols [3].

Khan et al applied a machine learning approach to their research on oil palm farming, such as knowing the class of fresh fruit bunches (FFB), disease stage of oil yield, harvest time and soil fertility from the years (2011–2020) [4]. In addition, the study revealed that machine learning is still underutilized in the agriculture and oil palm industry. Smart systems are being combined with the machine and artificial vision intelligence to revitalize the oil palm agriculture industry. Based on the study, the project aims to develop a fruit maturity detection system that can detect the maturity grade of oil palm FFB based on deep learning of the CNN model and mobilenet_v2.

1.1 Problem Statement

Each year, a healthy oil palm tree will produce about 26 FFB [5]. Referring to the website of MJM (Palm Oil Mill) Sdn Bhd, golden red or orange palm fruit is a fruit that has quality oil [6]. This makes the selection or grading of oil palm FFB very important to improve the quality and quantity of palm oil. In addition, the process of selecting and grading oil palm FFB quickly and thoroughly using machines is not so extensive. Practically, some use manual and traditional methods by using experienced and trained manpower to select the oil palm FFB category.

Based on the problem statement, this project has constructed two algorithms for deep learning projects about the CNN model and the mobilenet_v2 model to solve the problem of classification of oil palm FFB ripeness based on 10 categories.

2. Methodology

This project uses CNN and mobilenet_v2 models to conduct experiments on the classification of oil palm FFB where the CNN model is the main algorithm while mobilenet_v2 is the model to compare accuracy. Figure 1 illustrates the block diagram of the workflow of this project based on phase 1, phase 2, and phase 3. The experiment was conducted on the google Colab platform to build the CNN and mobilenet_v2 architecture. According to the workflow in phase 3, after this experiment has been completed, the CNN and mobilenet_v2 models will be tested using new images taken randomly on the google website to determine the accuracy of performance.

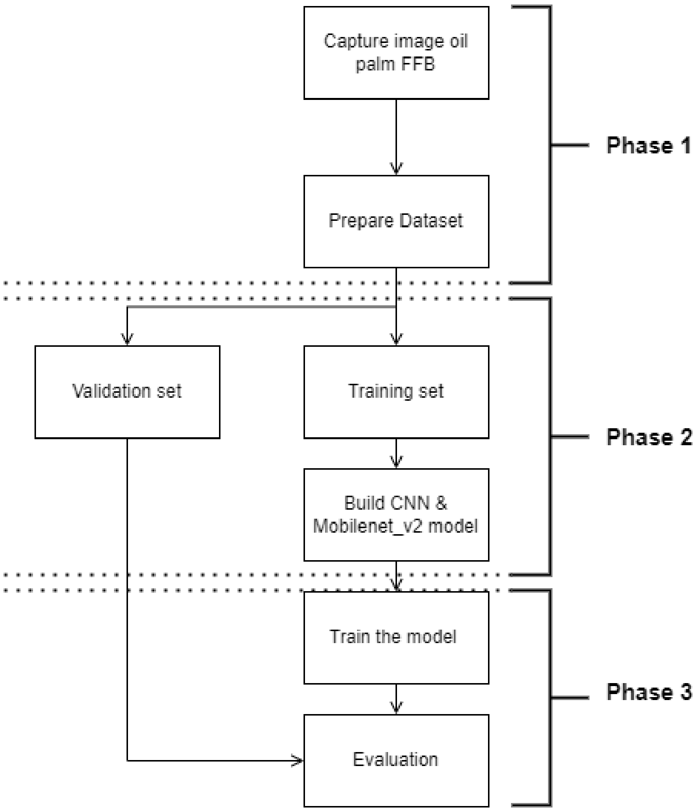

Figure 1: Workflow of project

2.1 Phase 1

To build a deep learning model, the most important component is the data set. This phase discusses the collection and preparation of data sets before building the deep learning model. Based on Figure 1, the main process in phase 1 is to capture images of oil palm FFB in oil palm orchards and plantations in the village Kampung Parit Surau Darat, Parit Raja, Batu Pahat, Johor. The pictures were taken using an Asus Zenfone 5z smartphone and stored in .jpeg format. The process of collecting pictures of oil palm FFB is carried out in the morning from 7.30 am to 12.00 noon and in the evening. The total number of BTS oil palm images that were successfully taken was 1542 images for 10 categories, which are Unripe Bunches, UnderRipe Bunches, Ripe Bunches, OverRipe Bunches, Loose Bunches, Rotten Bunches, Dirty Bunches, Small Bunches, Damaged Bunches and Dirty Bunches. Upon completion of the collection process, the images were stored in a computer with a file name as a data set. That file will be uploaded into google drive and then connect to google drive to the google Colab platform to show that the data set is ready for use.

2.2 Phase 2

Once the data set preparation has been completed, the data set will be divided into 2 sets, namely the training set and the validation set. 20% of the randomly selected data set will be used as a validation set. After that, all images in the data set will be resized to 180x180x3 with a group size of 32. Next, additional data encoding and dropout will be applied to the data set to reduce the overfitting effects that occur during the training and validation process. With the availability of additional data sets, it will help to increase the percentage of accuracy performance of CNN and mobilenet_v2 models to classify oil palm BTS images. Then the CNN and Mobilenet_v2 models were created and compiled before the training process and validation process was carried out.

2.3 Phase 3

In phase 3, the learning model will undergo a process of training and validation once the model is completed. These experiments used 10, 20 and 30 epochs for the training process. Based on the study of Hassan et. all, each deep learning model has a different epoch value to achieve optimal performance levels [7]. In addition, this experiment has used 3 different epoch values to identify whether those epoch values can make the CNN and MobileNet_v2 models achieve optimal performance in the training and validation process. The evaluation process will be conducted after the training and validation process has been completed to find out the percentage of accuracy performance for the CNN and Mobilenet_v2 models. To calculate the accuracy performance of these models, this experiment refers to the accuracy performance formula used by Devvi et. al and Valeria et. al in their studies [8]-[9].

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} = \frac{TP + TN}{P + N} \quad Eq. 1$$

Based on equation 1, TP stands for true positive, TN for true negative, FN for false negative, FP for false positive, P for positive and N for negative.

2.4 Predict new image

Upon completion of all these experimental processes based on the workflow in Figure 1, the CNN and Mobilenet_v2 models will be tested using random images taken on the google website to find out between CNN or mobilenet_v2 has the best accuracy performance based on the number of epoch values used in their training process.

3. Results and Discussion

The results from this study were obtained and recorded after the evaluation process was completed based on the data set used of 1542 images and different epoch values: 10, 20 and 30 for the CNN and MobileNet_v2 models.

3.1 Result based on value epochs

Results on accuracy during the training and validation process for the CNN and Mobilenet_v2 models were recorded in Table 1. The percentage of accuracy performance for the training and validation process was generated based on three (3) epoch values used in the experiments.

Table 1: Percentage of training and validation accuracy based on value epoch.

Models	Epochs	Training Accuracy	Validation Accuracy
CNN	10	59.92%	53.57%
Mobilenet_v2	10	56.29%	35.08%
CNN	20	77.47%	62.99%
Mobilenet_v2	20	68.68%	37.38%
CNN	30	89.95%	61.84%
Mobilenet_v2	30	67.19%	37.38%

Based on Table 1, training accuracy and validation accuracy for both models showed an increase in line with the epoch values used. At epoch value = 30, the CNN model has reached the optimum level based on the accuracy results during the training process with a value of 89.95% but the validation process did not reach the optimum level with 61.84% percentage. Whereas for Mobilenet_v2 accuracy results, from epoch = 10 to epoch = 30 does not reach more than 50% to reach the optimum level with percentage values between 30% to 40%.

Based on Figure 2 and Figure 3 shows the accuracy percentage graph and loss percentage graph during training and validation for CNN and Mobilenet_v2 models based on epoch value = 10. Based on the orange line graph representing the validation percentage, less overfitting effect occurs during the validation process CNN after epoch = 6. But for the Mobilenet_v2 model, the overfitting effect has occurred when epoch = 2. And the difference between the percentage accuracy on the blue line graph of the training process and the orange line graph of the validation process is too significant by 20% when epoch = 10. Figure 4 and Figure 5 are line graphs for percentage accuracy and loss during the training and validation process for epoch = 20, while Figure 6 and Figure 7 for epoch = 30 for the two models used in this experiment. Based on the results of the line graph exhibited, the higher the epoch value used, the higher the overfitting effect occurs.

Figure 2: Graph for training and validation on CNN (10 epoch)

Figure 3: Graph for training and validation on Mobilenet_v2 (10epoch)

Figure 4: Graph for training and validation on CNN (20 epoch)

Figure 5: Graph for training and validation on Mobilenet_v2 (20 epoch)

Figure 6: Graph for training and validation on CNN (30 epoch)

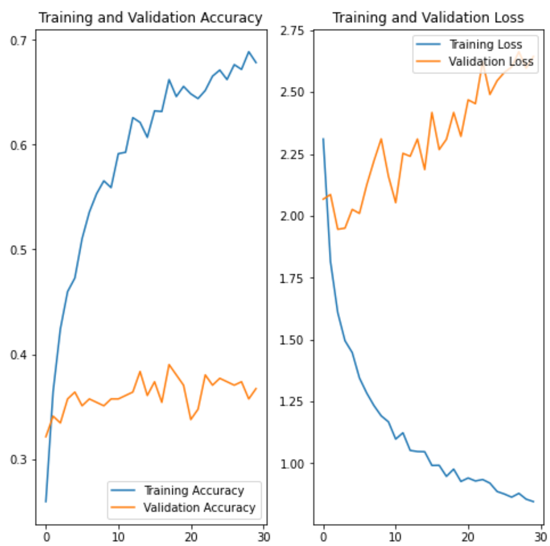

Figure 7: Graph for training and validation on Mobilenet_v2 (30 epoch)

A high overfitting effect occurs when the epoch value used is getting higher due to the data set used in this experiment is too small. The difference between the number of images for the training set and the images for the validation set is too large. In addition, the noise and corruption in the image of oil palm FFB can also be used as one of the causes that can cause overfitting effects.

3.2 Result for 30 random images

After the accuracy and loss results were successfully recorded for the CNN and Mobilenet_v2 models, the models were tested using 30 random images taken from the verification set to classify the oil palm FFB images according to the actual category of the images. Figure 8 and 9 show 30 random images based on the CNN Model.

Figure 8: Result classification for 30 random images based on the CNN model

Figure 9: Result classification for 30 random images based on the Mobilenet_v2 model

According to Figure 8, there are 16/30 images labeled with green captions. It is shown that the CNN model had successfully classified oil palm FFB images correctly based on their categories. While the Mobilenet_v2 model managed to classify the oil palm FFB image correctly by 7/30 images based on the result in Figure 9. The images labeled with red captions in Figure 8 and Figure 9 mean that the CNN or Mobilenet_v2 models did not manage to classify the images correctly based on their categories.

3.3 Result for new images

This section will show the classification results and accuracy for both the CNN and Mobilenet_v2 models against new images taken randomly within the google website.

Figure 10 and Figure 11 illustrate the classification results for both CNN and Mobilenet_v2 models in classifying new images taken from the google website respectively. In addition, Table 2 was constructed to show the percentage differences in classification accuracy for the CNN and Mobilenet_v2 models based on epoch values. Throughout the rising value of the epoch, the classification accuracy percentage for the CNN model also increased to 99.99% and the CNN model managed to classify the new images based on the correct categories. As for the Mobilenet_v2 model, it was not successful to classify new images based on epoch value increases with an accuracy percentage below 20%.

Figure 10: Result classification of a new image for the CNN model

Figure 11: Result classification of a new image for the Mobilenet_v2 model

Table 2: Result classification of a new image for CNN and Mobilenet_v2 based on value epochs

Model	Epoch	Accuracy percentage	Classification
CNN	10	89.73%	Correct
Mobilenet_v2	10	14.38%	Incorrect
CNN	20	99.65%	Correct
Mobilenet_v2	20	18.28%	Incorrect
CNN	30	99.99%	Correct
Mobilenet_v2	30	14.89%	Incorrect

4. Conclusion

This study has shown that the CNN model achieved better performance than the Mobilenet_v2 model based on the results obtained after the experiment was conducted. To create deep learning with better efficacy, the data sets for training and validation should have the same number of images so that the overfitting effect does not occur when the process of building the deep learning model is carried out. In addition, data augmentation with dropouts and fine-tuning is one of the keys to building an effective deep learning model. Finally, the CNN model managed to get a high enough performance to classify oil palm FFB images by using a data set of 1542 images based on 10 categories of oil palm FFB.

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