Improving System Accuracy by Modifying the Transfer Learning Architecture for Detecting Clove Maturity Levels

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***Abstract*—Detecting the maturity level of cloves is the initial stage in getting quality cloves. Early recognition of the maturity level of cloves is an essential stage in the clove industry. The maturity level of clove flowers can provide valuable information to clove farmers regarding clove harvest time. During the process of determining the level of maturity, it still relies on visual observation. This causes novice farmers and clove workers to still make mistakes in determining the start of the clove harvest. For this reason, in this research, initial detection of the maturity level of cloves was carried out based on images of clove flowers. There are four maturity levels: mature cloves, semimature cloves, overmature cloves, and dry cloves. The proposed research method is a modification of the transfer learning architecture. The research results show that modifying the Transfer learning architecture by adding three layers can increase system accuracy in the VGG16 and ResNet50 models by more than 5%, so that the highest accuracy obtained from modifying the VGG16 model is 95.5% and modifying the ResNet50 model is 87.75%. Meanwhile, for the VGG19 model, accuracy increased only when initializing the number of epochs to 10.**

***Keywords*—detection clove maturity, modified transfer learning, ResNet50, VGG16, VGG19**

I. Introduction

Loves are a type of spice plant native to Indonesia. However, clove plants have grown in several other countries, including India, Pakistan, and Bangladesh. In general, the benefits of cloves are primarily found in the flowers. Clove flowers have an oval and tapered shape of about 1–1.5 cm long. Clove flowers are green when they have not yet bloomed but will change color to red when they have bloomed. Another characteristic of cloves that is most distinctive is the aroma of cloves, which plays a significant role in using cloves as a spice.

The benefits of cloves are not only as a flavoring but have been processed into various kinds of products such as medicines and cosmetics. To manage cloves into various kinds of products, you need quality cloves. One of the initial stages for quality cloves is the early detection of clove maturity.

Early recognition of the maturity level of cloves is an essential stage in the clove industry. The maturity level of clove flowers can provide valuable information to clove farmers regarding clove harvest time. This is because if the harvest is late, the flower buds will bloom. If left untreated, the clove flowers will ripen, and they will no longer be suitable for harvesting but will be left for the clove seeding process. So, the optimal harvest time is when the clove flower buds are still attached because this will affect the cloves' quality and weight [1]. This will also affect the value of clove exports on the global market [2, 3].

So far, research on the maturity level of cloves has never been carried out. Only a few researchers classify cloves, but with different types of classes. As done by Prayogi *et al.* [4], the quality of cloves was classified using the Convolution Neural Network method. The experimental process was carried out only on the Epoch initialization parameters. Other experiments were not carried out that could increase the accuracy of the CNN method. Yaspin *et al.* [5] also classified cloves into four classes of dried cloves. In this study, the method used is the CNN method, but the feature extraction process is not involved in the CNN method. However, it is extracted separately using color features for the parameters tested, namely the provision of learning rate.

This proposed research recognizes the maturity level of clove flowers by comparing several deep-learning methods: ResNet50, VGG16, and VGG19. These methods have been applied in several other agricultural community studies [6–8] and each has advantages. For example, in the case of rice leaf disease, ResNet50 has better performance compared to VGG16 and VGG19 [9] Then, in tomato detection, VGG19 has better performance than VGG16 and ResNet50 [10] The proposed research not only

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compares the methods but also makes architectural modifications to ResNet50, VGG16, and VGG19 to increase the accuracy in the early detection of clove maturity levels.

The main contributions of this work are summarized below:

- Classify clove maturity levels into four classes;
- Improve the performance of ResNet50, VGG16, and VGG19 transfer learning models by modifying layers;
- Comparing transfer learning models for classifying clove maturity levels.

The remainder of this paper is structured as follows: Section II describes several studies regarding the classification of maturity levels in agriculture using learning transfer. Section III briefly describes the proposed methodology, including data collection information and the applied analysis model. Experimental results and evaluation of each model are presented in Section IV. finally, Section V concludes this paper.

II. Literature Review

Based on literature studies in international databases, the application of image processing for clove classification has only been found sometimes, in contrast to other agricultural commodities such as coffee, soybeans, tomatoes, watermelon, and rice, which are easy to find. However, there have been several researchers who have tried to carry out research related to the implementation of image processing on cloves. As carried out by Prayogi *et al.* [4], classifying cloves using the CNN method, the research results show that accuracy is good but can still be improved. Then, Chalik and Maki [11] carried out clove classification with CNN, but the feature extraction process used clove color features. The resulting accuracy can also still be improved. Meanwhile, Roth *et al.* [12] detected clove trees based on satellite imagery.

Several researchers have carried out the classification of maturity levels in agricultural commodities. As in the classification of durian maturity levels [13–16]. Thipsrirach *et al.* [13] compare convolution neural network architectures such as AlexNet, LeNet-5, and DuNet-12. This research only applies the pure architecture of each CNN architecture. No architectural modifications have been carried out, which means that the number of initialized epochs is still quite large, namely 350 epochs, to obtain the best accuracy.

Next is the classification of tomato maturity levels [10, 17, 18]. Begum and Hazarika [10] compared several transfer learning models such as VGG16, VGG19, InceptionV3, ResNet151, ResNet152. The results show that the performance of VGG19 is better than the others. This research has also made several parameter changes, such as initializing the number of epochs and batch size. However, it has yet to experiment with adding layers or modifying the architecture.

After that, in recognizing coffee maturity levels [19–22]. Tamayo-Monsalve *et al.* [19] compared several types of transfer learning, VGG16, VGG19, DenseNet201, and InceptionV3, which performed differently in each experiment, such as in handling imbalanced datasets. InceptionV3 was better than the others for undersampling, but when used for oversampling, DenseNet201 was better than the others. This study has not made parameter changes and modifications to the transfer learning architecture.

Several classifications of maturity levels of other agricultural commodities have also been applied [23–25]. Varur *et al.* [23] classified coconut maturity levels by comparing several transfer learning architectures. Of the several architectures compared to MobileNetV2 and ResNet152, it has achieved excellent accuracy, but layer modifications still need to be made to the transfer learning model. The proposed research classifies clove maturity levels by comparing VGG16, VGG19, and ResNet50 transfer learning modifications.

III. Materials and Methods

A This research uses a transfer learning method whose architecture has been modified by adding layers. There are three layers added. Three transfer learning methods are tested, namely ResNet50, VGG16, and VGG19. For the performance evaluation process of each model, accuracy, recall, precision, and F1-Score calculations are used. An overview of the proposed model is shown in Fig. 1.

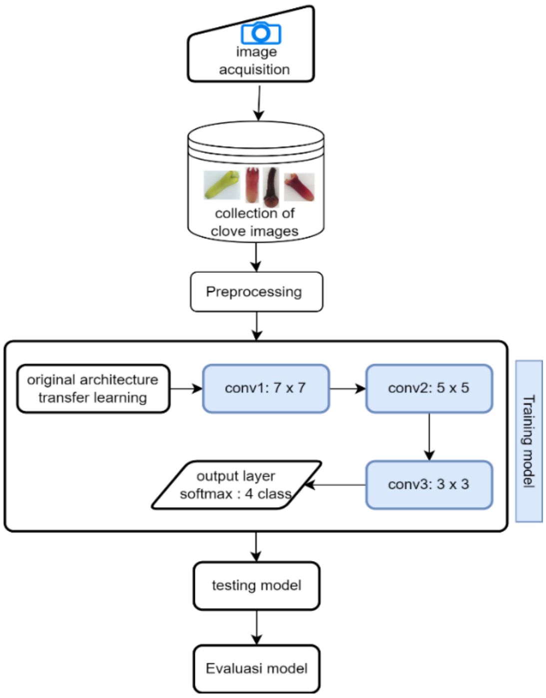


Fig. 1. The proposed modified transfer learning architecture model.

This research starts with the image acquisition process. Image acquisition involves hardware, namely a camera. The study used the OPPO A31 smartphone camera with rear camera specifications, namely 12 MP+2 MP+2 MP, ISO-142, 4096×3072, resolution 72 dpi—lighting with LED lights, collection box using cardboard, and white A3 paper. LED lights are installed on the left and right of the cardboard, and the camera position is above the cardboard at a distance of 20 cm. The illustration of the clove image capture box is shown in Fig. 2. This step aims to collect visual data that will be used in research for training and testing the model. The data that has been acquired is then stored in a database for subsequent use.

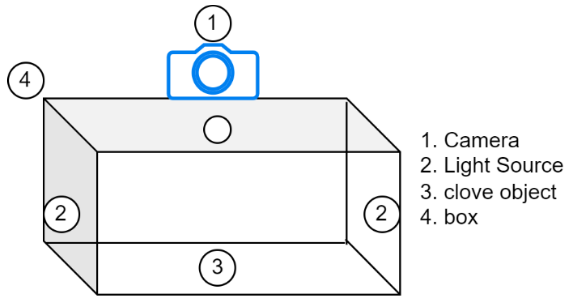


Fig. 2. Illustration of image acquisitions.

The next stage is pre-processing. In the pre-processing step of the research, several things were done, namely, rescale or minimize pixels and crop. The aim was to reduce computing time [26]. Next is the process of implementing the transfer learning model. The transfer learning models applied are ResNet50, VGG16, and VGG19, which have been modified by adding three layers to the original architecture. The modified models then calculated accuracy, precision, recall, and F1-Score using Eqs. (1)–(4) through the confusion matrix model, as shown in Table I [27].

TABLE I. CONFUSION MATRIX

Classification		Predicted Class	
		True	False
Observed class	True	True Positive (TP)	False Negative (FN)
	False	False Positive (FP)	True Negative (TN)

$$Precision = \frac{\sum TP}{\sum TP + \sum FP} \times 100\% \tag{1}$$

$$Recall = \frac{\sum TP}{\sum TP + \sum FN} \times 100\% \tag{2}$$

$$F1-Score = 2 \times \frac{precission\ x\ recall}{precisin + recall} \times 100\% \tag{3}$$

$$Accuracy = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FP + \sum FN} \times 100\% \tag{4}$$

IV. RESULT AND DISCUSSION

This research begins with the clove image acquisition process. The way to take an image of a clove is to make a box and then provide lighting, as in the image acquisition illustration shown in Fig. 2. The photo was taken using a smartphone camera. The distance between the camera and the object is 20 cm. There are four clove maturity levels: mature, immature, overmature, and dry. The data was 955, classified as 265 mature, 233 immature, 229 overmature, and 228 dry. Some example images are shown in Fig. 3.

After the data has been collected, the preprocessing stage is carried out. In the preprocessing location, several actions are applied, namely rescale and minimize pixels. The image size is 4096×3072 pixels when an acquisition is carried out. After preprocessing, it becomes 616×462 pixels, as the preprocessing results are shown in Fig. 4.

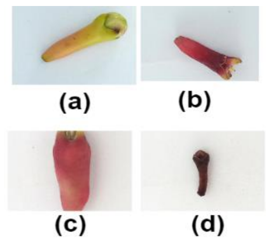


Fig. 3. Example of a clove maturity level dataset, Clove Mature (a), immature (b), Overmature (c), dry (d).

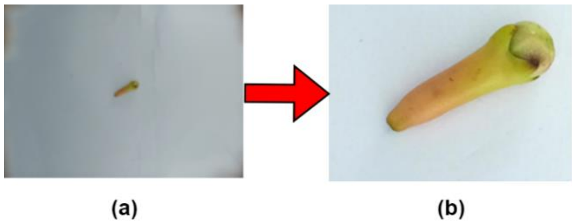


Fig. 4. Original clove image 4096×3072 pixels (a), preprocessing results (b).

A. *Training and Validation*

The training and validation process corresponds to the number of experiments carried out. There are 955 datasets divided into four classes—446 data as training data, 109 as validation data, and 400 as testing data. The total number of experiments was 18, using six models. The parameters being compared are the determination of the epoch. The optimizer used is Adam Optimizer, with a learning rate of 0.001.

B. *Results of Training and Validation of the Applied Model*

Fig. 2 shows the training and validation results with the highest accuracy for each model applied. For the ResNet50 model, the highest training and validation accuracy is when the number of epochs initialized is 100 epochs. As the results are shown in Fig. 5(a), from this graph, the accuracy is still below 95% and is still very dynamic. Furthermore, in the ResNet50 modification, training accuracy gets better when the number of epochs initialized is 100 epochs, but validation accuracy is still below 85%, as shown in Fig. 5(b). At the 60th epoch, the accuracy has reached 100%. Next, in the VGG16 model, the training and validation accuracy is above 90% when the number of epochs is 100, as shown in Fig. 5(c). However, when the architecture of VGG16 was modified by adding three layers, the training accuracy reached 100 at the 20th epoch and looked stable. Likewise, the validation accuracy was stable at above 90% at epoch 40. For the VGG19 model, the accuracy improved when the number of epochs was 100. The graph shown in Fig. 5(e), has not reached 100% accuracy. Meanwhile, in modifying the VGG19 architecture, the accuracy has reached 100% and has been stable since the 10th epoch, the same as validation, but the accuracy is still below 90%.

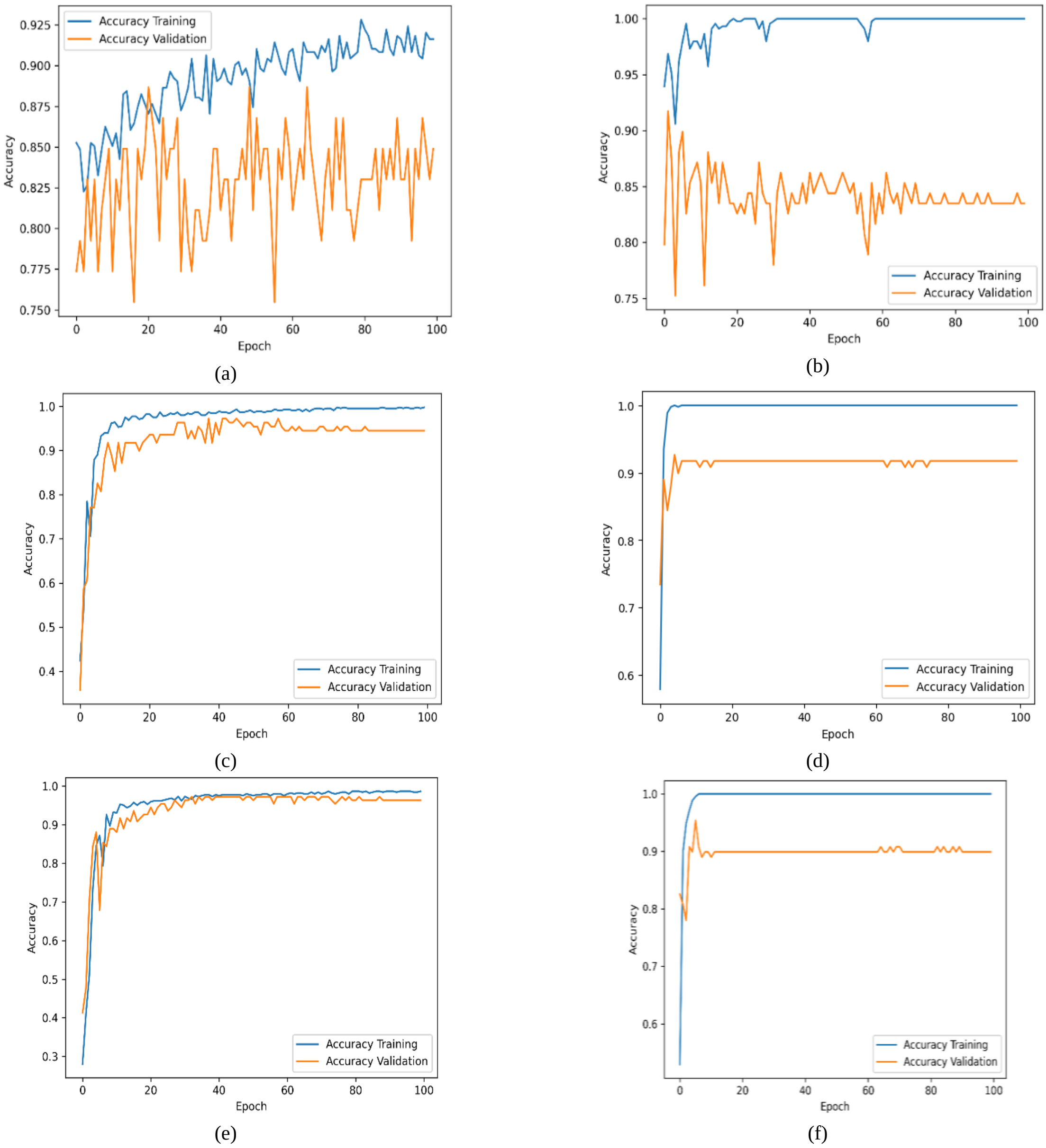


Fig. 5. Result of accuracy training and validation: (a) ResNet50; (b) modified ResNet50; (c) VGG16; (d) Modified VGG16; (e) VGG19; (f) Modified VGG19.

TABLE II. RESULT OF EXPERIMENTS CLASSIFYING MATURITY LEVELS

Model	Epoch	Accuracy	Precision	Recall	F1-Score
ResNet50	10	53.50%	74.00%	54%	47%
ResNet50	50	77.25%	81%	77%	77%
ResNet50	100	82.25%	83%	82%	82%
Modifed ResNet50	10	78.50%	80%	78%	79%
Modifed ResNet50	50	80.00%	86%	80%	80%
Modifed ResNet50	100	**87.75%**	**88%**	**88%**	**88%**
VGG16	10	87.75%	90%	88%	88%
VGG16	50	94.00%	94%	94%	94%
VGG16	100	94.50%	95%	95%	94%
Modified VGG16	10	95.00%	95%	95%	95%
Modified VGG16	50	95.25%	95%	95%	95%
Modified VGG16	100	**95.50%**	**96%**	**95%**	**95%**
VGG19	10	88.25%	89%	88%	88%
VGG19	50	95.25%	95%	95%	95%
VGG19	100	**95.25%**	**95%**	**95%**	**95%**
Modified VGG19	10	92%	92%	92%	92%
Modified VGG19	50	92.50%	93%	93%	92%
Modified VGG19	100	92.00%	92%	92%	92%

C. Classifications Results

The data that has been trained and validated is then calculated for the accuracy of each proposed transfer learning model, then tested or classified to obtain the performance of each model that is applied to the classification process of clove maturity level through Recall, Precision, F1-Score, and Accuracy calculations. There were 18 experiments in the study. The results of all experiments are shown in Table II.

D. Evaluation of ResNet50 and Modified ResNet50

Based on the research results on the ResNet50 model and ResNet50 modifications, the highest accuracy was when the epoch was initialized to 100. The ResNet50 model obtained an accuracy of 82.25%, Precision of 83%, Recall of 82%, and F1-Score of 82%. Meanwhile, the modified ResNet50 model obtained an accuracy of 87.75%, Precision of 88%, Recall of 88%, and F1-Score of 88%. The confusion matrix results from the two models are shown in Fig. 6(a), for ResNet50 and Fig. 6(b), for Modified ResNet50. The two images show that the class that is easily recognized is the Dry class, with a percentage of 97% for ResNet50 and 98% for modified ResNet50. Meanwhile, the class with the lowest level of accuracy is semi-mature, with a percentage of 68% using ResNet50 and 80% using Modified ResNet50. Overall, there was an increase in accuracy of more than 5%.

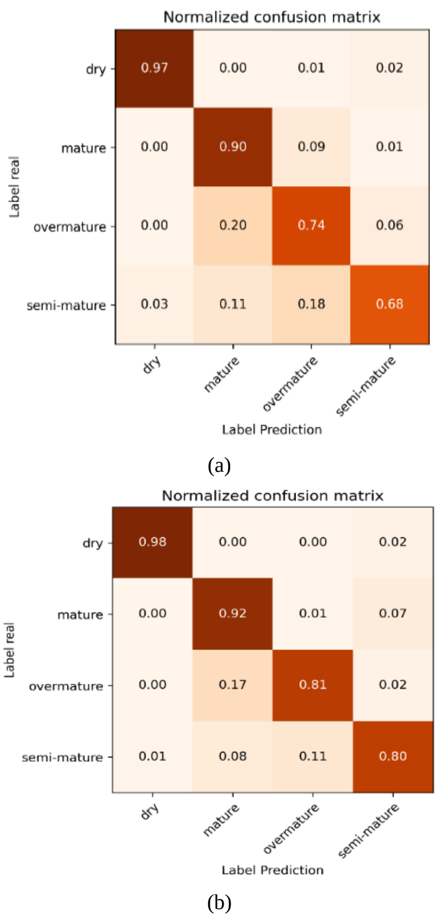


Fig. 6. Result of confusion matrix: (a) ResNet50; (b) Modified ResNet50.

E. Evaluation of VGG16 and Modified VGG16

The results of the VGG16 test on the clove maturity level classification obtained different accuracy, but the increase in accuracy was not too significant between the 50 and 100 epoch values. The performance of VGG16 with 100 epochs obtained an accuracy value of 94.50%, 95% precision, 95% recall, and F1-Score 94%. For the modification of the VGG16 architecture, all epoch determination experiments have obtained an accuracy of more than or equal to 95%. This also follows the training results in Fig. 5(d). The accuracy is already static at the 10th epoch. The results of comparing the two models are shown in Fig. 7(a) and Fig. 7(b).

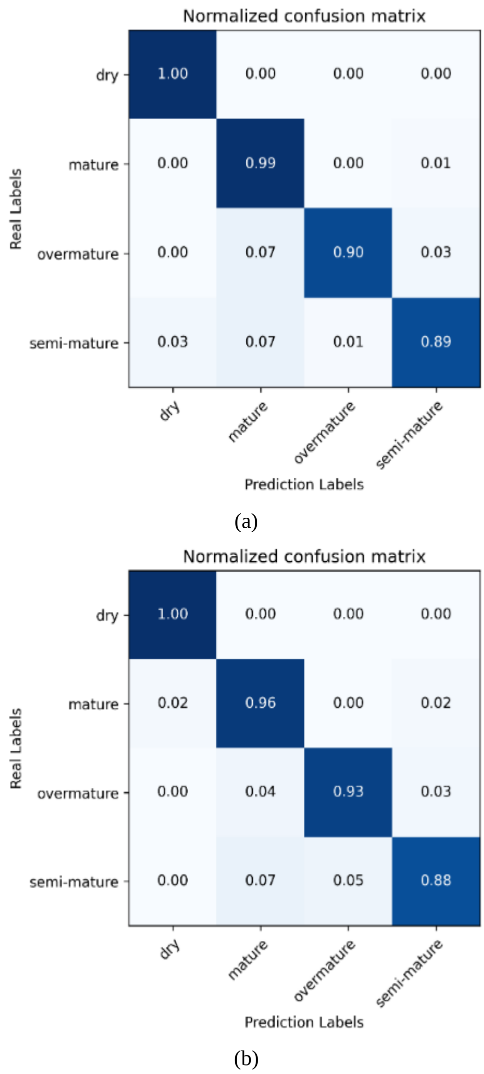
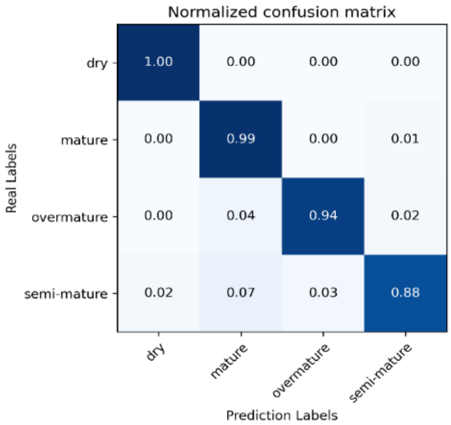


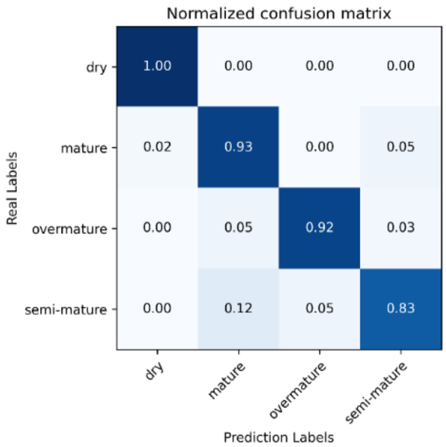
Fig. 7. Result of confusion matrix: (a) VGG16; (b) Modified VGG16.

F. Evaluation of VGG19 and Modified VGG19

The accuracy of applying VGG19 is better than that of the VGG19 modification when initialized epochs are 50 and 100. The VGG19 model with 50 and 100 epochs has produced an accuracy of 95.25%, while the architectural modification of VGG19 has obtained an accuracy of 92.00%. The value of the confusion matrix is shown in Fig. 8(a) for the original model VGG19 and Fig. 8(b) for the modified model VGG19. These results indicate that adding layers to VGG19 can add complexity, causing overfitting or difficulty during training. These results can also be seen during the training process and model validation in Fig 5(e) and Fig. 5(f). Fig. 5(e) is the original VGG19 model with accuracy and validation values above 90%, and Fig. 5(f) is a modified VGG19 with an accuracy of 100%. However, the validation value is still below 90%. This experiment also shows that not all architectural modifications to transfer learning by adding layers can improve system accuracy.



(a)



(b)

Fig. 8. Result of confusion matrix: (a) VGG19; (b) Modified VGG19.

V. Conclusion

Based on the results of tests on the classification of clove maturity levels by comparing the transfer learning models ResNet50, VGG16, VGG19 and modifications of the three architectures. Shows that modifying the architecture by adding three layers to ResNet50 and VGG16 can increase the system's accuracy in classifying clove maturity levels. In contrast, in changing the VGG19 model, the accuracy only increases at an initialized number of 10 but will decrease when the number of epochs is 50 and 100. Not all modified transfer learning models will experience increased algorithm performance. The accuracy produced by the VGG16 model modification of 95.5% and the ResNet50 model modification of 87.75% can still be improved with various changes to other parameters. Then, in this research, it is also necessary to apply it to mobile so that farmers can use it directly to control the detection of clove maturity levels. This research also has limitations because the image acquisition process takes a lot of time. Then, the image processing process is carried out sparingly, such as the image segmentation. This is because the image acquired is single. For this reason, it is necessary to carry out image acquisition in groups so that the image segmentation process, in this case, can be seen.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

The contributions of each author are described as follows: Conceptualization and methodology, Rosihan, Tempola; implementation the of methodology, Tempola; data validation, Sutoyo; formal analysis, Gunawan; investigation, Rosihan, Gunawan; writing—original draft preparation, Sutoyo; writing—review and editing, Tempola; supervision, Tempola. All authors had approved the final version.

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