Classification of Rhizomes Using Pre-trained Convolutional Neural Network Method

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ABSTRACT
Rhizomes have many types, aromas, and colors. Manual identification of rhizome types can be done based on their aroma, shape, and color characteristics. Some types of rhizomes have similarities that are difficult to identify by human vision. The purpose of this study is to identify five types of rhizomes including ginger, A. galanga, curcuma, B. pandurata, and K. galanga appropriately using machine vision methods based on convolutional neural networks (CNN). The samples used in this study were 250 samples of each type of rhizome which were divided into two data sets, namely 200 data for training-validation and 50 data for testing. The pre-trained CNN models used in this study are GoogLeNet and ResNet-50. The results of this study show that GoogLeNet achieved the highest accuracy value of 100% when using the Adam optimizer and a learning rate of 0.00005. Meanwhile, ResNet-50 achieved the highest accuracy of 100% when using the RMSProp optimizer and a learning rate of 0.0001. From the testing results, GoogLeNet and ResNet-50 achieved the highest accuracy of 99.2% and 95.6%, respectively.

Keywords: *Convolutional Neural Network, GoogLeNet, Rhizome, ResNet-50.*

1. INTRODUCTION

Indonesia is famous for its biodiversity, one of which is various types of rhizomes [1]. Rhizomes are one type of plant that grows creeping below the soil surface that produces new shoots and roots from each segment. Rhizomes are used as spices or seasonings, herbal medicines for health, aromatherapy, and basic ingredients in the herbal beverage industry [2]. Rhizomes have various characteristics of color, shape, aroma, and taste. Some types of rhizomes are difficult to distinguish their characteristics using human vision. Therefore, a machine vision approach is needed to replace human vision in identifying rhizome types [3].

Deep learning is one part of machine vision science that utilizes artificial neural networks to model problems that have high complexity, especially in agriculture [4]. One of the methods in deep learning that can recognize image objects is the convolutional neural network (CNN). This method has been widely used to solve problems related to object detection or image classification. Several studies have proven the effectiveness of CNN in classifying agricultural products. Hendrawan et al. [5] classified Indonesian coffee types using pre-trained CNN AlexNet. The accuracy reached 100%. Hendrawan et al. [6] classified the moisture content level of cassava chips during drying using pre-trained CNN AlexNet, GoogLeNet, ResNet-50, and SqueezeNet. The results show a validation accuracy of 100% and also a testing accuracy of 100%. Hendrawan et al. [7] classified the purity level of Luwak coffee using four pre-trained CNN models consisting of SqueezeNet, GoogLeNet, ResNet-50, and AlexNet. In the training and validation process, using the best CNN model, the highest accuracy reached 89.65%, while the testing accuracy was 85%. Hendrawan et al. [8] have also successfully classified the maturity level of large green chili using four types of pre-trained CNN networks i.e. SqueezeNet, GoogLeNet, ResNet50, and AlexNet. Classification accuracy using the best CNN model on training and validation data reached 93.89% and the accuracy of testing data was 91.27%. Hendrawan et al. [9] have successfully made a CNN-based soybean tempe classification system. Four types of pre-trained CNN networks were used in this study i.e. SqueezeNet, GoogLeNet, ResNet-50, and AlexNet. The training and validation accuracy of the best CNN model reached 100%, while the testing accuracy reached 98.33%. Hendrawan et al. [10] have also successfully built a water stress detection system in plants using CNN. Four types of pre-trained CNN (SqueezeNet, GoogLeNet, ResNet-50, and AlexNet) were compared to get the best model. The best

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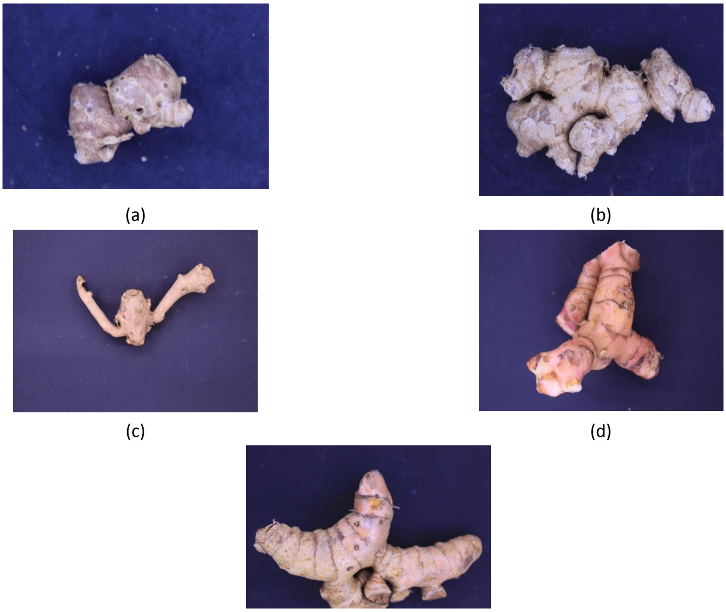
CNN model can classify water stress in plants with training-validation accuracy of 87.5% and testing accuracy of 94.15%.

Types of rhizomes that are still difficult to distinguish include ginger (*Zingiber Officinale*), A. galanga (*Alpinia galanga*), curcuma (*Curcuma xanthoriza Roxb*), B. pandurata (*Boesenbergia pandurata (Roxb) Schlecht*), and K. galanga (*Kaempferia galanga L.*). Ginger has a rhizome-shaped root with a yellow to reddish color [11]. A. galanga has a cylindrical shape with a diameter of 2-4 cm. The outer skin color on A. galanga is brownish-white to reddish-white [12]. Curcuma which has stems and branches with dark yellow to brownish outer skin [13]. The physical characteristics of B. pandurata have a diameter of up to 2 cm and are brownish yellow on the outer skin [14]. The purpose of this research is to identify five types of rhizomes including ginger, A. galanga, curcuma, B. pandurata, and K. galanga correctly using the CNN-based machine vision method.

2. MATERIALS AND METHODS

The main materials used in this study were five types of rhizomes namely ginger, A. galanga, curcuma, B. pandurata, and K. galanga obtained from Malang, East Java, Indonesia. Image acquisition was performed using a CANON EOS 1300 D camera (CMOS, 5184 × 3456 pixels, JPG, ISO 100, 6400, Autofocus). A mini box studio (40 × 25 cm, white LED lighting) was used in the image acquisition process. Data processing was performed using a computer (Intel Core i3-10105 processor, 64-bit, 16 GB RAM, Windows 10). CNN modeling used a MATLAB R2019b application.

Figure 1 shows images of five types of rhizomes used in the study, namely ginger, A. galanga, curcuma, B. pandurata, and K. galanga. The number of images obtained from the image acquisition process is 250 images of each type. The image data is then divided into two categories, namely 200 images as training-validation data and 50 images for testing data. All sample data is modeled into the Matlab application using pre-trained GoogLeNet [15] and ResNet-50 [16] to determine the accuracy and error values in the data.



(a) (b) (c) (d) (e)

Figure 1 Five types of rhizomes: a) K. galanga, b) ginger, c) B. pandurata, d) A. galanga, e) curcuma.

The CNN method is useful for modeling input to output and classifying the output accurately. To get the optimal CNN model, it is necessary to do sensitivity analysis through optimal hyper-parameter settings. In preliminary research, an epoch value of 30 and a mini batch-size of 20 were found to be optimal for use in this study. Two types of pre-trained networks CNN are used in this study, namely GoogLeNet and ResNet-50. The optimizers compared in this study are SGDm, Adam, and RMSProp. The learning rate used has two variations, namely 0.0001 and 0.00005. CNN structure can be seen in Figure 2. CNN structure consists of convolution layer, polling layer, and fully connected layer. The testing process is carried out using a confusion matrix to see the accuracy of the CNN model generated using different data sets from the training-validation data.

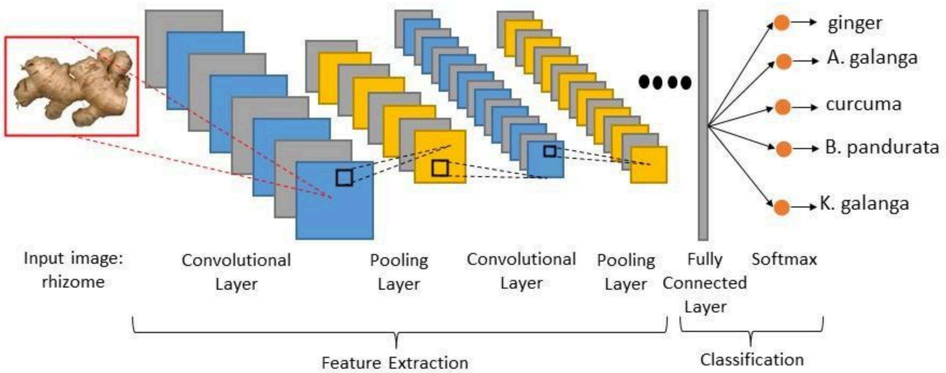


Figure 2 CNN structure for rhizome classification.

3. RESULTS AND DISCUSSION

In testing using pre-trained GoogLeNet, the highest accuracy value obtained was 100% when using the Adam optimizer and a learning rate of 0.00005. The time required to run the model is 412 minutes 54 seconds. The table of CNN modeling results can be seen in Table 1. From the GoogLeNet architecture (Adam optimizer and learning rate 0.0001) results in 99.67% accuracy. In the RMSProp optimizer with a learning rate of 0.0001, the accuracy result is 99.67%. In the SGDM optimizer with a learning rate of 0.0001, the accuracy result is 98.67%. In the Adam optimizer with a learning rate of 0.00005, 100% accuracy is obtained. In the RMSProp optimizer with a learning rate of 0.00005, the result is 99.67%. In the SGDM optimizer with a learning rate of 0.00005, 95.00% accuracy is obtained. The graph of the training and validation process of the GoogLeNet model using the Adam optimizer and learning rate 0.00005 can be seen in Figure 3. The accuracy and loss graphs show a steady increase and decrease with little fluctuation. This shows that the learning process is optimal.

The pre-trained ResNet-50 model produces the highest accuracy value of 100% when using the RMSProp optimizer and a learning rate of 0.0001. The time required to run the best model is 674 minutes 32 seconds. The table of ResNet-50 model running results can be seen in Table 2. The pre-trained ResNet-50 model on the Adam optimizer and a learning rate 0.0001 produces an accuracy of 98.00%. On the RMSProp optimizer and learning rate 0.0001, 100% accuracy is obtained. On the SGDM optimizer and learning rate 0.0001, 99.67% accuracy is obtained. In the Adam optimizer and learning rate 0.00005, the accuracy result is 99.00%. In the RMSProp optimizer and learning rate 0.00005, the accuracy result is 99.67%. In the SGDM optimizer and learning rate 0.00005, the accuracy result is 99.33%. The training-validation process graph of the ResNet-50 model with the RMSProp optimizer and learning rate 0.0001 can be seen in Figure 4. The accuracy and loss graphs show a steady increase and decrease with little fluctuation. These results show that the learning process has also been effective and optimal.

Table 1. Results (training-validation) of the GoogLeNet model.

Optimizer	Learning Rate	Accuracy (%)	Time (minutes)
Adam	0.0001	99.67	404 min 39 sec
RMSProp	0.0001	99.67	442 min 46 sec
SGDm	0.0001	98.67	408 min 14 sec
Adam	**0.00005**	**100**	412 min 54 sec
RMSProp	0.00005	99.67	407 min 50 sec
SGDm	0.00005	95	408 min 20 sec

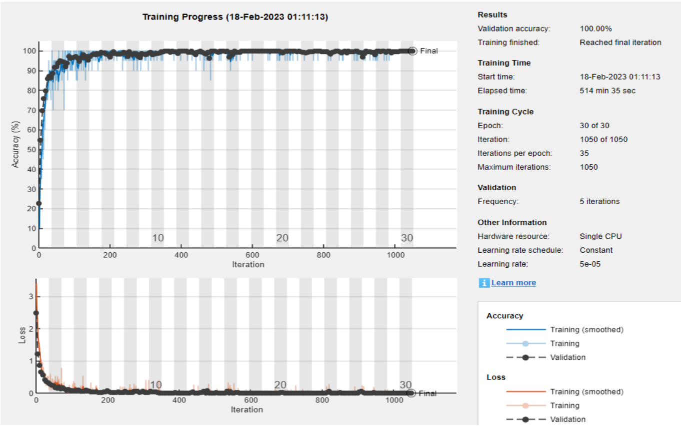


Figure 3 Graph of training-validation test results on the GoogLeNet model.

Table 2. Results (training-validation) of the ResNet-50 model.

Optimizer	Learning Rate	Accuracy (%)	Time (minutes)
Adam	0.0001	98	639 min 42 sec
RMSProp	**0.0001**	**100**	674 min 32 sec
SGDm	0.0001	99.67	612 min 23 sec
Adam	0.00005	99	644 min 24 sec
RMSProp	0.00005	99.67	640 min 17 sec
SGDm	0.00005	99.33	624 min 58 sec

After obtaining the results of the training-validation data, testing is then carried out on the testing data using different data sets. In this test, the data used is 25% of the training-validation data. So from the overall data, 50 data are taken from each rhizome category. The results of the testing process can be seen in Table 3. Table 3 shows that the highest accuracy of the GoogLeNet model of 99.2% is produced when using the Adam optimizer and a learning rate of 0.0005. While from the ResNet-50 model, the highest accuracy was 95.6% when using the RMSProp optimizer and the learning rate 0.0001.

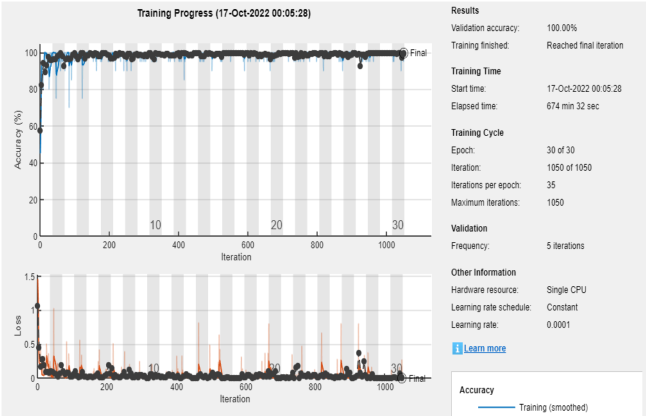


Figure 4 Graph of training-validation test results on the ResNet-50 model.

Tabel 3. Testing accuracy.

Architecture	Optimizer	Learning rate	Accuracy (Testing)
GoogLeNet	Adam	0.0001	86.8%
	RMSProp	0.0001	95.5%
	SGDm	0.0001	87.2%
	Adam	**0.00005**	**99.2%**
	RMSProp	0.00005	93.6%
	SGDm	0.00005	88.0%
ResNet-50	Adam	0.0001	80.0%
	RMSProp	**0.0001**	**95.6%**
	SGDm	0.0001	80.0%
	Adam	0.00005	81.2%
	RMSProp	0.00005	80.0%
	SGDm	0.00005	79.2%

Confusion matrix is used as a testing method for classification using testing data. Confusion matrix is used to express the number of incorrect test data and correct test data and is presented in tabular form. The confusion matrix results for the best GoogLeNet model from this study can be seen in Figure 5. Figure 5 shows the results of the best confusion matrix test obtained, namely GoogLeNet with the Adam optimizer and a learning rate of 0.00005, where of the five types of rhizomes, 50 samples were correctly classified as ginger so that an accuracy value of 100% was obtained, but 2 samples were misclassified as ginger and 48 samples were correctly classified as K. galanga so that an accuracy value of 96% was obtained. Furthermore, 50 samples were correctly classified as B. pandurata so that an accuracy value of 100% was obtained. Then 50 samples were correctly classified as A. galanga so that 100% accuracy was obtained. Then 50 samples were correctly classified as curcuma so that an accuracy value of 100% was obtained. From the overall accuracy value, an average of 99.2% was obtained. The confusion matrix results for the best ResNet-50 model can be seen in Figure 6. Figure 6 shows the confusion matrix of the RMSProp optimizer and learning rate 0.0001. Based on the classification results can be seen in the confusion matrix, where 43 samples were correctly predicted as ginger, 7 samples were incorrectly predicted and included in the K. galanga category. The second column shows that 49 samples were correctly predicted as K. galanga. In the K. galanga sample, 50 samples were predicted correctly. In the B. pandurata sample, 47 samples were predicted correctly, but 3 samples were predicted incorrectly. In the A. galanga sample, 49 samples were predicted correctly and 1 sample was predicted incorrectly. In curcuma samples as many as 50 samples were predicted correctly, so that the overall average accuracy value was 95.6%.

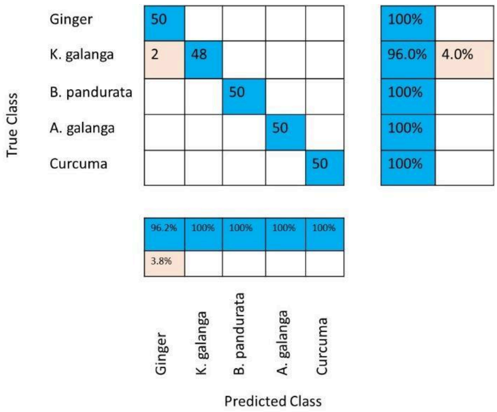


Figure 5 Confusion matrix of GoogLeNet with Adam optimizer.

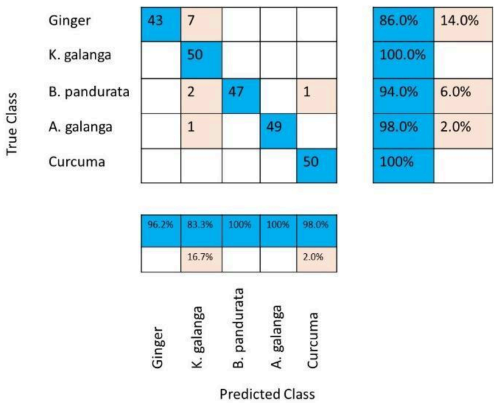


Figure 6 Confusion matrix of ResNet-50 with RMSProp optimizer.

4. CONCLUSION

The CNN method with pre-trained GoogLeNet and ResNet-50 is able to identify five types of rhizomes including ginger, A. galanga, curcuma, B. pandurata, and K. galanga. The accuracy results obtained on training-validation data with the GoogLeNet model ranged from 95% - 100% while the accuracy of the ResNet-50 model ranged from 98% - 100%. The accuracy results of testing data with the GoogLeNet model ranged from 86% - 99% and the ResNet-50 model ranged from 79% - 95%. Based on training-validation data, in the GoogLeNet model, the highest accuracy value of 100% is obtained with the Adam optimizer and a learning rate of 0.00005. While in the ResNet-50 architecture, the highest accuracy value of 100% is obtained with the RMSProp optimizer and a learning rate of 0.0001. From the testing data, the GoogLeNet model achieved the highest accuracy value of 99.2%, while in the ResNet-50 model the highest accuracy value was 95.6%.

AUTHORS' CONTRIBUTIONS

All authors and co-authors have contributed equally to the research.

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