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Color-based Classification of Dried Cocoa Beans from Various Origins of Indonesia by Image Analysis Using AlexNet and ResNet Architecture-Convolutional Neural Networks

Wahyu Kristianingsih[1*], Bambang Dwi Argo[1], La Choviya Hawa[1], Misnawi[2], Noor Ariefandie Febrianto[2], Yusuf Hendrawan[1], Mochamad Bagus Hermanto[1], and Bagus Rahmatullah[1]

[1]Department of Agricultural Engineering and Biosystem, Universitas Brawijaya, Jl. Veteran-Malang, Indonesia
[2]Indonesian Coffee and Cocoa Research Institute, Jl. PB. Sudirman 90, Jember 68118, Indonesia
[*]Corresponding author: wningsih975@gmail.com
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Abstract

Cocoa plant is widely cultivated in Indonesia and spread across various regions. Diversity in geographical conditions has been known to significantly affect the quality of cocoa beans. Practically, cocoa beans are often mixed without considering the variation in the quality and its origin. This resulted in reduced global quality and product inconsistency. Improved recognition and classification methods are needed to solve those problems. Non-destructive classification methods can be used to provide a more efficient classification process. The use of artificial intelligence with computer-based deep learning methods was used in this study. Beans samples of various origins (Aceh, Bali, Banten, Yogyakarta, East Kalimantan, West Sulawesi, and West Sumatera) were evaluated. From the collected samples, 9100 images were then taken for data processing. Data pre-processing included denoising of the background image, cropping, resizing and changing the storage extension through the training-validation stage and the testing process. AlexNet and ResNet architectures on a Convolutional Neural Network were used for classification. The results showed that the average accuracy of cocoa image classification based on color identification by computer machines using Alexnet and ResNet was high (99.91% and 99.99%, respectively). This method can be applied to provide more efficient color-based cocoa bean classification for industrial purposes.

Keywords: Sortation, grading; deep learning; non-destructive; artificial intelligence

INTRODUCTION

Cocoa plants are one of the most important cash crops in Indonesia. It is widely cultivated by farmers in various regions in Indonesia. The diversity of geographical conditions, agronomical practices, and locally adopted post-harvest practices resulted in a high variety in the quality of cocoa beans produced. Currently, cocoa beans are a commodity with high selling value and a diverse consumer market (Fajardo *et al.*, 2022). Therefore, high consistency and traceability of cocoa beans are needed to meet the needs of the domestic and international markets. The quality of cocoa beans is the fulfillment of several parameters in accordance with Indonesian National Standard (SNI) for cocoa beans, including those related to the moisture content, authenticity of the product, impurities level, and fungal infestations (SNI 2323:2008). One of the most determining analyses of cocoa bean quality is the cut test, where the inside part of the beans are classified by their color. However, the outer appearance of cocoa beans is also important since it represents the uniformity of the origin and process. These analyses rely on the use of sensorial evaluation. This method, even though it is convenient due to the lack of use of analysis instruments, is exhausting and time-consuming. Improvement in those processes, to provide more efficient analysis, is urgently required.

Digital technology that is increasingly developing has been widely used and applied in various fields of automation, one of which is in the agricultural sector. Among the processing of agricultural products, automation at the control system stage and classification of food products has been successfully carried out by Kusuma *et al.* (2017). This method helped to avoid losses in large scale production processes. Practically, some of the sensorial-based analysis on cocoa beans can be carried out using computer sensing. Classification methods based on the use of digital imaging and Artificial Intelligent (AI) technology, that utilizes machine learning, have been rapidly developed. Machine learning is a branch of AI whose data input can be in the form of digital images. These images are then used for the iterative learning process of AI so that it will be able to identify objects without the need to go through a destructive process. The use of digital cameras in data collection for development of AI technology has been successfully carried out in several studies (Sabilla, 2020; Sharpe *et al.*, 2020; Bernacki, 2021). The use of this method is convenient. It can use commercial digital cameras and readily available MatLab software (Mustamin *et al.*, 2021).

Convolutional Neural Network (CNN) is a method for modelling that is widely applied in image processing-based classification processes. Its combination with AlexNet and ResNet architecture types capable of producing high accuracy (>90%) in grouping random samples into appropriate classes (Setiawan, 2020; Sunanthini *et al.*, 2022). The working principle of CNN is that it can classify images through several configurations, including the parameter number of epochs, the convolution model and the type of activation function (Naufal *et al.*, 2021). Input data from these two methods will go through the training-validation and testing stages to determine the error value and the level of system learning ability. The amount of inputted data relates to the learning process and the accuracy of the system. This research aimed to develop a system with best accuracy and validation results for cocoa classification utilizing image analysis and CNN. The samples of dried cocoa images from 7 different regions in Indonesia based on several types of input color parameters were used to obtain the best modeling. It was expected that the classification using digital imaging with computer-based deep learning methods can be carried out to provide a more efficient method to classify cocoa beans.

MATERIALS AND METHODS

Sample Preparation

Seven samples of dried cocoa beans (Aceh, Bali, Banten, Yogyakarta, East Kalimantan, West Sulawesi, and West Sumatra) were collected by Indonesian Coffee and Cocoa Research Institute (Table 1). The beans were approximately 2 kg each and in fermented condition. The moisture content was in the range of 5-8%.

Image Collection of Cocoa Beans

Image acquisition process began by inserting a sample container that has been filled with ±200 g of beans into the black box and positioning it right in the middle, perpendicular to the camera (SONY/DSC-H200-20.1Mp) and then the image was taken. The images were then saved using the format of "origin" followed by the "number" of images, for example "Aceh1" to images "Aceh1300" for cocoa beans from Aceh. The same steps were applied in the process of taking cocoa images from other regions until a total of 9100 images were obtained. The test data images are then sorted into two main sections, namely training-validation data of 7000 images and testing data of 2100 images. This data set will later be used as input in the development of the CNN classification model with the AlexNet and Resnet architectures.

Digital Image Preprocessing

Acquired digital images were then preprocessed. The images were then modified by several stages, including image cropping stage, image size normalization (resize image), and image conversion process. The image cropping process was carried out using the Microsoft Photos software by selecting the square format as the aspect ratio used and positioning the edge in the sample container as the outer boundary of the image (Figure 1). Furthermore, the process of normalizing the size of the image in the dimensions of 500

Table 1. Information of the cocoa beans samples

No	Sample origin	Number of sample (kg)	Sample code
1	Kudeungo Sugata-Pidie Jaya, Aceh	2	Aceh
2	Jembrana, Bali	2	Bali
3	Tanahlaut-Pandeglang, Banten	2	Banten
4	Yogyakarta	2	Jogja
5	Kampung Merasa-Berau, East Kalimantan	2	Kaltim
6	Limboro-Polewali Mandar, West Sulawesi	2	Sulbar
7	Saiyo-Solok, West Sumatera	2	Sumbar

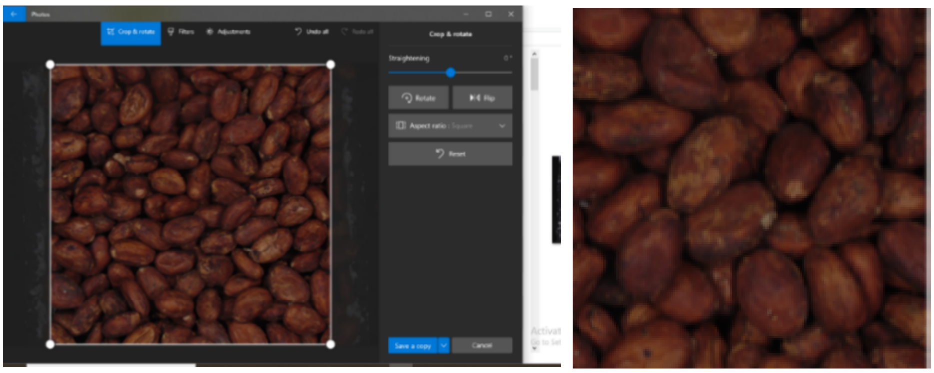

Figure 1. Process (left) and results (right) of test image cropping

x 500 pixels is carried out using the Microsoft Office Picture Manager software. Then convert the image from the JPG file to a bitmap image or BMP file so that a degraded image is obtained, which facilitates the extraction process for SVM testing and will be able to be processed in CNN modeling (Bernacki, 2021).

Training-Validation CNN

Modification of the CNN Architecture

Modification of the CNN architecture was done by replacing the last convolutional with the “fullyConnectedLayer” layer and setting the output size to a value of 7 (based on the type of the samples). Furthermore, the classification layer was set to detected auto, which means that the number of output classes had adjusted the settings in the previous layer.

CNN Data Input

The data input process was carried out by selecting a folder containing 7000 training-validation images. The settings were on the “split from training data” option and the desired specific percentage was 30%. Then the option to randomize columns was selected as executed through “import”. Through this setting, a total of 7000 test sample images were randomly selected and automatically divided into 4900 images as training data and 2100 other images as validation data in building the model.

Hyperparameter Settings of CNN

The parameters were adjusted including the type of solver, total learning rate, validation frequency, maximum epoch, and minimum batch size. The choice of solver types included SGDm, Adam, and RMSProp with learning rates of 0.0001 and 0.00005. Then the validation frequency was set at 50 and 20 for maximum epoch and 20 for minimum batch size. After adjusting to the composition of the hyper-parameter variation as shown in Table 2 below, the settings were then applied alternately until a graph of the training results is obtained.

CNN Testing

The testing process was continued after the training and data validation stages had been completed. The amount of image data for the testing process is 300 images for each class (total of 2100 image data). The testing process was carried out by changing the coding in the import data testing section and adjusting it to the location folder where the image data was stored. Shortly after the data had been processed, it produced a matrix of classification results that was used in the next stage.

Table 2. Hyperparameter setting variations CNN

CNN Architecture	Solver	Learning rate	Validationf requency	Max Epoch	Minimum batch size
AlexNet	SGDm	0.0001	50	20	20
	Adam	0.0001	50	20	20
	RMSProp	0.0001	50	20	20
	SGDm	0.00005	50	20	20
	Adam	0.00005	50	20	20
	RMSProp	0.00005	50	20	20
ResNet	SGDm	0.0001	50	20	20
	Adam	0.0001	50	20	20
	RMSProp	0.0001	50	20	20
	SGDm	0.00005	50	20	20
	Adam	0.00005	50	20	20
	RMSProp	0.00005	50	20	20

Constructing the CNN Confusion Matrix

The matrix previously generated was then copied to MATLAB and set into two main rows, namely the TRUE column or the actual image identity and the PREDICTED column. In order to convert the data into the desired confusion matrix layout, “Column Vector” was selected in the output type settings section and then pressed import. After these steps had been completed, a confusion matrix was obtained as the final result of the CNN classification process.

RESULT AND DISCUSSION

Image Characteristics of Cocoa Dried Beans

The test sample image of dry fermented cocoa beans samples is shown in Figure 2. The cocoa beans samples shared some similarity in the appearance, namely dominant brown color but with slightly different color intensity from one another. The brown color of fermented cocoa beans developed during the post-harvest process. During fermentation, the pulp of the cocoa beans undergoes biochemical changes due to microorganisms’ activity, resulting in a change of color. Furthermore, the browning reaction during the drying process also resulted in the brown appearance of cocoa beans. Variability in color thus represents the degree of post-harvest processing done to the cocoa beans (CAOBISCO/ECA/FCC, 2015). Unfermented and washed cocoa beans tend to have brighter color while the occurrence of white mycelium on the shell represents the fungi infestation. The appearance of the Aceh sample tends to be grayish brown or dark brown compared to other samples, however it looks almost similar to the West Sumatra sample. While the Jogja sample appears to have the lightest brown color, followed by the Banten sample and then the other three samples, namely the Bali, East Kalimantan and West Sulawesi samples. This color, when mixed, could have a physical appearance that tends to be difficult to distinguish directly with human visualization.

Test Treatment and Variation of CNN Hyperparameters

The distribution of training-validation data with a ratio of 70%:30% has been considered through a literature study process (Rani, *et al.*, 2018; Gadze, *et al.*, 2021). Then the parameter values of CNN with three types of solvers, namely Sgdm, Adam and RMSProp have been determined as an

Figure 2. Coded sample: Aceh (A), Bali (B), Banten (C), Jogja (D), Kaltim (E), Sulbar (F), and Sumbar (G)

optimization algorithm to update the weights iteratively and together with the learning rate setting it will affect the learning time of the model. It is known that in this study, with a total training data of 4900 and the use of a batch size value of 20, a value of 245 iterations per epoch is obtained. Setting an epoch value of 20 on the training-validation data of 4900 images with a validation frequency of 50 iterations has been achieved entirely so that it is stated that the modeling process is running well.

Data Analysis of CNN Training-Validation Results

Data from training-validation results are presented in the form of process achievement graphs (Figure 3). The red graph represents the learning loss or error value and the blue graph represents the successful achievement of the training process. Complete information on the results of training-validation of each variation of the hyperparameter is shown in Table 3.

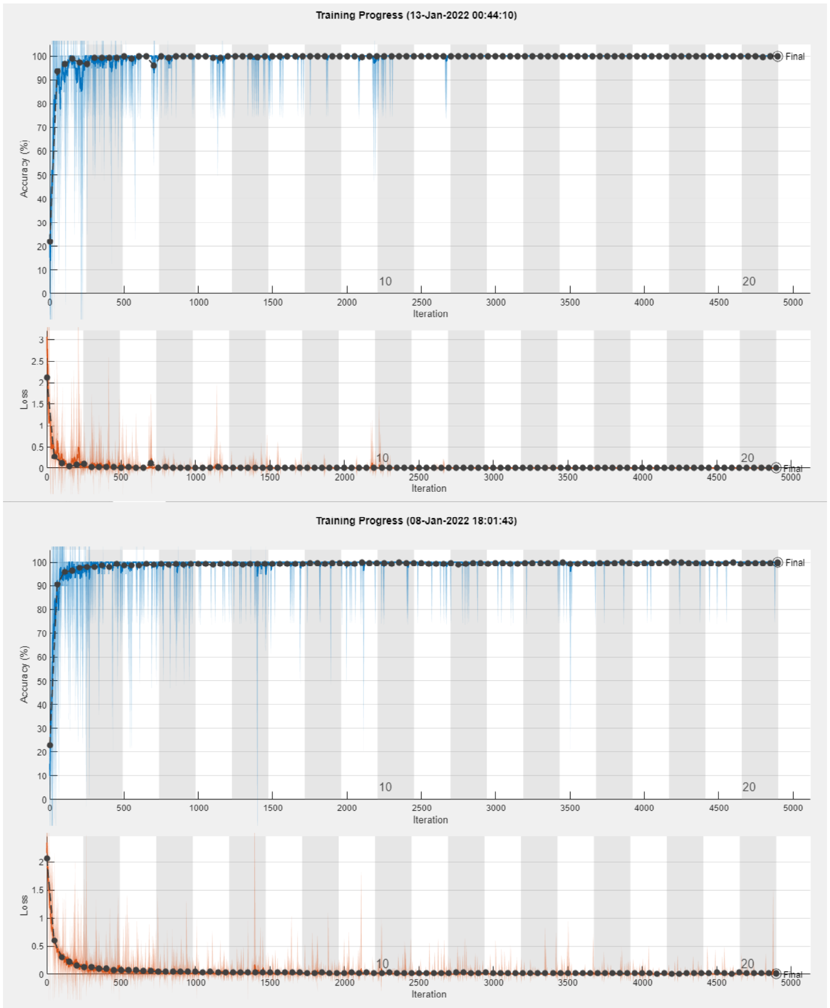

Figure 3. Training-validation result of CNN on cocoa beans samples

The best results for the Alexnet architecture with the SGDM solver type and a learning rate of 0.0001. It was able to produce 100% learning accuracy in a processing time of 53 minutes 28 seconds, validation frequency value of 50 and an applied epoch value of 20. Meanwhile, for the ResNet architecture, the best value was obtained using the SGDM solver type. The learning rate was 0.0001 and produced 100% learning accuracy in a processing time of 134 minutes 21 seconds, a validation frequency value of 50 and an applied epoch value of 20.

During the training-validation process, CNN could classify the input image into different regional classes by implementing a machine learning system and back propagation algorithm. Various components that make up specific colors such as contrast, homogeneity, energy, entropy, and inverse different moment (IDM) values between one image and another become parameters that are processed by CNN modeling software to produce different training-validation values (Agaputra, *et al.*, 2013). In general, the AlexNet architecture was able to provide an average training-validation accuracy of 99.89% and a processing time of 52 minutes. Whereas the ResNet architecture produces an average accuracy of 99.83% and a processing time of 152 minutes.

Data Analysis of CNN Testing Results

On the analysis of cocoa beans samples using optimized parameters, Alexnet architecture was capable of producing 100% testing accuracy on hyperparameter settings with the SGDM solver type and a learning rate of 0.0001. On the other hand, ResNet architecture produced the best accuracy of 100% using the SGDM solver type and a learning rate of 0.0001. In general, the classification process by CNN with the Alexnet and ResNet architecture could be completed in between 0.02-1 second according to research by Sabilla (2020) using samples in the form of fresh fruit. Furthermore, through the process of analyzing the data from the testing results, it was found that the best modeling of the two architectural groups used in this study was ResNet rather than that of AlexNet. The Resnet architecture is the best because it had an average testing accuracy value of 99.99%, while the AlexNet architecture provided an average testing accuracy of 99.91%.

Table 3. Training-Validation CNN result

CNN architecture	Solver	Learning rate	Validation	Epoch frequency	Training time	Validation accuracy
AlexNet1	SGDM	0,00005	50	20	49 min 45 sec	99.90%
AlexNet2	Adam	0,00005	50	20	56 min 30 sec	100%
AlexNet3	RMSProp	0,00005	50	20	47 min 42 sec	99.81%
AlexNet4	SGDM	0,0001	50	20	53 min 28 sec	100%
AlexNet5	Adam	0,0001	50	20	53 min 40 sec	99.81%
AlexNet6	RMSProp	0,0001	50	20	51 min 34 sec	99.81%
ResNet1	SGDM	0,00005	50	20	121 min 21 sec	99.95%
ResNet2	Adam	0,00005	50	20	170 min 11 sec	99.14%
ResNet3	RMSProp	0,00005	50	20	176 min 9 sec	100%
ResNet4	SGDM	0,0001	50	20	134 min 21 sec	100%
ResNet5	Adam	0,0001	50	20	154 min 19 sec	100%
ResNet6	RMSProp	0,0001	50	20	155 min 29 sec	99.90%

Table 4. CNN analysis result

CNN architecture	Solver	Learning rate	Training time	Validation accuracy	Testing accuracy	Error testing
AlexNet1	SGDM	0,00005	49 min 45 sec	99.90%	99.91%	0.09%
AlexNet2	Adam	0,00005	56 mi 30 sec	100%	100%	0%
AlexNet3	RMSProp	0,00005	47 min 42 sec	99.81%	99.90%	0.10%
AlexNet4	SGDM	0,0001	53 min 28 sec	100%	100%	0%
AlexNet5	Adam	0,0001	53 min 40 sec	99.81%	100%	0%
AlexNet6	RMSProp	0,0001	51 min 34 sec	99.81%	99.67%	0.33%
ResNet1	SGDM	0,00005	121 min 21 sec	99.95%	99.96%	0.04%
ResNet2	Adam	0,00005	170 min 11 sec	99.14%	100%	0%
ResNet3	RMSProp	0,00005	176 min 9 sec	100%	100%	0%
ResNet4	SGDM	0,0001	134 min 21 sec	100%	100%	0%
ResNet5	Adam	0,0001	154 min 19 sec	100%	100%	0%
ResNet6	RMSProp	0,0001	155 min 29 sec	99.90%	99.96%	0.04%

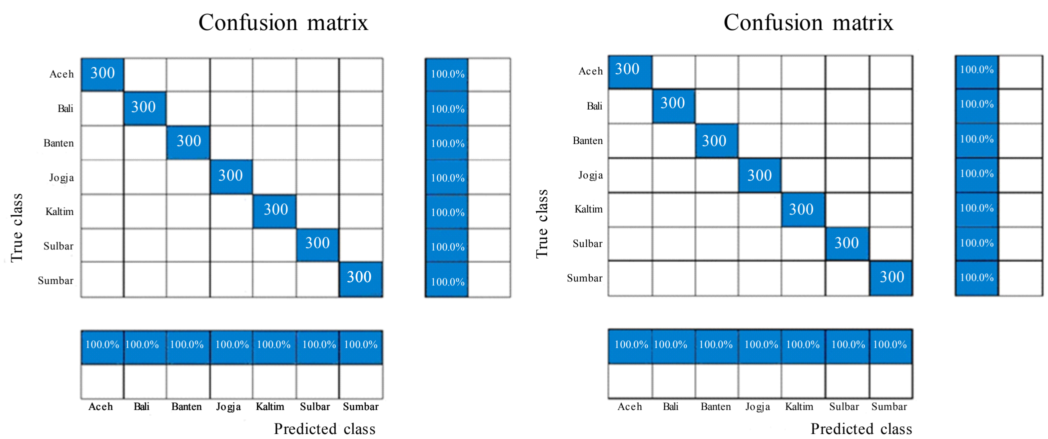

Figure 4. Best confusion matrix results: (A) AlexNet4 dan (B) Resnet4: Both presented the best classification results, from a total of 2100 samples with 300 random samples for each region, successfully identified 100% correctly in their class

General Discussion

The classification of cocoa bean samples based on their color was successfully carried out using CNN utilizing ResNet and AlexNet architecture. This could be used to complement a subjective, time-consuming, and labor-intensive sensorial approach. Cocoa beans are a highly valued commodity for the confectionery market. In its quality determination, the color and appearance of the beans are highly related to flavor and taste, the most important quality of cocoa beans. Browning and discoloration of cocoa beans color represent various biochemical reactions such as Maillard non-enzymatic browning, oxidation of polyphenol compounds and their polymerization, an infestation of unwanted organisms (fungi and insect), and contamination (Febrianto *et al.*, 2021; CAOBISCO/ECA/FCC, 2015; Febrianto & Zhu, 2020). The rapid and accurate (>99% accuracy) classification feature as proposed by this study will surely be beneficial to provide a more efficient method for sorting and grading.

Considering the coverage of this study, the implementation of this method might still need to be evaluated and improved. While the outer appearance of cocoa beans could represent various quality aspects, this method cannot be used to determine the quality of cocoa beans itself. Combination with other image-based analyses such as spectroscopic-based and hyperspectral imaging techniques can be done to further enhance the functionality of this analysis (Alvarado *et al.*, 2023). This combination will provide a holistic analysis on the outer and inner part of cocoa beans, representing the actual physical quality of cocoa beans.

The effectiveness of this method in identifying mixture samples may become the further direction of this study. There are huge variations in post-harvest practices on the farmer's levels, resulting in a huge diversity of cocoa beans appearance. In this study, the uniformity of the samples could be ensured due to the traceable sourcing of the cocoa bean samples. However, in the market, the samples may be a mixture of cocoa beans from various sources. Database-based analysis, containing data on the relationship of appearance with quality parameters, might be needed to improve the accuracy of this analysis. By developing the database of cocoa beans from various sources and quality levels, this method may provide a rapid and comprehensive non-destructive method for quality determination, classifications, and traceability of cocoa beans.

CONCLUSION

Classification of dried cocoa beans based on color from various origins in Indonesia was successfully carried out by utilizing the Alexnet and Resnet architectures. The best accuracy was obtained by the Resnet and Alexnet architecture with an SGDM solver and a learning rate of 0.0001. With Convolutional Neural Network, the average accuracy of cocoa image classification based on color identification by computer machines was 99.91% (AlexNet) and 99.99% (ResNet). This showed that this modeling can be applied to increase the efficiency of cocoa bean classification. A further study utilizing mixed samples, a combination with other image-based analysis, and database-based analysis are needed to provide a more comprehensive method for rapid and accurate quality determination of cocoa beans.

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