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# Deep Learning to Detect and Classify the Purity Level of Luwak Coffee Green Beans

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## ABSTRACT

Luwak coffee (palm civet coffee) is known as one of the most expensive coffee in the world. In order to lower production costs, Indonesian producers and retailers often mix high-priced Luwak coffee with regular coffee green beans. However, the absence of tools and methods to classify Luwak coffee counterfeiting makes the sensing method's development urgent. The research aimed to detect and classify Luwak coffee green beans purity into the following purity categories, very low (0-25%), low (25-50%), medium (50-75%), and high (75-100%). The classifying method relied on a low-cost commercial visible light camera and the deep learning model method. Then, the research also compared the performance of four pre-trained convolutional neural network (CNN) models consisting of SqueezeNet, GoogLeNet, ResNet-50, and AlexNet. At the same time, the sensitivity analysis was performed by setting the CNN parameters such as optimization technique (SGDm, Adam, RMSProp) and the initial learning rate (0.00005 and 0.0001). The training and validation result obtained the GoogLeNet as the best CNN model with optimizer type Adam and learning rate 0.0001, which resulted in 89.65% accuracy. Furthermore, the testing process using confusion matrix from different sample data obtained the best

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CNN model using ResNet-50 with optimizer type RMSProp and learning rate 0.0001, providing an accuracy average of up to 85.00%. Later, the CNN model can be used to establish a real-time, non-destructive, rapid, and precise purity detection system.

*Keywords:* Classification, convolutional neural network, Luwak coffee green beans, purity

## INTRODUCTION

The two most popular coffee varieties are *Coffea canephora* L. (Robusta) and *Coffea arabica* L. (Arabika) (Skowron et al., 2020). As one of the expensive and popular coffees derived from those two varieties, Civet coffee (also known as Luwak coffee in Indonesia) is produced less than 127 kg per month, and the price ranges from USD 200-400 per kg, creating this a hundred times more costly than regular coffees (Muzaifa et al., 2019; Jumhawan et al., 2016). Currently, Indonesia has become the main producer of Luwak coffee, followed by East Timor, the Philippines, Thailand, Vietnam, and Ethiopia. Luwak coffee is made of Arabica or Robusta passing through the civet (*Paradoxurus hermaphroditus*) digestive system (Suhandy & Yulia, 2017). Civet can identify the best and ripe coffee beans.

After consuming the beans, the fermentation process occurs on the civet digestive system then changes the chemical structure of coffee beans, which later produces smoother coffee beans and a lesser bitter taste. The high price and scarcity of Luwak coffee trigger producers and retailers to fraud the product by mixing Luwak coffee with another cheaper coffee affecting its purity level; this also affects the coffee taste, quality, pH value, and antioxidant content. It often occurs in Indonesia as the third largest coffee producer after Brazil and Vietnam, and the case gradually increases in the food industry and becomes a serious problem to overcome to assure the quality for consumers' satisfaction (Amirvaresi et al., 2021).

As a conventional method, human sensing by the smelling aroma of coffee is utilized to distinguish between Luwak coffee and regular coffee. However, since the method relies on the human perspective, this may result in different outcomes among panelists. So, human sensing cannot be a standard method, and other procedures need to be developed. Some researchers have been developed to detect Luwak coffee purity, i.e., using electric nose (E-nose) and gas chromatography (Marcone, 2004). Jumhawan et al. (2013) has developed research using citric acid, malic acid, and inositol to distinguish roasted Luwak coffee and roasted regular coffee. However, this method is lengthy, destructive, high cost, and not real-time. Moreover, Jumhawan et al. (2015) have also developed a gas chromatography/flame ionization detector to authentic the Asian palm civet coffee (Luwak coffee).

This research has successfully developed a method to distinguish commercial civet coffee, regular coffee, and coffee blend with 50% civet coffee. Nunez et al. (2021) and Pauli et al. (2014) have also observed the use of non-targeted HPLC-FLD fingerprinting methods to detect the counterfeiting of Arabica coffee and regular Robusta coffee with prediction error results below 3.4%. Sezer et al. (2018) has used laser-induced breakdown spectroscopy (LIBS) to determine the counterfeiting level of Arabica coffee, with a prediction result showing a coefficient value of the highest determination 0.996. Cebi et al. (2017) researched using rapid ATR-FTIR to detect tea and regular coffee product by accuracy result 100%. Finally, Daniel et al. (2018) detected regular coffee counterfeiting using capillary electrophoresis-tandem mass spectrometry (CE-MS) with a significant prediction, i.e., the highest coefficient of determination value 0.995.

Combes et al. (2018) has successfully developed a rapid DNA-based method to detect counterfeiting of Arabica coffee and regular Robusta coffee. Furthermore, Lopetcharat et al. (2016) has also successful developed the electronic tongue (E-tongue) to differentiate civet coffee and regular coffee. The weakness of E-nose is that it depends on the environmental conditions such as temperature and water content, and the weaknesses of gas chromatography (Ongo et al., 2012), HPLC-FLD, LIBS, ATR-FTIR, CE-MS, DNA-based method, and E-tongue are high cost, need a longer time, and destructive-sensing testing. Yulia and Suhandy's (2017) research developed a coffee authenticity detection method using UV-Visible spectra. Combining the UV-Visible spectra tool and partial least square (PLS) regression method obtained a good prediction result, yet this method requires expensive instrumentation.

Therefore, computer vision is proposed in this research as it is non-destructive, rapid, real-time, low-cost, and accurate. This method has been widely used to detect counterfeiting in various food products. For example, Song et al. (2021) used two smartphone-based low-cost computer vision (Samsung Galaxy C5 and A9s) to detect minced beef counterfeiting with root mean square error ranging from 0.04 to 0.16. Kiani et al. (2017) combined computer vision (CCD digital camera) and E-nose to detect saffron counterfeiting. The result was quite good, with the prediction accuracy up to 89%. Anami et al. (2019) successfully used a commercial digital camera (PENTAX MX-1) to identify and classify bulk paddy grain counterfeiting rate by accuracy value up to 93.31%.

The commercial digital camera was also used in research by Lin et al. (2020), which analyzed the counterfeiting rate of safflower using a Nikon D90 digital SLR camera. Reile et al. (2020), in their research, proved that the effectiveness of low-cost commercial digital camera, i.e., Sony digital camera (model DSC-W830, resolution of 20.1 Mpixels) to detect ketchup product counterfeiting with $R^2$ value reached 0.96. A low-cost digital camera was also very practical used in the research by Silva and Rocha (2020) to detect the counterfeiting rate of dairy products using an LG K10 Pro smartphone equipped with a 13-megapixel camera. According to several types of research conducted, using a low-cost digital camera was highly possible to detect counterfeiting rates in food products, particularly coffee.

Other than that, some researchers have widely used artificial intelligence (AI) to develop a detection model to understand adulterants on food. For example, Wojcik and Jakubowska (2021) used a deep neural network to predict adulteration in apple juice with an R2 prediction that reached 0.98. Moreover, the AI has successfully detected butter counterfeit with 82.66% accuracy (Iymen et al., 2020). Likewise, Support Vector Machine (SVM) (kind of AI) can detect cassava starch adulteration (86.9% accuracy) (Cardoso & Poppi, 2021) and white rice counterfeiting (90% accuracy) (Lim et al., 2017). Furthermore, an artificial neural network (ANN) was also popular to detect counterfeiting of Muscatel wines (Cancilla et al., 2020), edible bird's nests (90% accuracy) (Huang et al., 2019), and coffee chemical compounds (such as phenol, pH, and coffee purity) up to 90% accuracy and mean square error 0.0442 (Hendrawan et al., 2019). Above that, recent research in convolutional neural networks (CNN), another type of AI, gave more practical results on detecting honey adulteration resulting in up to 97.96% accuracy (Li et al., 2021; Izquierdo et al., 2020a), extra virgin olive oil with 97% accuracy (Izquierdo et al., 2020b), and counterfeiting in Arabica and Robusta coffee with an error below 1% (Lopez et al., 2021). Hence, CNN was more potential to detect coffee quality and authenticity than other learning machines.

The combination of low-cost commercial visible light camera and deep learning is promising as an alternative for rapid, real-time, and non-destructive detection with high prediction accuracy but affordable than other non-destructive methods. Therefore, the research aims to detect and classify Luwak coffee green beans into several purity categories: very low (0-25%), low (25-50%), medium (50-75%), and high (75-100%) using low-cost commercial visible light camera tool tandem with deep learning model. Furthermore, it includes four pre-trained CNN (SqueezeNet, AlexNet, GoogLeNet, and Resnet 50), which have been tested elsewhere (Nayak et al., 2021).

## MATERIAL AND METHODS

Two coffee samples, Arabica Luwak coffee green beans, and pure Arabica regular coffee green beans were set. In each image data acquisition, one hundred sixty coffee beans were randomly mixed between Arabica Luwak coffee green beans and pure Arabica regular coffee green beans. The percentage of the mixture was calculated using the beans unit. Several conditions from the sample were then arranged into four different purity mixtures: very low (0-25% or 0-40 Luwak coffee beans), low (25-50% or 40-80 Luwak coffee beans), medium (50-75% or 80-120 Luwak coffee beans), and high (75-100% or 120-160 Luwak coffee beans). Samples of some mixtures of Luwak coffee green beans are shown in Figure 1. The sample images were acquired using a visible light digital camera (Nikon Coolpix A10, 16 megapixels, Japan). The initial image resolution was 1024 × 768 pixels and was cropped into 500 × 500 pixels. Four hundred twenty-eight images were obtained from each mixture, creating 1712 images in total for four mixtures. All samples for CNN analysis

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

*Figure 1*. 500 × 500 pixels image of Luwak coffee green beans in several purity levels: (a) high (75-100%); (b) medium (50-75%); (c) low (25-50%); and (d) very low (0-25%)

were then divided into three data set: training, validation, and testing (Bragagnolo et al., 2021). 70% of total data (1200 images) were set as training data, and 30% of total data (512 images) for validation (Medus et al., 2021). The testing data were acquired separately at a different time with 400 images of Luwak coffee green beans at different purity conditions.

CNN has been widely used, and it is a popular deep learning method for detecting food product counterfeiting and purity based on computer vision (Liu et al., 2021). The usage of CNN features could capture the high-level features, which can be the central key for segregating an image's color, morphology, and textural features (Simon & Uma, 2020). The deep CNN can capture the low detail features from the initial convolution layers, and layers are propagated to generate the high-level features in the last layers. Different filters in CNN were generated by efficient convolution and pooling operation to recognize color, morphology, and textural features. The features were extracted from certain layers of the network and later considered for training classifiers. Unlike conventional machine learning, CNN does not require image feature extraction and feature selection process, providing a more efficient, effective, and accurate prediction model (Yu et al., 2021).

CNN can directly process raw images to classify output by tuning parameters in the convolutional and pooling layers. In the classification process, deep learning architecture was used to classify sample images of Luwak coffee green beans at four purity levels (very low, low, medium, and high). The structure of typical CNN can be seen in Figure 2. The CNN structure involves image acquisition, convolutional layer, pooling layer, and fully connected layer. The research used four types of pre-trained CNN models (SqueezeNet (Ucar & Korkmaz, 2020), GoogLeNet (Raikar et al., 2020), ResNet-50 (Mkonyi et al., 2020), and AlexNet (Jiang et al., 2019)) provided in Matlab R2020b. SqueezeNet is a convolutional neural network that is 18 layers deep. It begins with a standalone convolution layer, followed by 8 Fire modules, ending with a final conv layer. The number of filters per fire module gradually increases from the beginning to the end of the network. GoogLeNet is a 22-layer deep convolutional neural network, a variant of the Inception Network, a deep CNN developed by researchers at Google.

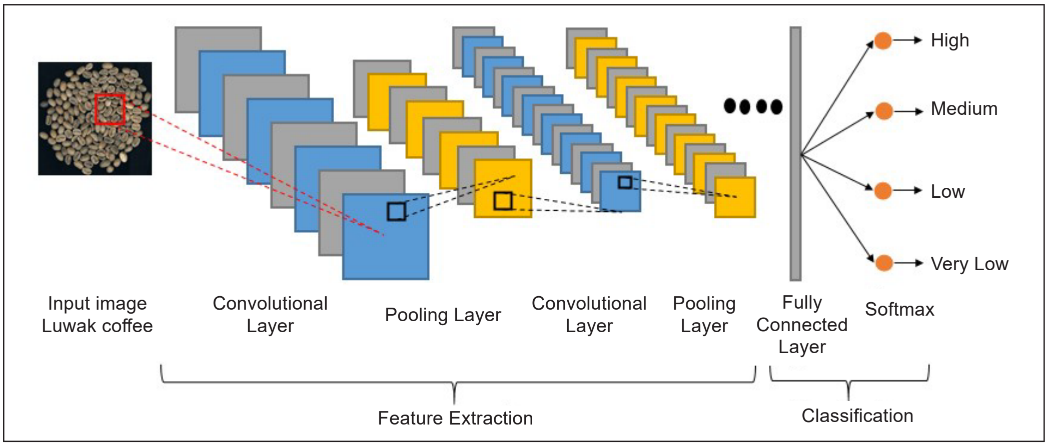



*Figure 2*. Proposed computer vision to classify the purity level in Luwak coffee green beans using deep learning

This architecture uses techniques such as 1 × 1 convolutions in the middle of the architecture and global average pooling. ResNet-50 is a convolutional neural network that is 50 layers deep. ResNet architecture makes use of shortcut connections to solve the vanishing gradient problem. The basic building block of ResNet is a Residual block that is repeated throughout the network. AlexNet is a convolutional neural network that is eight layers deep. The network consists of 5 convolutional layers and three fully connected layers. The activation used is the Rectified Linear Unit (ReLU). The activation function of ReLu was used in every hidden layer, and the softmax function was applied in the final layer to ensure the output value consistently ranging between 0 and 1, which ReLu and softmax have been described in the research by Lin and Shen (2018). AlexNet addresses the over-fitting problem by using drop-out layers where a connection is dropped during training with a probability of p=0.5. Figure 3 shows the flow chart of the four pre-trained CNN models used in this study (Hendrawan et al., 2021).

In the training process, the maximum epoch was set at 20 (Eltrass et al., 2021), the mini-batch size was set at 20 (Tian et al., 2020), maximum iteration at 1200, 60 iterations per epoch, momentum 0.9, and loss function used binary cross-entropy. Thenmozhi and Reddy (2019) research obtained the best learning rate in the CNN model at the value of 0.0001 and 0.00005, so the initial learning rate was set at 0.0001 and 0.00005 in this research. The optimization techniques (optimizers) used in the research were stochastic gradient descent with momentum (SGDm) adaptive moment estimation (Adam), and root means square propagation (RMSProp) (Manninen et al., 2021). SGDm accelerated the convergence by changing the actual gradient with an estimate, which was calculated from subset data that was selected randomly. Adam is an algorithm to optimize the learning rate by combining the advantages of RMSProp and SGDm. The CNN program was run on a computer with the following specifications, Intel Core i3-4150 CPU @3.50GHz (4

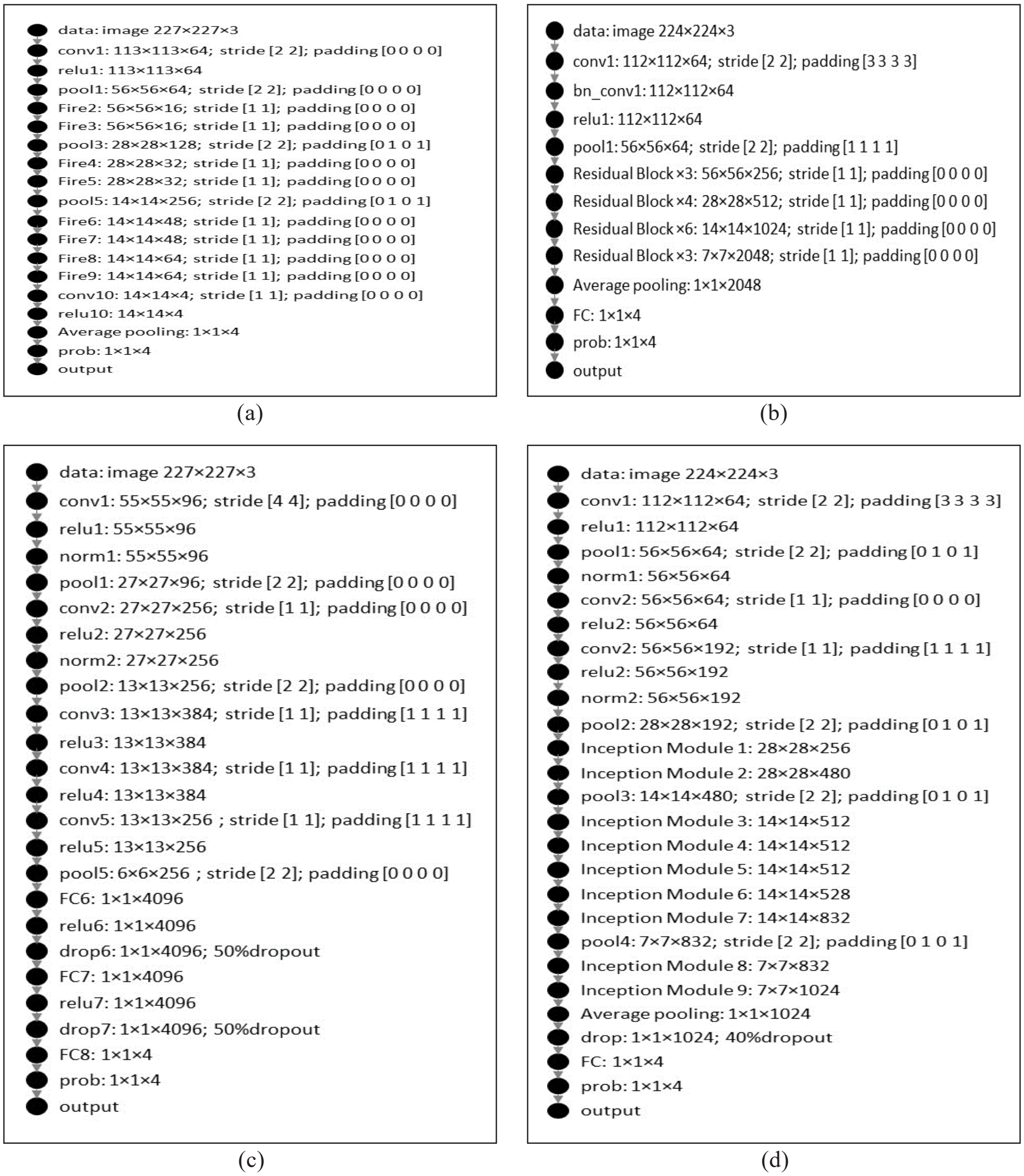



*Figure 3*. Schematic representation of pre-trained CNN model: (a) SqueezeNet; (b) ResNet-50; (c) AlexNet; (d) GoogLeNet

CPUs) 10 GB of RAM. The 24 types of CNN models built then were evaluated based on the validation data to retrieve the best 5 CNN models. These best five CNN models were later tested using confusion matrix and testing data according to the classification accuracy. The confusion matrix method was implemented to see the prediction error rate in the testing data (Ruuska et al., 2018). The accuracy of each CNN model is the main parameter that determines model performance.

## RESULTS AND DISCUSSIONS

All total 24 CNN models provided accuracy validation ranging from 61.52% to 89.65%, depending on the number of layers and structure. Additionally, the selection of optimization techniques also affected the prediction accuracy. Table 1 shows the accuracy result of validation data obtained from the learning process using deep learning architecture. The sensitivity analysis was done by tuning the optimization technique and learning rate in each CNN model, i.e., SqueezeNet, GoogLeNet, ResNet-50, and AlexNet. Not all CNN models produced high accuracy. The highest accuracy value obtained by each model is presented in Table 1. Five CNN models producing highest accuracy were generated by GoogLeNet (optimizer = Adam; learning rate = 0.0001), ResNet-50 (optimizer = RMSProp; learning rate = 0.0001), GoogLeNet (optimizer = Adam; learning rate = 0.00005), ResNet-50 (optimizer = Adam; learning rate = 0.0001), and GoogLeNet (optimizer = RMSProp; learning rate = 0.0001) with accuracy value of validation data respectively 89.65%, 89.26%, 88.67%,

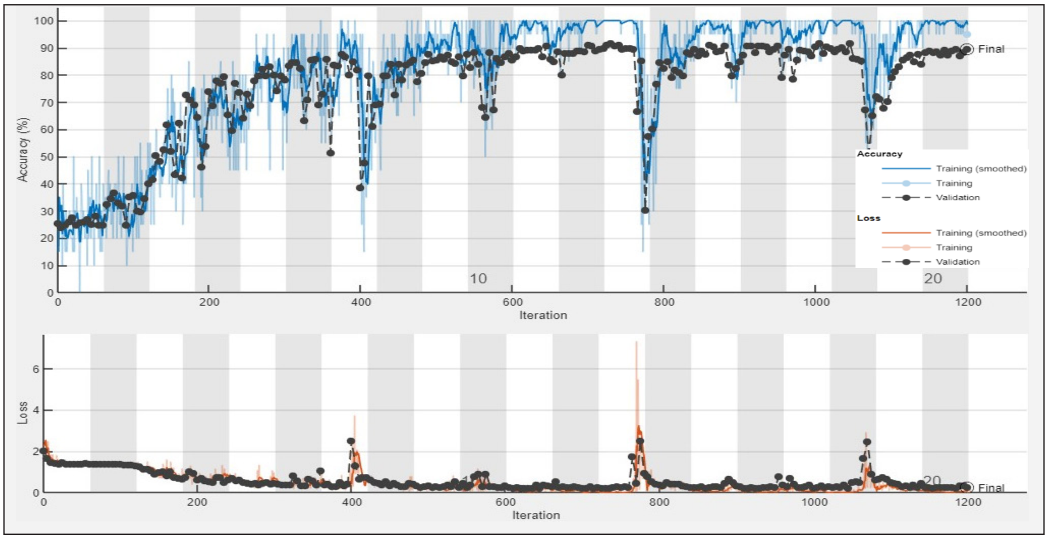
Table 1
*Result and parameter used in the deep learning method*

| Architecture | Optimizer | Learning Rate | Accuracy (%) | Training Time (minutes) |
|---|---|---|---|---|
| SqueezeNet | SGDm | 0.00005 | 77.34 | 118 |
| | Adam | 0.00005 | 75.59 | 118 |
| | RMSProp | 0.00005 | 73.24 | 119 |
| | SGDm | 0.0001 | 72.27 | 118 |
| | Adam | 0.0001 | 80.47 | 118 |
| | RMSProp | 0.0001 | 77.54 | 119 |
| GoogleNet | SGDm | 0.00005 | 64.41 | 241 |
| | **Adam** | **0.00005** | **88.67** | **251** |
| | RMSProp | 0.00005 | 78.71 | 245 |
| | SGDm | 0.0001 | 82.42 | 242 |
| | **Adam** | **0.0001** | **89.65** | **254** |
| | **RMSProp** | **0.0001** | **85.94** | **268** |
| ResNet50 | SGDm | 0.00005 | 80.66 | 587 |
| | Adam | 0.00005 | 81.64 | 605 |
| | RMSProp | 0.00005 | 81.64 | 641 |
| | SGDm | 0.0001 | 76.95 | 601 |
| | **Adam** | **0.0001** | **86.52** | **642** |
| | **RMSProp** | **0.0001** | **89.26** | **653** |
| AlexNet | SGDm | 0.00005 | 66.6 | 117 |
| | Adam | 0.00005 | 72.85 | 115 |
| | RMSProp | 0.00005 | 61.52 | 127 |
| | SGDm | 0.0001 | 77.73 | 108 |
| | Adam | 0.0001 | 69.53 | 117 |
| | RMSProp | 0.0001 | 27.93 | 141 |

86.52%, and 85.94%. In a single layer of GoogLeNet, multiple types of feature extractors were present. It indirectly helps the network perform better, as the network at training itself has many options to choose from when solving the task. It can either choose to convolve the input or pool it directly.

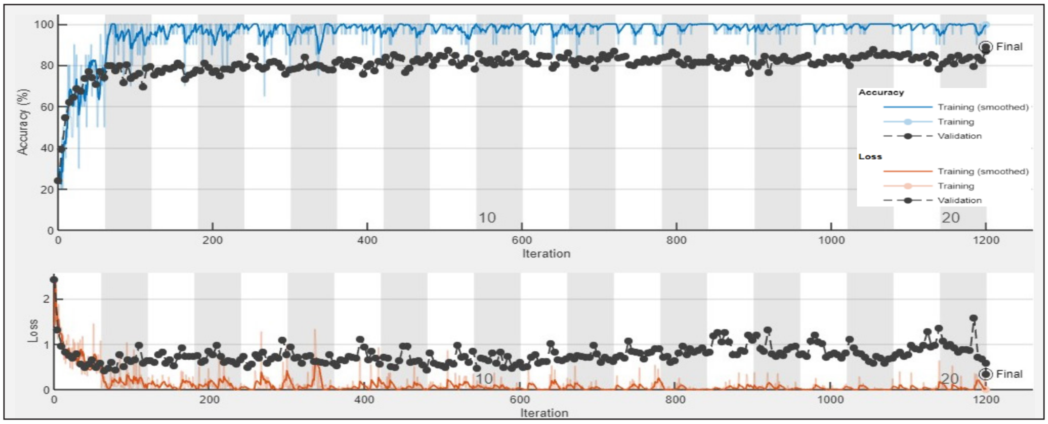
The GoogLeNet architecture contains multiple inception modules as most of the topmost layers have their output layer. It helps the model converge faster compared to other networks. Thus, it is in line with research conducted by Huitron et al. (2021), which detected the disease in the tomato leaves using CNN which the pre-trained model GoogLeNet and ResNet had more superior performance than other pre-trained CNN. However, since the classification of purity level only relies on visual appearance (brownish-black color, morphology, and texture) and the appearance between two mixtures (Arabica Luwak and Arabica regular) is similar, classifying all samples has only reached 89.65% accuracy. However, this accuracy was acceptable and defined as good. The performance of the five best CNN models can be seen in Figure 4. Figure 4 illustrates a comparison between classification accuracy and loss and learning iteration numbers. Based on the performance results, the continuous performance improvement was seen by the increase of iteration.

The CNN performance graph also showed that the accuracy increased with the increase of iteration. The loss graph also reduced with the increase of iteration and gradually became convergent nearing 0. Thus, all CNN models nearly have the same pattern. The performance improvement runs very fast at the initial epoch, i.e., epoch 1 to epoch 10. Then, the accuracy value was increased, followed by minor improvements in training and validation data performance. In Figure 4(a), there were fluctuations in the accuracy and

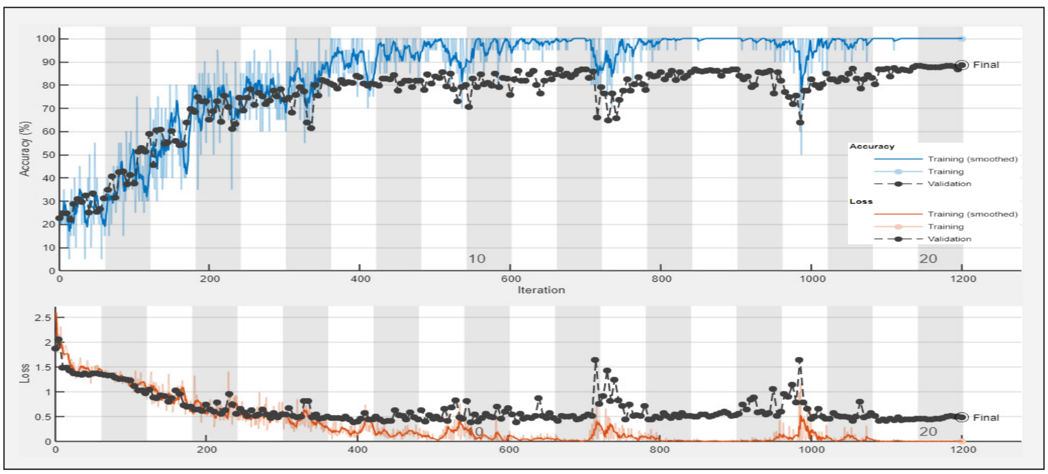



(a)

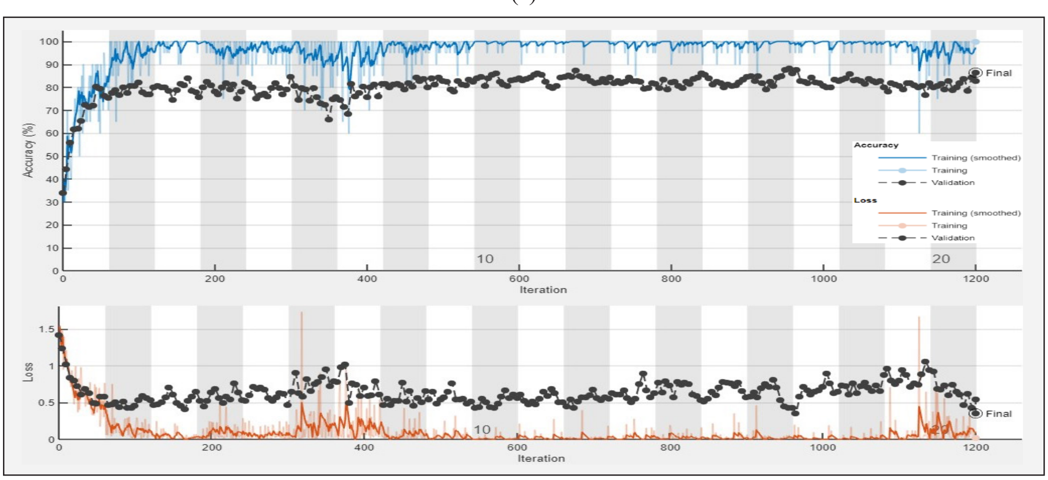
*Figure 4*. Accuracy and loss versus the number of iterations: (a) GoogLeNet (optimizer = Adam; learning rate = 0.0001)




(b)

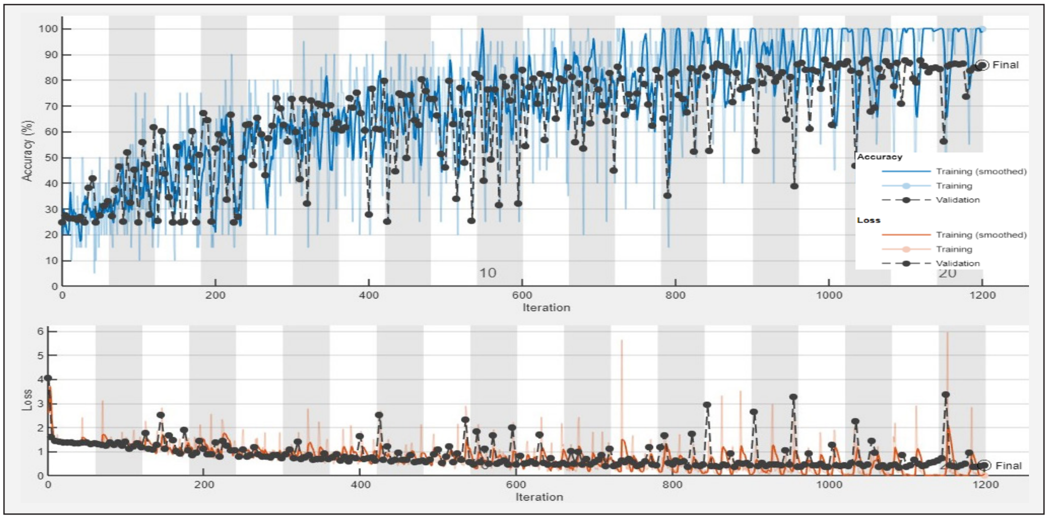



(c)




(d)

*Figure 4 (continue)*. Accuracy and loss versus the number of iterations: (b) ResNet-50 (optimizer = RMSProp; learning rate = 0.0001); (c) GoogLeNet (optimizer = Adam; learning rate = 0.00005); (d) ResNet-50 (optimizer = Adam; learning rate = 0.0001)




(e)

*Figure 4 (continue)*. Accuracy and loss versus the number of iterations: (e) GoogLeNet (optimizer = RMSProp; learning rate = 0.0001)

losses which indicated that some portion of the example was classified randomly, which produced fluctuations. Updating network weights during the training process and noisy data also affected the occurrence of fluctuations. However, validation loss fluctuations during training are natural for most machine learning algorithms as long as the training pattern generally increases steadily during iterations (Takase, 2021). The pattern accuracy and loss graph obtained by CNN in the research was in line with research by Azimi et al. (2021), in which the accuracy value pattern was significantly increased at the initial epoch, but the loss value pattern exhibited the reverse and would be convergent nearing 0. Overall results in Figure 4 show that several parameters such as optimization technique and learning rate also affect the validation accuracy. It was clear that the learning rate value of 0.0001 creates higher accuracy (79.65%) than the learning rate of 0.00005 (75.23%), which was in line with Thenmozhi and Reddy (2019). The study revealed that the 0.0001 learning rate is better than the other (0.00005, 0.0005, and 0.001).

Figure 5 illustrates the confusion matrix result using testing data in five best CNN models namely GoogLeNet (optimizer = Adam, learning rate = 0.00005); GoogLeNet (optimizer = Adam, learning rate = 0.0001); GoogLeNet (optimizer = RMSProp, learning rate = 0.0001); ResNet-50 (optimizer = RMSProp, learning rate = 0.0001); and ResNet-50 (optimizer = Adam, learning rate = 0.0001). Furthermore, the individual classification rate data for every category was described by comparing the predicted value (abscissa) with true value (ordinate). Distribution of value in the confusion matrix in five best CNN models showed that purity mixture of both high (75 to 100%) and very low (0 to 25%) purity performed higher accuracy compared to other two categories which accounted


*Figure 5*. Confusion matrix of testing data: (a) GoogLeNet (optimizer = Adam, learning rate = 0.00005); (b) GoogLeNet (optimizer = Adam, learning rate = 0.0001); (c) GoogLeNet (optimizer = RMSProp, learning rate = 0.0001); (d) ResNet-50 (optimizer = RMSProp, learning rate = 0.0001); (e) ResNet-50 (optimizer = Adam, learning rate = 0.0001)

for 99.00% and 92.80%, respectively. In fact, in the three CNN models, GoogLeNet (optimizer= Adam; learning rate = 0.00005), ResNet-50 (optimizer = RMSProp; learning rate = 0.0001), and ResNet-50 (optimizer = Adam; learning rate = 0.0001), gave better accuracy to classify high purity reaching 100% accuracy. Therefore, this proved that CNN model could classify accurately (up to 100% accuracy) between Luwak coffee green beans with high purity (75 to 100%) and other purity categories (<75%). Low purity (25 to 50%) provided the lowest classifying accuracy on the testing process, accounting for 65.80%. Meanwhile, medium purity (50 to 75%) provided 72% accuracy. If it is based on the testing data accuracy using a confusion matrix, it can be said that the highest accuracy was reached by the CNN model using ResNet-50 (optimizer = RMSProp, learning rate = 0.0001) with the average accuracy value of testing data that is 85.00%, followed by GoogLeNet (optimizer = RMSProp, learning rate = 0.0001), GoogLeNet (optimizer = Adam, learning rate = 0.0001), GoogLeNet (optimizer = Adam, learning rate = 0.00005), and ResNet-50 (optimizer = Adam, learning rate = 0.0001) with the average accuracy value 83.25%, 82.25%, 82.00%, and 79.50%, respectively. By the highest average of testing, data accuracy reached 85.00%. Thus, it can be concluded that the CNN model produced in the research can effectively classify the purity level of Luwak coffee green beans.

## CONCLUSIONS

This research used four pre-trained CNN models (SqueezeNet, GoogLeNet, ResNet-50, and AlexNet) to classify four purity mixtures consisting of very low (0-25%), low (25-50%), medium (50-75%), and high (75-100%). Based on the training and validation result, the model exhibited an accuracy ranging from 61.52% to 89.65%. The highest accuracy value, 89.65%, was obtained using GoogLeNet pre-trained with optimizer type = Adam and learning rate value = 0.0001. Other than that, according to the testing result, the model provided the highest accuracy, 85.00%, using ResNet-50 with optimizer type = RMSProp and learning rate = 0.0001. Therefore, the CNN model generated from the research was a high potential for field-trial to classify Luwak coffee green beans purity. Moreover, since it was feasible as a rapid, real-time, and accurate method, this can be a basis for further classification study for other crops and agricultural products.

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