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Classification of soybean tempe quality using deep learning

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Abstract. Tempe is a traditional food originating from Indonesia, which is made from the fermentation process of soybean using *Rhizopus* mold. The purpose of this study was to classify three quality levels of soybean tempe i.e., fresh, consumable, and non-consumable using a convolutional neural network (CNN) based deep learning. Four types of pre-trained networks CNN were used in this study i.e. SqueezeNet, GoogLeNet, ResNet50, and AlexNet. The sensitivity analysis showed the highest quality classification accuracy of soybean tempe was 100% can be achieved when using AlexNet with SGDm optimizer and learning rate of 0.0001; GoogLeNet with Adam optimizer and learning rate 0.0001, GoogLeNet with RMSProp optimizer, and learning rate 0.0001, ResNet50 with Adam optimizer and learning rate 0.00005, ResNet50 with Adam optimizer and learning rate 0.0001, and SqueezeNet with RSMProp optimizer and learning rate 0.0001. In further testing using testing-set data, the classification accuracy based on the confusion matrix reached 98.33%. The combination of the CNN model and the low-cost digital commercial camera can later be used to detect the quality of soybean tempe with the advantages of being non-destructive, rapid, accurate, low-cost, and real-time.

1. Introduction

Indonesia, a country with more than 300 distinct native ethnic groups, has a variety of traditional foods [1]. One of the food products that are popular and often consumed by the Indonesian people is soybean tempe. Indonesia is the largest soybean tempe producing country globally and is the largest market for soybeans in Asia. The average consumption of soybean tempe per person per year in Indonesia is estimated at around 6.45 kg. Apart from being produced in Indonesia, since 1984, there have been several soybean tempe companies in Europe, the USA, and Japan [2]. Tempe is a traditional food originating from Indonesia, which is made from the fermentation process of soybean using *Rhizopus* mold [3]. The mold that grows on soybean seeds hydrolyzes complex compounds into simple compounds easily digested by humans [4]. Soybean tempe contains lots of dietary fiber, calcium, vitamins B, and iron. Soybean tempe can also be a functional food containing antibiotics to cure infections and antioxidants to prevent degenerative diseases (atherosclerosis, coronary heart disease, diabetes mellitus, cancer, etc.) [5]. Soybean tempe also contains antibacterial substances that cause diarrhea, lower cholesterol, reduce hypertension, etc. The nutritional composition of soybean tempe, protein, fat, and carbohydrate content, does not change much compared to soybeans [6]. However, because of the digestive enzymes produced by soybean tempe mold, the protein, fat, and carbohydrates in soybean tempe are easier to digest in the body than those found in soybeans. Soybean tempe can be consumed by all ages, from infants to the elderly. Soybean tempe contains sufficient amounts of macro and micro minerals [7].

The Indonesian National Standardization Agency has published the quality standard for soybean tempe, i.e., SNI 3144: 2009. The quality requirements for soybean tempe include: (1) normal smell, color and taste; (2) maximum water content of 65%; (3) maximum ash content of 1.5%; (4) fat content of at least 10%; (5) protein content of at least 16%; (6) the maximum crude fibre content is 2.5%; (7) metal contamination (Cd max 0.2, Pb max 0.25, Sn max 40, Hg max 0.03); (8) contamination of As max 0.25; (9) microbial contamination (coliform max 10). However, the external appearance of soybean tempe quality requirements is still not determined and has not been widely studied. The external appearance of soybean tempe is the easiest, fastest, non-destructive, and inexpensive way to determine the feasibility of the consumption and the quality levels of soybean tempe.

Many studies have proven the effectiveness of computer vision and artificial intelligence in detecting the quality of food products [8]. Hendrawan et al. [9] have successfully used computer vision to inspect the quality of Luwak coffee green beans using an artificial neural network with an accuracy result of the mean square error validation of 0.0442. Hendrawan et al. [10] have also succeeded in detecting the quality of soybean tempe using computer vision based on texture analysis with a validation error value of 2.39%. Computer vision systems have the potential to replace manual methods of detection, therefore gaining wide acceptance in industries as a tool for quality inspection of numerous food products, for example, food grain quality evaluation [11], fruit quality inspection [12], and vegetable quality detection [13]. Saha and Manickavasagan [14] have examined the benefits of computer vision in evaluating the quality of food products, including detecting mechanical damage in mushrooms, detecting cold injury in peaches and apples, and detecting adulteration in honey, detection of mites in flour, etc. Tang et al. [15] have successfully classified grape disease using a convolutional neural network (CNN) and computer vision with the final model that achieves 99.14% accuracy. Shen et al. [16] have also succeeded in detecting impurities in wheat by using CNN and computer vision with a recognition accuracy of 97.56%. Many studies on deep learning have shown CNN's performance to classify the quality of food products accurately. The use of computer vision and CNN methods can be used to classify the quality of soybean tempe based on external appearances in a non-destructive, rapid, low-cost, and accurate manner. The purpose of this study was to classify three quality levels of soybean tempe i.e., fresh, consumable, and non-consumable using CNN.

2. Material and methods

This study used a low-cost digital commercial camera to collect soybean tempe image data. The image acquisition process was carried out using a closed black box with evenly distributed lighting over the surface of the soybean tempe object. A low-cost digital commercial camera (Logitech C270 HD camera 3-megapixel snapshots) was used for image acquisition with a distance of 300 mm from the camera to the object's surface. The image was obtained from the image acquisition process with a resolution of 300×300 pixels in JPEG format. A total of 472 image data with three quality categories i.e., fresh, consumable, and non-consumable, were used as training and validation data. The augmentation process of image data is carried out to increase the amount of data. Parameter settings for data augmentation include random rotation min = 0 and max = 90 degrees, and random rescaling min = 1 and max = 2. All image data, then divided into two parts i.e. 70% for training data and 30% for validation data. Figure 1 shows an example of soybean tempe with fresh, consumable, and non-consumable qualities. It can be seen that soybean tempe in each class looks almost identical and is difficult to distinguish by observations from external appearances.

(a) (b) (c)

Figure 1. 300×300 pixels image of soybean tempe in different quality categories: a) fresh; b) consumable; c) non-consumable.

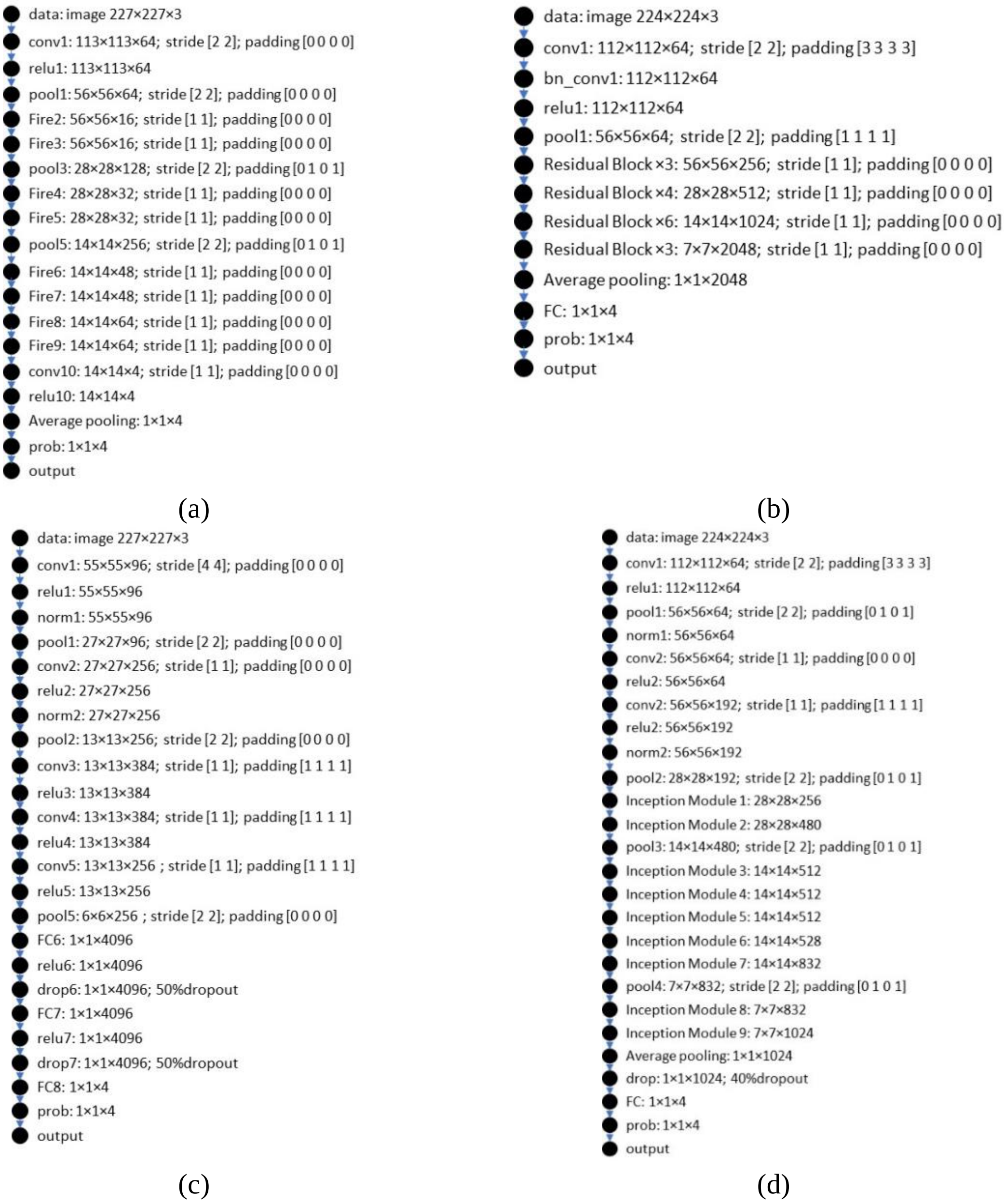

Figure 2. Schematic representation of CNN model: (a) SqueezeNet; (b) ResNet50; (c) AlexNet; (d) GoogLeNet.

The deep learning method was used to model image data in categorizing the quality of soybean tempe. Four types of CNN pre-trained networks (as shown in Figure 2) [17] were used in this study i.e. SqueezeNet, GoogLeNet, ResNet50, and AlexNet. The CNN SqueezeNet algorithm was described in the research of Ucar and Korkmaz [18], GoogLeNet in the study of Raikar et al. [19], ResNet50 in the study of Mkonyi et al. [20], and AlexNet on Jiang et al. [21]. The CNN structure for classifying soybean tempe quality, in general, can be seen in Figure 3. Some of the parameters that were set on each CNN pre-trained included: optimizer (SGDm, Adam, RMSProp) [22], initial learning rate (0.00005 and 0.0001) [23], epoch 20, minibatch size 20 [24], sequence padding value = 0, sequence padding direction = right, L2Regularization = 0.00001, learning rate drop factor = 0.1, learning rate drop period = 10, and momentum = 0.9. After the CNN modeling process had been carried out, the best model was tested on 20 data sets in each quality category. The testing data set was image data of soybean tempe taken separately from training and validation data. The performance of the CNN model was measured from the classification accuracy of the testing-set data using the confusion matrix method [25].

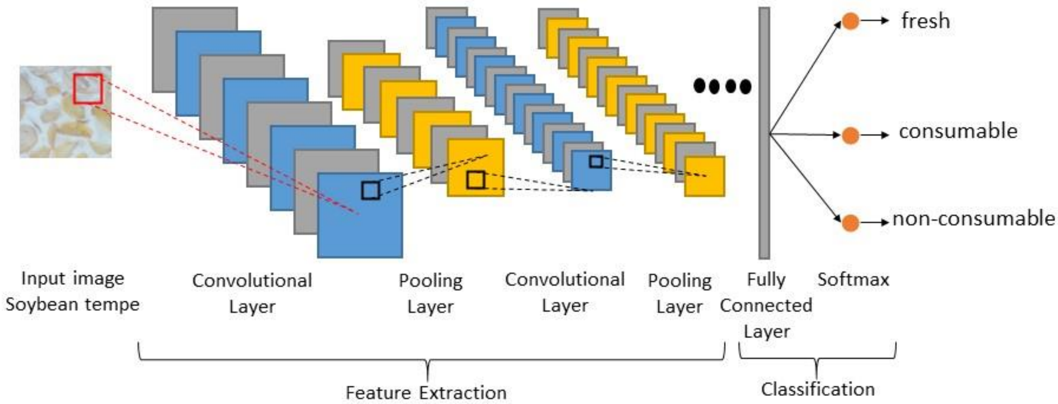

Figure 3. Structure of CNN model to classify soybean tempe quality.

3. Results and discussion

The performance of CNN's pre-trained network can be seen in Table 1. Four models of the pre-trained network were used to classify the quality of soybean tempe, i.e., AlexNet, GoogLeNet, ResNet50, and SqueezeNet. Sensitivity analysis was carried out by varying the optimizer method, i.e., SGDm, Adam, and RMSProp, and varying the initial learning rates of 0.00005 and 0.0001. The obtained results showed that the four pre-trained networks CNN models produced different classification accuracy with an accuracy ranging from the lowest 89.44% to the highest 100%. Overall, based on the value of the initial learning rate, it was proven that the learning rate of 0.0001 produced a higher average classification accuracy of 97.13% compared to the learning rate of 0.00005, which resulted in an average classification accuracy of 96.19%. This is in line with research conducted by Thenmozhi and Redy [22], where a learning rate of 0.0001 works better than a learning rate of 0.00005 or 0.0005. Based on CNN's pre-trained network architecture, it can be seen that the ResNet50 model had the highest average classification of 98.94%, followed by AlexNet, GoogLeNet, and SquezeeNet with average classification accuracy values of 96.83%, 96.01%, and 94.84%, respectively. These results are in line with research conducted by Sravan et al. [26] which proved the performance effectiveness of ResNet50 compared to other CNN pre-trained network models. However, Table 1 also shows the weakness of ResNet50 is that the training process required was very long with an average learning time of 85.16 minutes. The fastest learning process was achieved when using the CNN SqueezeNet model, which was about 17 minutes. Based on the optimizer method used, it was proven that RMSProp produced the highest average classification accuracy of 98.15% compared to Adam and SGDm which had an average classification accuracy of 96.39% and 95.42%, respectively. It can be concluded that the RMSProp optimizer works very well in CNN modeling [27]. The overall sensitivity analysis results showed the highest classification accuracy was 100% which can be achieved when using six CNN models i.e., AlexNet with SGDm optimizer and learning rate of 0.0001; GoogLeNet with Adam optimizer and learning rate 0.0001, GoogLeNet with RMSProp optimizer, and learning rate 0.0001, ResNet50 with Adam optimizer and learning rate 0.00005, ResNet50 with Adam optimizer and learning rate 0.0001, and SqueezeNet with RSMProp optimizer and learning rate 0.0001. The training process in the six CNN models can be seen in Figure 4. From Figure 4, all CNN models showed an effective training process performance where the accuracy value increased with increasing iteration. The opposite applied to the loss value, where the loss value decreased with increasing iteration. The six best CNN models showed almost the same patterns. The training and validation performance chart patterns appeared to move quickly at the initial epoch and converged at the next epoch where the accuracy value moved increasingly converging to a value close to 100% and the loss value converged closer to the value 0. The validation value, both accuracy and loss moved according to the training value. In terms of the stability of the learning process, it can be seen in Figure 4 that ResNet50 with Adam's optimizer and a learning rate of 0.00005 showed a reasonably stable training and validation process compared to other CNN models.

Table 1. Performance of pre-trained network CNN to classify soybean tempe quality.

Architecture	Optimizer	Learning rate	Accuracy (%)	Time (minutes)
AlexNet	SGDm	0.00005	99.30	18
	Adam	0.00005	95.07	18
	RMSProp	0.00005	99.30	17
	SGDm	0.0001	100	17
	Adam	0.0001	89.44	18
	RMSProp	0.0001	97.89	18
GoogLeNet	SGDm	0.00005	93.66	37
	Adam	0.00005	92.25	35
	RMSProp	0.00005	97.18	34
	SGDm	0.0001	92.96	34
	Adam	0.0001	100	34
	RMSProp	0.0001	100	33
ResNet50	SGDm	0.00005	98.59	81
	Adam	0.00005	100	81
	RMSProp	0.00005	99.30	86
	SGDm	0.0001	97.18	85
	Adam	0.0001	100	86
	RMSProp	0.0001	98.59	92
SqueezeNet	SGDm	0.00005	90.85	17
	Adam	0.00005	95.77	17
	RMSProp	0.00005	92.96	17
	SGDm	0.0001	90.85	17
	Adam	0.0001	98.59	17
	RMSProp	0.0001	100	17

After the best results were obtained in the training and validation process, the next step was to test the CNN model's performance using the testing-set data. Of the six best CNN models when tested using the testing-set data, they all produced the same performance, the same accuracy value, and the same error value. So that for the confusion matrix in this study, one confusion matrix result was shown representative of the best six CNN models. The results of the confusion matrix can be seen in Figure 5. From the confusion matrix results, it appeared that the average accuracy of the testing-set data was 98.33%, where this accuracy value was very high for classifying the quality of soybean tempe. In detail, the soybean tempe class of fresh and consumable, the CNN model accurately calculated 100% without

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the slightest error. While in the non-consumable soybean tempe class, the CNN model only made an error of 5% (based on the confusion matrix calculation) and was still able to classify non-consumable soybean tempe with an accuracy of 95%. With this very high accuracy result, it can be concluded that the CNN model that had been built can work effectively to classify soybean tempe into fresh, consumable, and non-consumable quality classes. In future work, the combination of the CNN model and the low-cost digital commercial camera can be used to detect the quality of soybean tempe with the advantages of being non-destructive, rapid, accurate, low-cost, and real-time (provide output instantaneously).

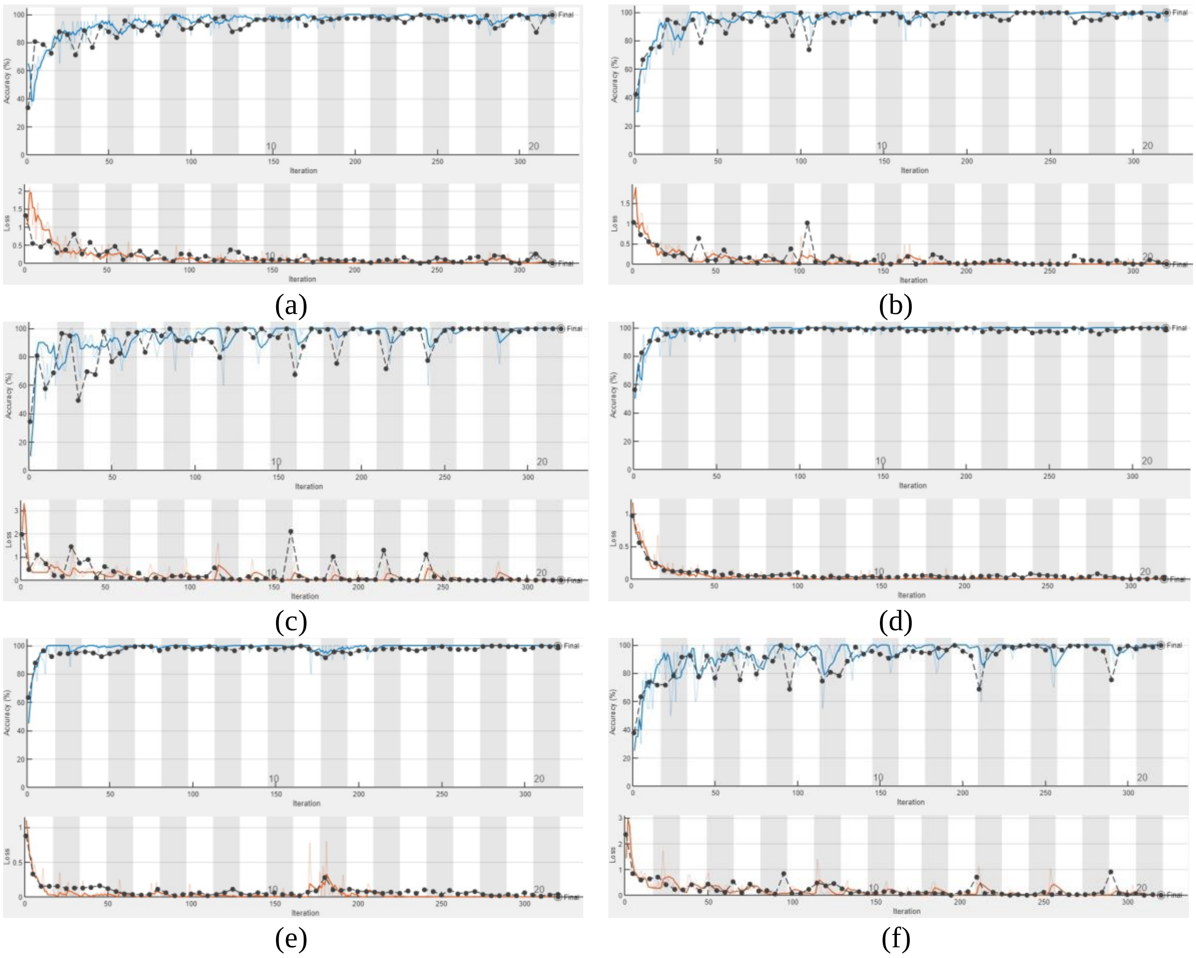

Figure 4. Performance of CNN to classify soybean tempe using pre-trained network: (a) AlexNet (optimizer = SGDm, learning rate = 0.0001); (b) GoogLeNet (optimizer = Adam, learning rate = 0.0001); (c) GoogLeNet (optimizer = RMSProp, learning rate = 0.0001); (d) ResNet50 (optimizer = Adam, learning rate = 0.00005); (e) ResNet50 (optimizer = Adam, learning rate = 0.0001); (f) SqueezeNet (optimizer = RMSProp, learning rate = 0.0001).

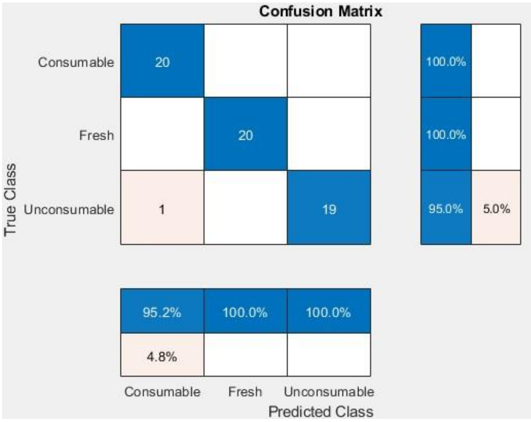

Figure 5. Performance of testing-set data using a confusion matrix.

4. Conclusions

The quality of soybean tempe was divided into three classes i.e. fresh, consumable, and non-consumable. CNN's pre-trained network models used in this study included AlexNet, GoogLeNet, ResNet50, and SqueezeNet. The research results showed very high accuracy in the training and validation process. Six best CNN models i.e. AlexNet with SGDm optimizer and 0.0001 learning rate; GoogLeNet with Adam optimizer and learning rate 0.0001, GoogLeNet with RMSProp optimizer and learning rate 0.0001, ResNet50 with Adam optimizer and learning rate 0.00005, ResNet50 with Adam optimizer and learning rate 0.0001, and SqueezeNet with RSMProp optimizer and learning rate 0.0001 were able to achieve training and validation accuracy up to 100%. The classification accuracy based on the confusion matrix reached 98.33% in further testing using the testing-set data. The combination of the CNN model and the low-cost digital commercial camera can later be used to detect the quality of soybean tempe with the advantages of being non-destructive, rapid, accurate, low-cost, and real-time.

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