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Classification of large green chilli maturity using deep learning

Y Hendrawan[*1], B Rohmatulloh[1], I Prakoso[2], V Liana[3], M R Fauzy[4], R Damayanti[1], M B Hermanto[1], D F Al Riza[1], Sandra[1]

[1]Laboratory of Mechatronics and Agro-industrial Machineries, Department of Agricultural Engineering, Universitas Brawijaya, Jl. Veteran, Malang, ZIP 65145, Indonesia
[2]Department of Agricultural Product Technology, Universitas Brawijaya, Jl. Veteran, Malang, ZIP 65145, Indonesia
[3]Department of Agroindustrial Technology, Universitas Brawijaya, Jl. Veteran, Malang, ZIP 65145, Indonesia
[4]Department of Industrial Engineering, Universitas Merdeka, Jl. Terusan Raya Dieng 62-64, Malang, ZIP 65146, Indonesia

E-mail: yusuf_h@ub.ac.id

Abstract. Chili (*Capsicum annuum* L.) is the source of various nutraceutical small molecules, such as ascorbic acid (vitamin C), carotenoids, tocopherols, flavonoids, and capsinoids. The purpose of this study was to classify the maturity stage of large green chili into three maturity levels, i.e. maturity 1 (maturity index 1 / 34 days after anthesis (DAA)), maturity 2 (maturity index 3 / 47 DAA), and maturity 3 (maturity index 5 / 60 DAA) by using convolutional neural networks (CNN) based deep learning and computer vision. Four types of pre-trained networks CNN were used in this study i.e.SqueezeNet, GoogLeNet, ResNet50, and AlexNet. From the overall sensitivity analysis results, the highest maturity classification accuracy of large green chili was 93.89% which can be achieved when using GoogLeNet with SGDmoptimizer and learning rate of 0.00005. However, in further testing using testing-set data, the highest classification accuracy based on confusion matrix was reaching 91.27% when using the CNN SqueezeNet model with RMSProp optimizer and a learning rate of 0.0001. The combination of the CNN model and the low-cost digital commercial camera can later be used to detect the maturity of large green chili with the advantages of being non-destructive, rapid, accurate, low-cost, and real-time.

1. Introduction

Chili (*Capsicum annuum* L.) is the source of various nutraceutical small molecules, such as ascorbic acid (vitamin C), carotenoids, tocopherols, flavonoids, and capsinoids [1]. Chili is rich in bioactive contents such as carotenoids (β-carotene and β-cryptoxanthin), capsaicinoids, flavonoids, and micronutrients, such as phenolic compounds and vitamin C with antioxidant properties. The content of these compounds is influenced by several factors i.e. hybrid varieties, maturity levels at harvest, climatic conditions, and treatment of storage and processing of chili [2]. Large green chili has a higher vitamin C content than other types of chili. One factor that can affect the content of vitamin C in chili is the level of maturity. The level of maturity of chili can be seen from color changes, and color will affect quality.

The higher the maturity index of the chili, the more intense the color of the chili so that the nutritional content and quality of the chili will be higher. Chili at a higher maturity level has a higher vitamin C content compared to chili at a low level of maturity. Increased accumulation of ascorbic acid or vitamin C in chili is associated with an increase in chili shelf life and improved post-harvest chili quality [3].

In general, chili has nine maturity indices [4], where differences in each index can be seen based on increasingly mature color changes as shown in Figure 1. Each maturity index has characteristics as follows: Index 1 light yellowish green; Index 2 bright and shiny green; Index 3 bright green, shiny, and slippery; Index 4 dark green, glistening, and slippery; Index 5 dark green or blackish and shiny green; Index 6 green mixed with red, shiny, and waxy; Index 7 dominant colored red mixed with green, slightly shiny, very slippery; Index 8 the dominant colored is red and there is a slight green or overall bright red color, shiny, and slippery; Index 9 overall dark red or blackish red, slightly shiny, and slippery.

Figure 1. Chili maturity index.

Hendrawan et al. [5-8] have proven the effectiveness of computer vision in the classification and identification of agricultural products with various advantages including precision, rapid, non-destructive, real-time, and low-cost. Convolutional neural networks (CNN) can improve the performance of computer vision in classifying and identifying agricultural products. Parvathi and Selvi [9] have proven CNN's excellence in using the ResNet50 pre-trained network for detecting coconut maturity from real-time images on farms with an accuracy rate of up to 99%. Behera et al. [10] have successfully identified and classified papaya fruits using CNN with several pre-trained networks such as ResNet101, ResNet50, ResNet18, VGG19, VGG16, GoogLeNet, and AlexNet. The accuracy results are also very good because the CNN models have managed to achieve 100% accuracy. Ismail and Malik [11] have developed research to grading apples and bananas at several maturity levels using several CNN pre-trained network models i.e.ResNet, DenseNet, MobileNetV2, NASNet, and EfficientNet. The results show a high accuracy value of 96.7% for apples and 93.8% for bananas. This shows the efficacy of the CNN model that has been developed. Nasiri et al. [12] in their research sorted dates into several classifications of maturity using the CNN model with VGG-16 architecture. The result shows good accuracy of 96.98%. Wan and Goudos [13] have succeeded in classifying several fruits such as apples, oranges, and mangoes into several ripeness categories using the CNN model. The highest accuracy for apples was 92.51%, while oranges were 90.73%, and mangoes were 88.94%.In another study, Ni et al. [14] also proved the effectiveness of CNN in identifying the ripeness of berries with high accuracy of 97.3%. The reliability of CNN in identifying fruit maturity was also demonstrated in the study of Habaragamuwa et al. [15] who have succeeded in classifying strawberries (mature and immature) using a deep convolutional neural network (DCNN). The accuracy achieved in this study reached 88.03%.

However, from various studies on computer vision and CNN in modeling the maturity of agricultural products, there are no studies that have examined the benefits of computer vision and CNN in classifying and identifying large green chili maturity. This study aims to classify the maturity stage of large green chili into three maturity levels, i.e. maturity 1 (maturity index 1 / 34 days after anthesis (DAA)), maturity 2 (maturity index 3 / 47 DAA), and maturity 3 (maturity index 5 / 60 DAA) by using CNN and computer vision. The level of maturity of this chili is based on the research of Hendrawan et al. [16] as a basis for classification.

2. Materials and methods

In this study, large green chilies were harvested from chili plantations in Tawang Argo Village, KarangPloso District, Malang, Indonesia. Maturity 1 was harvested at 34 DAA, maturity 2 was harvested at 47 DAA, while maturity 3 was harvested at 60 DAA. This study used a low-cost digital commercial camera to collect large green chili image data. The image acquisition process was carried out using a closed black box with evenly distributed lighting over the surface of the large green chili object. The light was provided by two 22W lamps (EFD25N/22, National Corporation, Japan). Light intensity over the object surface was uniform at 300 lux in the center of the region during image acquisition.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. From the image acquisition process, the image was obtained with a resolution of 300 × 300 pixels in JPEG format. The augmentation process of image data is carried out to increase the amount of data.Each level of maturity used a sample of 100 chilies. After the augmentation stage, 400 chili image data were obtained for the training and validation process. Then at each level of maturity, 20 more chili samples were taken, which after augmentation became 80 image data for the testing process. A total of 1200 image data with three maturity categoriesi.e.maturity 1, maturity 2, and maturity 3 were used as training and validation data. Image data wasdivided into two parts i.e. 70% for training data and 30% for validation data.

Figure 2 shows an example of large green chili with maturity 1, maturity 2, and maturity 3. Large green chili in each maturity class looks almost the same and is difficult to distinguish by observations from external appearances. The deep learning method was used to model image data in categorizing the quality of large green chili. Four types of CNN pre-trained networks were used in this studyi.e.SqueezeNet, GoogLeNet, ResNet50, and AlexNet. The CNN SqueezeNet algorithm was described in the research of Ucar and Korkmaz [17], GoogLeNet in the study of Raikar et al. [18], ResNet50 in the study of Mkonyi et al. [19], and AlexNet on Jiang et al. [20].

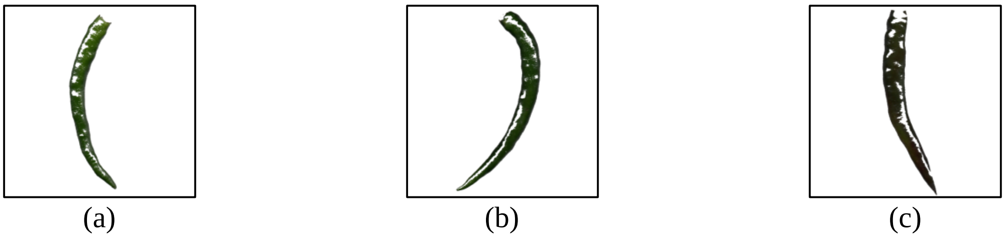

Figure 2. 300×300 pixels image of large green chili in different maturity levels: a) maturity 1; b) maturity 2; c) maturity 3.

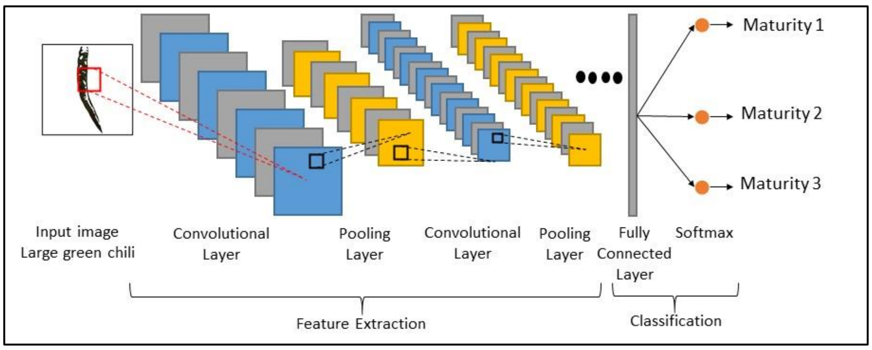

Figure 3. Structure of CNN model to classify large green chili maturity.

The CNN structure for classifying large green chili maturity, 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) [21], initial learning rate (0.00005 and 0.0001) [22], epoch 20, minibatch size 20 [23], 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 80 data sets in each quality category. The testing data set was image data of large green chili 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 [24].

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 maturity of large green chili 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. Based on the obtained results, it showed that the four pre-trained networks CNN models produced different classification accuracy with an accuracy ranging from the lowest 82.22% to the highest 93.89%.

Table 1. Performance of pre-trained network CNN to classify large green chili maturity.

Architecture	Optimizer	Learning rate	Accuracy (%)	Time (minutes)
AlexNet	SGDm	0.00005	92.22	78
	Adam	0.00005	86.11	78
	RMSProp	0.00005	86.39	78
	SGDm	0.0001	86.94	75
	Adam	0.0001	83.61	78
	RMSProp	0.0001	82.22	84
GoogLeNet	SGDm	0.00005	93.89	181
	Adam	0.00005	91.94	149
	RMSProp	0.00005	88.89	148
	SGDm	0.0001	87.78	148
	Adam	0.0001	93.89	149
	RMSProp	0.0001	89.72	149
ResNet50	SGDm	0.00005	90.83	350
	Adam	0.00005	90.56	341
	RMSProp	0.00005	89.72	369
	SGDm	0.0001	91.39	357
	Adam	0.0001	93.06	358
	RMSProp	0.0001	88.61	374
SqueezeNet	SGDm	0.00005	87.78	83
	Adam	0.00005	91.11	79
	RMSProp	0.00005	88.61	80
	SGDm	0.0001	86.94	80
	Adam	0.0001	87.22	78
	RMSProp	0.0001	92.78	79

Overall, based on the value of the initial learning rate, it was proven that the learning rate of 0.00005 produced a higher average classification accuracy of 89.84% compared to the learning rate of 0.0001 which resulted in an average classification accuracy of 88.68%. Based on CNN's pre-trained network architecture, the GoogLeNet model had the highest average classification of 91.01% followed by ResNet50, Squeezenet, and AlexNet with average classification accuracy values of 90.69%, 89.07%, and 86.25%, respectively. These results are in line with research conducted by Li et al. [25] which proved the performance effectiveness of GoogLeNet for classification. However, Table 1 also shows the weakness of ResNet50 and GoogLeNet is that the training process required was very long with an average learning time of 358 minutes for ResNet50 and 154 minutes for GoogLeNet. The fastest learning process was achieved when using the CNN AlexNet model, which was about 78.5 minutes. Based on the optimizer method used, it was proven that SGDm produced the highest average classification accuracy of 89.72% compared to Adam and RMSProp which had an average classification accuracy of 89.68% and 88.36%, respectively. From the overall results of sensitivity analysis, the highest classification accuracy was 93.89% which can be achieved when using GoogLeNet with SGDm optimizer and learning rate 0.00005.

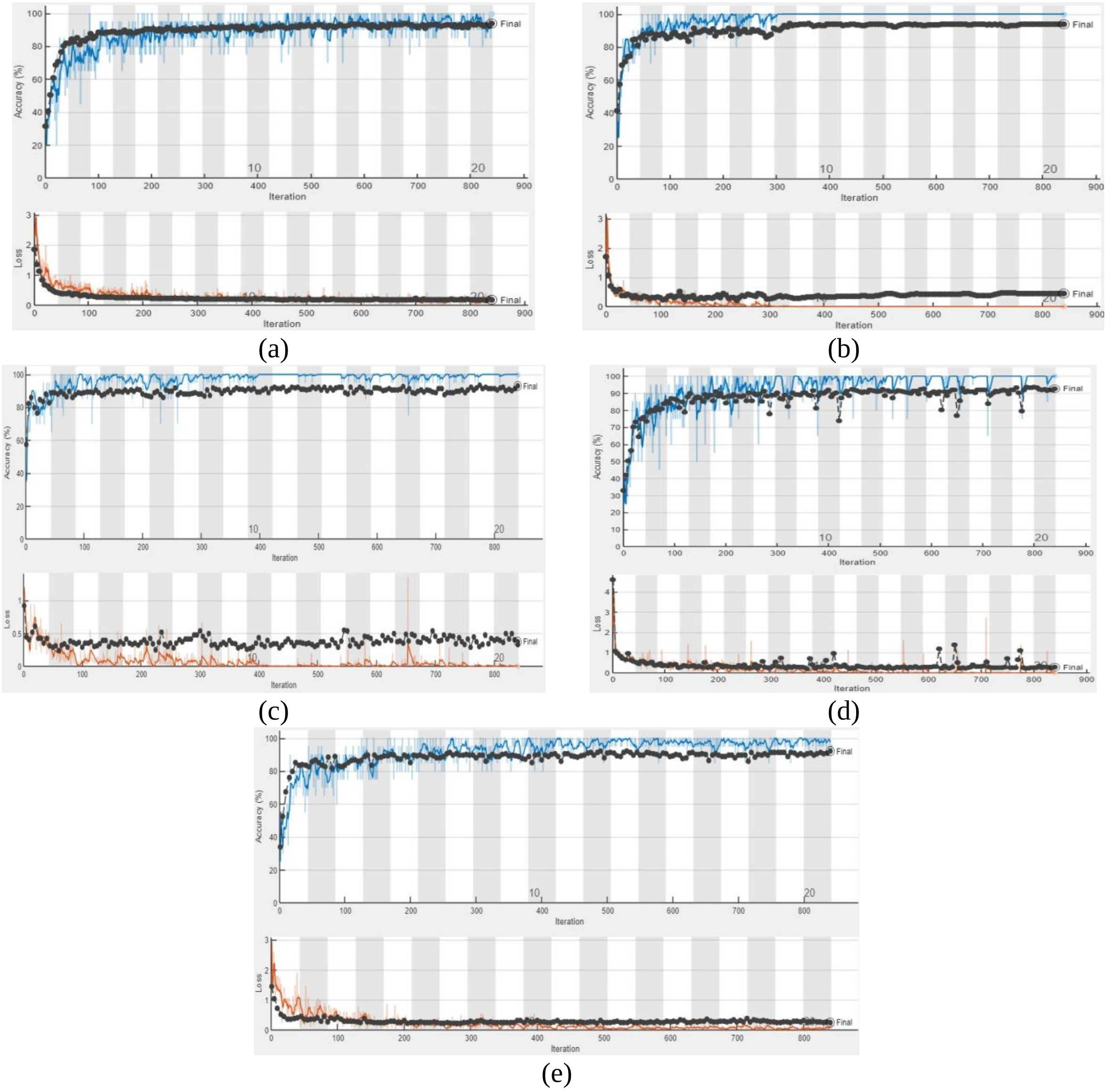

Figure 4. Performance of CNN to classify large green chili maturity using pre-trained network: (a) GoogLeNet (optimizer = SGDm, learning rate = 0.00005); (b) GoogLeNet (optimizer = Adam, learning rate = 0.0001); (c) ResNet50 (optimizer = Adam, learning rate = 0.0001); (d) SqueezeNet (optimizer = RMSProp, learning rate = 0.0001); (e) AlexNet (optimizer = SGDm, learning rate = 0. 00005).

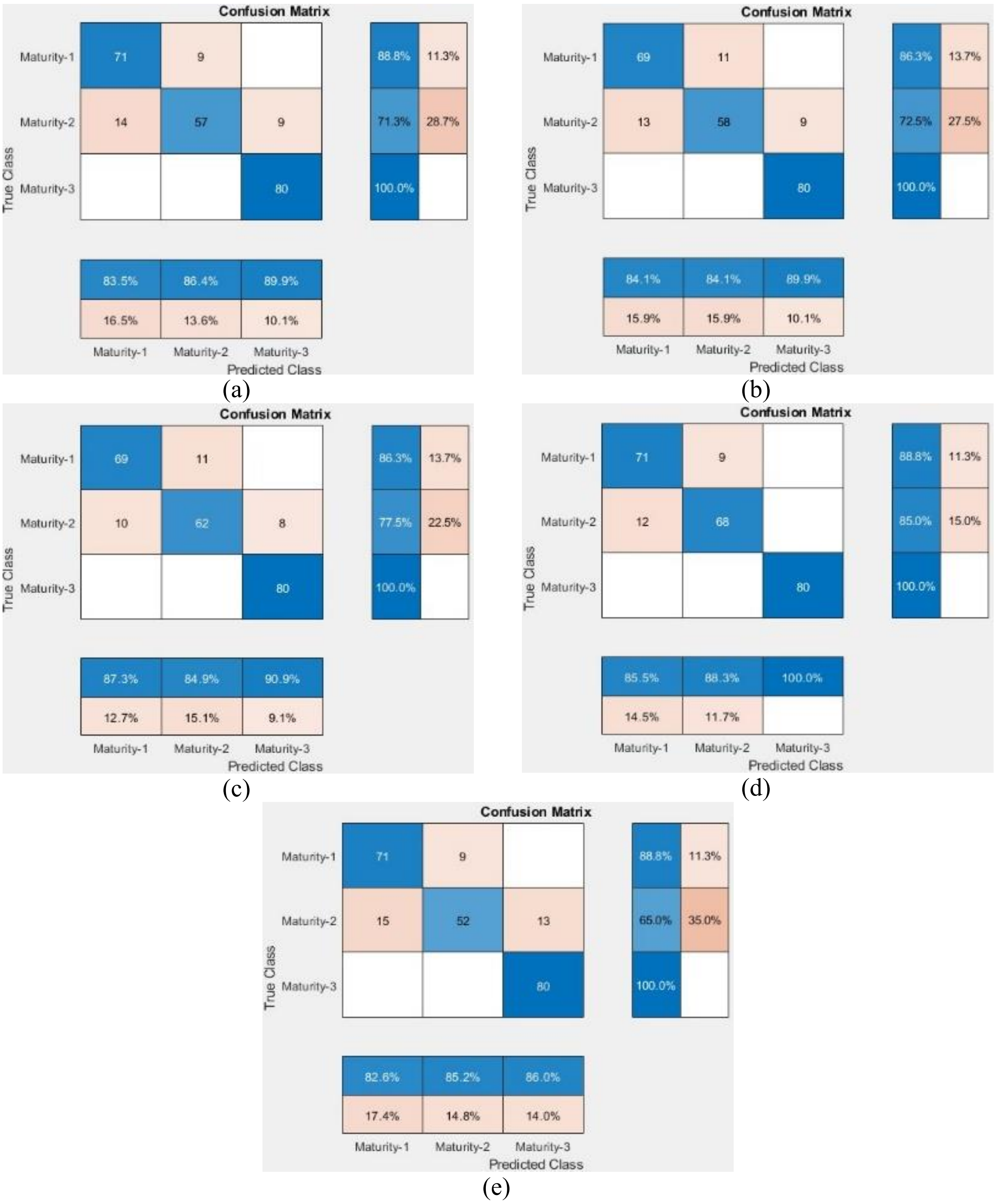

Figure 5. Performance of testing-set data using a confusion matrix: (a) GoogLeNet (optimizer = SGDm, learning rate = 0.00005); (b) GoogLeNet (optimizer = Adam, learning rate = 0.0001); (c) ResNet50 (optimizer = Adam, learning rate = 0.0001); (d) SqueezeNet (optimizer = RMSProp, learning rate = 0.0001); (e) AlexNet (optimizer = SGDm, learning rate = 0. 00005).

The training process in the five best 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[26]. The opposite applied to the loss value, where the loss value decreased with increasing iteration. Almost the same patterns were shown by the five best CNN models. 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 GoogLeNet with Adam optimizer and learning rate of 0.0001 showed a fairly stable training and validation process compared to other CNN models.

After the best results were obtained in the training and validation process, the next step was testing the performance of the CNN model using the testing-set data. Of the five 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 [26]. So that for the confusion matrix in this study, one confusion matrix result was shown representative of the best five CNN models. The results of the confusion matrix can be seen in Figure 5. From the results of the confusion matrix, it appeared that the highest average accuracy of the testing-set data was 91.27% achieved by SqueezeNet with RMSProp optimizer and learning rate 0.0001, where this accuracy value was very high for classifying the maturity of large green chili. In the large green chili class of maturity 3, the CNN model was able to accurately calculate 100% without the slightest error. While in the maturity 1 and maturity 2 class, the CNN model made an error of 12.2% and 25.74%, respectively, and was still able to classify the maturity 1 and maturity 2 class with an accuracy of 87.80% and 74.26%, respectively. With this accuracy result, it can be concluded that the CNN model that had been built can work effectively to classify large green chili into maturity 1, maturity 2, and maturity 3 classes. In future work, the combination of the CNN model and the low-cost digital commercial camera can be used to detect the maturity of large green chili with the advantages of being non-destructive, rapid, accurate, low-cost, and real-time.

4. Conclusions

The maturity of large green chiliwas divided into three classes i.e. maturity 1 (maturity index 1 / 34 days after anthesis (DAA)), maturity 2 (maturity index 3 / 47 DAA), and maturity 3 (maturity index 5 / 60 DAA). 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. Fivebest CNN models i.e. GoogLeNet (optimizer = SGDm, learning rate = 0.00005); GoogLeNet (optimizer = Adam, learning rate = 0.0001); ResNet50 (optimizer = Adam, learning rate = 0.0001); SqueezeNet (optimizer = RMSProp, learning rate = 0.0001); AlexNet (optimizer = SGDm, learning rate = 0. 00005)were able to achieve training and validation accuracy up to 93.89%. In further testing using the testing-set data, the highest classification accuracy based on the confusion matrix was reaching 91.27%. The combination of the CNN model and the low-cost digital commercial camera can later be used to detect the maturity of large green chiliwith the advantages of being non-destructive, rapid, accurate, low-cost, and real-time.

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