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Classification of durian maturity using a convolutional neural network

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Abstract

The maturity of a durian fruit is one of the important factors that are considered when assessing the appropriate quality of fruit for export worldwide. In order to verify the maturity, a high level of professional expertise and long-term experience are required. The best current method for classifying images is a convolutional neural network (CNN), a branch of deep learning. In this study, a CNN method is proposed to classify and predict the stages of maturity of durian fruit. In this experiment, durians were separated into five classes based on the harvesting period: (i) 96 days; (ii) 103 days; (iii) 110 days; (iv) 117 days; and (v) 124 days. Following this, the durian fruits were analyzed to define the dry weight and to allow the stages of maturity to be inspected. The results showed that the average dry weights were 11.31%, 17.76%, 26.65%, 38.94% and 42.13%, respectively. Mature durians have a dry weight of 32% or more, meaning that durians harvested at 117 and 124 days can be classified as mature, while the rest are classified as immature. Data were then collected for all five classes of durian, with 300 images per class, giving a total of 1,500 images. This study mainly focused on comparing three CNN architectures: LeNet-5, AlexNet, and DuNet-12 (our proposed CNN architecture). We also compared two activation functions, tanh and ReLU, and four optimization algorithms: AdaGrad, AdaDelta, RMSProp and Adam. The DuNet-12 architecture with the ReLU activation function and Adam optimizer was the most effective method over a training period of 350 epochs, and yielded a testing accuracy of 98.96%. It had the highest prediction accuracy of 100%. However, the results also demonstrated the efficiency of the proposed durian classification method, and the findings of our experiment could be used to develop equipment for the durian export industry in the future.

Keywords: Maturity, Classification, Convolutional neural network, Durian

1. Introduction

The durian (*Durio zibethimus*) is an important fruit export from Thailand, and is one of the most popular tropical fruits in Asia and in the West due to its unique aroma and flavor [1-4]. It also contains nutrients, fatty acids, bioactive compounds, and antioxidants that are beneficial to health [5-8]. Durian exports from Thailand increase every year; for example, they increased by 2.419% in the second half of 2020, and by 13.480% in 2021 [9]. In 2021, Thailand was the world's largest exporter of fresh durians, with a total export volume of 833,355 tons, worth 102,573 million baht [10]. "Monthong" is the variety that is primarily exported to the world market. China is the most important market for Thai durians, followed by Hong Kong, Vietnam, Taiwan, USA, Malaysia, South Korea, Japanese, Australia, and the United Kingdom [9].

Today, there is increased demand from customers for high-quality and safe food. In response to this demand, the Ministry of Agriculture and Cooperative of Thailand has developed policies to encourage durian farmers and exporters to comply with good agricultural practice (GAP) standards to ensure the export quality of durians [11, 12]. The dry weight is used as a criterion for durian export standards; in the minimum stage of maturity, a "Monthong" durian should not be less than 32% dry weight [13, 14], and this percentage will rise with an increase in the number of days after anthesis (DAA) [15, 16]. In practice, however, the high price of durians in the early season causes farmers to harvest both immature and mature fruits at the same time. When sorted by exporters, mistakes may be made, causing the export of immature durians. This has a serious impact on the export industry, affects customer confidence, and also causes huge economic damage. Thus, exporters must pay attention to the selection of durians with the correct degree of maturation, in order to ensure the supply of quality durian fruit. The selection of mature durians requires a high level of skill and experience, as the criteria used to assess the maturity include the number of DAA, its shape, shell color, the spine tip color (which should be dark brown), the carpel lines (which should be dilated), the sound pitch after trapping [3], and the percentage of dry matter or the dry weight of the fruit [13].

A number of research studies have proposed non-destructive techniques for determining the maturity of durians. For example, Timkhum and Terdwongworakul [15] proposed a maturity classification method using visible spectroscopy of the spine of the durian. A model using absorbance spectra transformed by the standard normal variate achieved the best classification accuracy (94.7%) when four classes of maturity were considered (113, 120, 127 and 134 DAA). Somton et al. [16] scanned the rind and stem of durians with near-infrared spectroscopy to obtain spectral data for indirect prediction of pulp dry matter as a reference for maturity. Their results showed that a combination of spectral data on both the rind and stem at the selected wavelength provided the highest accuracy of

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classification (94.4%). Yantarasri et al. [17] used medical X-ray computed tomography (CT) to scan an image of durian pulp to obtain CT numbers, and used near-infrared (NIR) spectroscopy to scan the pulp. These methods were evaluated and compared to a sensory test, and the results showed that there was a significant correlation between the stage of maturity and the CT number. Kongrattanaprasert [18] determined the maturity of durian fruit with 90% accuracy using a measurement of frequency response from the vibration in the region between the prickles, located in the middle of the durian. Rutpralom et al. [19] proposed a technique for determining the maturity of durians using 3 GHz microwave radiation had the best output. Sawetmethikul and Nimkerdphol [20] carried out measurements using a 3.4 GHz microwave sensor base planar structure, and their experimental results showed that the predictions of durian maturity were 91.55–99.0% accurate. Cheepsomsong and Siriphanich [21] compared the traditional specific gravity method with the 3D scanning method for different levels of maturity of durians, and found that there was no significant difference between the two methods. In practice, these methods are quite difficult for farmers and exporters to implement. However, image-based classification of agricultural products is starting to replace human labor in the agricultural industry.

Deep learning (DL) is a method based on artificial neural networks (ANNs) that has been shown to be an effective tool for handing large amounts of data. An ANN model consists of an input layer, a hidden layer and an output layer. DL methods are variously applied with image data as it improves ANN to have more hidden layers, which could strengthen the effectiveness of calculation, thus increasing the pattern recognition capabilities. One of the most popular DL models used for image processing is the convolutional neural network (CNN), which was introduced in 1990. Following the rapid development of these techniques, many additional models have been proposed in the literature, including LeNet, AlexNet, ZFNet, GoogLeNet, VGG, and ResNet. The LeNet architecture was proposed by LeCun et al. in 1998 [22]. The winner of the 2012 ImageNet Large Scale Visual Recognition Competition (ILSVRC) was AlexNet, a deep CNN architecture introduced by Krizhesky et al. [23]. It achieved outstanding performance, and made CNNs popular again. Many high-quality CNN models have been developed for the field of computer vision. GoogLeNet, the winner of ILSVRC2014, yielded a significant improvement over ZFNet (the winner in 2013), and had relatively low error rate compared with VGGNet (first runner-up in 2014). VGGNet was developed by the Visual Geometry Group (VGG) at the University of Oxford. A residual network (ResNet) is a deep learning model used for computer vision applications that is based on a CNN architecture, and is designed to support hundreds or thousands of convolutional layers. CNNs have gained immense popularity as an efficient method for classifying images in many areas, for instance in medical treatment [24-26], face recognition [27, 28], and investigation of the causes of plant diseases [29-31]. It is especially widely used in agriculture for the classification of a variety of fruits [32-35], including mangosteen [36, 37], apples [38-40], pear [41], oranges [42] and durians [43-45].

The CNN technique has been applied to image classification of fruits. In this case, Azizah et al. [36] was used CNN architecture for detecting the defect on mangosteen before exports, CNN model includes 4-fold cross validation process. Their results showed that the model was 97% accurate. Kunakornvong and Asriny [38] employed CNN architecture to classification of apples by comparing activation function with ReLU and Tanh. Their results showed that ReLU function is more accurate than Tanh function with 95 percent accuracy. Mohtar et al. [37] employed V3 inception CNN model for ripeness classification of mangosteen fruit. Their results showed that the CNN model achieved an accuracy of more than 90%. Zeng et al. [41] employed LeNet architecture for the classification of bruises of pears. Their results showed that the proposed architecture achieved great performance, producing an accuracy of 99.3%. Asriny et al. [42] employed CNN to classified oranges by comparing ReLU function and Tanh function. Their results showed that ReLU function is more accurate than Tanh function with 96 and 93.8%, respectively.

In prior research, CNN techniques have been used in combination with other methods to determine the maturity of durians. Lim and Chuah [43] developed a method for the effective identification of durian varieties based on the visual features of the crop using a CNN. The trained model had a prediction accuracy of 82.50% when applied to perfect bottom-view images. Kharanat et al. [44] used a method based on a knocking sound to predict the stages of maturity of durian fruits. They set a mel-frequency cepstral coefficient (MFCC) as a standard to divide durians into three classes: (i) ripe; (ii) mid-ripe; and (iii) unripe, and captured images to classify the ripeness using a CNN. Their results showed that the model was 90.78% accurate on the validation set and 89.40% accurate on the testing set. Uy and Villaverde [45] applied Canny edge detection and a CNN to identify six varieties of durian from the Philippines based on their shape, color and the differences in their thorns. Image data were obtained by photographing durians in an orchard and a market. They collected a total of 830 images, and a technique for increasing the number of images was applied to increase this to 3,492 images. The results showed that the accuracy of the model was 71.429% and a total sum of precision was 500%. However, the prediction of maturity of the durians using this method was less accurate. Schemes in previous studies are insufficient to accurately predict the maturity of individual durian fruits.

Consequently, in this study, we propose a method of identifying durians using a CNN in combination with the dry weight of the fruit, to improve the prediction accuracy. Images of fruit were collected using five different harvesting periods: 96, 103, 110, 117 and 124 DAA. The model presented in this study can be used to develop a tool for investigating the maturity of durians in the future.

Table 1 Summary of related research on fruit classification

Fruit	Method	Performance Results	Author(s)
Mangos-teen	CNN	97.% accuracy	Azizah et al. (2017) [36]
Durian	CNN	Prediction was 82.50% accurate	LIM and CHUAH (2018) [43]
Mangos-teen	V3 Inception CNN	90% accuracy	Mohtar et al. (2019) [38]
Orange	Two-layer deep CNN, two activation functions	96% accuracy for ReLU 93.8% accuracy for Tanh	Asriny et al. (2019) [42]
Pear	LeNet architecture	99.25% accuracy	Zeng et al. (2020) [42]
Durian	Canny edge detection and CNN	71.429% accuracy	Kharamat et al. (2020) [44]
Durian	Four-layer CNN	90.78% accuracy on validation data	Uy and Villaverde (2021) [45]
Apple	Three-layer deep CNN	99.97% accuracy on training sets size up to 50%	Rhamadiyanti and Suyanto (2021) [39]
Apple	Two-layer deep CNN ANN Support vector machine (SVM) *k*-nearest neighbors (KNN)	96.5% for CNN 89.5% for ANN 95.93% for SVM 91.68% for KNN	Benmouna et al. (2022) [40]

2. Materials and methods

Our scheme for classification of durian maturity was based on a combination of the dry weight and a CNN. The process was divided into two steps: (i) determination of the dry weight for analysis of the maturity of the durian, and (ii) classifying the maturity of durian fruit from images using a CNN.

2.1 Determination of the dry weight

2.1.1 Durian samples

In Thailand, Chantaburi province is one of the main areas in which durians are grown, and "Monthong" is the most famous cultivar for export; we therefore considered "Monthong" durians in this research. Data were collected by selecting buds with more than 10 flowers that were 3 mm in diameter. When the flowers had fully bloomed, they were pollinated and tagged to identify the date for harvesting [46] (Figure 1).

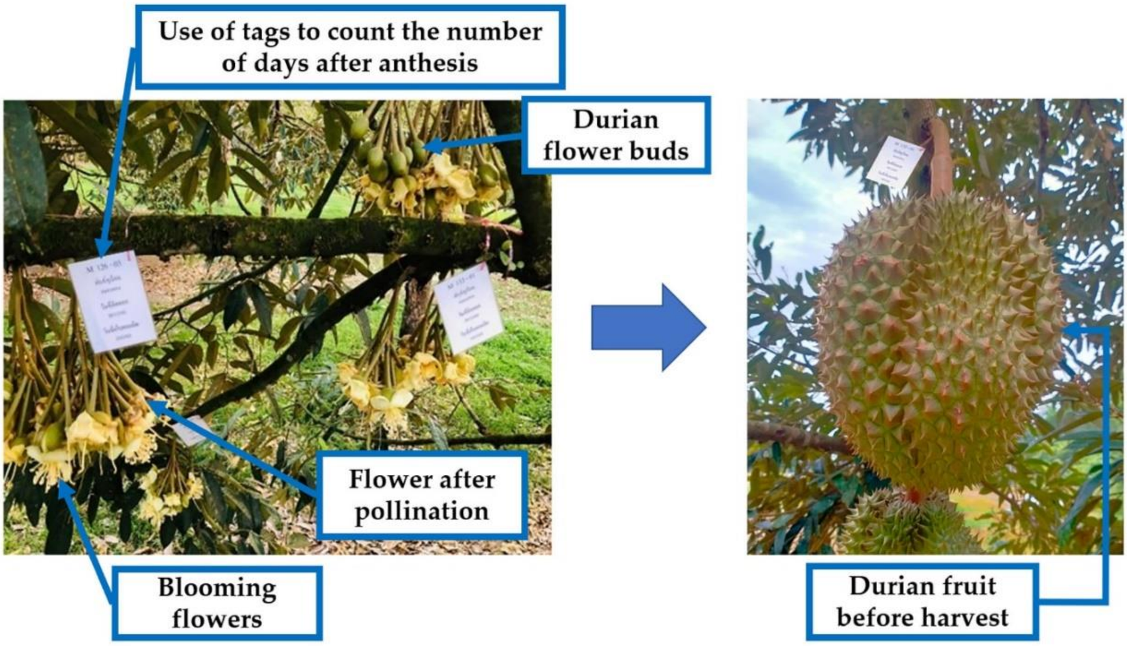


Figure 1 Attachment of tags to the flowers to identify the number of days after anthesis.

To examine the dry weight of the durians, fruits were collected from orchards located in the Chantaburi province and were harvested at five different periods: 96, 103, 110, 117 and 124 DAA. Each durian was taken from a different tree to ensure the accuracy of the results. A total of 30 durian fruits were randomly sampled from the tagged clusters in each group. The moisture content and dry weight were the important indicators for the perfect harvesting time.

2.1.2 Determination of the dry weight

The percentage dry weight of the durian fruit was used as an index of maturity. During growth, the dry weight increases with the age of the durian. The process used for determination of the dried pulp weight of a durian is regulated by the National Bureau of Agricultural Commodity and Food Standard, 2013 [13], and is as follows: each fruit is opened and three lobes randomly removed, and the pulp at the middle of each lobe is collected. The sample is sliced and then mixed thoroughly. A 20 grams sample is randomly selected per fruit, and placed in a container. The sample is dried in an infrared moisture meter at 70°C until the dried weight becomes constant (Figure 2). An infrared moisture meter is equipment that substitutes a loss on drying method used for moisture determination. The percentage dry weight is calculated using the following formula:

$$\text{Dried pulp weight } (\%) = \frac{\text{Weight after drying}}{\text{Weight before drying}} \times 100 \tag{1}$$

2.2 Classification of the maturity of durians

2.2.1 Dataset preparation

We photographed the durians using a mobile phone camera under a room light environment, and each durian was placed in front of a white surface. As shown in Figure 3, the durian was hung in position for photography with the camera set 30 cm from the fruit. Each durian was photographed from five sides. Five classes of fruit were considered, corresponding to harvesting at 96, 103, 110, 117, and 124 DAA (Figure 3). We collected a total of 1,500 images, with 300 images for each class. The images were divided, with 80% (1,200 images) of the total dataset used as training data, 10% (150 images) as validation data, and 10% (150 images) as testing data.

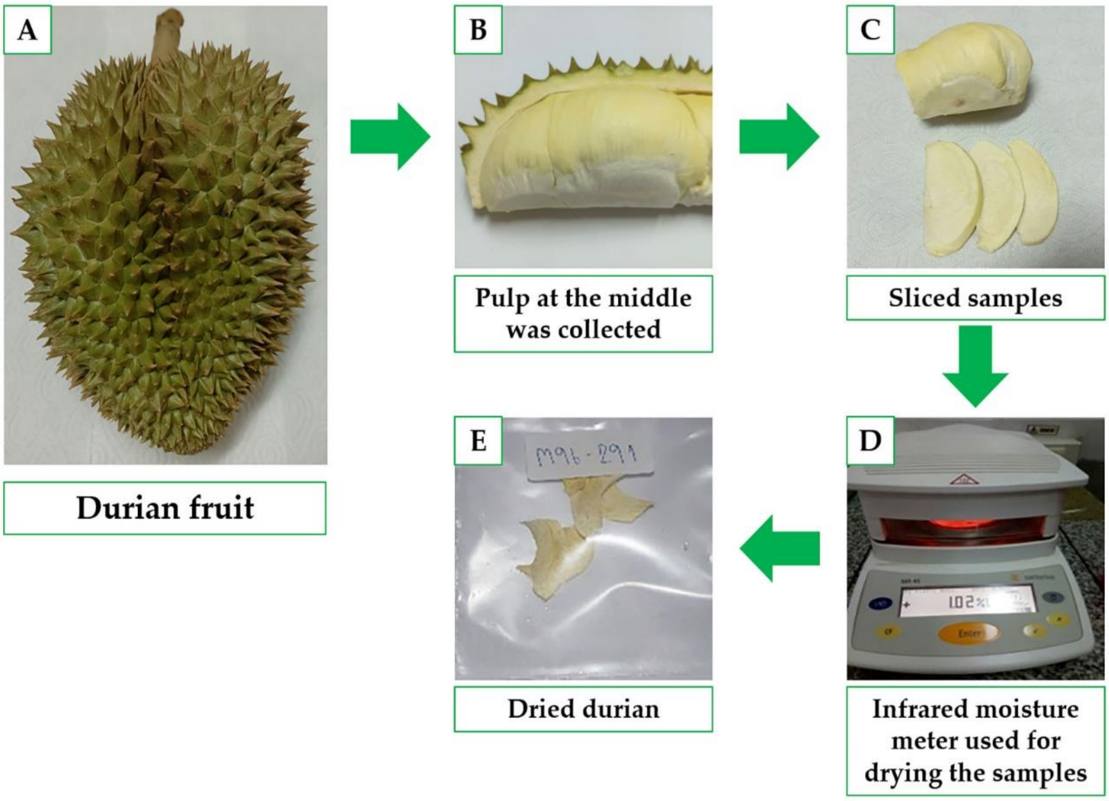


Figure 2 Determination of the dry weight: (a) a fresh durian fruit; (b) random removal of three lobes; (c) sample slices from the pulp; (d) an infrared moisture meter used for drying the sample; and (e) dried durian, post-drying method.

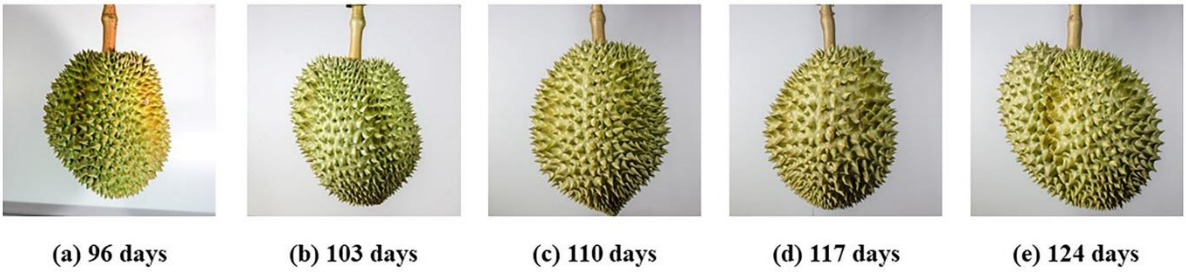


Figure 3 Samples of durian images

2.2.2 Pre-processing

The images used in this study had different dimensions: the dimensions of the images from the mobile phone camera were 3456 x 3456 pixels, while those taken with a camera had two sizes, 5184 x 3456 pixels and 6000 x 4000 pixels. Larger images take a longer time to process, and reducing the size of the image can reduce the processing time. The pre-processing stage was therefore divided into two steps: the image input was resized to 224 x 224 pixels, and rescaled as 1.0/255.

2.2.3 Classification using a CNN

A CNN can be used to view image features. The deeper the image layers, the more complex the operation of the CNN in terms of studying these features, which allows the CNN to classify images according to the actual class. A CNN is often used to solve problems related to computer vision, such as detecting objects and classifying or annotating images. The network consists of three layers: a convolution layer, a pooling layer, and the output layer.

This paper proposes a deep learning method using a CNN, and compares three architectures: LeNet-5, Alexnet, and an architecture that was specifically designed for this paper called Durian Network-12 (DuNet-12) (Figure 4).

The LeNet-5 architecture has a simple architecture, consisting of a multi-layer CNN for image classification with between one and 10 classes. The network has seven layers, of which five layers have learnable parameters. The first layer handles the input RGB image, but this layer is not considered a layer of the network. The first convolutional layer, with six filters, has a kernel of size 5 x 5 and a stride of one. The next layer is an average pooling layer with a filter of size 2 x 2 and stride two. The second convolution layer with 16 filters has a kernel of size 5 x 5 and stride one. The next layer is an average pooling layer, with a filter of size 2 x 2 and stride two. The last convolutional layer contains 120 filters with a 5 x 5 kernel and stride one. The next is a fully connected layer with 84 neurons. The final layer is an output layer with five neurons and the Softmax activation function. The optimizer used in this case is Adam.

The AlexNet architecture, this model is based on a multi-layer CNN for image classification with between one and 1,000 classes. The network has 11 layers, eight of which have learnable parameters. The first layer handles the input RGB image, which is passed to the first convolutional layer with 96 filters. The size of the kernel is 11 x 11 and the stride is four. The next layer is a max pooling layer with a filter of size 3 x 3 and stride two. The second convolution layer contains 256 filters, with a 5 x 5 kernel, a stride of one and padding of two. The next layer is a max pooling layer with a filter of size 3 x 3 and stride two. The third and fourth convolutional layers have 384 filters, with a kernel of size 3 x 3, stride one and padding one. The fifth convolutional layer has 256 filters, with a 3 x 3 kernel, a stride of one and padding of one. The last max pooling layer has a filter of size 3 x 3 and stride two. After that, the first dropout layer is applied, with a rate set to 0.5. The first fully connected layer contains 4,096 neurons, and the dropout rate is fixed at 0.5. The next is a fully connected layer with 4,096 neurons. The last is the output layer, with five neurons and a Softmax activation function. The optimizer used is Adam.

Previous researches in durian image classification, however, showed that using other CNN architecture by Lim and Chuah [43], CNN by Kharamat et al. [44], and the 4 convolutional layers by Uy and Villaverde [45], still has less accuracy. We therefore propose an architecture with 14 layers, albeit the DuNet-12 architecture had l2 layers with learnable parameters, and our network contains six convolutional layers. The first layer is an input RGB image which is passed to the first convolutional layer with 32 filters, and the size of kernel is 3 x 3 with stride one. The next is a max pooling layer with filter size 2 x 2 and stride two. The second to sixth convolutional layers have 64 filters, with a kernel of size 3 x 3 and stride one. The next convolutional layer is also a max pooling layer, and the second to sixth max pooling layers have filters of size 2 x 2 and stride two. The next is a fully connected layer with 64 neurons, and the last is a output layer with five neurons. The Softmax activation function was applied for classification.

For each architecture, we carried out a comparison of two activation functions: the hyperbolic tangent (tanh) and the rectified linear unit (ReLU). Furthermore, we considered a comparison of four optimization functions (AdaGrad, AdaDelta, RMSProp, and Adam) and compared the training of model on the dataset over 50, 100, 150, 200, 250, 300, 350 and 400 epochs. A categorical cross entropy function was used to calculate the error. Since our model was a multi-class classification network, it was the most appropriate choice for us.

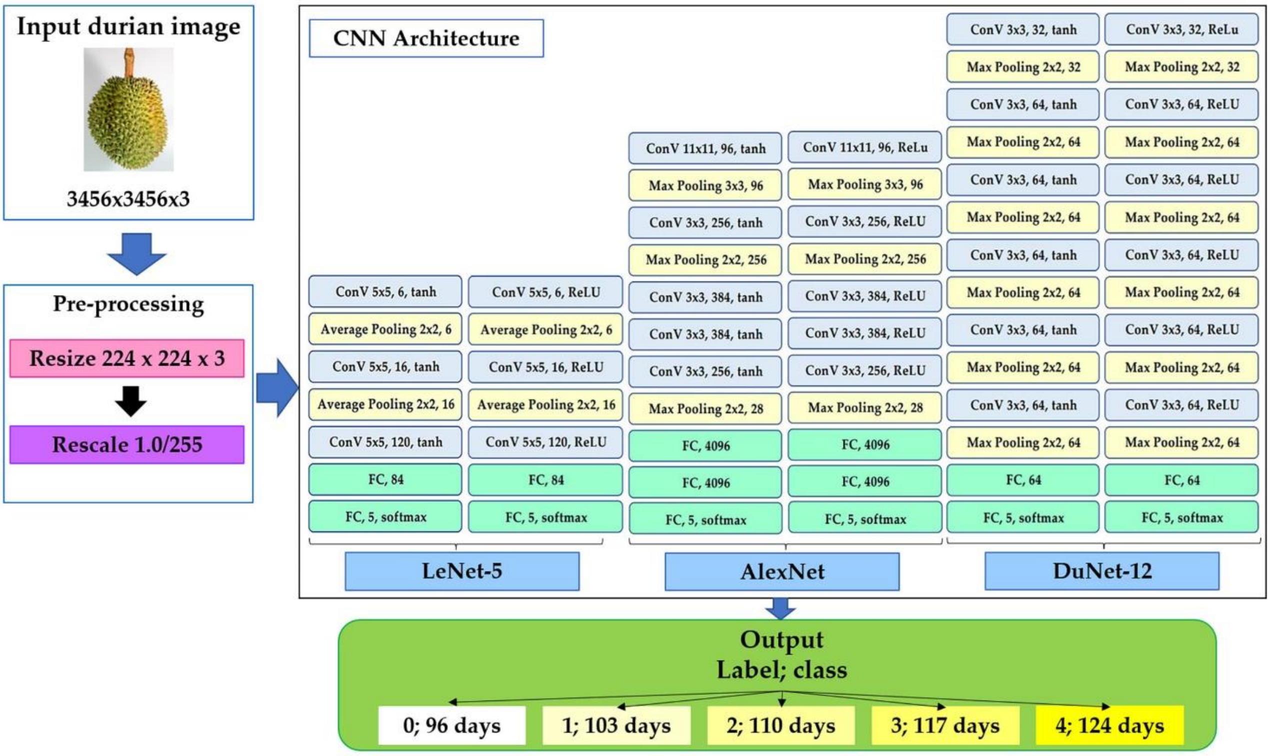


Figure 4 Experimental classification of durian maturity with the LeNet-5, AlexNet and DuNet-12 architectures

2.2.4 Performance evaluation

The performance of each model was assessed using a confusion matrix, which contains the numbers of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) results from the model. TP represents the case where data are classified correctly, and the output has valid values. FP indicates that the data were classified incorrectly, but the output had the correct value. TN shows that the data were classified appropriately, but the output was wrong, while FN refers to data that were classified incorrectly where the output was also wrong.

The performance of each model was verified in terms of the accuracy [40] and prediction, which were calculated using Equation (2). The accuracy was defined as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100 \tag{2}$$

To determine the prediction performance in this study, we calculated the number of correct predictions divided by the total number. We randomly selected images of durians from five classes, with 45 samples per class, giving a total of 225 images. We tested the model by predicting these images and calculating the percentage that the model correctly predicted from the total number of images.

3. Results and discussion

3.1 Dry weight of durians

In this study, we analyzed the dry weight pulp of “Monthong” durians at 96, 103, 110, 117 and 124 DAA to verify their maturity. For export, “Monthong” durians that are considered mature according to international standards [14] must contain more than 32% of dry weight, as set out in an announcement from the National Bureau of Agricultural Commodity and Food Standard in 2013 [13]. Our results showed that the average dry weight increased with durian age. Durians harvested at 96, 103, and 110 DAA contained 11.31%, 17.76% and 26.65% of dry weight, respectively, and these groups were therefore considered immature (unripe). Fruit harvested at 117 and 124 days contained 38.94% and 42% of dry weight, and were considered mature (ripe), as presented in Figure 5. Normally, the “Monthong” durian matures at approximately 106 DAA [47]. In addition, the moisture content decreases with age. It was clearly seen that immature durians contained higher rates of moisture content than mature fruits. As presented in Table 1, the moisture content of durians harvested at 96 days was 88.69%, a higher value than for durians harvested at 124 days, for which the moisture content was 57.87%. Consequently, ripe durians are lighter than unripe ones and give a louder knocking sound, and some researchers have employed the specific gravity of the fruit [48] to classify its maturity by means of visible spectroscopy of the spine [15]; they have also evaluated the maturity of “Monthong” durians using spectral information from the rind and stem [16], and have used the frequency of the knocking sound to classify the stages of maturity of these fruits [44].

The proposed method was used to analyze the dry pulp weight of durians, in order to investigate the relationship between the dry weight and the stages of maturity. The results showed that this was a more effective process compared with checking the appearance (such as its shape, peel color, sepals, or thorns), the sound frequency [44], or using microwave radiation to measure the thorns [46]. As a durian becomes older, the dry pulp weight and fructose level increase [3]. The total nonstructural carbohydrate (TNC) and total sugar content in “Monthong” durians were found to be higher as they grew older, reaching the highest level at 127 DAA [47].

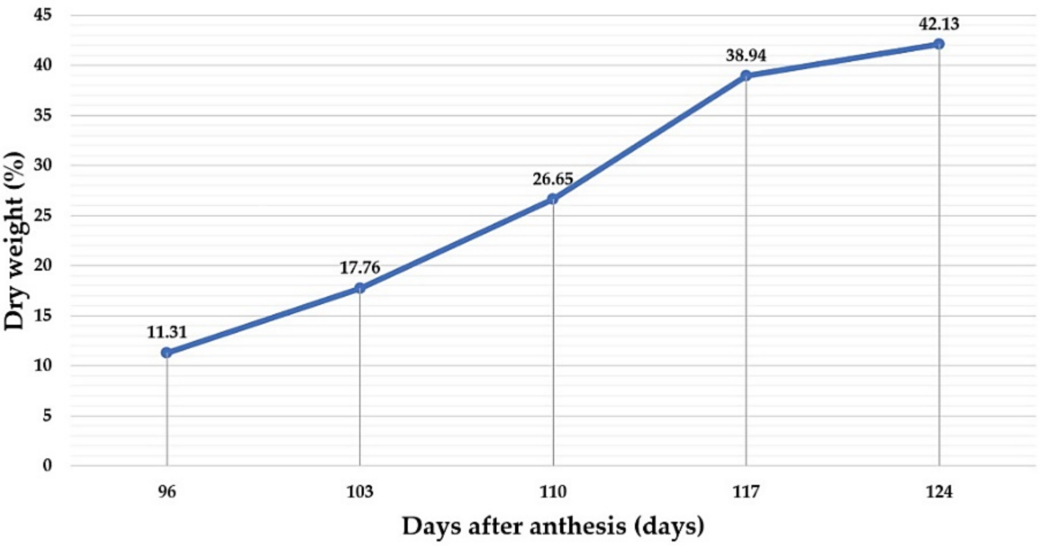


Figure 5 Change in the percentage dry weight of durian flesh with the number of days after anthesis

3.2 Classification of durian maturity

In this part of the experiment, we considered durian images that were categorized into five classes depending on the harvest time (96, 103, 110, 117 and 124 days). We used a dataset containing 300 images of durians for each class, with a total of 1,500 images. The experiment investigated three different architectures: LeNet-5, AlexNet, and our proposed architecture (DuNet-12). The performance of two activation functions (tanh and ReLu) was also explored, and the number of epochs was set to 20 and 50. The result showed that the accuracy of ReLU was higher than that of tanh for all architectures. As presented in Table 2, the best accuracy on the testing data was achieved by the LeNet-5 architecture after a training period of 50 epochs, with 95.83% accuracy, followed by DuNet-12 after a training period of 50 epochs (94.88%). The best prediction performance was found for LeNet-5 after a training period of 50 epochs, with a value of 93.78%, followed by DuNet-12 after a training period of 50 epochs, with a value of 91.56%. The tanh activation function enabled better training performance for multilayer neural networks, but was limited in terms of resolving missing gradients, while ReLU activation function was to solve the problem. Tanh is commonly used with recurrent neural networks to enhance the speed of recognition tasks and natural language processes [49]. However, ReLU is the most widely used in DL applications, and gives state-of-the-art results [50]. Comparisons of the tanh and ReLU activation functions have previously been carried out to study the sorting of fruit such as oranges [42] and apples [38]. Classification results for oranges using tanh and ReLU indicated that the accuracy on the training data for these activation functions was 98.6% and 100%, respectively, while the values on the validation data were 92.8% and 93.2%, respectively, and the values for the testing data were 96% and 93.8% [42]. The results for the classification of apples showed that the accuracy of the ReLU activation function was 95%, while that of the tanh activation function was 90% [38].

Table 2 Comparison of architectures used to classify the maturity of durians

Architecture	Epochs	Activation Function	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)	Prediction (%)
LeNet-5	20	tanh	20.00	6.25	19.79	15.11
	50	tanh	20.42	15.62	17.71	52.00
LeNet-5	20	ReLU	99.58	90.62	94.79	90.22
	50	ReLU	100	96.88	95.83	93.78
AlexNet	20	tanh	20.00	21.88	23.96	32.44
	50	tanh	20.21	15.62	20.83	15.11
AlexNet	20	ReLU	63.13	68.75	62.50	82.67
	50	ReLU	79.17	87.50	77.08	76.00
DuNet-12	20	tanh	88.96	96.88	88.54	84.89
	50	tanh	100	90.62	93.75	90.67
DuNet-12	20	ReLU	83.53	84.38	83.58	87.11
	50	ReLU	87.50	90.62	89.58	91.56

Table 3 shows a comparison of the performance of four optimization algorithms using three architectures. The architectures were LeNet-5, AlexNet and DuNet-12, and the optimization algorithms were Adagrad, Adadelta, RMSprop and Adam. For these experiments, we used 300 samples of durian images for each class, with a total of 1,500 images. The models were trained for 50 epochs. The results showed that for all the architectures, the best performing algorithm was Adam, as it gave better training, validation, testing and prediction accuracy than the other algorithms. However, when used with the LeNet-5 architecture, the RMSprop and Adam optimizers yielded the same accuracy for training, validation and testing while predicting different values. Different neural network architectures and image resolutions affect the behavior of the algorithm during training [51]. The optimization algorithm aims to improve the accuracy of the model. Of the various optimizers considered with other architectures, Adam has been found to be the most efficient [52]. As a result, DL can be made more efficient.

The performance of the model is summarized in Table 4. In this section, we examine the output of each architecture using the ReLU activation function and the Adam optimizer in terms of classifying the maturity of durians when the models were trained for different numbers of epochs (50, 100, 150, 200, 250, 300, 350, and 400). In this experiment, 300 durian images were used per class, giving 1,500 images in total.

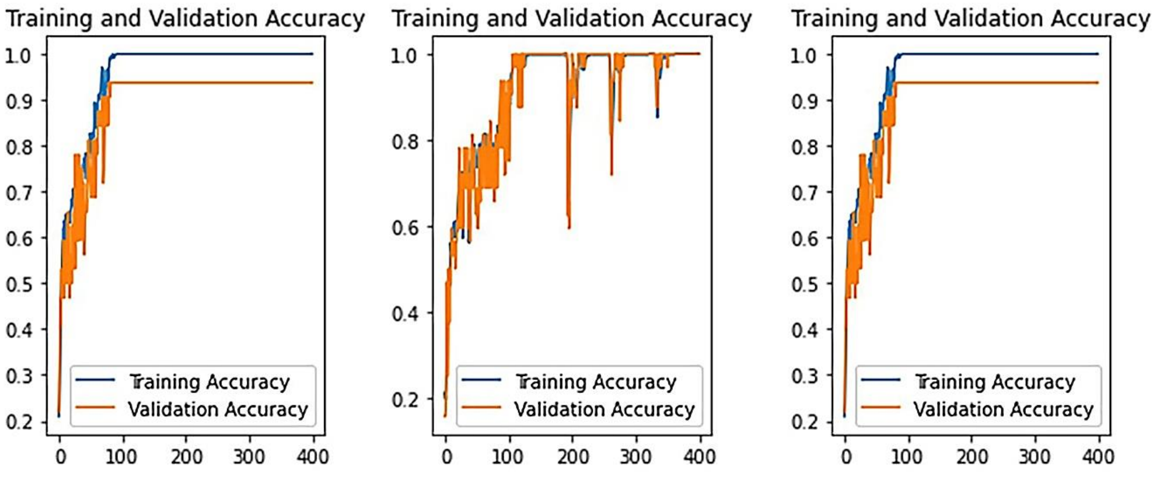
The results showed that LeNet-5 gave its best testing accuracy after a training period of 150 epochs, with a value of 96.88%. After a training period of 300 epochs, AlexNet yielded its best testing accuracy with a value of 95.83%, while DuNet-12 reached its best testing accuracy after a training period of 350 epochs, with a value of 98.96%. A graph of the training and validation accuracy for the models trained on the dataset with three different architectures for 400 epochs is shown in Figure 6. In the task of image processing, the size, resolution, and sharpness of each type of image affect the number of epochs required. For example, research by Zaheer and Shaziya in 2019 [52] found that the optimal training for MNIST was 1.00 with RMSProp and Adam over 200 epochs; for Fashion-MNIST, it was 1.0 with RMSProp and Adam over 400 epochs; for CIFAR-10, the optimal values were 1.0 with RMSProp over 200 epochs, and for 100 epochs with Adam. Kharamat et al. [44] reported that the sound frequency of durian image achieved an accuracy on the validation data of around 90.78% at epoch 150.

Table 3 Performance of various optimization algorithms

Architecture	Optimization algorithm	Training accuracy (%)	Validation accuracy (%)	Testing accuracy (%)	Prediction (%)
LeNet-5	Adagrad	64.17	59.38	59.38	43.56
	Adadelta	65.00	65.62	69.79	73.78
	RMSprop	100	96.88	95.83	91.11
	Adam	100	96.88	95.83	93.78
AlexNet	Adagrad	67.71	62.50	76.04	70.22
	Adadelta	57.08	78.12	58.33	65.33
	RMSprop	58.75	18.75	25.00	19.56
	Adam	79.17	87.50	77.08	76.00
DuNet-12	Adagrad	33.96	37.50	31.25	32.44
	Adadelta	19.79	31.25	26.04	32.44
	RMSprop	87.45	87.50	83.33	87.11
	Adam	87.50	90.62	89.58	91.56

Table 4 Performance of models trained for various numbers of epochs

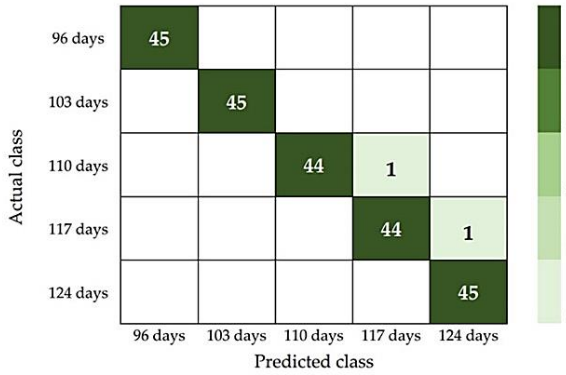
Architecture	Epochs	Time (s)	Training accuracy (%)	Validation accuracy (%)	Testing accuracy (%)	Prediction (%)
LeNet-5	50	619	100	96.88	95.83	93.78
	100	1108	100	96.88	93.75	93.33
	150	1611	100	96.88	96.88	99.11
	200	2325	100	93.75	91.67	84.89
	250	2620	100	96.88	92.71	92.89
	300	3109	100	96.88	93.75	93.33
	350	3233	100	90.62	95.83	98.67
	400	3680	100	93.75	95.83	99.11
AlexNet	50	669	79.17	87.50	77.08	76.00
	100	1215	96.88	96.88	92.71	89.33
	150	2074	100	96.88	91.67	84.89
	200	2717	100	96.88	92.71	97.78
	250	2860	100	96.88	92.71	97.78
	300	3597	100	93.75	95.83	98.67
	350	3934	100	87.50	93.75	97.78
	400	4882	100	100	90.62	97.78
DuNet-12	50	724	87.50	90.62	89.58	91.56
	100	1280	100	93.75	94.79	97.78
	150	2024	100	100	91.67	97.33
	200	2686	100	96.88	96.88	99.11
	250	3378	100	90.62	94.79	99.56
	300	4186	100	93.75	93.75	98.67
	350	5034	100	96.88	98.96	100
	400	5736	100	93.75	96.88	99.11



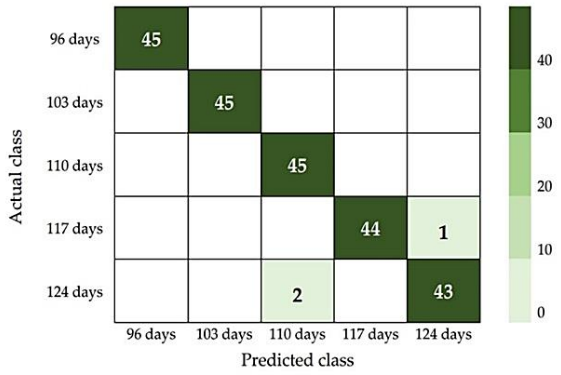
(a) LeNet-5 **(b) AlexNet** **(c) DuNet-12**

Figure 6 Graphs of the training and validation accuracy for three models over 400 epochs: (a) LeNet-5; (b) AlexNet; and (c) DuNet-12.

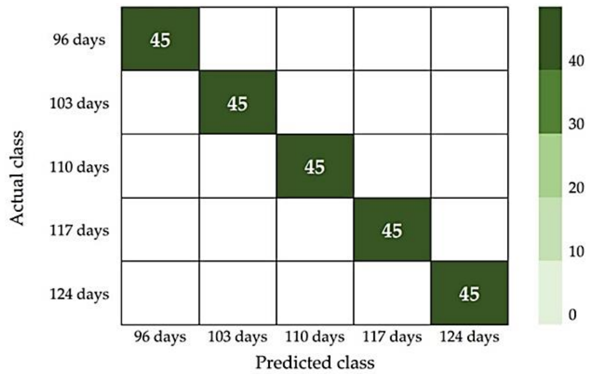
Figure 7 shows confusion matrices for the three tested architectures, LeNet-5, AlexNet, and DuNet-12. In a confusion matrix, the ordinate represents the actual class, and the abscissa shows the predicted class. The diagonals of the confusion matrix are the numbers of samples that were correctly classified. The three architectures were able to identify durian fruits with scores of 99.11%, 98.67%, and 100%, respectively.



(a) Confusion matrix for LeNet-5, 150 epochs



(b) Confusion matrix for AlexNet, 300 epochs



(c) Confusion matrix for DuNet-12, 350 epochs

Figure 7 Confusion matrices for durian images based on the best performance of the three models: (a) LeNet-5, 150 epochs; (b) AlexNet, 300 epochs; and (c) DuNet-12, 350 epochs.

4. Conclusions

In this study, we aimed to create a suitable model for sorting durian fruit, and to use the results to develop tools for solving the problem of inadvertently exporting immature durians to foreign countries, which can cause great economic damage. Our approach also allows farmers to accurately determine the maturity of durians before harvesting. In this study, we consider the use of the dry weight and apply a CNN to classify the maturity of the durians. The standard criterion indicating that a “Monthong” durian is mature enough to be exported is a dry weight of 32%. This value increases with the age of the durian, and durian harvested at 117 DAA were found to be suitable for export. The DuNet-12 architecture developed in this study was shown to be the most efficient model for durian classification, as it successfully predicted results with 100% accuracy based on images of durians.

Future work should include the study of CNN architectures and optimization algorithms with a variety of parameters (such as learning rate, number of filters and so on). The architecture of a deep learning model should be considered when selecting a suitable optimization algorithm. Furthermore, the results of our experiments are very important for the durian export industry, as it can be seen that an architectural structure needs to be developed and suitable parameters need to be found to enable the rapid processing of durian images, and for the further development of tools or applications for inspecting the quality of durian fruit before sending it to foreign countries.

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