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Classification the Melon Rinds Using Convolutional Neural Network

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Abstract. The first signal that a melon is getting ripe is the colour that the rind changes. Unfortunately, it is not the best indicator since the colour is not significantly different between the ripe ones and the ones that are not. This article verifies the classification between 2 types of melons, young melons and ripe melons, using the Convolutional Neural Network (CNN) method with a dataset of 500 images of the fruits. The dataset is classified into 2 parts, training data and testing data. While the classification method using 2 groups of datasets have been prepared results the accuracy value 99%, the latest melon image dataset input produces an accuracy of 52%. The difference of classification accuracy is 47% since the images are taken at different times and lighting conditions. Therefore, it produces different images and results in different accuracy values.

INTRODUCTION

Melon in Latin is called L. One type that comes from the pumpkin family or Cucurbitacca. This fruit contains nutrients and minerals that are very good for health [1]. Currently, there are 94 superior melon varieties in Indonesia, one of them is a type of Sky Rocket Melon. The Sky Rocket Melon variety is the most widely planted. Reviewed from the national creation information, this melon commodity is always increasing. In 2010, it increased by 85,161 tons, and increased up to 150,347 tons in 2014.

Fruits that we know so far are divided into two groups, the first is the climacteric group and the second is the non-climacteric group. In this case melon belongs to the non-climacteric group, where in this non-climacteric group the fruit must be harvested in a ripe condition [2]. Therefore, there are still many farmers who harvest melons at the same time. In which, at the time of harvesting melons certainly have different ripeness. The results of research observation, stated that melon can produce 5 to 6 melons in each plant. The level of ripeness of melon is difficult to distinguish between young and ripe melon because the rinds color are almost the same.

The classification of melon rinds color between unripe and ripe can be conducted using one of the deep learning concepts, namely the Convolutional Neural Network (CNN) theory. Color differences are a problem for the human eye, which has limitations in capturing color light, therefore using CNN can be a solution in color classification. In theory, CNN will detect image pixels uniquely from each input image. In the classification of melon rinds color will be grouped into 2 classes, namely the color of unripe rinds and ripe rinds. CNN is a deep learning method capable of performing various tasks of image classification, segmentation, object detection, and image recognition [3]. Considerations for utilizing deep learning methods with 2 main approaches, namely the creation of a model that is fully trained using input images and a transfer learning concept approach in which knowledge from previous problems is used to solve different problems, but still correlated [4]. The deep learning method on melon image classification can be connected to the internet network through the internet of things technique, so that observations are carried out in real time [5][6].

Convolutional Neural Network has a deep network consisting of several layers. It is a development of Multilayer Perceptron (MLP) and designed to process large-dimensional data, so that it is widely applied to image or visual data

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[7]. In the use of CNN in the recognition and classification of diseases, several CNN architectures are known such as Alexnet which has 8 layers, GoogleNet with 22 layers and Resnet which consists of 100 layers or more. Based on the function of the CNN architecture, there are 3 layers namely Convolutional Layer (CONV), Subsampling Layer (SUBS) and Fully Connected (FC). CNN has several CONV and SUBS layers followed by an FC layer. On CNN, there is 1 parameter that is often added, namely drop-out (DO) which serves to reduce overfitting in the hope that classification will be more accurate. The occurrence of overfitting is usually due to very large and large training data. When the training data is processed, this DO parameter will negate the activation function randomly with a certain probability. Meanwhile, at the time of testing all activation functions will be used, but DO will give weighting with a certain number [7]. Figure 1 shows the CNN architecture with 3 convolution processes and max polling [8].

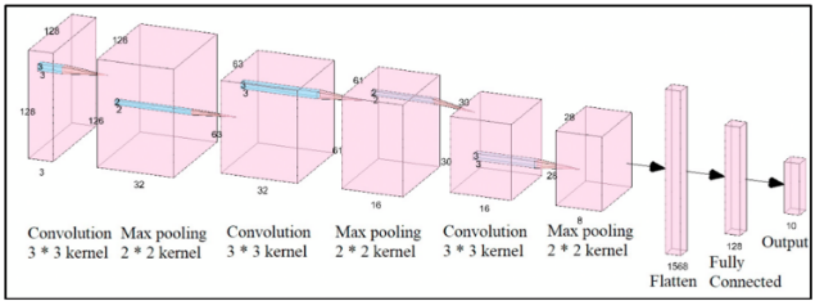


FIGURE 1. CNN architecture with 3 convolutions and max pooling

The convolution layer is an interaction to obtain pixels that depends on the actual pixel value and the part that includes the kernel is called the part that handles the weighting. It is very important for this stage in CNN engineering. This stage performs the convolution procedure on the past layer results. This layer is the main interaction that underlies the engineering organization of CNN. Convolution is a numerical term in which the utilization of one capacity to produce another capacity is repeated. The convolution process is a process in two capacities of two real-valued argument functions. This activity applies the work result as a feature map of the input image. The input and output of this process can be seen as two real-valued arguments. The convolution operation can be written in the following formula:

$$s(t) = (x * t)(t) = \sum_{a}^{\infty} = -\infty x(a) * w(t - a) \quad (1)$$

Information:

S(t) = Function of convolution operation results
X = Input
W = Weight (kernel)

Pooling is the reduction of the size of the matrix by utilizing the pooling operation. Pooling Layer generally comes after conv. Basically, the pooling layer consists of channels with a certain size and step which will then move again in the feature map area. There are two kinds of pooling in the pooling layer, namely average pooling and maxpooling. The value taken in average pooling is the average value, while in max-pooling is the maximum value. The embedded unification pooling layer between the progressive convolution layers in the CNN model engineering can dynamically reduce the result of volume size on the Feature Map, in this way reducing the number of limits and computations in the channel to control overfitting. The pooling layer handles each stack of feature map and reduces its size. The overall type of unification layer is to utilize 2x2 channels which are applied in two stages and work on each input piece [9].

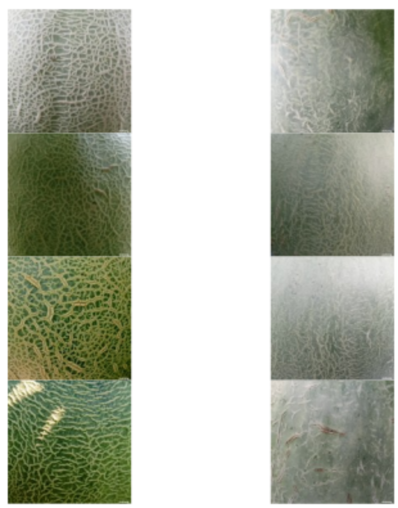
ReLU (Rectified Linear Unit) is a very familiar activation function used in deep learning formation. This process returns to 0 if it gets negative input, if it is for a positive value x, it will return to the first value. Therefore, it is surprising that the basic function (consisting of 2 linear parts) can enable the model for processing non-linearity and interaction well [9].

Fully-Connected Layer is a layer in which all applicable neurons from the previous layer are actually connected to the neurons in the next layer, very similar to ordinary neural networks. Basically, this layer is usually used in MLP (Multi-Layer Perceptron) which aims to change the size of the data dimensions so that the data can be classified linearly. The difference between a Fully-Connected layer and a regular convolution layer is that the neurons in the convolution layer are connected to a specific area in the input, whereas the Fully-Connected layer has neurons that are actually connected. Nevertheless, the two layers actually function as dot items, so the capacities aren't that unique [9].

Softmax activation is a speculation of the loistic function. The results of this softmax can be used to overcome the dissemination interaction of a class. Softmax function is used in various characterization processes, for example multinomial logistic tregression, multiclass linear discriminant analysis, neural network, dan naive bayes classifier. Overall, this function is usually used in the classification technique of multinomial logistic regression and multiclass linear discriminant analysis. Softmax also gives more intuitive results and has a better probabilistic understanding than other clustering calculations. Softmax allows us to ascertain the probabilities for all signs. From the current sign, the original value vector will be taken and converted into a vector with a value somewhere in the range of 0 and 1 which is when all additions will be one [2].

MATERIALS AND METHODS

The image acquisition of melon fruit was taken using a smartphone camera with a distance of about 50-60 cm during the day. The distance and time of image acquisition greatly affect the resolution of the resulting image, so that image acquisition is carried out at the same time. In this study, the dataset used was 350 images divided into 2 classes, namely unripe and ripe fruit. Each class will be divided into training and testing data with a ratio of 70: 30. Figure 2 shows the image of ripe and unripe melons.



(a) Ripe (b) Unripe

FIGURE 2. Image of ripe and unripe melons

The stages of melon fruit classification can be seen in Figure 3. Classification used 3 methods, namely k-NN, Decision Tree and svm.

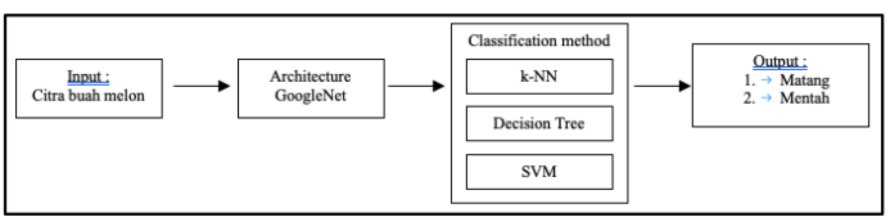


FIGURE 3. The stages of melon fruit image classification

RESULT AND DISCUSSION

The research process starting from image input to the end of the classification using the CNN algorithm and 3 classification methods resulted in the accuracy of training and testing data as shown in Figure 4. This epoch used 30 epochs with a batch size of 5. When the calculation enters epochs above 25, there is a decrease in accuracy, especially in the testing dataset. This condition occurs due to the difference in dataset resolution during image acquisition. However, when the epoch enters the end, the accuracy of the data increases to close to 1. The results of training and testing accuracy are also influenced by the determination of the batch size and the batch itself so that it will simplify the neural network process and produce overfitting and underfitting conditions.

FIGURE 4. Accuracy chart of training and testing data

Table 1 shows the results of the accuracy and *loss* of the training and testing data by obtaining the accuracy value in the *training* cycle (99%). This precision value can be communicated on a *spectrum* graph of the *training* cycle after running 30 *epochs* using *tensorflow.* The results of accuracy are inversely proportional to the loss results, the higher the accuracy, the smaller the loss value, which means that in this condition the designed model can be used as a classification model for determining ripe and unripe melon rinds.

TABLE 1. Accuracy training and testing results

NO	Training Data		Testing Data	
	Accuracy	Loss	Val_Accuracy	Val_Loss
1.	0,9667	0.0999	0,9867	0,0618
2.	0,9733	0,0952	0,9533	0,2158
3.	0,9667	0,1710	0,9733	0,1428
4.	0,9867	0,0412	0,9867	0,0702
5.	0,9533	0,5573	0,9800	0,0746
6.	0,9933	0,0260	0,9867	0,0718
7.	0,9600	0,1152	0,9933	0,0467
8.	0,9600	0,1405	0,9867	0,0510
9.	0,9733	0,0789	0,9867	0,0560
10.	0,9467	0,1000	0,9933	0,0471
11.	0,9867	0,0314	0,9867	0,0245
12.	0,9600	0,2606	0,9867	0,0942
13.	0,9933	0,0177	0,9667	0,0910
14.	0,9800	0,0530	0,9933	0,0803
15.	0,9733	0,1098	0,9867	0,0632
16.	0,9933	0,0193	0,9867	0,0837
17.	1,0000	0,0025	0,9933	0,0590
18.	0,9933	0,0197	0,9933	0,0673
19.	1,0000	0,0057	0,9933	0,0512
20.	0,9733	0,1757	0,9933	0,0949
21.	0,9933	0,0168	0,9933	0,0627
22.	1,0000	9.3453	0,9933	0,0609
23.	0,9867	0,0383	0,9933	0,0207
24.	1,0000	4.3045	0,9933	0,0134
25.	1,0000	4.7105	0,9933	0,0471
26.	0,9733	0,1540	0,9867	0,0577
27.	1,0000	0,0051	0,9933	0,0508
28.	0,9933	0,0269	0,9400	0,5323
29.	0,9600	1,0555	0,9933	0,0739
30	0,9867	0,0219	0,9733	0,1891

In Figure 5, it is shown a graph of value *loss*, *training* and *testing* data. Besides the level of accuracy in the classification of the ripeness level of the melon rinds, the error rate or loss in the training and testing dataset are also calculated. The results of the training and testing loss show the highest loss is at 0.9 in the testing data. The existence of training and testing loss which is showing low values indicates that the algorithm classification of melon rind ripeness level can be used as an image classification model.

FIGURE 5. *Loss* graph in *training* and *testing* data

From the results of the tests that have been carried out using training, testing, and validation data, it is known that if the validation data is used to control system performance during the training process and is read every epoch, then the testing data makes data that has not been read by the CNN algorithm during the training process. This shows the data can be applied as a reference when the system is implemented with real data. Under certain conditions, a study with certain data can be carried out perfectly, but will fail when applied to real conditions in the field. Therefore, the test is carried out using data that is divided into several groups with the most ideal percentage. The results of system testing are shown in the tables and graphs that have been presented previously.

CONCLUSION

With the CNN architecture, this research uses 4 *layers convolution*, *Epoch* 30, *input shape* 180x180 with a *training* dataset of 150 images, and testing *dataset* of 150 images. Provides 99% *accuracy training* and 99% *accuracy testing* in identifying melon images. And using new data as many as 150 images obtained an *accuracy rate of* 52%. From several trials and errors with several parameters, the explanation is as follows: (1) The more the *epoch* value parameter is used, the higher the accuracy value obtained, the results of research trials using 30 epoch data obtained an accuracy value of 99%; (2) By using 4 *layer convolution*, the *accuracy* value is 99%; and (3) The results of utilizing *input shape* using a size of 180x180 piksel, obtained a high *accuracy* value of 99%.The CNN algorithm is quite good for image-based identification of melon ripeness. The results of training with 30 epochs using a learning rate of 0.001 obtained a training accuracy of 99%. After using 150 new data, the accuracy value was 52%.

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