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Determining The Ripeness Level Of Crystal Guava Fruit Using Backpropagation Neural Network

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Abstract

The ripeness of crystal guava fruit is currently sorted conventionally by analyzing the colour of the rind visually with the human eye. However, this method has several weaknesses that result in low accuracy and inconsistency. Therefore, automatic determination of ripeness level is necessary to increase accuracy and obtain precise information. This research uses the HSI colour space as an interpretation of fruit image characteristics and uses the Backpropagation algorithm to perform classification. This study utilizes image data of crystal guava fruit, categorizing them into four stages of ripeness: unripe, half-ripe, ripe, and very ripe. There are 140 fruit image data with 35 data for each ripeness category. Each image will be processed with median filter, cropping and segmentation. The HSI value will be taken from the image and processed at the classification stage using the Backpropagation algorithm. In classification using Backpropagation Neural Network, the best network model in this study was achieved in the 3 10 4 network architecture with a binary sigmoid activation function, learning rate = 0.3, and batch size = 64. This model produces a loss value of 0.5364 with an accuracy of 0.9 in testing process.

Keywords: *fruit ripeness, crystal guava, HSI, image preprocessing, Backpropagation Neural Network*

1. Introduction

Technology is advancing very rapidly over time. The use of technology is widely applied in various fields, especially in agriculture. Currently, many agricultural productions require more contribution from technology to reduce some inaccuracies in the cultivation process. A wide range of agricultural production is developed to produce superior varieties that are more promising, one of which is the crystal guava plant.

Crystal guava is in high demand among the public, so the demand for production continues to increase from time to time. This needs to be supported by intensive cultivation technology to obtain good fruit quality. One of the factors determining the quality of a fruit can be seen from the level of ripeness, so it is necessary to sort the right fruit to harvest [1]. The ripeness of crystal guava fruit is currently sorted conventionally by analyzing the colour of the rind visually with the human eye. However, this method has several disadvantages, including the labour required is more and requires a relatively long process. In addition, human judgement is subjective and the level of accuracy is low and inconsistent, considering that the colour of crystal guava skin is almost the same in raw to ripe conditions [2]. Therefore, It is essential to employ digital image processing for the automatic assessment of crystal guava fruit ripeness, thereby enhancing accuracy and obtaining precise information.

Determination of the ripeness level of crystal guava fruit has been done by Kamsyakawuni [3] using the Fuzzy Mamdani method based on RGB colour of the fruit image. The research obtained an accuracy rate of 83.5%. However, Edha [4] said that RGB colour as the base colour is still not suitable for several image processing applications, one of which is in object recognition applications. Edha [4] has also conducted research on determining the level of ripeness of sweet mango fruit based on Hue, Saturation, Intensity (HSI) colour space it has. The study obtained an accuracy rate of 87% and concluded that the HSI colour space can be used as an interpretation in detecting ripeness in fruit. So based on this research, it is suspected that the determination of

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the ripeness level of crystal guava fruit can also be done based on the HSI colour in the crystal guava fruit image. In addition, the HSI colour model is considered to have a colour space system that is similar to the human eye, so it is considered more natural and intuitive to human eye vision [4]. Therefore, this research uses the Hue, Saturation, Intensity (HSI) colour space as a characteristic interpretation of the fruit image.

Based on the HSI colour of the crystal guava fruit image, the ripeness level of the fruit can be determined using an appropriate classification method. The Backpropagation artificial neural network method is a type of classification methods that resembles the workings of the human brain where problems are solved by learning or training the network. Backpropagation artificial neural networks are widely used to solve pattern recognition problems, one of which is classification [5]. Utami and Ulama [6] said that artificial neural networks can be used in problems with non-linear data. Its ability to learn is also an interesting characteristic in artificial neural networks, where learning algorithms are very useful in solving complex perception problems [7]. In addition, Singh & Chaudhury [8] have also compared the Backpropagation method with the Naive Bayes, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) methods in classifying rice grains. The results show that classification with the Backpropagation method produces the greatest average accuracy of more than 96%. Therefore, this research utilizes the Backpropagation artificial neural network method to determine the ripeness level of crystal guava fruit.

2. Research Methods

2.1 Research Data

The research data used in this study consists of 140 crystal guava image data with the categories of unripe, half-ripe, ripe, and very ripe fruit. The research data is segmented into 120 training data and 20 testing data, with 30 training data and 5 testing data for each category. Example of the research data is presented in Table 1.

Table 1. Research Data

Label	Fruit Image	Label	Fruit Image
Unripe 01		Ripe 01	
Unripe 02		Ripe 02	
Unripe 03		Ripe 03	
...	...	...	...
Half-ripe 33		Very Ripe 33	
Half-ripe 34		Very Ripe 34	
Half-ripe 35		Very Ripe 35	

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2.2 Image Pre-Processing

The image data pre-processing stage consists of three stages, namely the filtering, cropping, and segmentation stages. In general, this stages is aims to prepare the image for the feature extraction process. All stages are carried out using Python 3.10.12 software. Figure 1 shows the scheme of image pre-processing stage.

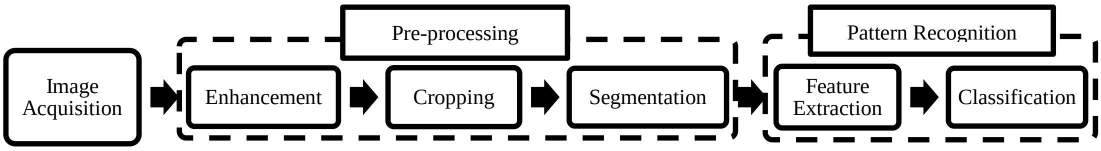

Figure 1. Research scheme

2.2.1 Enhancement using Median Filter

The image data that has been collected, then the filtering stage is carried out. This stage aims to remove noise in the crystal guava image so that noise does not affect the feature extraction process in the image. The median filter is performed by replacing the pixel value at position (x,y) with the middle value of the pixel and its neighbours using a predetermined kernel [9]. In this research, the kernel used is the 3x3 kernel. The Figure 2 (a) shows the fruit image before filtering process and Figure 2 (b) shows the outcome of the filtering process

(a) (b)

Figure 2. (a) Original Image **(b)** Image with median filter

2.2.2 Cropping

The cropping stage is aims to crop the part to be extracted so that it can make the process of extracting image characteristics to be more focused on certain parts. The certain part is the part that can represent the colour of each crystal guava image [10]. The images will be cropped with a size of 200x200 pixels. The Figure 3 shows the outcome of the image cropping process.

Figure 3. Image cropping

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2.2.3 Segmentation

Image capture is always affected by light, so there are reflections in the fruit image that can affect the extraction results based on its colour. Therefore, image data needs to be segmented to remove light reflections in each image automatically. In this research, the segmentation method used is the Otsu thresholding method, where the truecolour image will be converted into a binary image using a threshold that is determined automatically [11]. The Figure 4 shows the outcome segmentation process to remove light reflections in the image.

Figure 4. Image without light reflection

2.3 Feature Extraction

At the feature extraction stage, images that have passed the pre-processing stage will be extracted into parameters that distinguish one image from another at the identification stage. Extraction is done by taking the average Red, Green, and Blue (RGB) value at each image pixel which is then transformed to Hue, Saturation, and Intensity (HSI) by applying Equation (1) to Equation (4) [12]. The extracted image data will be used as an interpretation to determine the level of ripeness in the fruit image.

$$H = \begin{cases} \theta, & B \leq G \\ 360° - \theta, & B > G \end{cases} \tag{1}$$

with

$$\theta = cos^{-1}\left\{\frac{\frac{1}{2}((R-G)+(R-B))}{\sqrt[2]{(R-G)^2+(R-B)(G-B)}}\right\} \tag{2}$$

$$S = 1 - 3\frac{\min(R,G,B)}{(R+G+B)} \tag{3}$$

$$I = \frac{1}{3}(R+G+B) \tag{4}$$

2.4 Data Normalization

At this stage, normalization is carried out on the data resulting from the feature extraction process. This stage is carried out to adjust the data value to the range in the activation function used in the classification stage, where the function used is a binary sigmoid function that has an input range of 0 to 1. The feature extraction data will be normalised into data in the range 0 to 1. The normalization method used is the min-max normalization method with Equation (5). The following is the min-max method formula [13].

$$x_{norm} = \frac{x-\min(x)}{\max(x)-\min(x)} \tag{5}$$

2.5 Classification using Backpropagation

This step involves creating a system to categorize the ripeness level of crystal guava fruit based on its image. HSI data that has been obtained and normalised will be input to the classification process. This process is performed to identify the most suitable network model for classifying the ripeness level of crystal guava fruit. The network is designed to model the way the human brain

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learns patterns and will store insights based on the learning which then becomes a store of useful knowledge [14]. Various experiments were conducted to test different architectures, focusing on the number of hidden layer neurons and learning rate. In this research, the architecture involves 3 neurons in the input layer, 1 hidden layer, and 4 neurons in the output layer, as shown in Figure 5. Each layer of the network uses a binary sigmoid activation function and the input data is the average of Hue, average of Saturation, and average of Intensity. Table 2 shows some parameter variations that will be experimented in the network formation process.

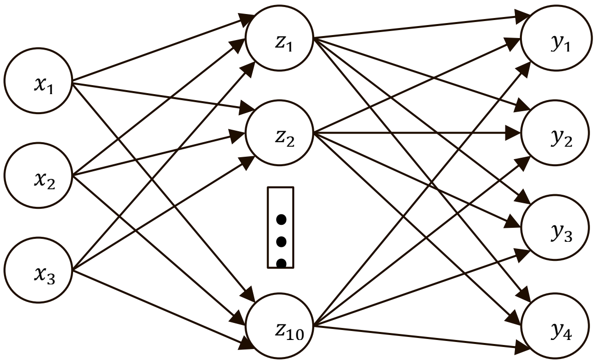

Figure 5. Network architecture

Table 2. Parameter variations

α	Number of Hidden Layer Neurons				
0,1	1	2	3	6	10
0,2	1	2	3	6	10
0.3	1	2	3	6	10
0,4	1	2	3	6	10
0,5	1	2	3	6	10

Furthermore, the training process aims to impart knowledge to the network, achieved by adjusting the parameters until the network model attains the appropriate weight settings. In the training process, weights are set iteratively using several parameters and network architecture to obtain a model with the best accuracy.
Following the training phase, the acquired weights are utilized in the testing phase, where previously unused crystal guava image data is employed. This data, known as the test data, is used to assess the functionality of the network model. Throughout both training and testing, the performance is evaluated through the computation of accuracy, precision, recall, and F1-score values from the confusion matrix for each parameter variation.

3. Result and Discussion

The Backpropagation artificial neural network method was utilized to assess the ripeness of crystal guava fruit through a training and testing process. Various factors may impact the results of artificial neural networks, but this research specifically concentrates on evaluating the outcomes of different learning rate values and the quantity of neurons in the hidden layer. The architecture involves 3 neurons in the input layer, 1 hidden layer, and 4 neurons in the output layer, all utilizing a binary sigmoid activation function, maximum epoch of 1500, and batch size of 64. The assessment of the optimal network model is based on the loss value and accuracy for each parameter variation. The results improve as the loss value decreases. Inversely proportional to the loss value, the model results will be better if the accuracy value is greater. The results of the evaluation of the training and testing process for each parameter variation in the learning rate and number of hidden layer neurons are presented in Table 3.

Table 3. Training and testing evaluation results

Neuron	Training	Testing

Learning Rate		Loss	Accuracy	Loss	Accuracy
0,1	1	0,7954	0,6583	0,5818	0,7500
	2	0,7437	0,6833	0,5610	0,8000
	3	0,7167	0,7000	0,5527	0,8000
	6	0,6917	0,7083	0,5013	0,8500
	10	0,6792	0,7250	0,5819	0,9000
0,2	1	0,7935	0,6750	0,5647	0,8000
	2	0,7334	0,6750	0,5490	0,8000
	3	0,6975	0,6917	0,5227	0,8000
	6	0,6599	0,7000	0,5165	0,8000
	10	0,6034	0,7250	0,6005	0,8500
0,3	1	0,8288	0,6667	0,5409	0,8500
	2	0,7232	0,6750	0,5445	0,8500
	3	0,6817	0,6667	0,5996	0,8500
	6	0,6936	0,6917	0,5399	0,8500
	10	0,5954	0,7583	0,5364	0,9000
0,4	1	0,8012	0,6500	0,5841	0,7500
	2	0,7261	0,7167	0,5353	0,8500
	3	0,7791	0,6750	0,5574	0,8000
	6	0,7424	0,6917	0,4830	0,9000
	10	0,6472	0,7417	0,4396	0,8500
0,5	1	0,8126	0,6500	0,5491	0,8000
	2	0,7451	0,6500	0,5885	0,8000
	3	0,7172	0,6833	0,5199	0,8500
	6	0,7807	0,6667	0,5423	0,8000
	10	0,7702	0,6833	0,5615	0,8000

During training and testing, the accuracy of predictions is heavily impacted by the learning rate and the number of neurons in the hidden layer. Assessment outcomes from both training and testing reveal that higher neuron counts in the hidden layer tend to result in better predictive models. Conversely, the learning rate produces inconsistent outcomes. Nevertheless, the initial weights, which are randomly set, can also impact the model's accuracy, causing the results to vary with each training process execution.
The evaluation results of the training and testing processes show that the optimal model performance is obtained when achieving the highest accuracy value in both the training and testing processes, which is achieved at a learning rate of 0.3 and 10 neurons in the hidden layer. Variations in these parameters resulted in the lowest loss value of 0.5954 and an accuracy of 0.7583. Similarly, during testing, utilizing a learning rate of 0.3 and 10 hidden layer neurons also led to the lowest loss of 0.5364 and an accuracy of 0.9. The outcomes of the model evaluation can be observed in the following matrix.

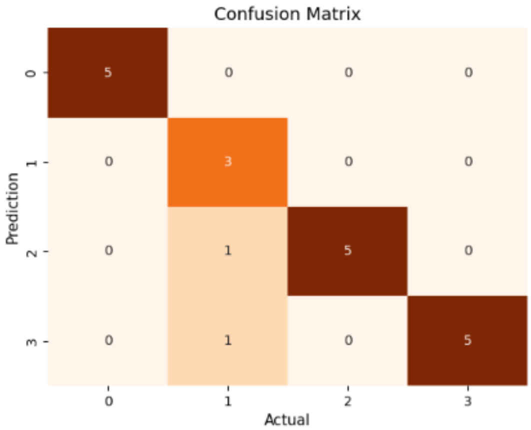

Figure 6. Confusion matrix results

Figure 5 is the result of the confusion matrix of the network model. The confusion matrix is an N × N matrix used to measure the amount of accuracy of classification algorithms with more than 2 classes, where N is the number of target classes. This matrix will compare the actual target with the classification result [15]. Based on the confusion matrix of the network model at a learning rate of 0.3 with 10 neurons in the hidden layer resulting from the testing process, it shows that:

a. The model can correctly predict the overall image of unripe, ripe, and very ripe crystal guava fruits.
b. The model only partially predicts the half-ripe category of crystal guava images correctly. Where there are 2 images that are predicted into the ripe and very ripe categories.

The performance test results from the confusion matrix can measure the accuracy of a model by calculating the accuracy, precision, recall and F1-score values for each parameter. Table 5 is the results of the confusion matrix performance test from the best model.

Table 4. Confusion matrix performance test

Performance Test	
Recall	0,9000
Precision	0,9200
F1-score	0,8920
Accuracy	0,9000

The recall value shows how well the model can recognize the class correctly. Based on the performance test obtained, the recall value shows 0.9, which means the model is quite good at recognizing the class. The precision value shows the accuracy of the model in predicting a class correctly. The precision value of 0.92 obtained shows that the model can predict a class correctly. The F1-score value indicates a balance between precision and recall values. The F1-score value of 0.892 indicates that the precision and recall values of the model are balanced. Meanwhile, accuracy shows how accurately the model can detect data correctly. The model has an accuracy value of 0.9, which shows the model can detect almost all data correctly.

4. Conclusion

The results and discussion of the research that has been carried out show that determining the level of ripeness of crystal guava fruit using Backpropagation artificial neural networks can be done by extracting features on fruit images that have been prepared using filtering, image cropping and segmentation processes to eliminate light reflections in the fruit image. The mean Hue, Saturation, and Intensity values for each image serve as input in the classification process following feature extraction. Additionally, the most optimal model was attained with a network architecture consisting of 3 neurons in the input layer, 10 neurons in the hidden layer, and 4 neurons in the output layer, utilizing a learning rate of 0.3. This model yields a loss value of 0.5364 along with a recall of 0.9, precision of 0.92, f1-score of 0.892, and accuracy of 0.9 during the testing phase.

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