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Identification of Color and Texture of Ripe Passion Fruit with Perceptron Neural Network Method

Siswanto[1], Riefky N. Sungkar[2], M. Anif[3], Basuki Hari Prasetyo[4], Subandi[5], Ari Saputro[6], Buana Suhurdin Putra[7]
[1,2,3,4,5.6]Teknik Informatika, Fakultas Teknologi Informasi, Universitas Budi Luhur, Jakarta
[7]Teknik Informatika, STMIK Mercusuar, Kota Bekasi
[1]siswanto@budiluhur.ac.id, [2]riefkyns@gmail.com, [3]muhammad.anif@budiluhur.ac.id, [4]basuki.hariprasetyo@budiluhur.ac.id, [5]subandi.spd@budiluhur.ac.id, [6]ari.prasetyo@budiluhur.ac.id, [7]buana@mercusuar.ac.id

Abstract

Research using artificial neural network methods has been developed as a tool that can help human tasks, one of which is for passion fruit UMKM entrepreneurs. The problem so far that has been faced by UMKM entrepreneurs of passion fruit is that it is difficult to identify ripe passion fruit with sweet and sour taste, because there are 6 colors of passion fruit and the color of passion fruit skin is visually slightly different, as well as the texture of maturity. The main purpose of this study was to identify the color structure and texture of the ripeness of passion fruit, in order to recognize the color and texture of the ripeness of passion fruit which is good for processing into syrup, jam, jelly, juice, passion fruit juice powder by entrepreneurs of UMKM of passion fruit. This study empirically tested the color and texture of the ripeness of 10 passion fruit using the perceptron artificial neural network learning method. The data is obtained from an image that will be entered into the program. The results of the identification process using the perceptron artificial neural network from the tests that have been carried out previously, the highest calculation results obtained with the best results using a learning rate of 0.8 and 500 epoch iterations and producing an accuracy of 80%.

Keywords: *color identification, ripeness texture, passion fruit, perceptron*

1. Introduction

How to identify the color and texture of ripeness that is carried out by UMKM entrepreneurs of passion fruit still uses the manual method. The manual method is based on direct visual observation of the passion fruit to be identified. The weakness of manual identification is strongly influenced by the subjectivity of sorting operators, so that under certain conditions the identification process is inconsistent.

The problem so far that has been faced by the UMKM entrepreneurs of passion fruit is that it is difficult to identify a ripe passion fruit that tastes sweet and sour, because there are 6 colors of passion fruit and the color of the skin of the passion fruit is visually slightly different, as well as the texture of maturity. The development of information technology allows identification of fruit based on color characteristics with the help of computers. This computational method is carried out by indirect visual observation using a camera as an image processor from the recorded image (image processing) and then processed using computer software. In this study, identification of passion fruit species based on color and color was carried out ripeness texture passion fruit. This identification uses an Artificial Neural Network (ANN) application with the perceptron learning method. Objects observed, namely passion fruit with different colors, skin textures fine, rough, and wrinkled along with red, yellow, purple, golden yellow, greenish yellow and green. Image information of passion fruit observed using the help of image files.

Passion fruit is one of Indonesia's fresh fruit products that are in great demand by domestic and foreign consumers. Passion fruit is a fruit that can be consumed in the form of fresh can also be in the form of juice, syrup or in the form of jelly. The konyal passion fruit, which the Karo people call the Bandung passion fruit (*Passiflora ligularis Juss*), is a large fruit when compared to the purple passion fruit which the Karo people call the black passion fruit (*Passiflora edulis*

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var), which is medium in size. *Passiflora ligularis Juss* and *Passiflora edulis var.* The edulis are round. The color of the fruit skin of *Passiflora ligularis Juss* is yellow, and the skin of the fruit of *Passiflora edulis var.* dark purple. Passion fruit is the main product of the passion fruit plant that can be consumed as food. Inside the fruit contains many seeds with a fleshy seed coat (wrapper) containing a liquid (juice) that tastes sour or sweet . *The pulp of Passiflora ligularis Juice* is whitish in color and has a sweet taste . *Pulp* of *Passiflora edulis var.* yellow. This part is consumed in fresh form or in processed form as fruit juice, juice, or syrup [1].

Passion fruit (*Passiflora edulis*) or Passion fruit in English-speaking countries, is a species of fruit tree native to Peru, southern Brazil, Paraguay, and northern Argentina. Passion fruit is widely cultivated commercially in tropical and subtropical regions because of its sweet and delicious fruit. There are several varieties of passion fruit with different outward appearances. the '*flavicarpa'* variety has a bright yellow rind color, also known as yellow or golden passion fruit, and can grow to the size of a grapefruit. While the 'edulis' variety has a dark purple skin and is smaller than a lemon, but has a sweeter aroma and taste. Passion fruit trees are cultivated to harvest their fruit, it can be said that almost all countries in the world have their own passion fruit gardens. In the United States, passion fruit trees are grown in Florida, Hawaii, and California. The tree must be protected because it does not ground in frost for areas that have snow or are subtropical. In Indonesia, there are two types of passion fruit, namely white meat passion fruit and yellow meat passion fruit. The white ones are usually eaten straight, while the yellow ones are usually further processed to make juice or thick syrup [2].

The main objective of this research is to identify the structure of the color and texture of passion fruit maturity, in order to recognize the color and texture of ripe passion fruit which is good for processing into syrup, jam, jelly, juice, passion fruit juice powder by UMKM entrepreneurs of passion fruit. This study empirically examines the color and texture of ripeness 10 passion fruit using perceptron artificial neural network learning method.

Each Cucumber (*Cucumis sativus L*) is a plant that produces edible fruit. In Indonesia, cucumbers have a wide market share ranging from traditional markets to modern markets. The government always tries to increase production to meet market demand even though cucumber is not a leading horticultural commodity, based on 212 existing datasets, the proposed method in this study is able to achieve a good accuracy of 89.6% [3].

Purple passion fruit (*Passiflora edulis L.)* is one of the fruit commodities from North Sumatra. The purple passion fruit producing center is located in Karo Regency, Berastagi, the results showed that the average sensor accuracy in determining the ripeness of passion fruit in 3 replications was 90.56%, the average tester effectiveness capacity was 0.967 kilograms per minute [4].

Backpropagation Artificial Neural Networks based on Digital Image Processing. The proposed method consists of 5 main stages, namely image acquisition, preprocessing, segmentation, morphological operations, feature extraction, and classification. The proposed method provides an accuracy of 80% of classification results and 20% misclassification. While the time required to execute a test image is 0.2 seconds [5].

The coffee fruit maturity level classification system uses the K-Nearest Neighbor method to classify the coffee fruit maturity level by utilizing RGB, HSV and Area color features using 90 coffee fruit image training data and 45 coffee fruit image test data with 3 fruit maturity classes, namely raw, quite ripe and ripe. The results of the accuracy of the classification of the maturity level of coffee cherries using the KNN method are 97.77% with a value of K = 3 obtained from 44 test data with accurate classification, and 2.23% from 1 test data with inaccurate classification [6].

The approach used in this community service is an Entrepreneurship counseling approach and training to make processed passion fruit that has economic value, which can later be sold as a source of income. The results of this community service activity, the community gains insight into entrepreneurship and how to make processed passion fruit in the hope that it can be developed [7].

This study uses a dataset of 80 banana images taken from the Kaggle website. The research data uses feature extraction to determine the level of maturity through the color feature, namely RGA. From these features, classification testing was carried out using the SVM method, after testing the maturity accuracy was obtained by 75% of the 80 banana image data tested [8].

Perceptro*n* method is able to recognize the pattern recognition of intestinal nematode worms and is able to analyze it with precise results by comparing the *output* value and the target value that has been entered first [9].

Examples of perceptron calculations for learning with the input of the letter A, as for the input vector for the letter A and the initial weight (0.3 0.5 0.4 0.3 0.5 0.5 0.4 0.3), the results of this application are testing and training still using one letter or number on the keyboard, the more training is carried out, the result of letter recognition shows a higher percentage of correctness [10].

Artificial Neural Networks with the Perceptron method are able to determine the type of disease in pineapple plants according to the disease pattern that is trained based on the input value and the predetermined target . 2. The speed of training in the perceptron method affects the amount of learning rate (rate of understanding) [11].

Based on the image data of citrus fruits, it can recognize the pattern of citrus fruits that have a maturity level that is in accordance with digital images using the backpropagation method , with an accuracy level of training and testing data that is 100% [12].

Backpropagation Artificial Neural Network with Principal Component Analysis , it will produce a faster face recognition. This study tries to implement both methods into a face recognition application. And as a result the system performs facial recognition faster [13].

The results of the research predict the yield of vegetable crops with backpropagation algorithm The best architectural model is the 2-1-1 model with an accuracy rate of 75.0% and an *epoch* of 1392 iterations in 00:07 seconds [14].

Backpropagation neural networks in predicting the area of pest attack on onion plants in Brebes Regency for six months in 2016 obtained the smallest error percentage (MAPE) when prediction was 0.194% or had an accuracy rate of 99.81%. From the high level of accuracy and the small value of MAPE, it shows that the network can predict well [15].

The mango plants used consisted of 10 types, namely Golek mango, Honey, Arumanis, Apple, Manalagi, Lalijiwa, Shrimp (Curut), Keweni, and Pakel (Ambacang), and Kemang. The highest accuracy was obtained in testing the scanner data using 450 image data with a comparison of 90% training data: 10% test data, which is 49% using 1 hidden layer consisting of 1000 neurons with a learning rate of 0.01. While testing on training data, leaf images can be recognized well up to 100%. The Canny algorithm can be used for edge detection, but in the case of this study it is not able to recognize the leaf bone structure because the image used is resized [16].

The test results, the parameters of the BPNN algorithm with a data ratio of 4:1, the architectural model of 5-10-10-10-1, the learning function trainlm , the learning rate of 0.5, the error tolerance of 0.01 and the epoch of 1000 have obtained good accuracy with the mean value. square error (MSE) of 0.00015464 [17].

The results of the research predicting the yield of vegetable crops with the backpropagation method obtained the best architectural model is the 2-1-1 model with an accuracy rate of 75.0% and an epoch of 1392 iterations in 00:07 seconds [18].

The gap and renewal in this study from previous research is the color and texture of passion fruit maturity and the use of a learning rate of 0.8.

2. Research Method

In this study, the research methods that have been carried out, as shown in Figure 1 include: pre-process, identification process of passion fruit color & texture (perceptron architecture design, perceptron *training* design, and perceptron identification process design) and application design:

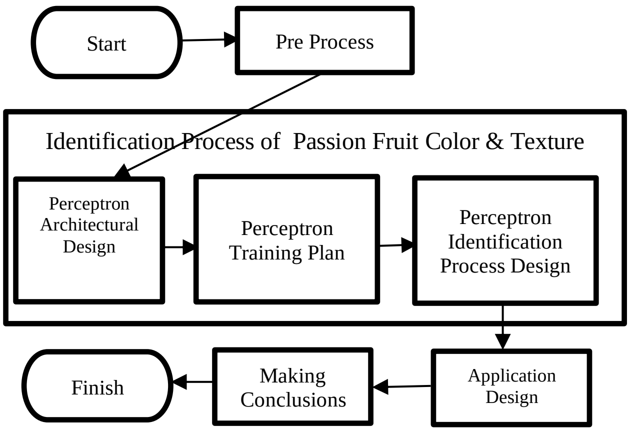


Figure 1. Research Method

2.1 Pre-Process

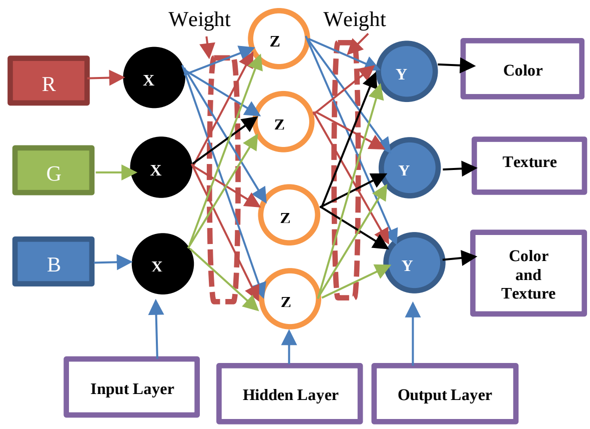
Pre-process includes: image of passion fruit in the form of an image file, the resulting image will undergo image processing, namely the color histogram process.

2.2 The Process of Identification of Passion Fruit Color & Texture

The process of identifying the color & texture of passion fruit maturity includes 3 things, namely:

2.2.1 Perceptron Architectural Design

Perceptron architecture design uses 3 input units, 4 hidden layer nodes and 3 output units, as shown in Figure 2.



Perceptron Architectural Design

2.2.2 Perceptron *Training* Plan

Pattern →color histogram →image→ *training* →weight.

2.2.3 Perceptron Identification Process Design

Color histogram →image of identification →pattern →(from weight).

2.3 Application Design

Broadly speaking, the process can be grouped into two parts, namely the data training process (perceptron training) and the process of identifying the color and texture of passion fruit. The training process is useful for training the system by entering input data into the Neural Network system and then the data is processed using the perceptron method.

2.3.1 Data Training Process

The data training process (perceptron training) can be seen in Figure 3.

Figure 3. Data Training Process

2.3.2 Data Identification Process

The process of identifying the color and texture of passion fruit maturity can be seen in Figure 4.

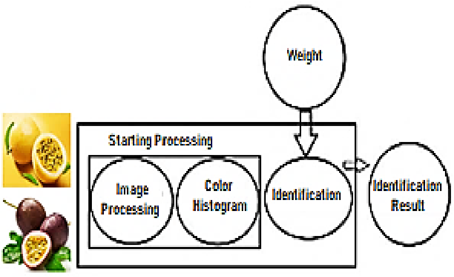


Figure 4. The process of identifying the color and texture of passion fruit ripeness

2.4 Making Conclusions

The last step of the research method is to draw conclusions from the results of application testing of application accuracy in identifying the color and texture of passion fruit maturity.

3. Results and Discussion

This stage is implementing the methodology and application design by making an application using the matlab programming language, so that an application can be obtained that can identify the color and texture of passion fruit maturity based on the color and texture of passion fruit maturity.

3.1. Test Data Results of Color Histogram Data Training Process

Initial processing was carried out with several histogram data retrievals for passion fruit which had different colors and textures of passion fruit maturity. The data used in the identification process are three photos containing three kinds of passion fruit, the first passion fruit is passion fruit with green color and the level of maturity is still raw, passion fruit with yellowish green color and the level of maturity is still half-ripe and passion fruit with red color and ripeness level is ripe. Figure 5 is one of the data from several data retrieval histogram values of color and texture of passion fruit maturity.

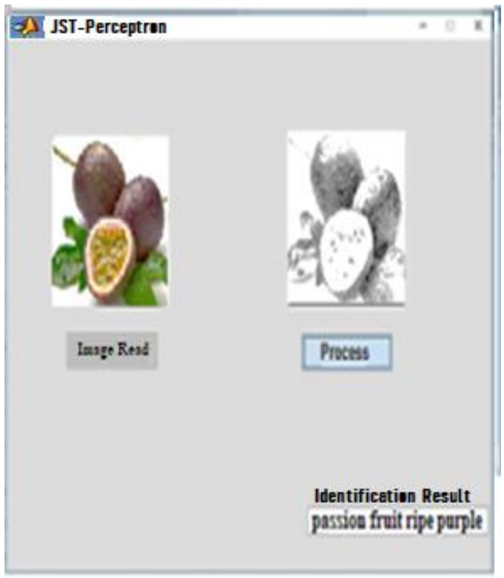


Figure 5. Passion Passion Color Acquisition

The results of the test data are inputted with a passion fruit image as shown in Figure 5, after running the application process for identifying colors and shapes, the results h istogram of the color and texture of the ripeness of passion fruit with the perceptron method can be identified/recognized as "**passion fruit ripe purple**".

3.2. Passion Fruit Identification Process

The results of processing color and texture images of passion fruit ripeness using the *perceptron* method can be identified as "**passion fruit raw Green**" can be seen in Figure 6.

Figure 6. Image Processing

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The results of the perceptron process. The subplot of the color and texture of the ripeness of the passion fruit can be seen in Figure 7.

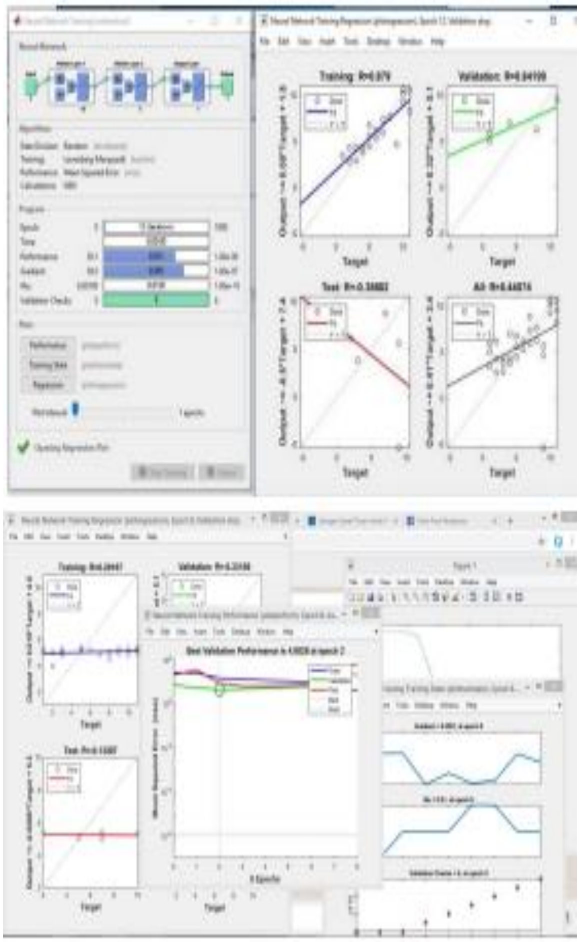

Figure 7. *Perceptron Subplot*

3.3. Discussion of Application Testing Results

In the test recap in table 1 shows the number of purple passion fruit images used is 10 samples. The accuracy level of the application test results in identifying the color and texture of passion fruit maturity can be seen in table 1.

Table 1. Application Testing Accuracy

Learning Rate	Epoch	Color Accuracy	Texture Accuracy	Color and Texture Accuracy
0, 8	100	9 -- x 100% = 90% 10	3 -- x 100% = 30% 10	(90% + 30%) / 2 = 60%
	200	6 -- x 100% = 60% 10	10 --x 100% = 100% 10	(60% + 100%) / 2 = 80%
	500	10 -- x 100% = 100% 10	10 -- x 100% = 100% 10	(100% + 100%) / 2 = 100%
			Average	240% / 3 = 80%

From the various accuracy values of the learning rate of 0.8 with various epoch variations (100, 200, and 500), the application of identifying the quality of purple ripe passion fruit based on the color and texture of the ripeness of passion fruit using the perceptron artificial neural network method can be applied with a high level of 80 % accuracy.

4. Conclusion

The conclusions that can be drawn from the results of research and testing of this application : the application with the perceptron method can identify the color and texture of the ripeness of passion fruit more accurately than the identification of the color of passion fruit because of the influence of lighting and from the tests that have been carried out previously, the highest calculation results obtained with the best result is using a learning rate of 0.8 and 500 iterations/epochs and produces an accuracy of 80 %.

Some suggestions are expected for the development of this application: it is hoped that the development of this application can overcome the lighting problem by including the method and specifications of the webcam, so that passion fruit is identified more accurately and it is hoped that the development of an application to identify the color and texture of the ripeness of the passion fruit This can later be done in real time.

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