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Ripeness identification of chayote fruits using HSI and LBP feature extraction with KNN classification

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Abstract
This study aims to build a system to identify the ripeness level of chayote that can be done easily and without damaging the quality of the chayote. This study employs digital image processing technology using Hue Saturation Intensity color feature extraction and texture feature extraction of Local Binary Pattern with K-Nearest Neighbor classification so that the process of identifying the ripeness level of chayote will be easier and more effective. This study uses 100 image datasets and is carried out by taking photos of chayote. The stages in this study include the input of chayote images followed by the image pre-processing stage. Next is feature extraction which is divided into three scenarios, namely HSI feature extraction, LBP feature extraction and a combination of the two feature extractions. The final stage is to classify objects that are closest to the object being tested using the KNN method. By determining the value of K in the KNN classification method, the results show that the use of the Chebyshev distance calculation model in LBP feature extraction with K = 5 is a test that has the best accuracy of 90%.

Keywords: *Hue Saturation Intensit; Local Binary Patern; K-Nearest Neighbor; Labu Siam*

Introduction

Indonesia is an agricultural country that is rich in agricultural products. The geographical location of Indonesia, which is crossed by the equator, makes Indonesia located in the tropics. These conditions make Indonesia has biodiversity including fruit and vegetable commodities [1]. Chayote is included in the type of seasonal vegetables that contribute to production in the province of South Sulawesi with a total production of 14,304 tons in 2020 [2].

Chayote is a vegetable that is known to be healthy. The nutritional content in it has an important role in maintaining a healthy body. In the pharmaceutical field, many studies have been conducted to identify the health benefits of chayote, for example the use of chayote extract for reducing blood pressure in hypertensive patients [3]. In addition to its benefits, the delicious taste of chayote makes it popular in culinary. This makes chayote popular in people's cooking. Chayote can be used as a vegetable, soup or desert. People generally use young chayote as lodeh (vegetable cooked in coconut milk), sayur asam (sour vegetables) or brongkos, kind of culinary originally from Jogjakarta. The ripe fruit is used as a mixture in making Manado porridge and South Sulawesi-style vegetables [2]. The abovementioned facts and the results of existing research implies how important and useful chayote is. Therefore, it has potential to be cultivated and processed so that it can provide more benefits such as increasing employment and increasing people's income.

Chayote has physical characteristics including surface texture and fruit color [4]. For color, the young chayote is dark green and the old chayote has a pale green color. For skin texture, young chayote has a fairly smooth skin texture, while old chayote has a rough and curvy skin texture. [5]. So far, the determination of the ripeness of the chayote is generally conducted manually. This is not accurate because the human eye is sometimes inconsistent in distinguishing analogous colors (colors that look similar but are actually different). Another detection process is done by pressing the chayote with your finger or fingernail. Unfortunately, this can damage the texture and quality of the chayote. Based on these problems, a tool is needed to identify the ripeness of chayote without destroying its quality. One of the tools that can be used is an android camera by utilizing digital image processing technology. The data from the chayote fruit is processed by digital image processing techniques through a feature extraction process

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to obtain data on the characteristics of the chayote fruit. Then, the machine learning algorithm will study these features for the learning process which will then group the previously studied data.

In previous studies, the identification of the ripeness of chayote fruit has been carried out by Dzulhijjah et al [6] using HSV feature extraction and KNN classification methods. They obtained an accuracy rate of 85%. Research conducted by Thoriq et al related to the identification of banana ripeness using HSI feature extraction and KNN classification obtained the best accuracy rate of 91.33% [7]. In a study to identify the ripeness of vegetable tomatoes using LBP feature extraction with the KNN classification, the highest accuracy was obtained using the K = 3 value of 70% [8]. The KNN classification in some of these studies only tested the variation of the K value. This study will test the variation in the K value by using the Eucliden, Chebyshev, Manhattan, and Minskowsi distance calculation formulas to get the best results.

This research will identify the ripeness of chayote using HSI and LBP feature extraction with KNN classification. The proposed method consists of 4 main stages; image acquisition, pre-processing consisting of resizing and cropping processes, feature extraction which is divided into three scenarios namely, HSI feature extraction, LBP and a combination of the two feature extractions and the last is the classification stage. This method is expected to provide good accuracy of classification results and it is also hoped that the system built can assist the community in identifying the level of maturity of the chayote fruit as well as a reference for the development of chayote cultivation technology.

Methods

This study employs four main methods, namely data collection, image preprocessing, feature extraction and identification using the KNN classification method. These methods are used to identify the level of maturity of the chayote.

A. Data Collection

Data collection aims to obtain data used for research. The data was obtained by taking pictures of chayote images at the vegetable sales center located at the Palakka Central Market, Bone Regency. The data of this study consisted of 2 levels of ripeness of chayote, young and old chayote.

B. Image Preprocessing

At this stage, there are several simple image processing techniques that are carried out before identifying objects using KNN. For the image preprocessing process, libraries related to image processing are used which are available in python using google colab. In this study, the preprocessing performed consisted of resizing and cropping the image. Resizing is done to change the resolution of images with various sizes to 500x500 pixels so that the image resolution used is uniform. Cropping is done to take the part of the image that is needed and remove the part that is not needed.

C. Extraction of Hue Saturation Intensity (HSI) Color Feature

Color feature extraction is suitable for describing and representing color images. Color feature extraction is analyzing the color of an image (image) which is composed of pixels that have a size of each color intensity [9]. The HSI color feature defines color in terms of Hue (H), Saturation (S), Intensity (I). Hue describes a color representing the basic color, and is determined by the dominant wavelength in the distribution of the light wavelength spectrum; Saturation is a color attribute that describes a pure color (pure color); The intensity or brightness of a color is a parameter describing the lightness or darkness of a color [9]. This HSI feature extraction applies the Hue, Saturation and Intensity features obtained from the equation below [10]:

Calculate θ

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

Calculate *Hue*

$$\mathrm{H} = \begin{cases} \theta \text{ Jika} & \mathrm{B} \leq \mathrm{G} \\ 360 \text{ Jika} & \mathrm{B} > \mathrm{G} \end{cases} \quad (2)$$

Calculate *Saturation*

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

Calculate *Intensity*

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

Note:
R = Intensity of Red Color (red)
G = Intensity of Green Color (green)
B = Intensity of Blue Color (blue)

D. Extraction of Local Binary Pattern (LBP) Texture Feature

Extraction of texture features of an image is information in the form of surface structure arrangement of an image. Texture features are suitable for visualizing surface patterns and properties. It provides information about the variation in the surface intensity of the image [11]. Local Binary Pattern (LBP) is one of the methods used to extract texture features in an image. In general, the framework for the LBP method is a texture feature extraction process by dividing the image into several local regions and extracting all local regions to obtain local binary patterns. LBP is a kind of gray level in the scope of texture measurement to support local image contrast measurement [12]. LBP transforms an image into an array of integer labels that describe the small-scale appearance of an image. If the gray level of the neighboring pixels is higher or equal, the value is changed to one, otherwise the value is zero. The descriptor describes the outcome of the environment as a binary pattern [13]. **Figure 1** shows an example of LBP feature extraction [14]. In this LBP feature extraction will use three types of features, namely Mean, Variance, and Entropy.

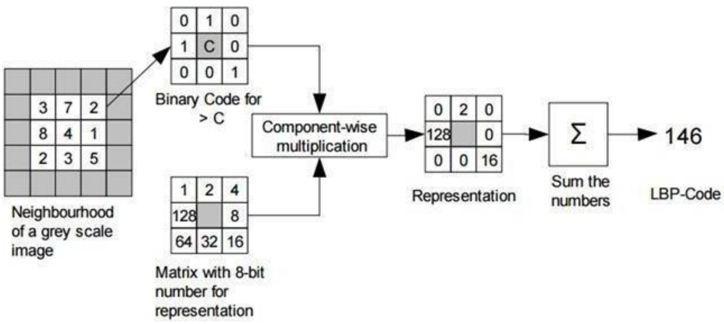

Figure 1. Example of LBP Feature Extract

The calculation of the three types of features can be seen from the equation below [15] :

$$mean = \sum_i \sum_j P(i,j) * i \tag{5}$$

$$variance = \sum_i \sum_j P(i,j) * (i - mean)^2 \tag{6}$$

$$entropy = \sum_i \sum_j P(i,j) log\ P(i,j) \tag{7}$$

Note:
$\sum_i$ = Sum of the value in row i
μ = The average value of the elements in the matrix
$P(i,j)$ = Elements in the matrix in row i and column j

Mean is the average value of pixels in an image. The mean value can be determined by dividing the number of images by the number of image pixels. Variance shows the variation of the gray color in an image. The value of variance will increase when the value of the gray level is different from the mean [16]. Entropy shows the complexity of an image. The entropy value will be high when the image is not uniform. Image with a complex texture will tend to have a high entropy value [17]. In equation (5), (6), (7) Pi,j is the pixel value whose position is in the row position (i, j) which is the gray level of the image pixel [15].

E. KNN (K-Nearest Neighbor)

KNN is a method for classifying objects based on training data (neighbors) that are nearest to the object [18]. The KNN method is divided into two phases, namely learning (training) and classification (testing). In the learning phase, this algorithm only performs feature vector storage and classification of learning data. In the classification phase, the same features are calculated for the data to be tested (whose classification is unknown). The distance from this new vector to all training data vectors is calculated, and as many of k closest neighbors are taken. A point will be predicted for its type based on the most classification of neighbors in its surround [19]. After the image is extracted, the next step is to classify the image based on its maturity level using the KNN method. The initial stage of the k-NN algorithm is to determine the value of k and continued to the process of calculating the distance between each data to be evaluated with all training [20]. In this research, the Euclidean, Chebyshev, Minkowski and Manhattan distances will be tested. If the distance calculation has been carried out, the minimum distance (the greatest similarity) will be chosen so that the results of the identification of the ripeness of the chayote will be obtained based on the most similar to the image data that has been previously labeled. The formula for defining the distance between two objects is as follows:

Euclidean

$$d(x,y) = \sqrt{\sum_{i=n}^{n}(xi-yi)^2} \tag{8}$$

Chebyshev

$$d(x,y) = max_i(xi-yi) \tag{9}$$

Minkowski

$$d(x,y) = \sqrt{\sum_{i=n}^{n}(xi-yi)\,p} \tag{10}$$

Manhattan

$$d(x,y) = \sum_{i=1}^{n}(xi - yi) \tag{12}$$

Note :
d = Proximity distance
x = Testing Data
y = Training Data
n = Number of attributs 1 to n

Results and Discussion

This section presents the results and discussion of the research that has been carried out. The results presented are data collection, image preprocessing, feature extraction and results using the KNN classification method.

A. Data Collection

The data used in this study is primary data obtained from data collection of chayote images taken using a smartphone camera with a resolution of 13MP. The image taking distance (between the chayote and the camera) is 30 cm. The image is taken in the morning outdoors using a white background. The data used in this study were 100 images of chayote taken from 50 young chayote and 50 old chayote, see in **Figure 2**.

(a) (b)

Figure 2. Young chayote data (a) Old chayote data (b)

There are 100 images obtained from the data collection process. The data is divided into training images and test images, so that 80 samples of training images are obtained consisting of 40 samples of young and old chayote respectively and test data of 20 image samples consisting of 10 samples of young and old chayote respectively.

B. Preprocessing

The data obtained is then processed at the preprocessing stage. **Figure 3** below illustrates the stages of image preprocessing.

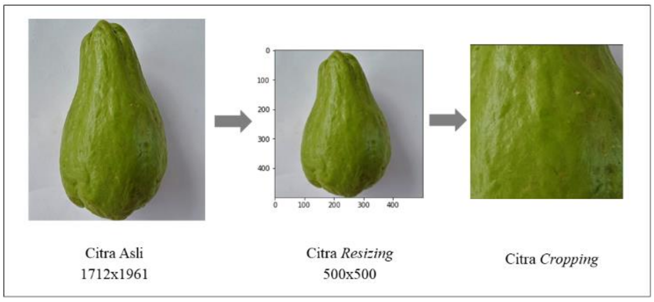

Figure 3. Stages of Image Preprocessing

Figure 3 shows the stages of image preprocessing. The resizing process is carried out on the original image which is to change the image size of 1712x1961 to 500x500. After the resizing process, the image will be cropped right in the middle of the chayote image to remove unnecessary parts

C. *Feature Extraction*

1) Scenario 1 (Extraction of HSI feature)

HSI Feature Extraction is carried out to obtain feature values from HI: hue, saturation, and intensity. The results of the feature extraction will be used in the classification process. Sample of the calculation results on the image features can be seen in **Table 1** below.

Table. Extraction of HSI feature

No	*Hue*	*Saturation*	*Intensity*	Class
1	190.5882	0.698452	0.44183	Young
2	172.3279	0.804285	0.320261	Young
3	169.1566	0.729851	0.449673	Young
4	132.8859	0.486717	0.282353	Young
5	177.0492	0.782482	0.324183	Young
..	..	..	..	..
76	200.4123711	0.637769585	0.508496732	Old
77	200.8421053	0.438919669	0.649673203	Old
78	200.4123711	0.467203881	0.492810458	Old
79	299.5949367	0.299783521	0.733333333	Old
80	225.6923077	0.500316963	0.525490196	Old

2) Scenario 2 (Extraction of LBP Feature)

Before performing the LBP feature extraction, the previous chayote input image was converted to a grayscale image. The conversion is done because the LBP operation can only be performed on grayscale images. In this case the configuration of the rotation variant used is 3 radius (R) by taking 24 neighbors (P) [21]. The sample in **Table 2** below is an example of the results of feature calculations in the image.

Table 2. Extraction of LBP Feature

No	Mean	Variance	Entropy	Class
1	18.99058	82.64614	10.42274	Young
2	19.60913	74.32699	10.44892	Young
3	16.44528	63.52146	10.45004	Young
4	17.8677	78.86795	10.42299	Young
5	18.77593	75.81787	10.44096	Young
..	..	..	..	..
76	18.577775	77.88430105	10.43264914	Old
77	18.770025	79.9857865	10.42860296	Old
78	18.0806	68.62880364	10.45316598	Old
79	19.4078	79.73679916	10.43334888	Old

80	18.2183	74.71204511	10.43788008	Old

3) Scenario 3 (Combination of Extraction of HSI and LBP feature)

At this stage, the process of merging the HSI color features and LBP texture features is carried out. In this process, combining the feature extraction values of HSI and LBP is to obtain the feature values of hue, saturation, intensity, mean, variance and entropy. The following table 3 shows the sample of the results of the combined HSI and LBP feature calculations in the image.

Tabel 3. Extraction of HSI and LBP feature

No	*Hue*	*Saturation*	*Intensity*	Mean	Variance	Entropy	Class
1	190.5882	0.698452	0.44183	18.99058	82.64614	10.42274	Young
2	172.3279	0.804285	0.320261	19.60913	74.32699	10.44892	Young
3	169.1566	0.729851	0.449673	16.44528	63.52146	10.45004	Young
4	132.8859	0.486717	0.282353	17.8677	78.86795	10.42299	Young
5	177.0492	0.782482	0.324183	18.77593	75.81787	10.44096	Young
..	..	..	..	..	..	..	..
76	200.4124	0.63777	0.508497	18.57778	77.8843	10.43265	Old
77	200.8421	0.43892	0.649673	18.77003	79.98579	10.4286	Old
78	200.4124	0.467204	0.49281	18.0806	68.6288	10.45317	Old
79	299.5949	0.299784	0.733333	19.4078	79.7368	10.43335	Old
80	225.6923	0.500317	0.52549	18.2183	74.71205	10.43788	Old

D. Test and Evaluation

This research is a dataset test using the previously discussed methods. KNN classification method using python programming on google collaborative is applied. The testing phase begins with the extraction of image features so that the distance calculation process can be carried out properly. Furthermore, the image dataset is divided into 80% training data and 20% test data. The nearest neighbor K values used in the test are K = 1, K=3, K=5, K=7. This test applies 3 test scenarios, namely HSI color feature extraction, LBP color feature extraction, and a combination of HSI and LBP feature extraction. Based on the determined K, the chayote image dataset that has gone through the feature extraction process will be classified using Euclidean, Chebyshev, Manhattan, Minkowski distances. The results of each test are presented in the following **Table 4**:

Table 4. Comparison of Distance Model Accuracy Levels in Scenario 1 Testing (Extraction of HSI Feature)

K	*Euclidean*	*Chebyshev*	*Manhattan*	*Minkowski*
1	70.00%	70.00%	60.00%	70.00%
3	65.00%	65.00%	55.00%	65.00%
5	65.00%	60.00%	55.00%	65.00%
7	55.00%	60.00%	55.00%	55.00%
Average	63.75%	63.75%	56.25%	63.75%

The test results based on **Table 4** above show that Euclidean, Chebyshev, and Minkowski in the distance calculation model resulted the same average accuracy value. However, in Euclidean and Minkowski, the K value is the same for each accuracy. This is consistent with the results of previous studies [22]. For Mahattan, the average accuracy of distance obtained is 56.25%, lower than the results of Euclidean, Chebyshev and Minkowski, with a difference of only 0.27%. For more details, it is shown from the graphic image below

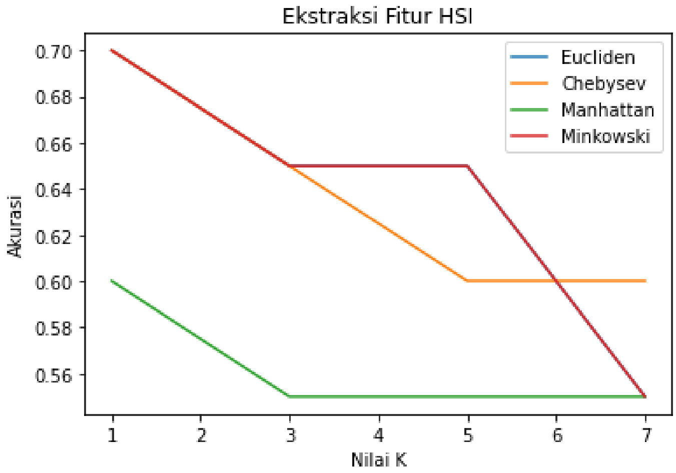

Figure 4. Graph of Scenario 1 Testing (Extraction of HSI Feature)

Table 5. Comparison of Distance Model Accuracy Levels in Scenario 2 Testing (Extraction of LBP Feature)

K	*Euclidean*	*Chebyshev*	*Manhattan*	*Minkowski*
1	60.00%	60.00%	60.00%	60.00%
3	60.00%	70.00%	75.00%	60.00%
5	80.00%	90.00%	70.00%	80.00%
7	40.00%	65.00%	30.00%	40.00%
Average	60.00%	71.25%	58.75%	60.00%

The test results in scenario 2 based on the table above show that Euclidean and Minkowski have the same average accuracy and K values, while in Manhattan, the average accuracy obtained is 58.75%, lower than the results of Euclidean and Minkowski. The highest average accuracy is the Chebyshev distance model with an average accuracy value of 71.49%. This is different from research [23]which states that Chebyshev is a distance calculation model with the lowest accuracy. For more details, shown from the graphic image below:

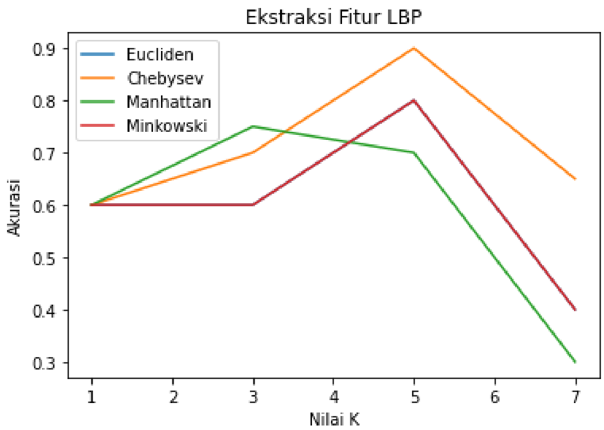

Figure 5. Graph of Scenario 2 Testing (Extraction of LBP Feature)

Tabel 6. Comparison of Distance Model Accuracy Levels in Scenario 3 Testing (Extraction of the combination of HSI and LBP Feature)

K	*Euclidean*	*Chebyshev*	*Manhattan*	*Minkowski*
1	75.00%	75.00%	75.00%	75.00%

K	*Euclidean*	*Chebyshev*	*Manhattan*	*Minkowski*
3	75.00%	80.00%	75.00%	75.00%
5	70.00%	70.00%	75.00%	70.00%
7	60.00%	50.00%	60.00%	60.00%
Average	70.00%	68.75%	71.25%	70.00%

The test results in **Table 6** above show that Euclidean and Minkowski in the fixed distance calculation model have the same average accuracy value and K value. Then at Chebyshev, the average accuracy obtained is 68.75%, lower than the results of Euclidean, Manhattan and Minkowski. The average accuracy of the Manhattan distance model is 71.49%. However, the test with the highest accuracy is in the Chebyshev distance calculation model with a value of K = 3 and an accuracy of 80%. For more details, shown from the graphic image below:

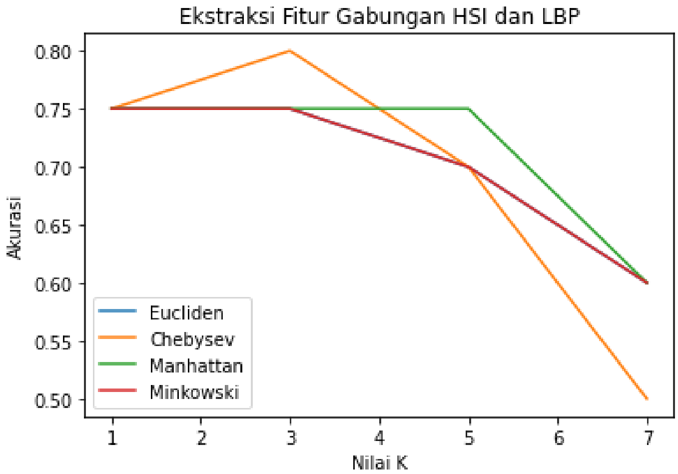

Figure 6. Graph of Scenario 3 Testing (Extraction of the Combination of HSI and LBP Feature)

The highest accuracy results for each feature extraction scenario of the distance model are shown in the following table:

Table 6. The Highest Accuracy Result of Feature Extraction Scenario

Feature Extraction	Highest Accuracy	Distance Model	K Value
Scenario 1 (HSI)	70%	*Euclidean Minkowski*	1
Scenario 2 (LBP)	90%	*Chebyshev*	5
Scenario 3 (HSI and LBP)	80%	*Chebyshev*	3

Based on the table above, the highest accuracy value is the use of Chebyshev in the LBP feature extraction method when using K=5. This proves that the Chebyshev distance calculation method is suitable to be applied to images to extract texture features using LBP.

Conclusion

The KNN classification to identify the ripeness of chayote has been successfully carried out by using a library for image processing available in python. The system designed can work effectively to identify the level of maturity of chayote. Tests carried out using the scenario proposed in this study indicate that scenario 2 which is the use of LBP texture feature extraction, has the best performance with an accuracy of 90% on the Chebyshev distance calculation method with a value of K=5. Based on the results of the analysis during the research, the performance in the classification for which accuracy has not reached perfect is caused by the lighting factor when taking the chayote image which affects the results of the identification of ripeness. This happens because there are still several parameters from the young and old classes whose feature extraction values are close. For example, in Table 1, the value of the saturation and intensity parameters in the old and young chayote classes have close values so that it is possible for the system to make errors in the training and testing process in recognizing the class. Therefore, it is recommended in further research to pay attention to image taking on chayote, especially the lighting factor because if the light intensity at the time of image capture is low, the color on the chayote will be dark which causes the texture details on the fruit skin to become less clear. This causes an error in the identification process. Alternatively, improvements to the parameters or classification methods used can be made.

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