Papaya Fruit Type Classification using LBP Features Extraction and Naïve Bayes Classifier

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Abstract— **This research proposes the classification method of papaya types based on leaf images using the Naïve Bayes classifier and LBP feature extraction. Papaya leaves are used because they have a unique pattern and texture from their leaf bones, besides leaf-based classification can be done before papaya trees produce fruit. In the preprocessing process, three stages are carried out in which conversion to grayscale, image adjustment and resize, to produce a good LBP feature extraction. The resize process is useful to reduce computational time during the training and testing process, where this process is done at the end of the preprocessing process to get a better pixel value. Image adjustment is used to sharpen the papaya leaf bone which is the main pattern of the papaya leaf. At the feature extraction stage, an image zoning process is carried out, by dividing the image into nine zones, to produce nine LBP features for each image. In the implementation phase, a total of 150 papaya leaf images were used which consisted of 125 training images and 25 testing images. Based on the results of the classification using the Naïve Bayes classifier by using nine zones each with 128-pixel cell size and image adjustment resulting 96% accuracy. The results of this accuracy are better than using cell sizes 32 and 64 and without image adjustment.**

Keywords—Naïve Bayes Classifier, LBP Features Extraction, Papaya Classification, Image Adjustment, Zoning Image

I. INTRODUCTION

Papaya (Carica Papaya L.) is a type of tropical fruit plant that is popular and commonly consumed. This papaya fruit has several types, including California papaya, Hawaiian papaya, Bangkok papaya, Cibinong papaya, Gunung papaya, and many more. These types of papaya are papaya which is very popular in Indonesia, where each papaya type has a relatively higher selling price. Each type has a different shape and texture of fruit and leaves[1]. Where before the papaya fruitful introduction will be easier through the form of leaves. Because the price of papaya is different, the price of the seeds will be different, so the classification process of papaya will be very important.

Classification can be defined as training/learning to target functions that map each set of attributes (features) to one of several available class labels. The training will produce a model that is then stored as memory. The classification algorithm uses training data to create a model. The model that has been created is then used to predict class labels from new unknown data [2]. The classification done on papaya leaves can be done earlier and gives more features than the fruit. When viewed from several papaya leaves such as Sumatera papaya leaves, California papaya leaves, Cibinong papaya leaves, Hawai papaya leaves, and Bangkok papaya leaves, can be seen leaf bones and morphological forms as the main characteristics[3]. So logically the leaf textures feature can give better accuracy compared to the color feature. Because the color of the leaves can change due to climate change or due to several diseases [4].

Before the classification stage in the leaf image, the pre-processing and feature extraction stages are needed. Pre-processing can affect the effectiveness of the extraction process and computational time. Generally, the preprocessing process is resizing to reduce computation time, cropping, contrast or lighting enhancements, color conversion, and so on, which is useful for getting optimal feature values. In the previous classification research which needed a process of differentiation, the method of extracting local binary pattern (LBP) features was quite widely used[5]–[8]. LBP can be used to analyze textures that have simple operators that are efficient for depicting local image patterns [6] when applied to the papaya leaf classification it can determine the leaf texture characteristics. LBP represents the relationship of each pixel and is located in a circle around the pixel by a binary pattern and uses a histogram of the patterns for texture classification [7]. The advantage of LBP is that monatomic grayscale changes do not change, computational complexity is low, and easy multiscale extensions [8].

At the classification stage, one of the classifiers that are widely used is Naïve Bayes (NB)[3], [9]–[13]. Naïve Bayes is a simple probability-based prediction method based on the Bayes Theorem. In the Naïve Bayes method, it has a strong independence assumption and the model used is an independent feature model. The Naïve Bayes classification is the simplest method using existing opportunities, wherein it is assumed that each variable is independent [2] [14]. Several previous related studies on the classification of dermoscopy images using Naïve Bayes and Decision Tree Techniques results show that the accuracy rate using Decision Tree is 92.86%, while Naïve Bayes provides a higher accuracy rate of 98.8% [11]. In other studies of Classification of Plant Leaves based on shape and texture features, the results of the classification accuracy of the high model with broad ROC curves are 0.981. This shows that the positive rating is very good and the average of false positives with a rating of 0.09% is considered very minimal [13]. Which proves that the naïve bayes method is very good for image classification. The purpose of this study is to classify papaya fruit types based on leaf images using LBP feature extraction and Naïve Bayes classifier.

II. Related Work

Several previous related studies, including conducted by Partiningsih et al.[5] proposed a handwriting recognition method using LBP and contrast enhancement. Classification is done by the K-Nearest Neighbor classifier. In his research, 360 images from three different people's writing were used. LBP was chosen because it was considered to be able to analyze textures, shapes, and patterns of handwriting, the result has obtained an accuracy of 95%, but with preprocessing in the form of contrast enhancement recognition accuracy could be increased to 96.67%.

Padao and Maravillas [13], using Naïve Bayes for classification of plant leaves based on the shape and texture of the features using a 340 image dataset and divided into 30 classes. The results obtained from these studies indicate the classification accuracy with a ROC curve area of 0.981. These results indicate that the actual positive rating is very good and the average of false positives is at a rating of 0.09% which is considered to be very minimal and acceptable.

Heba et al [3], using Naïve Bayes to identify plant types using leaf images. The identification system is proposed by combining leaf biometric features, where the shape and venation features are used for the classification of leaf images. Biometric features of the leaf extraction are then identified by Naïve Bayes. In this study, using 1907 leaf images for dataset and 32 different types of plants. The results of the average identification accuracy show a value of 97% of the proposed identification model.

Arasi et al [11], comparing Naïve Bayes and Decision Tree for Dermoscopy classification using 206 datasets including 119 malignant images and 87 benign images. Dermoscopy images were taken from DermIS and DermQuest, image enhancements were obtained from various pre-processing techniques. The extracted features are based on Hybrid Discrete Wavelet Transform (DWT) and Principle Component Analysis (PCA) and texture features. These features will be input for the classification of Naïve Bayes and Decision Tree to classify malignant or benign lesions. The accuracy of using Hybrid DWT and PCA with the classification of the Decision Tree is 92.86%, while the classification using Naïve Bayes produces higher accuracy than the Decision Tree which is 98.8%.

Based on several related studies, this research proposes the Naïve Bayes method to classify papayas based on leaf images. Because the image of leaves of each type of papaya has different textures and shapes, LBP feature extraction is also proposed in this research.

III. Theories

A. Local Binary Pattern (LBP)

LBP is one texture analysis that has a simple operation that is efficient for depicting local image patterns based on pixel relationship modeling [6]. LBP also provides a good texture discrimination property, is very powerful for monotonic grayscale changes, and is efficient in its calculations. But LBP can be disturbed if there is noise in the image[15]. Therefore, the image capture process needs to be done properly and can minimize the occurrence of noise. If there is noise in the image, it is better to pre-process the image to reduce the noise. For a more detailed look at how LBP basic algorithm works, see Fig. 1

LBP works by taking image sub-block images. Generally, by using the size 3 × 3. But in the development LBP can be done based on the pixel area of the greater neighborhood. Based on Fig.1 it can be described as follows:

Step 1: 3 × 3 image sub-block, determined by the middle pixel, in Fig. 1 is 54, where the center pixel value will be used as a benchmark in step 2.

Step 2: Give a value of 1 for each neighboring pixel around the middle pixel that has a larger pixel value, instead give a value of 0 for the smaller pixel value. In this process, a binary pattern will rotate clockwise from the top left corner. The binary pattern obtained from Fig.1 is 10000111.

Step 3 and Step 4: In both of these steps the resulting binary pattern is formed into a base value of 10. The method is to multiply each binary value with a displacement of 2^0 in the top left corner until 2^7 turning clockwise, see Step 3 in Fig.1, while the results multiplication is presented in step 4

Step 5: The results add up the calculation results in step 4, then place them on the center pixel.

LBP has limitations on the dimensions of 3 × 3, so LBP was developed in a larger area to get texture in a larger area. Where the texture from the T area can be calculated by Eq. 1.

$$T = t(r_c, r_0, \dots, r_{p-1}) \tag{1}$$

Where r_c is the value of the neighboring center pixel with r_p, P is the pixel value of the grayscale image, where ($P = 0, \dots, P = P-1$) has a radius of R ($R > 0$). Incorrect neighbor pixel values that fall on pixels will be calculated using bilinear interpolation [16]. Then 2^p u binomials are used to convert the difference between neighboring pixels into LBP binary values, which are assigned to each pixel $s(r_p - r_c)$. This value will be the decimal value used to be the value of the texture characteristics around (ac, bc), see Eq. 2

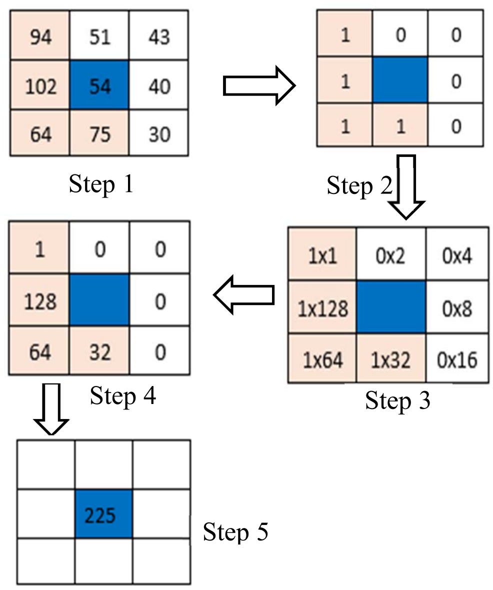

Fig. 1. LBP work process

$$LBP_{P,R(ac,bc)} = \sum_{P=0}^{P-1} s(r_p - r_c)2^p \quad (2)$$

Where the function $s(x)$ is defined in Eq. 3.

$$s(x) = \begin{cases} 1 \; if \; x > 0 \\ 0 \; if \; x < 0 \end{cases} \quad (3)$$

B. Naïve Bayes Classifier

The Naive Bayes classification is probabilistic based on the Bayes theorem [14]. Classification can be defined as learning training to target functions that map each set of attributes (features) to one of several available class labels. The Naïve Bayes algorithm is a probability calculation based on the Bayes theorem [11]. The Naïve Bayes method has strong independent assumptions and the model used is an independent feature model based on probability to classify [2]. The steps for classification using Naïve Bayes are as follows [13] :

1. Suppose D is a dataset that will be used for training data. This set consists of n number of attributes, $A1, A2, A3, \ldots., An$. Each data in the dataset is associated with class identifiers or labeling. These data are named by a vector, $X = (X1, X2, \ldots Xn)$

2. Suppose X, calculates the probability of each attribute value in X of all classes in the training data. The class prediction for X is done by referring to the class with the last probability, see Eq. 4.

$$P(X|C_i)P(C_i) \quad (4)$$

   Where: i = based on class frequency; P = Probability; X = Data with unknown classes; and C = Hypothesis data of a specific class

   The probability of class X cannot be changed, only the probability of X for a particular class must be multiplied by the probability of the same class in all training data to be expanded. This process is repeated for each class in the training data.

3. The probability of attribute values that each class has in the training data can be estimated. Equations 5 and 6 will present how the probability value of this attribute can be used to determine class labels.

$$P(X|C) = \sum_{i=1}^{n} P(X_i|C) \quad (5)$$

$$P(X|C) = P(X_1|C)x\; P(X_2|C)x \ldots.x\; P(X_n|C) \quad (6)$$

4. For classification with the contingent, data used the Gaussian Density formula. In equation 7, the Gaussian distribution will assume the average value and standard deviation and then be given the attribute value so that the probability of the attribute value is generated, as in equation 8.

$$g(x, \mu, \sigma) = \frac{1}{\sqrt{2x\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (7)$$

$$P(X_n|C_i) = g(X_n, \mu c_i, \sigma c_i) \quad (8)$$

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (9)$$

$$\sigma = \left[\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2\right]^{0.5} \quad (10)$$

   Where: P = probability; X = Attribute; C = Class; μ = Mean, the average of all attributes; σ = Standard deviation, variants of all attributes

5. To determine class X, equation (4) is applied to all classes. The class with the highest probability value is considered for the class label prediction.

IV. Proposed Method

The method proposed in this research is described in Fig. 2.

Based on Fig.2 in detail, the stages carried out in this research are explained as follows.

1. The input image is a papaya leaf image with an RGB image format with a JPEG extension.
2. Preprocessing is done by the process of conversion to grayscale, adjustments to get better contrast so that papaya leaf bones can be seen more clearly, and finally, the resize process.
3. LBP feature extraction is done by the zoning process, where the image is divided into nine zones. For example, see Fig. 3.
4. After completing feature extraction, the data is divided into two wherein, the training data is 83.33% and testing is 16.67%.

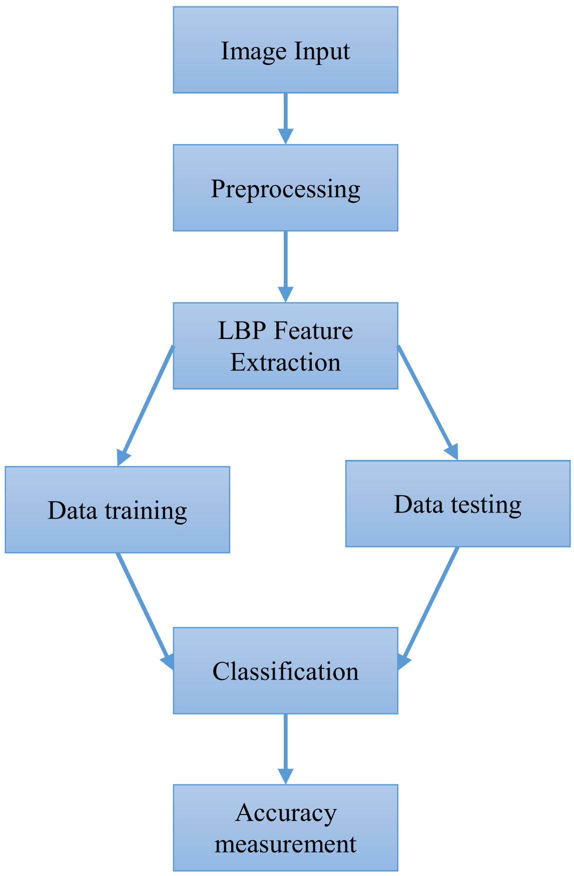

Fig. 2. Proposed Method

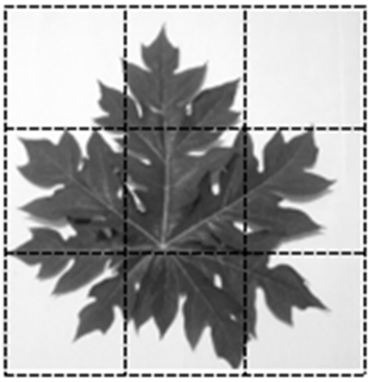

Fig. 3. Zoning in the image

5. In training data training is conducted with Naïve Bayes where the training data is given a class and the testing data is classified with Naïve Bayes.
6. Furthermore, the accuracy of classification results is measured

V. Results And Discussion

The image dataset used is five types of papaya leaves, namely Sumatra papaya, Hawaii papaya, Cibinong papaya, Bangkok papaya, and California papaya. The total image used is 150 where each type is 30 images. Furthermore, the image is divided into two data, namely training data and testing data, where 125 training data and 25 data testing data. When the image was taken at around 14:00 to 16:00 at the papaya plantation in the village of Ngaliyan Semarang. Taking pictures using the A37 Oppo smartphone with an 8-megapixel camera that has a resolution of 2448 x 2448 pixels, where papaya leaves are picked and placed on white paper as the background. Leaf image samples used in this research are presented in Figs. 4.

Then in the preprocessing stage, three process stages are carried out, namely conversion to grayscale with the rgb2gray () function, image adjustment with imadjust () function, and resize with the imresize () function, where the whole process uses Matlab. The resizing process is carried out at the last stage with the reason that optimal pixel values are obtained during the conversion process to grayscale and the adjustment process. Step by step and the preprocessing results are presented in Fig. 5.

The final preprocessing result is a grayscale image with dimensions 384 × 384. Furthermore, all the training image data was performed by feature extraction using LBP where in this study the image was divided into 9 zones, where each zone has a dimension of 128 × 128, as in the picture presented in Fig. 3. The results of the training image feature extraction are presented in Table 1.

Furthermore, the results of the feature extraction were conducted in training with the Naïve Bayes classifier. Whereas the classification data is performed, the results of the classification are presented in Table 2. Based on the results of the classification it can be seen that the classification results obtain very high accuracy which is 96%. Of the 25 testing images that have been tested, the error only occurs in no. 14, namely in the image with the name C3_029.jpg, which is the image of the Cibinong papaya leaf but is classified into a Bangkok papaya type.

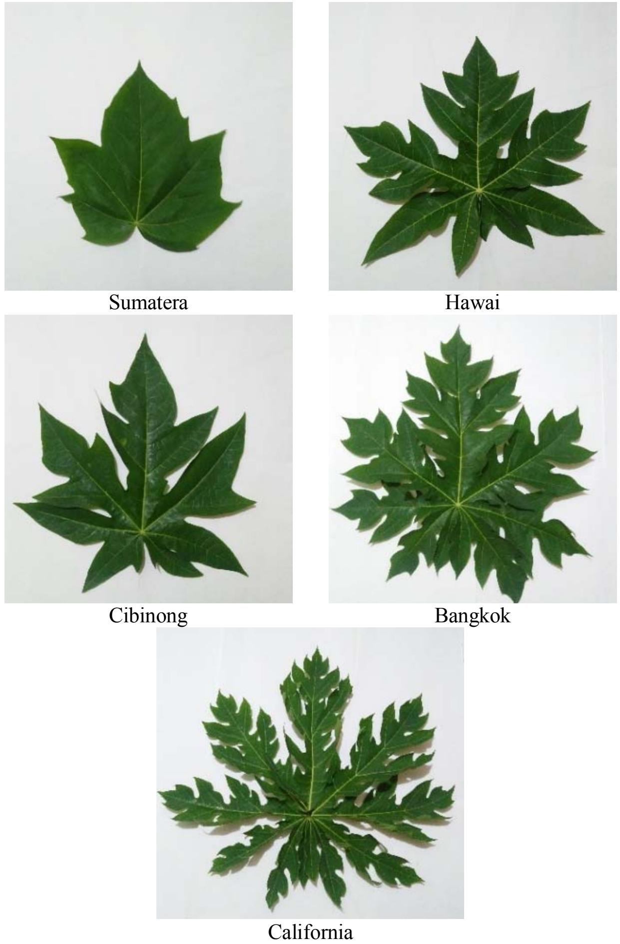

Fig. 4. Sample Image Used

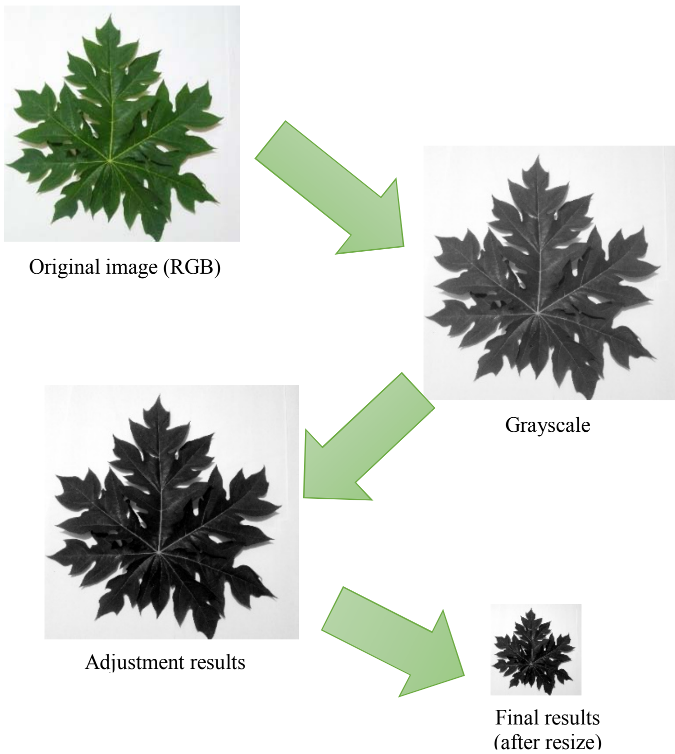

Fig. 5. Preprocessing steps and result

TABLE I. LBP FEATURE EXTRACTION RESULTS (TRAINING PHASE)

No	Image	LBP Features each zone									Class
		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	
1	C1_001.jpg	0.0673	0.1665	0.0469	0.2809	0.2058	0.4358	0.1911	0.2405	0.6708	Sumatera
2	C1_002.jpg	0.0683	0.1634	0.0483	0.2782	0.2019	0.4242	0.1920	0.2307	0.6821	Sumatera
3	C1_003.jpg	0.0422	0.1031	0.0349	0.2185	0.1710	0.3787	0.1220	0.1791	0.8250	Sumatera
…	…	…	…	…	…	…	…	…	…	…	Sumatera
25	C1_025.jpg	0.0530	0.1075	0.0453	0.2098	0.1769	0.3676	0.1329	0.1829	0.8229	Sumatera
26	C2_001.jpg	0.0875	0.1300	0.0560	0.2037	0.2826	0.3713	0.1342	0.1912	0.7814	Hawaii
27	C2_002.jpg	0.0733	0.1320	0.0540	0.2290	0.3083	0.4009	0.1505	0.1919	0.7411	Hawaii
28	C2_003.jpg	0.0759	0.1347	0.0584	0.2263	0.3043	0.3966	0.1579	0.1935	0.7444	Hawaii
…	…	…	…	…	…	…	…	…	…	…	Hawaii
50	C2_025.jpg	0.0938	0.1797	0.0634	0.2614	0.3240	0.4435	0.2034	0.2373	0.6147	Hawaii
51	C3_001.jpg	0.0706	0.1285	0.0649	0.2489	0.2967	0.4010	0.1551	0.1982	0.7385	Cibinong
52	C3_002.jpg	0.0792	0.1342	0.0673	0.2373	0.2877	0.3958	0.1614	0.2061	0.7369	Cibinong
53	C3_003.jpg	0.0771	0.1318	0.0630	0.2345	0.2797	0.3945	0.1544	0.2025	0.7469	Cibinong
…	…	…	…	…	…	…	…	…	…	…	Cibinong
75	C3_025.jpg	0.0784	0.1308	0.0637	0.2341	0.2828	0.3964	0.1572	0.2020	0.7454	Cibinong
76	C4_001.jpg	0.0845	0.1323	0.0791	0.2440	0.3682	0.3869	0.1571	0.1953	0.7101	Bangkok
77	C4_002.jpg	0.0872	0.1369	0.0796	0.2459	0.3723	0.4012	0.1540	0.1995	0.6967	Bangkok
78	C4_003.jpg	0.0852	0.1309	0.0779	0.2422	0.3705	0.3953	0.1541	0.1992	0.7053	Bangkok
…	…	…	…	…	…	…	…	…	…	…	Bangkok
100	C4_025.jpg	0.0640	0.1188	0.0629	0.2425	0.3349	0.4052	0.1340	0.1893	0.7407	Bangkok
101	C5_001.jpg	0.0986	0.1498	0.0647	0.2467	0.3805	0.4191	0.1494	0.2133	0.6709	California
102	C5_002.jpg	0.0854	0.1471	0.0685	0.2463	0.3926	0.4152	0.1504	0.2042	0.6774	California
103	C5_003.jpg	0.0972	0.1443	0.0659	0.2359	0.3834	0.4011	0.1390	0.2122	0.6947	California
…	…	…	…	…	…	…	…	…	…	…	California
125	C5_025.jpg	0.0896	0.1475	0.0656	0.2485	0.3876	0.4189	0.1480	0.2044	0.6734	California

TABLE II. CLASSIFICATION RESULTS

No	Image Name	Actual Class	Prediction Class
1	C1_026.jpg	Sumatera	Sumatera
2	C1_027.jpg	Sumatera	Sumatera
3	C1_028.jpg	Sumatera	Sumatera
4	C1_029.jpg	Sumatera	Sumatera
5	C1_030.jpg	Sumatera	Sumatera
6	C2_026.jpg	Hawai	Hawai
7	C2_027.jpg	Hawai	Hawai
8	C2_028.jpg	Hawai	Hawai
9	C2_029.jpg	Hawai	Hawai
10	C2_030.jpg	Hawai	Hawai
11	C3_026.jpg	Cibinong	Cibinong
12	C3_027.jpg	Cibinong	Cibinong
13	C3_028.jpg	Cibinong	Cibinong
14	C3_029.jpg	Cibinong	Bangkok
15	C3_030.jpg	Cibinong	Cibinong
16	C4_026.jpg	Bangkok	Bangkok
17	C4_027.jpg	Bangkok	Bangkok
18	C4_028.jpg	Bangkok	Bangkok
19	C4_029.jpg	Bangkok	Bangkok
20	C4_030.jpg	Bangkok	Bangkok
21	C5_026.jpg	California	California
22	C5_027.jpg	California	California
23	C5_028.jpg	California	California
24	C5_029.jpg	California	California
25	C5_030.jpg	California	California

Furthermore, this research also conducted a comparison where the proposed method was compared without using the image adjustment process and changing the size of the LBP area. The area size of LBP used is 32, 64, and 128, from the experimental results it is proven that the area size of 128 has the best results, namely 92% without image adjustment and 96% with image adjustment. The image adjustment process also affects every area, where without image adjustment, for area 32 it only gets 80% accuracy, and in area 64 it gets 88% accuracy. When the image adjustment is applied area 32 gets 84% accuracy and in area 64 gets 92% accuracy.

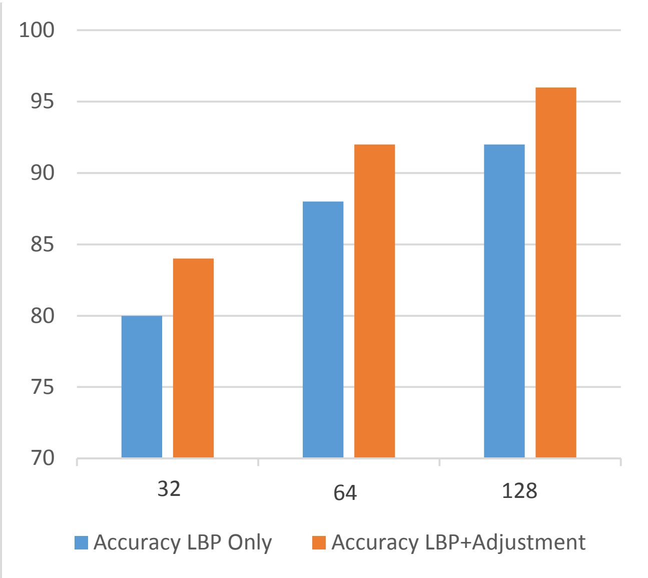

Fig. 6. Accuracy comparison based on zoning

The chart trends presented in Fig. 6. It also seems to increase when the LBP area gets bigger, this is possible because the image used in the crop and resized with a size that fills the image, so the pattern must be more accurately read with a larger area.

VI. CONCLUSION

LBP has the extraction of texture features that can be used to recognize the textures and patterns of an image. Papaya leaves have a characteristic in textures and shapes, especially on the leaf bone. By using LBP feature extraction and Naïve Bayes classifier, it was proven successful in classifying papaya species based on leaf images with very high accuracy. The process of taking pictures that are minimal noise and preprocessing also has an important role to improve classification accuracy.

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