

Neural Network based on GLCM, and CIE L*a*b* Color Space to Classify Tomatoes Maturity

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Abstract— Tomato (*Lycopersicum commune*) is one of the fruits that can be consumed directly or processed into food or drinks. In the harvesting season, tomatoes will be picked and sorted into different class depending on its size, shape, and color. The quality and the taste of tomatoes fruit depends on the maturity level of this fruit. There is some product that used a different level of tomato maturity. Therefore it is necessary to classify the ripeness of this fruit. The use of information technology such as computer vision can help the farmer to classify tomato based on maturity level. To be able to determine the ripeness of tomatoes from an image, a computer needs to identify the right parameters to determine the maturity of this fruit. The texture and color on the surface of tomatoes is a feature that easily recognized in determining the maturity of tomatoes. Therefore this research proposed the combination of GLCM texture extraction and CIE L*a*b* color space and also Backpropagation neural network (BPNN) to classify tomatoes maturity. GLCM feature extraction consisted of Contrast, Correlation, Energi, Homogeneity, and Entropy. GLCM was implemented in each RGB color layer, then the average of CIE L*a*b* was calculated. From 75 train set and 25 test set, BPNN model can classified tomatoes maturity with accuracy 100% and average accuracy 95.46%.

Keywords—Backpropagation Neural Network, CIE L*a*b* Color Space, Gray Level Co-occurrence Matrix, Tomatoes Maturity

I. INTRODUCTION

Tomato or *Lycopersicum commune* is one of the fruits that can be consumed directly or processed into food or drinks. Tomato processing also considers the level of maturity as well because it affects the taste and quality of the fruit itself. The maturity level of tomatoes can be seen from the color and surface texture of the fruit.

In the journal proposed by Arah, Isaac Kojo et al. [1] explained about preharvest and the postharvest process of tomato fruit. Based on their analysis, there are several

preharvest and the postharvest factor which affected the production of tomatoes. Preharvest losses can be 25 – 42%. Then, the losses of postharvest could be qualitative or quantitative. One factor which affects the quality of tomatoes is picking process. During the harvesting process, tomatoes will be picked and sorted into several classes according to the shape and color. The maturity level of tomatoes is separated into 5 classes, which are raw, quite mature, mature, very mature, and rotten based on their color [2]. Generally, the sorting process and class distribution of tomatoes are done manually by humans. However, manual sorting and class division are quite tiring and prone to errors [3]. In addition, differences in perception between workers also can influence the determination of the tomatoes ripeness level [4]. Based on these problems, the solution that can be used is to use computer technology. The use of computer technology such as digital image processing and data mining can improve the accuracy and performance of classification in determining the maturity level of tomatoes.

To be able to classify the ripeness level of tomatoes from an image, a computer needs to recognize the right parameters which are unique and can be used to represent the ripeness level of tomato. Some parameters that can be used are the texture and surface color of tomatoes [5]. The texture and color on the surface of tomatoes is a feature that is easily recognized in determining the maturity of tomatoes. In this study, to be able to recognize texture and color parameters on tomato images we used the Gray Level Co-occurrence Matrix (GLCM) calculation as image texture extraction and CIE L*a*b* color space model as color extraction of tomato images. From the GLCM calculation process, several main texture features are produced such as contrast, correlation, energy, homogeneity, and entropy.

In this study, GLCM will be implemented in each color layer of the tomato images. While the CIE L*a*b* consists of L* as brightness, a* is the red-green coordinate, and b* is the yellow-blue coordinate [6]. In this color space, the features

that will be used are the mean of L^* , a^* , and b^* . Then to be able to determine the ripeness of tomatoes based on these features, this study will utilize the classification method using Backpropagation Artificial Neural Networks (BPNN). To perform this proposed method, this research was utilized the dataset from previous work [5] which divided the dataset into 5 classes. These classes consisted of raw, quite mature, mature, very mature, and rotten.

II. RELATED RESEARCH

The combination of GLCM with color feature extraction in the classification process has been carried out in the following studies [7] [8] [9]. Meanwhile, the research that implemented the combination was proposed by Indriani et al. [5]. This research proposed a combination of GLCM and HSV color space to classified tomato maturity using K-NN classifier. In this research, several schemes have been tested and from the result achieved the best scheme which had the highest accuracy is GLCM with the distance is 9, and the value of k is equal to 3. This scheme can achieve 100% accuracy. The implementation of GLCM in this study was carried out by simply changing the RGB image to grayscale so that there were only 4 features that were used as parameters in the K-NN process. Besides that the use of different datasets will also make a difference in the use of k values so that the results of accuracy can be different.

Meanwhile, in the second study conducted by Kaur et al. [2] utilizing the RGB color feature extraction method to classify tomatoes. From the results of testing on several types of classification methods, it was found that the random forest method was able to produce the highest accuracy of 92.49%.

The use of color feature extraction was also carried out by Wan et al [10] who used RGB color and HSI feature extraction from the image of tomatoes which would then be classified using a neural network. Another research proposed by Opeña et al. [3] which used the Artificial Bee Colony (ABC) and color space models which are RGB, HSI/HSV, and CIE $L^* a^* b^*$ color space to determine the tomatoes maturity. A proposed method conducted with varied test set and trainset can achieve the highest accuracy equal to 98.19%. The use of CIE $L^* a^* b^*$ is also done by Sukmana and Rahmanti [6] which proposed Corn leaves disease segmentation using Connect Component Extraction and CIE $L^* a^* b^*$. From this study, the transformation of RGB into CIELAB color space is necessary because implemented CIELAB can precisely segmented the corn leaves disease. therefore, from researches above, we proposed the combination of GLCM which will be implemented in each color channel and also color feature extraction CIE $L^* a^* b^*$ as the parameter for Backpropagation Neural Network (BPNN) to identify the maturity of tomato fruit.

III. LITERATURE STUDY

A. Gray Level Co-occurrence Matrix (GLCM)

GLCM is a statistical-based feature extraction method that uses the occurrence of gray level of images to determine unique features of a grayscale image. GLCM will calculate the probability of the appearance of two neighboring pixels with a particular distance (d) and angle (θ) [11]. In general, GLCM has fourteen texture features obtained from the calculation process of probability matrices [12]. But the features that are often used are contrast, correlation, energy, homogeneity, and entropy [13].

1) Contrast

Contrast is a value that represents the difference in gray level variation between pixels that appears in the image. If the gray variation between pixels is constant, the value of contrast is 0 (zero). The equation of contrast calculation is shown in Eq.1.

$$Contrast = \sum_{i,j} |i - j|^2 p(i,j) \quad (1)$$

In Eq.1, i is the row value in the co-occurrence matrix, while j is the column value of the co-occurrence matrix. The value of p is the probability value between pairs i and j .

2) Correlation

The correlation value is a value that describes linear linkages between degrees of grayness in the image. Below is the equation used to determine the correlation value between pixel pairs.

$$Correlation = \sum_i \sum_j \frac{(i - \mu_i)(j - \mu_j)p(i,j)}{\sigma_i \sigma_j} \quad (2)$$

Where:

$$\mu = \text{Mean}$$

$$\mu_i = \sum_i \sum_j i p(i,j) \quad \mu_j = \sum_i \sum_j j p(i,j)$$

$$\sigma = \text{Standard Deviation}$$

$$\sigma_i = \sqrt{\sum_i \sum_j (i - \mu_i)^2 p(i,j)} \quad \sigma_j = \sqrt{\sum_i \sum_j (j - \mu_j)^2 p(i,j)}$$

3) Energi

The energy value of an image is the measurement of the similarity of the neighboring pixel in the image. The higher the image similarity, the higher the energy value.

$$Eng = \sum_i \sum_j p(i,j)^2 \quad (3)$$

Can be seen in Eq.3, the energy value can be calculated by summing the square of the probability of the pair of pixels in the co-occurrence matrix.

4) Homogeneity

The value of homogeneity is used to represent the level of similarity. The value of homogeneity will increase if all pixels have uniform values. To be able to calculate the value of homogeneity can use Eq.4 below:

$$Hom = \sum_i \sum_j \frac{p(i,j)}{1 + |i - j|} \quad (4)$$

5) Entropy

The entropy value is a value that represents the distribution of variations from the gray level of the pixel in the image [14]. In general, the entropy value of an image ranges from 0 to 8 because the gray level of the image ranges from 0 - 255 (2^8).

$$Entropy = - \sum_{i,j} p(i,j) \log(p(i,j)) \quad (5)$$

B. CIE L*a*b*

CIE L*a*b* or CIELAB is a color space formed by Commission International de l'Eclairage (CIE) in 1976. Unlike RGB or CMYK color spaces, the CIELAB color space is designed as closely as possible to the perception of human vision. To change the RGB color space to CIELAB, first the RGB image is transformed into XYZ form using the Eq.6 below [6]:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.6070 & 0.1734 & 0.2000 \\ 0.2990 & 0.5864 & 0.1146 \\ 0.0000 & 0.0661 & 1.1175 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (6)$$

Furthermore, the XYZ value can be converted to CIE L*a*b* with Eq.7 below.

$$\begin{aligned} L^* &= 116 f(Y/Y_n) - 16 \\ a^* &= 500(f(X/X_n) - f(Y/Y_n)) \\ b^* &= 200(f(Y/Y_n) - f(Z/Z_n)) \end{aligned} \quad (7)$$

Where the value of $X_n Y_n Z_n = 1$, while the value of f is calculated by Eq.8 below:

$$f(x) = \begin{cases} x^{\frac{1}{3}} & x > 0.008856 \\ 7.787x + \frac{16}{116} & x \leq 0.008856 \end{cases} \quad (8)$$

C. Backpropagation Neural Network (BPNN)

Backpropagation is a neural network-based artificial intelligence method developed by Rumelhart in 1985 [10]. Backpropagation (BPNN) is a method that calculates the gradient, where this gradient is needed to determine the weight of each perceptron. Actually, Backpropagation uses a multilayer perceptron (MLP) to form an artificial neural network. In general, the backpropagation network consists of 3 layers which are input layers (X), hidden layers (ϕ), and output layers (Y) [15].

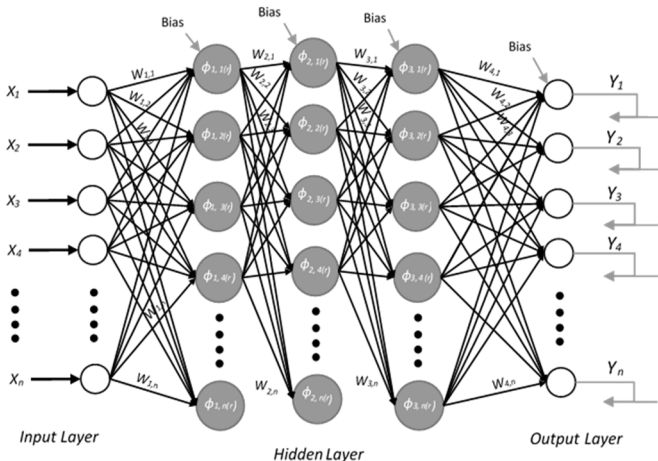


Fig. 1. The topography of BPNN with 3 hidden layers

IV. PROPOSED METHOD

Our proposed method in this study (figure 1) combines the extraction of GLCM textures and CIE L* a* b* as the parameter of tomato maturity classification.

In Fig.2, there are several series of processes such as pre-processing, feature extraction, classification process, and evaluation.

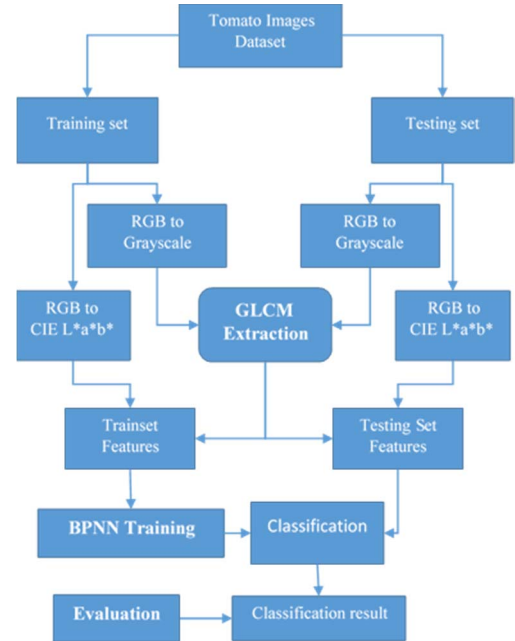


Fig. 2. Our Proposed Method

A. Pre-processing

In this process the image dataset will be divided into training data and test data, then it will be processed by converting RGB images into 3 layers based on the color layer and then processed using GLCM for each color layer.

B. Features Extraction

Feature extraction used in this study is GLCM and CIE L*a*b*. GLCM will be implemented in each color layer in the RGB image by using the mean of each angle (0, 45, 90, and 135) so that each image layer will have its own contrast, correlation, energy, homogeneity, and entropy features. After that, the RGB tomato image will be converted to CIE L*a*b*, then the average value will be calculated to get L^* , a^* , and b^* features.

C. Classification Process

Then the features that have been obtained from the dataset will be used as input for the Backpropagation Neural Network (BPNN) method. BPNN is used to classify tomatoes images based on its feature extraction result depend on the maturity level which is separated into 5 classes, consist of raw, quite mature, mature, very mature, and rotten. There are three different architecture used in this classification process. These schemes used to test the effect of the different nodes number in input layers.

D. Evaluation

The evaluation phase is carried out to determine the performance of the proposed method. At this stage, the accuracy value obtained from a combination of GLCM, CIE L*a*b*, and BPNN will be calculated in classifying the maturity level of tomatoes. Accuracy will be obtained using the confusion matrix. The confusion matrix is matrices which are formed into tables based on the number of classes used in the classification process. Suppose there are 5 classes (for example A, B, C, D, E) used in the classification process, then the confusion matrix that can be formed is:

TABLE I. CONFUSION MATRIX WITH 5 CLASSES

		Predict Result				
		A	B	C	D	E
Actual Result	A	AA	AB	AC	AD	AE
	B	BA	BB	BC	BD	BE
	C	CA	CB	CC	CD	CE
	D	DA	DB	DC	DD	DE
	E	EA	EB	EC	ED	EE

From Table 1, class in predict result is true if it matches with class in actual result. To be able to calculate the accuracy of the table, use the equation below:

$$Accuracy = \frac{AA + BB + CC + DD + EE}{Total\ Data} \times 100\% \quad (9)$$

Accuracy can be obtained with calculated the total of true classes then divides it with the number of data. after that multiply the result with 100 to generate the percentage of the accuracy.

V. EXPERIMENT AND TESTING RESULT

A. Dataset

The dataset that uses in this research is tomato images (*Lycopersicon commune*) which were taken from previous work [5]. From this previous research, the data will be separated into 5 classes, which are raw, quite mature, mature, very mature, and rotten. The dataset contains 100 tomatoes images which consisted of 75 images for train set and 25 images for the test set. Each class in training set has 15 images. While the test image has 5 images for each class. The image used is an RGB image of 250×250 pixels and formatted in *.jpg. Below is the example of the images in each class:

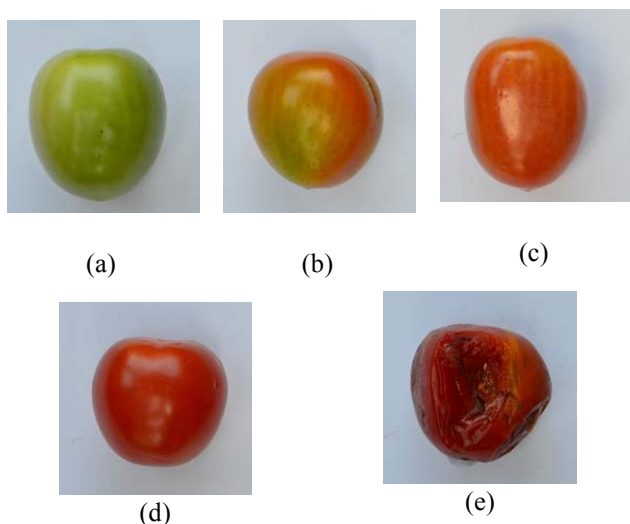


Fig. 3. Sample of Tomato images; (a) raw, (b) quite mature, (c) mature, (d) very mature, (e) rotten.

From Fig. 3 can be seen the difference of each class based on their appearance. The obvious feature that literally noticeable is their different color and surface texture.

B. GLCM and CIE L*a*b* Feature Extraction

In this process, the image of tomatoes is extracted with GLCM by using a distance scheme of 1 to 3 and using mean values from the following angles: 0, 45, 90, and 135. GLCM will be implemented for each layer in the RGB image. So that each layer in the RGB image will produce 5 GLCM features consisting of contrast, correlation, energy, homogeneity, and entropy. Then for color extraction, RGB images will be converted into CIE L* a* b* color space. furthermore, calculated the average of each color layers such as L*, a*, and b*. This extracting process produced 18 features for each image. Therefore for data train will have 75×18 set of features and for testing, the set will have 25×18 set of features.

C. Classification using BPNN

The classification process will classify the tomato into 5 classes. In this study there are 3 different scheme that is used in BPNN to classify tomatoes maturity level. These schemes have a different number of the input layer.

- The first scheme will use 15 nodes of first hidden layers, 5 nodes of second layers, and 3 nodes of third layers.
- The second scheme will use 18 nodes of first hidden layers, 5 nodes of second layers, and 3 nodes of third layers.
- The third scheme will use 21 nodes of first hidden layers, 5 nodes of second layers, and 3 nodes of third layers.

All scheme will be used epochs value equal to 100 and will be tested using a learning rate scheme with increment 0,2 to verify the best learning rate which produced the highest accuracy. Each scheme will be measured using the confusion matrix to determine accuracy.

TABLE II. PERFORMANCE USING THE FIRST SCHEME

First Scheme		
GLCM Distance	Learning Rate	Accuration (%)
1	0.2	96
	0.4	92
	0.6	100
	0.8	92
	1.0	92
2	0.2	88
	0.4	84
	0.6	96
	0.8	100
	1.0	96
3	0.2	92
	0.4	88
	0.6	96
	0.8	92
	1.0	92
Average		93.067

Table II presents the performance of BPNN in classifying tomatoes maturity based on the first scheme. In our first scheme which used 15 nodes of the input layer where is less than the total of used features can produce the average acceleration equal to 93.067%.

TABLE III. PERFORMANCE USING THE SECOND SCHEME

Second Scheme		
GLCM Distance	Learning Rate	Accuration (%)
1	0.2	68
	0.4	88
	0.6	84
	0.8	96
	1.0	92
2	0.2	100
	0.4	96
	0.6	92
	0.8	96
	1.0	92
3	0.2	76
	0.4	92
	0.6	88
	0.8	80
	1.0	96
Average		89,067

Table III shows the performance of BPNN based on our first scheme which used 18 nodes of the input layer where is same with the total of features that used. This scheme can produce an average accuracy equal to 89.067.

TABLE IV. PERFORMANCE USING THIRD SCHEME

Third Scheme		
GLCM Distance	Learning Rate	Accuracy (%)
1	0.2	96
	0.4	92
	0.6	92
	0.8	100
	1.0	92
2	0.2	100
	0.4	100
	0.6	96
	0.8	96
	1.0	100
3	0.2	84
	0.4	100
	0.6	96
	0.8	96
	1.0	92
Average		95.467

From Table IV can be seen the test result using BPNN based on our third scheme. Our third scheme used 21 nodes of the input layer which is larger than the total of features that used. The third scheme has the best average accuracy compared to another scheme. The average accuracy of the third scheme is 95.467%.

From the testing result, a parameter such as GLCM distance and Learning Rate have a contribution in producing higher accuracy. From testing result table, GLCM distance which equals 2 can produce better accuracy in each learning rates.

From Fig.4, the first scheme and second scheme has an unsteady graph compared to the third scheme. Therefore in our proposed method, BPNN can produce a better performance when used larger input layer.

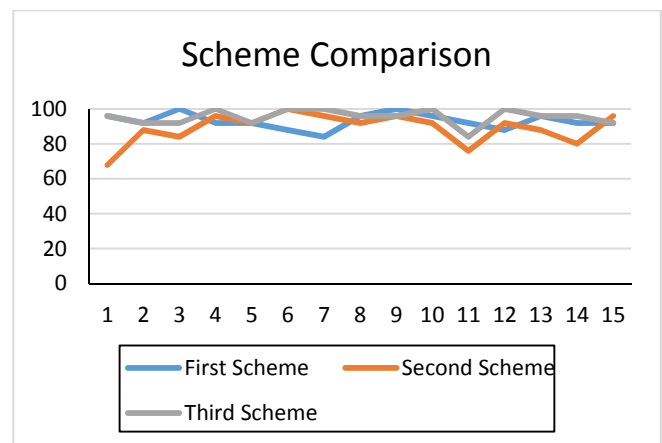


Fig. 4. Comparison graph of each scheme.

Comparison between our proposed method with the method proposed in [5] and [3] can be seen in table below:

TABLE V. COMPARISON WITH THE PREVIOUS METHOD

No.	Method	Algorithm	Average Accuracy (%)
1	Indriani, OR et al [5]	GLCM, HSV, and KNN	93.94
2	Opeña et al. [3]	RGB, HSI, CIE L*a*b* and ABC Neural Network	92
3	Our Proposed Method	Triple Layer GLCM, CIE L*a*b*, and BPNN	95.467

From Table 5 can be seen that using the same dataset, our proposed method can produce higher accuracy compared to other methods [5] [3].

VI. CONCLUSION

Our proposed method which combined GLCM, CIE L*a*b* color space, and Backpropagation Neural Network (BPNN) to classify the maturity of tomatoes has been conducted. Using 75 training images and 25 testing images, the maturity level of each testing images can perfectly be identified. We used three different scheme to examine the effect of different value of the node number in hidden layers, learning rate value, and GLCM distance in classifying the tomatoes maturity. The testing result denoted that our proposed method achieves the best accuracy 100% that appear in each scheme, and the best average accuracy 95.467% that reached by 3rd scheme.

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