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Characterization and Classification of *Citrus reticulata* var. Keprok Batu 55 Using Image Processing and Artificial Intelligence

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Abstract *Citrus reticulata* var. Keprok Batu 55 is one of the superior varieties of citrus originating from Batu City, East Java, which has a slightly sour-sweet taste with a sweetness level of 10-12°brix. Prediction of citrus maturity as a monitoring activity for pre- and post-harvest quality management is still done manually, whereas human judgment of the maturity level is subjective. One alternative to increase the monitoring productivity is the development of a portable system with image processing and destructive measurements of physico-chemical properties such as hardness, brix, and pH. This study aims to develop an image-based classification model and characterize the quality parameters of citrus. Measurement of maturity on *Citrus reticulata* var. Keprok Batu 55 has been carried out for image analysis with color index (RGB, L*a*b. and HSV). The image of citrus will be taken with the camera, which will later be taken partially (cropping) on the skin, which will then extract the color characteristics and calculate the level of color content from RGB and then converted it to HSV. A sufficient number of images with various conditions are needed to train the artificial intelligent model so that it can perform segmentation, calculation, and grade classification. A prediction model then was developed using color features and several machine learning modeling approaches.

Keywords Brix, Classification, Hardness, Machine Learning, Maturity, pH

1. Introduction

Citrus are sub-tropical fruits which are widely cultivated in many countries even in tropical countries such as Indonesia. Citrus can be grown in the lowlands to the highlands depending on the varieties. There are more than 250 citrus varieties cultivated in Indonesia. One of the Indonesia's superior qualities of citruses is the *Citrus reticulata* var. Keprok Batu 55. This citrus is popular due to its juiciness, high vitamin-C content (32.27 mg/100 g) and sweet taste with a sweetness level of 10-12 °brix [1].

In citrus cultivation, monitoring of plant conditions and fruit growth is needed for various things, such as prediction of peak harvest, yield prediction, implementation of precision agriculture in the fertigation process, and so on. The level of maturity is one of the factors that affect consumer preference. Maturity can be determined by several parameters such as fruit taste, fruit texture, and fruit color. Determination of the maturity level and physical characteristics of citrus fruits is still often neglected in developing countries, the sorting and grading sometimes are done manually by the farmer. The manual grading using visual physical characteristics could have different outcomes because humans have subjective values. Identification like this is tedious and should be automatized and standardized. The required measurement method is a technology that is able to carry out the maturity identification process objectively and consistently.

Computer vision methods could be used as a replacement for the human vision system which produces a digital image. A digital color image is a matrix consisting of values of RGB channels whose elements represent the intensity level of the image elements [2]. This digital image then could be used to characterize the citrusVisual features such as color, shape and texture could be identified by using digital image processing. Image processing techniques could be used to extract the important features of objects. These extracted features could be used as an input to a multivariate model to classify agricultural products such as fruits and vegetables [3]. Conventional mathematics or statistic model could be applied using the image features as an input. On the other hand, the machine learning method could also be applied to carry out classification and prediction tasks. Note that enough number of images with various conditions will be required to be obtained so the model could be trained well so that they can perform segmentation and grade classification. This method of color image processing has been carried out for various kinds of citrus, however, *Citrus reticulata* var. Keprok Batu 55 has a unique characteristic that has not been investigated yet. So, whether the common image processing pipeline method could be used for these varieties is still an open question.

In this research the visual features of *Citrus reticulata* var. Keprok Batu 55 will be evaluated using computer vision combined with the machine learning method. Several classifiers then will be trained and the results will be compared to predict the different maturity levels of the fruit.

2. Materials and Methods

The experiment was carried out from June to August 2021, in the Faculty of Agricultural Technology, Universitas Brawijaya and Integrated Laboratory of Balitjestro, Malang, Indonesia.

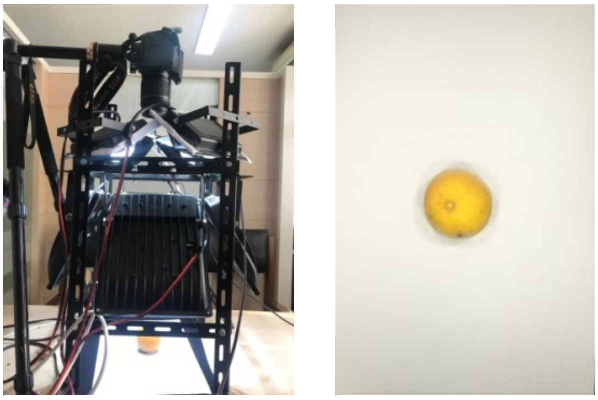
The tools used in this study were a mini studio which consist of Canon EOS 700D camera with four 50W LED flood lights, and a laptop equipped with an image acquisition software. Image processing has been carried out in Python version 3.7. The materials used in this study were *Citrus reticulata* var. Keprok Batu 55 with three levels of maturity. Image data of citrus with three categories of maturity level has been acquired. There are immature citrus, half-mature, and mature citrus as many as 2×308 images with image retrieval on two sides, top and bottom. Some sample images that have been collected are shown in Fig. 1.

(a) (b) (c)

Figure 1. (a) Immature citrus, (b) Half-mature citrus, (c) Mature citrus

2.1. Image Acquisition

The image of citrus has been acquired using standard white light with a polarizing filter so the specular reflectance could be avoided. The DSLR camera has been used and the setting adjusted to manual mode. The camera parameters are ISO 100, F-number of F6.3 and exposure time of 1/6. The image has been stored in the .JPG format with a size of 5184×3456. The computer vision setup and the image acquisition results example could be seen in Fig. 2.



(a) (b)

Figure 2. (a) Mini studio, (b) Citrus sample

2.2. Digital Image Processing

An image is a form of visual information so there is a lot of information that can be extracted from an image [5]. The process or steps are used to dig up the image information to produce output that can be used in particular interest is referred to as digital image processing. Digital imaging is a technical step in estimating the characteristics of objects. The image could be used to measure the visual features related to object color and geometry.

The application in the computer world, colors are formed on the interface screen using certain modeling, such as RGB modeling which is widely used in the world of computer as in the method of forming color on the monitor screen. Color model RGB is included in the additive color model where color is formed by combining the light intensity of the three main colors i.e. Red (R), Green (G), and Blue (B). The different levels of intensity in each of the main color components combined effect on the type of color that will be produced. Color intensity gradation on computer screens has 256 gradations (0-255) for each RGB component. In addition to the RGB color space, the HSV color space is also commonly used in image processing digital. The HSV color space is represented in 3 colors components which are Hue (H), Saturation (S), and Value (V). HSV color model is a non-linear model system that approximates the color perception of human vision [6]. The L*a*b color space consists of three components named Lightness (L) starting from 0 (black) to 100 (white) and two more components i.e. a representing the level of red-green color with levels (+60 red, -60 green) and component b representing blue to yellow with values ranging from –120 to +120 [7].

2.3. Data Analysis

The image analysis and modeling have been carried out using Python 3.7 with Jupyter Notebook IDE. The image analysis consists of data pre-processing, feature extraction, training and testing of the machine learning model. Some machine learning models including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM) have been trained and the results are compared.

Logistics Regression is a regression model used for classification. This model describes the relationship between the response and predictor variables where the response variable is binary. A decision tree, also known as top-down induction of decision trees (TIDIDT) is a supervised learning technique that builds a classification rule representation with a hierarchical sequential structure by recursively partitioning the training data set. SVM method will find the optimal hyperplane to classify the dataset. Hyperplane could divide the two classes with the farthest margin between classes. The random forest classifier is developed from the decision tree concept. It is the development of the CART method, by applying bootstrap aggregating (bagging) and random feature selection methods. In a random forest, many decision trees are grown to form a forest. The analysis is then conducted on the collection of trees [8].

The measurement of color intensity is red, green and blue. The RGB color model is used to calculate the color values and interpret the result. Data pre-processing was carried out to modify the image size to reduce the computational cost. The images have been resized by 30% from 5184 x 3456 pixels to 1555x1036. In addition, to obtain more information, color conversion from RGB to HSV and L*a*b* color space has been conducted. The RGB color components in image processing must be normalization is carried out. The normalization process is important to do because in general a number of images are captured under different lighting conditions. Normalized RGB color components will eliminate the influence of lighting, so that values for each color component can be compared to each other even though it comes from an image with unequal lighting conditions.

Segmentation is the stage in dividing the digital image area to focus on the object area. The input of this segmentation stage is a grayscale image. A historgram of the grayscale image will be used to determine the thresholding value. The Otsu method is carried out to obtain the most optimal threshold value of k. The class with the highest variance value is determined as the best threshold value. After obtaining the threshold value, the grayscale image will divide the two areas based on the threshold value, so that the object and background parts are obtained as a binary image. The binary image then could be further processed to mask the fruit area and exclude the background.

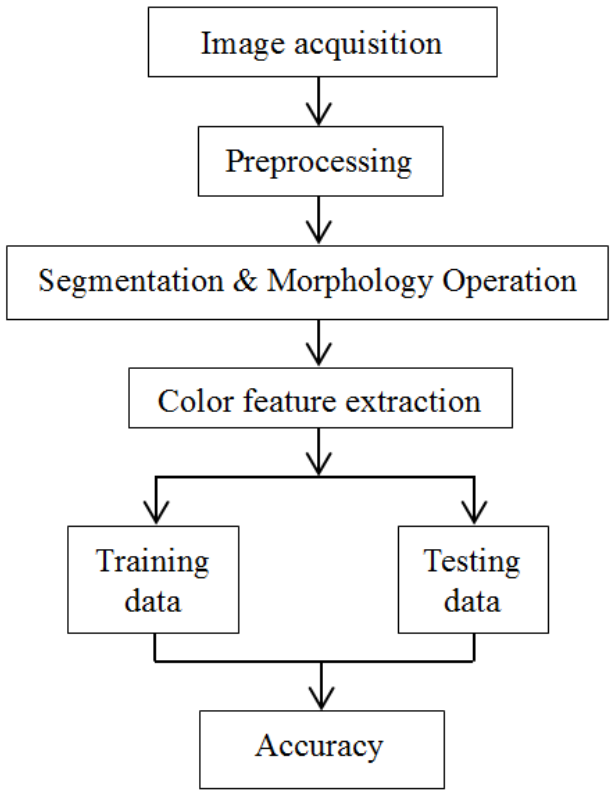


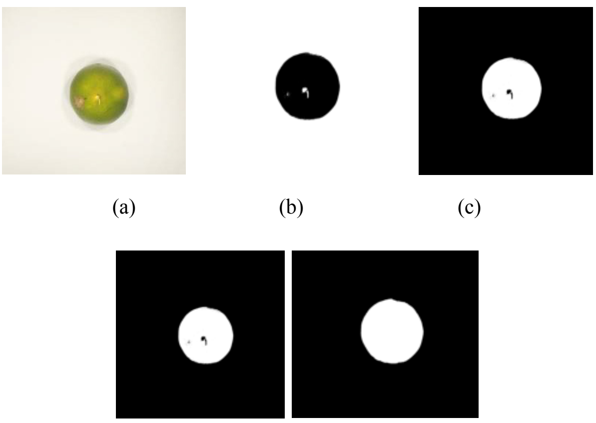
Figure 3. Image analysis flowchart

The image is mapped to pixels of a certain size so that it gives a fixed dimensional representation. The purpose of image normalization is to reduce image resolution that is useful during the image recognition process and also improves recognition accuracy [9] In this study, the feature used in the segmentation process is mean R , mean G, and mean B, and mean Gray. Whereas, when the classification process (determination of maturity) uses the average feature of the upper, lower, and both channels, these features of color are then used as the predictors in the machine learning model. An overview of the system to be made can be seen in the flowchart below (Fig. 3).

3. Result & Discussion

3.1. The Result of Segmentation

An image has 2 regions called the object region and the background region. The segmentation process is carried out by comparing the mean R, mean G, mean B and mean gray feature values of each pixel in the image as well as other pixels to the feature data [6]. The results of segmentation, image improvement, noise removal, can be seen in Fig. 4.



(a) (b) (c)

(d) (e)

Figure 4. (a) Original image, (b) Image segmentation (BGR), (c) Image segmentation (RGB), (d) Image with additional 1 pixel white border around, (e) Image after noise removal.

An image of figure 4(a) still has pixels that are not the area of the object to be segmented, where each object pixel still has a background pixel, it must be used as a digital binary image for the segmentation process. As can be seen in figure 4(b), the OpenCV Library on Anaconda software produces color feature conversions in the form of BGR (blue, green, red), it must be converted back into RGB features (red, green, blue) for the segmentation process as shown in Figure 4(c). In figure 4(d), where the image with the pixel point axis still shows that there are pixels in the object that still have a background area, noise must be removed. A segmented binary image is generated which shows the position of the object in the test image. Bhahri and Rachmat [10] explained that the segmentation procedure is carried out by dividing the image into parts to determine the boundaries between object and background, the next step is assigning a color index to each pixel that shows the part in a segmentation. The Otsu segmentation techniques will divide pixels of the objects with the background using the histogram pattern. The histogram pattern is used to determine and decide the thresholding level to separate objects andbackgrounds . Then thresholding could be carried out to convert the grayscale image to a binary image.

3.2. Image Pre-processing and Features Extraction

In digital image processing, the acquired images are continued with a preparation process (image pre-processing) by changing the size of the image (image resizing). The division of the image into its constituent parts is carried out in the segmentation process, where this process is used to group images according to the object of the image or as a technique to divide an image into several regions. Based on research conducted by Ifmalinda [3], digital image processing techniques can be used to process the visual perception of citrus fruit maturity. The mask obtained using the segmentation method then used to isolate the fruit area to extract the color features. In this study, segmentation is carried out using a color approach, where the system is first given a knowledge base in the form of the extracted values of RGB component features such as L*a*b and HSV color features. In this research, the maturity level is divided into 3 classses, which is commonly used also by the farmer to grade the citrus. 308 pairs of top and bottom part images have been processed and the color features have been extracted. Maturity level labelling also has been added to the data set using visual judgment and confirmed by the destructive test. Table 1 shows the sample of the extracted dataset including the label.

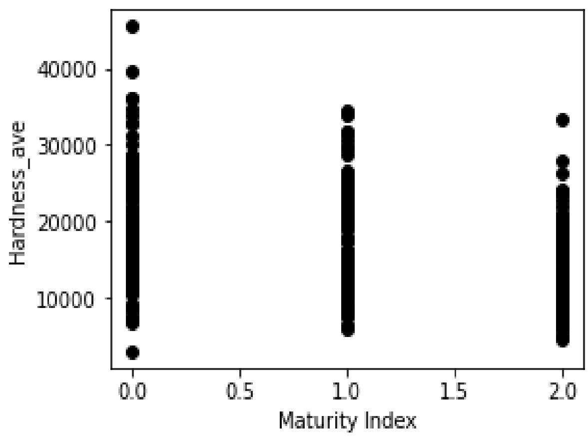
Table 1. Color features extraction dataset

Sample	R_avg	G_avg	B_avg	L_avg	a_avg	b_avg	H_avg	S_avg	V_avg	Maturity
1	129.559	139.045	50.354	141.711	112.370	171.762	33.632	161.743	140.263	0
2	106.545	125.774	56.299	127.012	109.896	162.202	39.110	138.360	125.868	0
3	161.096	151.733	59.524	158.092	120.116	175.498	28.245	159.342	163.802	0
…	…	…	…	…	…	…	…	…	…	…
194	233.745	164.241	52.807	185.187	144.881	190.327	18.348	194.448	233.745	1
195	228.465	161.389	50.730	181.895	144.091	189.608	18.609	195.488	228.465	1
196	229.585	178.309	68.645	193.093	136.699	186.855	20.406	176.023	229.585	1
…	…	…	…	…	…	…	…	…	…	…
306	91.599	105.401	56.703	108.065	114.344	153.277	38.792	117.306	105.706	2
307	87.828	102.474	57.965	104.957	114.356	151.133	40.165	111.137	102.751	2
308	144.114	144.883	50.784	149.051	115.802	174.597	31.096	164.726	149.685	2

3.3. Physico-Chemical Measurement

The hardness value of citrus as a result of the measurement decreased from the maturity level of index 0 (raw) to index 2 (ripe). The higher level of maturity of citrus fruits, the hardness value decreases as shown in Figure 4. In accordance with the opinion of Huber (1983) in [3], which states that maturity is always marked by a decrease in fruit hardness caused by changes in the structure and chemical content of the fruit. The cell wall carbohydrates in fruit tissue. Hardness is the resistance of the fruit to a given pressure. The correlation of the maturity index with the measurement of the hardness value can be seen in Fig. 5.

Total soluble solids (TPT) of citrus at 3 ripeness indices showed a change in the total dissolved solids content where from index 0 to index 1 increased, but from index 1 to index 2 slightly decreased. According to [3], states that the total dissolved solids content is directly proportional to the age of the fruit and reaches the highest level at the maximum age. The total dissolved solids content increases due to the change of starch into sugar. The results of observations of TPT levels or degrees of brix by using a brix meter showed significant differences in the 3 fruit maturity indices. As can be seen, the maturity index group 0 or unripe fruit to the fruit group with maturity index 1 increased to a maximum point of 15^{o}brix. However, the fruit from the maturity index 1 to the maturity index group 2 decreased until the maximum point was found at the value of 12^{o}brix. The characteristics of the brix value are in accordance with what is written by [9], where the level of sweetness in this orange is 10-12^{o}brix. The correlation of the maturity index with the measurement of the TPT value on the brix degree value can be seen in Fig. 6.



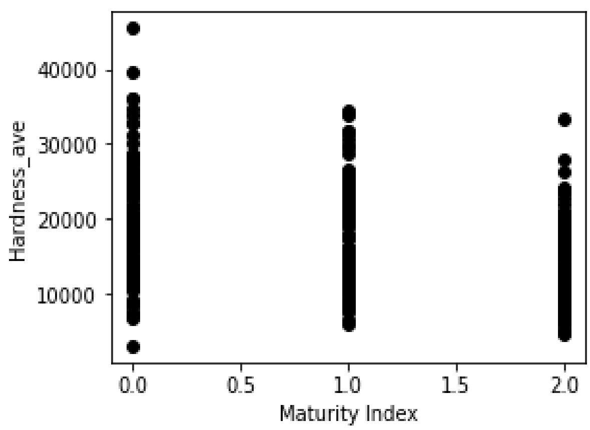


Figure 5. Correlation maturity index with a hardness value

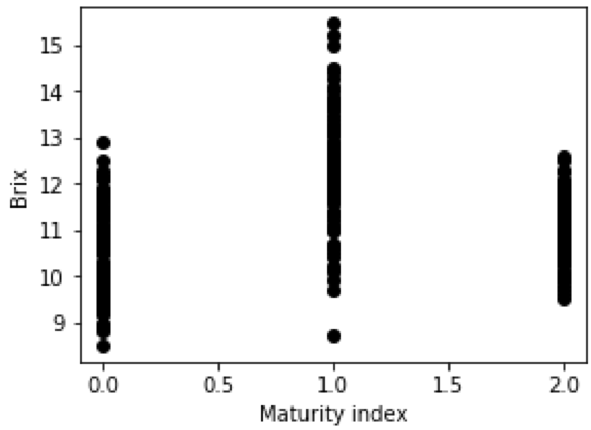


Figure 6. Correlation maturity index with a degree of brix

The value degree of acidity in the research data shows an insignificant difference. According to Novijanto (1997), organic acids decrease during maturity because they are used in respiration or converted into sugar. The acids can be considered as a reserve energy source for fruits, so they can be expected to decrease during the greater metabolic activity that occurs during ripening. The results of the correlation of the maturity index with the measurement of the degree of acidity can be seen in Fig. 7.

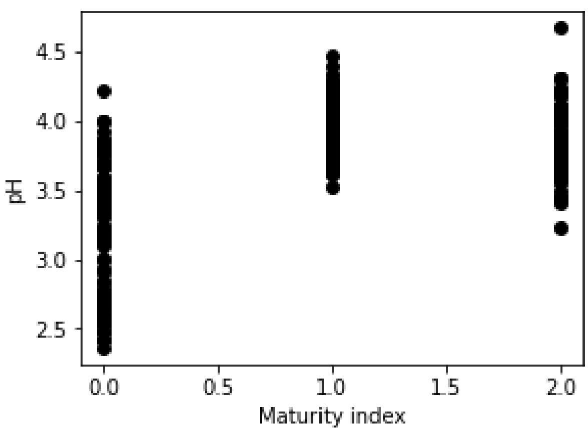


Figure 7. Correlation maturity index with a degree of pH

3.4. Machine Learning Models

Optimization modelling on machine learning with input color features that have been obtained from image processing. The learning model is divided into two parts, namely training data and test data. The machine learning model has been trained using 80% of the dataset and then the result was tested using the rest of the dataset. Table 2 shows the results of the accuracy of training and testing of several machine learning models.

Table 2. Accuracy machine learning model

Input features color		**Model**	**Training accuracy**	**Testing accuracy**
RGB	1	SVM (*Support Vector Machine*) (Kernel : RBF, gamma : 1.7)	88.57%	88.71%
L*a*b,	2	Decision Tree (criteria : *entropy*)	100%	88.71%
HSV	3	Logistic Regression (L.2 Regularization)	87.35%	88.71%
	4	Random Forest (n_estimator : 30)	100%	88.71%

The equation of accuracy results from the test data shows a uniform value. The classification performance evaluation model in this study uses a confusion matrix. The confusion matrix is a visualization tool that can generate accuracy values from algorithm validation against existing datasets such as supervised learning. The evaluation criteria can be seen in the computational or performance criteria and the utility or relevance criteria [11]. The evaluation results show that the values in the diagonal series are in the right direction (actual), where the prediction is the same as the actual value. Four machine learning models at the table, the SVM model shows the best data because the distance between training accuracy and the testing accuracy is very minimum. The confusion matrix image of the SVM model can be seen in Fig. 8 and the SVM model confusion matrix illustration can be seen in Table 3.

Table 3. SVM model confusion matrix illustration

Maturity index (*Predictive*)	**count**	**0**	**Output (*Actual*) 1**	**2**	**validation**	**%validation**
0	21	19	0	2	19	90%
1	16	0	14	2	14	87.5%
2	25	2	1	22	22	88%
			Total			88.5%

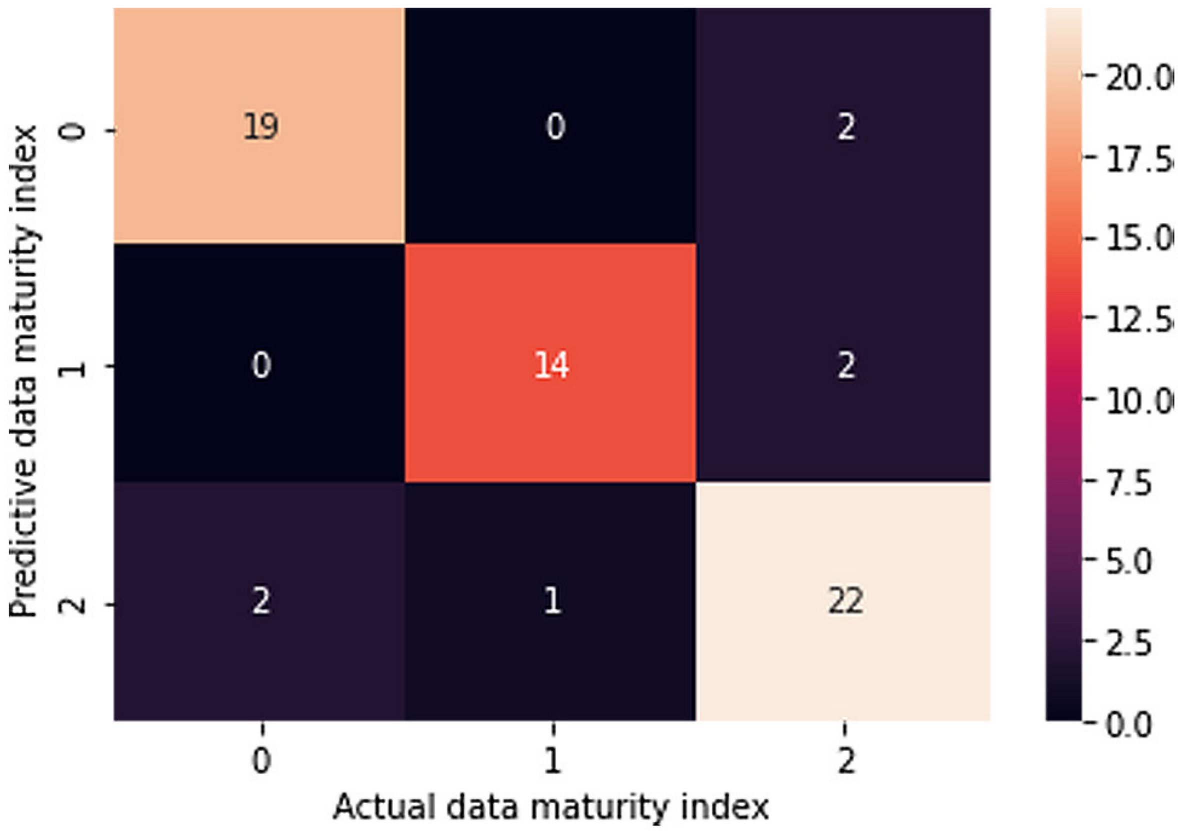


Figure 8. SVM model confusion matrix

From the confusion matrix above, the x-axis shows the actual data on the maturity classification, while the y-axis is the predicted data. In the SVM model above, the results of the maturity classification test show that at index 0 the predictive data produces 19 correct data from 21 total images, the remaining 2 are detected in the system including index 2, so that the correct percentage output is 90%. At index 1, the prediction data yielded 14 truths from 16 total images, the remaining 2 were detected in the input system in the index category 2, so that the percentage output obtained was 87.5%. In the actual data index 2 produces a total of 22 of the total 25 images, 2 other images are detected at index 0, and the remaining 1 is detected at index 1, so that the truth presentation output is 88.71%. The accuracy of the maturity prediction with the SVM model has included the good category. In previous research conducted by [11], the statistical feature extraction method and SVM can detect the level of maturity of melons based on the texture of the fruit skin giving an accuracy rate of 76%. Evaluation of the confusion matrix of the SVM model on the classification of the maturity level of citrus can be seen in the table 4.

Representatively, when choosing a model should be based on the problem and the dataset. The two previous equations have different variables where precision uses false positives while recall uses false negatives [11]. Determining the model that predicts the maturity level of oranges in this problem is a data model with a high precision value, because the greater the precision value, the higher accuracy of the fruit maturity prediction value.

Table 4. Confusion matrix evaluation

Machine learning model	Confusion matrix evaluation	Accuracy
Logistic Regression	Precision	0.893
	Recall	0.867
	F1-score	0.883
SVM	Precision	0.893
	Recall	0.87
	F1-score	0.867
Random Forest	Precision	0.883
	Recall	0.897
	F1-score	0.886
Decision Tree	Precision	0.883
	Recall	0.897
	F1-score	0.886

4. Conclusions

An image RGB color feature extraction can be used for feature extraction in images. The results of feature extraction are used as input for the classification model in recognizing image patterns and classifying the maturity level of citrus fruits. Classification of the maturity level was predicted by processing color imagery with RGB, L*a*b, and HSV color feature extraction as well as physico-chemical measurements which included measuring the value of fruit texture hardness, total dissolved solids value at brix degrees and the value of the degree of acidity. The higher the maturity level of citrus, the total dissolved solid, the value of color on texture will increase, but the total acid and value of hardness will decrease. A machine learning model with good accuracy in the classification of citrus, namely the SVM (Support Vector Machine) model provides an accuracy rate of 88.71%. The success of identifying is influenced by the features that are used as characteristics in the classification method. The low accuracy results require the addition of other features such as the level of texture, morphology or geometry.

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