Reliability Testing of Single Channel Co-Occurrence Matrix Texture Feature Extraction for Avocado Leaf Classification

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Abstract. There are quite a lot of superior types of avocado that are known to the public today. However, it isn't easy to differentiate one type from another based on the leaves. These can cause errors in variety selection, which can cause losses. Machine learning methods can help recognize avocado types based on leaves. This research uses the GLCM (Gray Level Co-occurrence Matrix) method which is applied to single-channel in the YUV color space, not GLCM in general. These have been proven effective in several previous studies. To measure the reliability of this feature extraction method, this study used four cameras of different brands and resolutions. The feature extraction results are then classified using several classification methods: SVM (Support Vector Machine), KNN (K-Nearest Neighbor), and Random Forest. To further increase accuracy, majority voting was carried out for the three classifiers. By conducting majority voting, it has proven successful in increasing accuracy compared to a single classifier. The highest classification results were achieved by the Random Forest classifier with an accuracy of 85.83%, and the results successfully increased to 87.50% by applying majority voting. This indicates that the selected feature extraction method is relatively reliable even when mixing datasets from camera sources with different specifications.

Keywords: Avocado leaf disease, GLCM feature extraction, majority voting accuracy

INTRODUCTION

Avocado plants are widely cultivated in Indonesia, which has a tropical climate. Avocados most likely originate from Mexico and have spread throughout the world in both tropical and subtropical [8]. Indonesia is the largest avocado producer in Asia and contributes 5.9% of world avocado production [5]. There are quite a lot of superior types of avocado plants currently circulating. The relatively large number of avocado varieties causes the problem of difficulty in distinguishing one type of avocado plant from another. One way to differentiate avocado plants is by looking at the characteristics of the leaves. However, the characteristics of one type of avocado leaf and another type are very similar, so ordinary people find it difficult to differentiate between several types of avocado plants if they look at the leaves alone.

The development of computer vision and machine learning for identification has caused major changes in botanical agriculture, one of which is the automatic identification of plant species [4]. To analyze an image, texture features are one of the most important feature, where the results of analyzing a texture feature can provide information regarding changes in color brightness or intensity and surface structure. Gray-level lo-occurrence matrix (GLCM) is a texture feature extraction method that has been proven to be very effective as a feature descriptor in representing the characteristic texture of an image [9]. This method will help overcome the problem of image-based texture analysis. Machine learning is a computing model that is currently widely used in various fields, one of which is agriculture. One of the algorithms contained in the machine learning model is often used and has very good accuracy in solving digital image classification problems, namely the Support Vector Machine (SVM) algorithm [10].

Research using GLCM and SVM methods has already been carried out, such as research [7] in early detection of plant stress to monitor the health status of eggplant plant leaves, with a dataset of 1000 leaf images for classifying healthy and unhealthy leaves, showing an average level of -average accuracy of 99.6%. Research on vegetation mapping [2] using GLCM and random forest achieved an accuracy of 92%. Classification of tomato ripeness levels [12] using KNN and GLCM in HSV color space produces accuracy up to 100% in several GLCM distance scenarios. Research on detecting plums in gardens [3] produced the highest accuracy using majority voting that uses 5-classifiers, getting an accuracy of up to 98.59%. Research [6] uses the GLCM feature extraction method and SVM classification

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to detect smoke for early monitoring of forest fires. Researchers carried out color filtering in the YUV color space and obtained an average accuracy value of 96.29%. Previous research [11] research on the classification of avocado plant types using the GLCM feature extraction method and canny edge detection as well as testing on a single channel in the YUV and HSV color spaces resulted in testing using the Single Channel Co-occurrence Matrix feature extraction method or on channels. The single YUV color space gets better accuracy values compared to texture feature extraction using the GLCM method on canny images. The accuracy value obtained is 93.33% on the U channel in the YUV color space [13].

Based on several studies above, this research is a follow up research conducted by [11] which will test the implementation of the Single Channel Co-occurrence Matrix feature extraction method in the YUV color space using different cameras. This aims to show whether different camera types affect the accuracy values obtained. The GLCM feature extraction method is good at detecting avocado leaf types, but this research cannot prove that if the test is carried out using a different camera, it is still good at recognizing avocado plant types. In research conducted by [1], several aspects that can influence the image recognition process include the shooting distance, type of acquisition tool, camera resolution, lighting techniques, magnification or zooming, distance and angle of image capture used in the acquisition process, so that during the feature extraction process it produces different values which can affect the accuracy values obtained.

The Single Channel Co-occurrence Matrix method is a derivative of the Gray Level Co-occurrence Matrix (GLCM) method. If in the GLCM method the input is in the form of greyscale image data, but in the Single Channel Co-occurrence Matrix method, the input is in the form of image data for each channel in the YUV color space. The RGB image will be converted first to YUV. Then the input from each YUV color channel will be searched for feature values in texture extraction using GLCM calculations. This research uses the SVM, KNN, and Random Forest methods in the image classification process. From the three methods, the ensemble method using the majority voting is then carried out to increase accuracy compared to the single classification method.

METHOD

The Dataset

The dataset used in this research uses primary data collected by ourselves by acquiring image data of three types of avocados using four different cameras on a white background. The three types of avocados are alligator, markus, and miki (Fig. 1 for examples). Each type of avocado consists of 50 images for each camera, so the total dataset produced is 50x4x3=600 images. Each camera has a resolution of 48, 12, 13, and 13 megapixels with different smartphone brands.

(a) (b) (c)

FIGURE 1. Types of avocados (a) alligator (b) markus (c) miki

The Methods

Fig. 2 shows the flowchart of the system in this research. First, the dataset is separated into 80% training data and 20% testing data. Then equalize the image size by resizing. The uniform image size is then converted to YUV color space from RGB color-space. Segmentation to remove background images is done in RGB color space using threshold values. The AND logic operation is then applied to the thresholded image and the YUV image to obtain a segmented YUV image. The extraction of 14 GLCM features is then applied to channel V of the YUV image. The feature extraction results are then used to train the selected classification model. Next is the evaluation process to measure model performance. Several scenarios were carried out to get the best model.

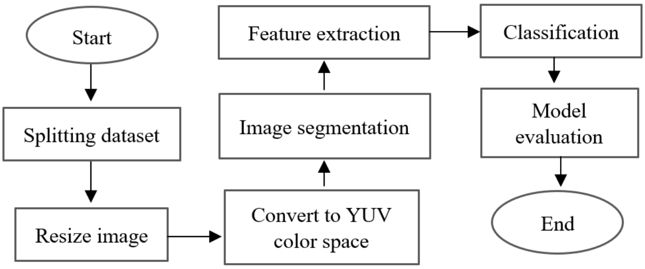

FIGURE 2. Flowchart of the system

Image Pre-Processing

The resolution of the four different cellphone cameras can provide bias in the feature extraction process. This is because the resulting co-occurrence matrix can provide different patterns. Therefore, it is necessary to normalize the image size or resolution to 1142 x 1701 pixels. This size was chosen after several trials using different image resolutions to achieve good accuracy with lower computation costs.

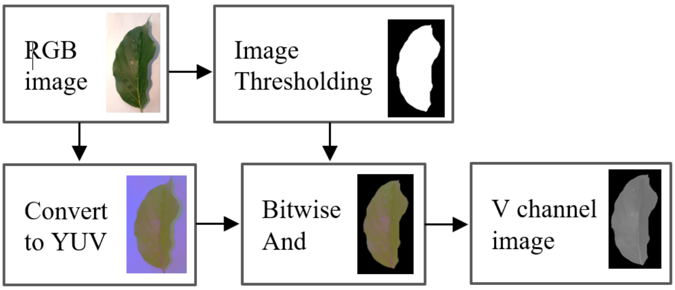

FIGURE 3. Segmentation process

Image Segmentation

Information on the type of avocado is in the avocado leaf area, so it is necessary to segment the image by removing the background image. Image segmentation carried out using thresholding on the RGB color channel because of the range of gray values of the red, green, and blue channels in the leaf area with different background values. Using a plain white background is also very helpful in the segmentation process of green leaf images. Fig. 3 shows the steps in the segmentation process. Image thresholding produces a black and white or binary image that will be operated to a YUV image using Bitwise And, and the output is a YUV image with a black background. YUV image with black background then split into Y, U, and V channels and only the V channel will be used then.

Feature Extraction

GLCM is a feature extraction method that has been proven very well in several previous studies. GLCM extracts gray-level image features, but in this research, GLCM use the V channel of YUV color images, which are single-channel images like gray-level images. There are 14 features extracted, starting from energy, entropy, etc., such as 14 Haralick texture features. The black background from the segmentation result is ignored in the GLCM calculation but only GLCM for the leaf area is calculated.

Classification Methods

The classification methods used in this research are SVM, KNN, and random forest. Based on previous research, the three classifiers can provide pretty good accuracy results. This research also combines the three classifiers using the majority voting or ensemble method, which generally can increase accuracy, such as the voting process in a random forest using a decision tree. The three classification methods have their advantages and are expected to increase accuracy by combining them into a new better classification method.

Model Evaluation

To measure model performance using several metrics, namely accuracy, precision, recall, and F1-score. These metrics can be calculated based on confusion matrices (CM) which is usually used to measure model performance by comparing predicted values and actual values (Zeng, 2020). Table 1 is a form of confusion matrix and the formula for each metric is shown in formulas 1 to 4.

TABLE 1. Confusion matrix

		Predicted class	
		Positive	Negative
Actual	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$precission = \frac{TP}{TP+FP} \quad (2)$$

$$recall = \frac{TP+TN}{TP+FN} \quad (3)$$

$$F1 = \frac{2\ x\ precission\ x\ recall}{precission + recall} \quad (4)$$

RESULTS AND DISCUSSION

For the reliability testing of the Single Channel Co-Occurrence Matrix Texture feature extraction method, all data from four cameras were combined. Each camera has different characteristics with resolutions of 48, 12, 13, and 13 megapixels and default settings that can produce different image details. The algorithm or method used must be able to produce the required information even with different data variations.

A total of 600 image data from four cameras were divided into 80% training data and 20% testing data to test system reliability. Image resizing is used to standardize or normalize image sizes. Image conversion to YUV color space obtains more optimal results because texture becomes more dominant in the V color channel compared to gray images based on experimental results. Several color channels in other color spaces have also been tested in previous research, but the best is the V channel in the YUV color space.

The GLCM extraction results on the YUV color channel are then used to train the SVM, KNN, and random forest methods. The result is a confusion matrix which is displayed in Tables 2, 3, and 4. Based on the confusion matrix, the accuracy of each method can be calculated. The accuracy of the training data was successful in obtaining SVM 75.42%, KNN 90.83%, and Random Forest 100.00%. Meanwhile, for testing data, SVM obtained 77.50%, KNN 85.83%, and Random Forest 85.83%.

TABLE 2. SVM confusion matrix results (a) training data (b) testing data.

		Predicted class		
		Alligator	Markus	Miki
Actual class	Alligator	125	14	21
	Markus	32	112	16
	Miki	26	9	125

		Predicted class		
		Alligator	Markus	Miki
Actual class	Alligator	32	2	6
	Markus	7	29	4
	Miki	7	1	32

TABLE 3. KNN confusion matrix results (a) training data (b) testing data.

		Predicted class		
		Alligator	Markus	Miki
Actual class	Alligator	152	5	3
	Markus	12	142	6
	Miki	12	6	142

		Predicted class		
		Alligator	Markus	Miki
Actual class	Alligator	39	1	0
	Markus	8	28	4
	Miki	3	1	36

TABLE 4. Random forest confusion matrix results (a) training data (b) testing data.

		Predicted class		
		Alligator	Markus	Miki
Actual class	Alligator	160	0	0
	Markus	0	160	0
	Miki	0	0	160

		Predicted class		
		Alligator	Markus	Miki
Actual class	Alligator	38	1	1
	Markus	6	29	5
	Miki	1	3	36

It appears that random forest can outperform the other two classifiers for both training data and accuracy. These results prove that the single-channel co-occurrence matrix feature extraction method is quite reliable, even with several different cameras the results are still very good. To further increase the accuracy of this panel, the researchers tried to combine the advantages of the three classifiers by using majority voting. The most votes will be the result of the prediction label and the results are shown in Table 5.

TABLE 5. Majority voting confusion matrix results (a) training data (b) testing data.

(a)

		Predicted class		
		Alligator	Markus	Miki
Actual class	Alligator	115	4	1
	Markus	2	155	3
	Miki	4	4	152

(b)

		Predicted class		
		Alligator	Markus	Miki
Actual class	Alligator	40	0	0
	Markus	8	29	3
	Miki	3	1	36

	precision	recall	f1-score	support
aligator	0.78	1.00	0.88	40
markus	0.97	0.72	0.83	40
miki	0.92	0.90	0.91	40
accuracy			0.88	120
macro avg	0.89	0.88	0.87	120
weighted avg	0.89	0.88	0.87	120

FIGURE 2. Classification report for majority voting method.

From Table 5, the calculation of training and testing accuracy is 96.35% and 87.50% respectively. It can be seen that the testing accuracy results using majority voting, increased from the accuracy of the single classifier random forest from 85.83% to 87.50%. The results of other metric calculations (precision, recall, and F1-score) are shown in Fig. 4. Testing was also carried out using 5-fold cross-validation and the average accuracy result was 85.17% from 5 accuracy values for each fold, namely 85.83%, 89.17%, 84.17, 83.33%, and 83.33%. Based on several metrics and 5-fold cross-validation, the model performance is still good, accuracy only decreases slightly for 5-fold cross-validation.

CONCLUSION

The single channel cooccurrence matrix in the V channel YUV color space was proven to still be reliable or function well even though it uses a mixture of datasets from 4 different cameras for avocado leaf image classification. The best accuracy of a single classifier is quite good, up to 85.83% using Random Forest. The majority vote of the three classifiers (SVM, KNN, and Random Forest) succeeded in increasing accuracy to 87.50%. For 5-fold cross-validation, the average accuracy obtained was 85.17%, a slight decrease from the best accuracy.

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