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The color features and *k*-nearest neighbor algorithm for classifying betel leaf image

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ABSTRACT

Piper betle L. (betel) is a species that belongs to the genus *Piper* and is a type of medicinal plant that is quite well known to the general population. The varieties of the leaf color may distinguish are red, green, and black betel. However, consumers still need assistance determining the differences between the many types of betel leaf. Therefore, using image processing techniques, this research contributes to building a classification method for distinguishing betel leaves based on color attributes. This approach anoints for the region of interest detection, feature extraction, and classification. In addition, three different classifiers, naïve Bayes, support vector machine, and *k*-nearest neighbors (*k*-NN), were used during the classification process. The evaluation for this study used a percentage split to divide a total of 180 images between the training and testing phases. The method's performance provided the highest accuracy value possible, 100%, by utilizing the color characteristics with the *k*-NN classifier.

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1. INTRODUCTION

Betel is a traditional growing plant that is significant all over the world due to the numerous health benefits it provides. Betel, a plant in the genus *Piper* and widely consumed in the Asian region, belongs to the *Piper* family [1], [2]. Betel is a genus belonging to the *Piperaceae* family, which contains many species that may be found around the tropics and subtropics, including in Indonesia [3]. In traditional medicine, betel leaf is employed as an anti-inflammatory agent, an antiseptic, an antibacterial agent, a bleeding stop, a cough reliever, a fart laxative, a salivary stimulant, a worm prevention agent, an itching reliever, and a sedative [4]. There are many different kinds of betel plants. Betel is distinguished because it is a long creeping tree that bears leaves between 4 and 7 inches long and between 2 and 4 inches wide [5]. The betel plant can be subdivided into a few distinct varieties, each distinguished by the color of the leaves. These include golden betel, white betel, red betel [6], green betel [7] and black betel [8]. Green betel, known scientifically as *Piper betel Linn*, and red betel, known scientifically as *Piper scrotum Ruiz* and *Pav*, are the most often cultivated betel in Indonesia. Because the leaves contain pharmacologically active phytochemicals, they are frequently utilized in various therapeutic applications [9].

Image processing techniques allow the classification of different types of betel plants according to the variations in the color of their leaves. Image processing can be characterized as a technology that uses computer algorithms to alter images stored digitally [10]. It is a broad definition, but it captures the essence of the concept. Image processing is converting pictures of objects into binary representations of a block outline network [11]. Brightness, contrast, contour, color, shape, and texture are the most fundamental components of an image captured digitally. The *k*-nearest neighbors (*k*-NN) approach is a valuable method for organizing information in image processing. Compared to other classification algorithms, *k*-NN stands out as a straightforward and successful approach [12]. *k*-NN is a method that may be used to locate the objects or groupings of objects in training data that are most similar to things in new data or test data. Additionally, the *k*-NN approach has high classification accuracy [13]–[16].

A previous study on the classification of image processing using the *k*-NN method includes research on the variety of Parijoto fruit (*Medinilla speciosa*), which acquired research results indicating that the *k*-NN approach can produce good accuracy with an accuracy value of 80% [16]. Other related studies include research on different varieties of fruit. Furthermore, the *k*-NN approach has been utilized in research projects to categorize the grade of vegetables based on the color of the vegetables. The *Bougainvillea papaya* fruit will serve as the focus of this investigation. According to the findings, the *k*-NN method is effective in classifying when utilizing random data, and the variation in *k* values 3, 4, 5, 6, 7, 8, and 9 all have an accuracy rate of 100% [17]. Other research employed the *k*-NN method in conjunction with first-order and second-order statistical characteristic extraction techniques and an approach based on the gray-level co-occurrence algorithm to determine the degree to which cucumbers have reached their peak level of maturity. Both methods yielded the same high accuracy value of 96.05% in their respective outcomes [18].

The research contributions utilize a practical feature extraction method for color characteristics based on RGB color spaces and identify the variety of betel leaves using machine learning. These color features include mean, standard deviation, variance, skewness, kurtosis, and entropy. It was decided to perform the following primary procedures: region of interest (ROI) detection, feature extraction, and classification. The efficiency of the method's performance was evaluated using three different classifiers: naïve Bayes, support vector machine (SVM), and *k*-NN. Due to the color characteristics' reliability in distinguishing between the many betel species, these characteristics have been applied.

2. MATERIAL AND METHOD

The betel classification method was divided into two distinct stages: training and testing. The following primary processes were included in each stage: ROI detection, feature extraction, classification, and evaluation method [19]. This method utilized an image of a betel leaf as the input data source. The leaf was categorized into three classes: green betel, red betel, and black betel. The procedure of detecting the ROI and performing any necessary preprocessing occurred first, with the intention of making the subsequent steps more straightforward. Afterwards, feature extraction was utilized to provide color and texture feature values to determine the qualities of the betel leaf. In the final step, classification was used to determine the type of betel leaf based on the image data. It was accomplished by analyzing the images. Figure 1 illustrates the progression of these processes in their proper order. Meanwhile, the subsequent subsection will describe the specifics of each primary process.

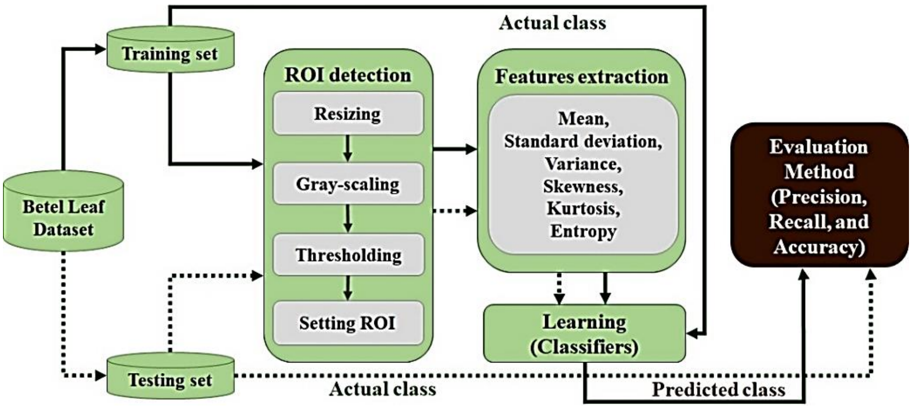


Figure 1. An overview of betel leaf classification method

2.1. Image acquisition

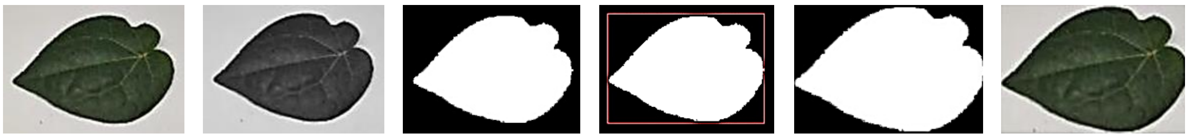
The image capture in this study was accomplished through the use of several tools, including a studio minibox, an LED strip light with 220 V of power and a distance of 27 cm, and a Xiaomi Mi 9 smartphone camera with a resolution of 48 megapixels, in addition to a tripod. The studio minibox is 27×27×23 cm in dimensions. The betel leaf was positioned precisely in the middle of the white studio minibox. The camera was tilted at a 45-degree angle on a tripod and pointed toward the object. About 20 centimeters separated the camera from the studio minibox. The acquired images may have three different colors of betel leaves: green, red, and black [20]. The generated JPEG file measured 4000×1844 pixels. A total of 180 leaf images were collected to form the dataset. It consisted of 60 images for each class. Figure 2 depicts the settings in which their images can be acquired, and Figure 3 presents examples of three different betel leaf types.

Figure 2. The scenario of image acquisition

Figure 3. The example image of three types of betel leaf

2.2. ROI detection

The image size was reduced since a sub-image containing most of the betel leaf area was formed by this process [20], [21]. The first step was to reduce the original image's dimensions from 4000×1844 to 640×480 [22]–[24]. The image is then grayscale after being resized. The area of the betel leaf was also estimated using the Otsu method in the thresholding step [25], [26]. An ROI image's boundary betel leaf area was calculated using the thresholding result as a reference. Figure 4(a)-(f) depicts the outcome images each step produces in the ROI detection.



(a) (b) (c) (d) (e) (f)

Figure 4. Resulting image of each step in this process: (a) resized, (b) gray scaling, (c) thresholding, (d) setting ROI (red box is the reference betel leaf area), (e) reference betel leaf area, and (f) ROI image

2.3. Feature extraction

A feature extraction process produces the necessary information to assess the efficiency of the classification method. Prior to image categorization, feature extraction was required [19]. It aims to extract the features from an input image. The classifier can be prompted into action during the classification process by the features extracted from an object [20]. In this study, the features of each betel leaf image were extracted using the first-order method. The first-order features were employed based on the color. Six features were extracted using first-order parameters, including mean, standard deviation, variance, skewness, kurtosis, and entropy [23]. The following are all the feature parameters [27], [28].

- Mean (μ) gives the average grey level of each region, which formula is in (1),

$$\mu = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} Pij \tag{1}$$

where $M \times N$ is the size of the image, P is the size of the image, and ij is the j pixel in the i color channel.
- Standard deviation (σ) is the variance's square root, representing the image contrast. Image contrast levels were evaluated with high and low variance values. The formula for σ is shown in (2),

$$\sigma = \sqrt{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(X_{ij} - X_i\right)^2} \tag{2}$$

where $M \times N$ is the size of the image, X is the image pixel, and $\underline{X}$ is *mean*.
- Variance shows the variation of elements in the histogram of an image. The variations are determined using (3).

$$\sigma^2 = \sum_n (fn - \mu)^2 \, P(fn) \tag{3}$$

- Skewness shows the relative slope of the histogram curve in an image, which can be found by (4).

$$a^3 = \frac{1}{\sigma^2} \sum_n (fn - \mu)^3 \, P(fn) \tag{4}$$

- Kurtosis is the relative height of the image histogram curve. For calculating kurtosis, the formula is in (5).

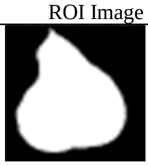
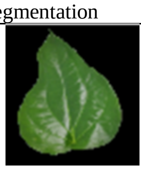
$$a^4 = \frac{1}{\sigma^4} \sum_n (fn - \mu)^4 \, P(fn) - 3 \tag{5}$$

- Entropy is a measure of the shape irregularity of the image. Entropy search is carried out using (6).

$$H = - \sum_n P(fn - \mu).^2 \, log \, P(fn) \tag{6}$$

First-order parameters yielded ten distinct features. The mean and standard deviation features were extracted in each channel of RGB color space. Table 1 displays the example result of feature extraction for each class.

Table 1. The feature extraction example utilizing three classes of betel leaf

ROI Image and Segmentation		Feature Extraction Result	
		• μR:83.5782 • μG:128.1491 • μB:60.6969 • σR:25.3576 • σG:17.8312 • σB: 29.4465	• S:3.433 • O:1.4084 • $\sigma 2$:443.587 • q:4.4043
Green Betel Leaf			
		• μR:52.0728 • μG:66.7755 • μB:44.6574 • σR:19.4376 • σG:17.8312 • σB: 18.2158	• S:3.433 • O:1.4084 • $\sigma 2$:443.587 • q:4.4043
Black Betel Leaf			
		• μR:91.7895 • μG:100.1152 • μB:80.46 • σR:41.5405 • σG:37.2215 • σB: 39.9909	• S:3.1305 • O:0.39183 • $\sigma 2$:1500.9 • q:2.0455
Red Betel Leaf			

2.4. Classification

The classification was the last step in the learning and testing process. The feature values generated by the subsequence procedure served as the input data in the present study. Many machine-learning strategies were used to sort betel leaves into the appropriate class according to their color. Three classifiers, including naïve Bayes, SVM, and *k*-NN, were carried out because of their validity while classifying a wide range of objects [29], [30].

2.5. Evaluation method

The evaluation method for classifying betel leaf employs a confusion matrix. The confusion matrix is a method for measuring a classifier's accuracy. This method can determine the newly formed class's precision, recall, and accuracy [31]. The confusion matrix resembles a square matrix of size N×N. N is the number of data classification classes, and the rows and columns represent the actual number of data classes [32]. This study evaluates the confusion matrix using three criteria: recall, precision, and accuracy. These parameters are derived using (7) to (9) [29].

$$precision = \frac{TP}{TP+FP}\ x\ 100 \quad (7)$$

$$recall = \frac{TP}{TP+FN}\ x\ 100 \quad (8)$$

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN}\ x\ 100 \quad (9)$$

True positive (TP) and true negative (TN) are the number of test data classified correctly (target class equal to output class). False positive (FP) is the number of actual data that was negative, but the method predicted a positive value. Meanwhile, false negative (FN) is the number of true positive values, but the model predicted a negative value. The number of TP, TN, FP, and FN is obtained based on the confusion matrix. The dataset of betel leaves was subdivided into k sets. The validation result of mean *k*-time was used as the final rate estimation. The study's performance was determined using 10-fold cross-validation.

3. RESULTS AND DISCUSSION

Each of the three classes used in the betel leaf classification method consists of 60 images; therefore, a total of 180 images were needed to complete the task. This method used color features and three machine learning techniques (naïve Bayes, SVM, and *k*-NN). Precision, recall, and accuracy were used to assess the classification method performance. The data was separated between a training set and a test set using a percentage value of 60:40 (108 images and 72 images, respectively), 70:30 (126 images and 54 images, respectively), and 80:20 (144 images and 56 images, respectively). Tables 2 to 4 highlight the evaluation results for the developed color feature-based technique.

Table 2. The classification results with the percentage-split value of 60%:40%

Classifiers	Green betel		Black betel		Red betel		Accuracy (%)
	Precision (%)	Recall (%)	Precision (%)	Recall (%)	Precision (%)	Recall (%)	
Naïve Bayes	95.83	76.67	70.83	94.44	100.0	100.0	88.89
SVM	95.83	100.0	80.95	94.44	100.0	85.71.0	93.06
k-NN	95.83	100.0	80.95	100.0	100.0	82.76	93.06

Table 3. The classification results with the percentage-split value of 70%:30%

Classifiers	Green betel		Black betel		Red betel		Accuracy (%)
	Precision (%)	Recall (%)	Precision (%)	Recall (%)	Precision (%)	Recall (%)	
Naïve Bayes	88.89	100.0	100.0	90.00	100.0	100.0	96.29
SVM	94.44	100.0	100.0	94.74	100.0	100.0	98.15
k-NN	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table 4. The classification results with the percentage-split value of 80%:20%

Classifiers	Green betel		Black betel		Red betel		Accuracy (%)
	Precision (%)	Recall (%)	Precision (%)	Recall (%)	Precision (%)	Recall (%)	
Naïve Bayes	91.67	100.0	100.0	92.31	100.0	100.0	97.22
SVM	91.67	100.0	100.0	92.31	100.0	100.0	97.22
k-NN	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Based on the accuracy values obtained, Tables 2 and 3 show that naïve Bayes obtained the lowest accuracy values, 88.89% and 96.29%, respectively. In contrast, Table 4 shows the accuracy value achieved by naïve Bayes similar to the SVM classifier, namely 97.22%. Furthermore, *k*-NN indicates to produce a maximum accuracy value of up to 100%, as shown in Tables 3 and 4. However, the accuracy achieved by *k*-NN has decreased with a value of 93.06% with a percentage-slit value of 60:40, as shown in Table 2. Even so, this value is the same as SVM and is a classifier capable of producing the best performance with the percentage-slit value of 60:40. Regarding each class's precision and recall values, naïve Bayes shows that errors often occur because green betel is classified as black betel. Meanwhile, the misclassification in applying SVM and *k*-NN, namely black betel, was classified as red betel.

Table 5 summarizes the performance results obtained from various prior works on leaf classification methods and the suggested method. This overview aims to present the progress made in leaf classification methods. The previous works employed distinct feature extraction and classification techniques applied to the specific datasets available. No research has been conducted on categorizing betel leaves using datasets comparable to those engaged in this research.

Table 5. Results of several performance methods for leaf classification in previous research

No.	Approach	Accuracy
1	The combination method of SVM and Gaussian mixture model [5]	83.69%
2	The genetic algorithm selected the best seven features out of 24 existing features with *k*-NN classifier [13]	100.00%
3	Features extraction applied gray-level co-occurrence matrix (GLCM), while the classification performed using *k*-NN [17]	80.00%
4	Extracting the statistical features with order one and two GLCM methods with *k*-NN [19]	96.05%
5	Proposed method using first-order parameters based on RGB colors space and *k*-NN	100.00%

4. CONCLUSION

The method for separating green betel, black betel, and red betel leaves was developed in this study. Image capture, ROI detection, feature extraction, and classification comprise the methodology's four core steps. A total of 180 images of betel leaves were taken and used for evaluation and practice. To find ROI, we used the Otsu thresholding approach, and then we extracted features. Color features were used to remove the features with first-order parameters. The dataset was split into a training set and a testing set following the 70:30 and 80:20 rule for the three machine learning algorithms (naïve Bayes, SVM, and *k*-NN) used in the classification. By utilizing both color features and the *k*-NN classifier, the approach reached a maximum accuracy of 100%. The evaluation findings indicated that the proposed technique adequately matched the study's dataset.

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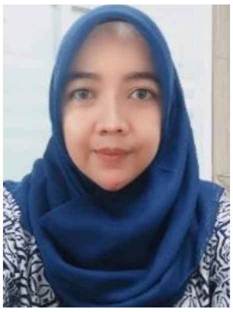

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