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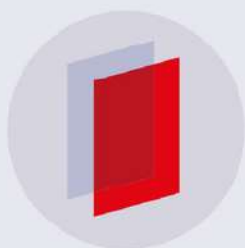
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Leaf feature extraction using glcm, moment invariant and shape morphology for indonesian medicinal plants recognition

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Abstract. This study aims to determine the extraction of GLCM texture features, shape morphology and moment invariant features on the leaf image of medicinal plants and determine the accuracy of plant recognition based on these three features by using Artificial Neural Network Classifiers. The procedure performed to classify medicinal plants based on their leaf image is image acquisition, image pre-processing, feature extraction, image classification and calculating the accuracy of test results. The introduction had tested for ten Indonesian medicinal plant samples, namely: Bangun-Bangun, Binahong, Jarak, Kemuning, Mangkoka, Mengkudu, Pegagan, Sambiloto, Sambung Nyawa, and Sirih. Based on the test results, obtained 97% accuracy with GLCM features, 69% with Shape Morphological features, 86% with GLCM and Shape Morphological features and 79% with moment invariant features.

1. Introduction

The wide variety of medicinal plants in Indonesian makes it difficult for most people to recognize existing plants. The introduction of plants can generally be using taxonomy/dendrology. Plants are identified based on their characteristics; these characteristics were informed from the leaves of plants. Leaves are one great plant that is often used to determine types of plants. Leaves are used object because each plant has a different leaf shape. Also, it is easier to obtain because it does not depend on the season. However, observing the characteristics of the leaves directly requires a relatively long and inefficient time. Therefore, we need a system that can recognize the types of medicinal plants.

In previous studies conducted by Chaki and Parekh [3] Classification of Plant Leaves Using Shape Features and Artificial Neural Networks resulted from accuracy of 80.56% and research conducted by Kadir et al. [6] Classification of Leaves Using Shapes, Colors, and Textures with The Artificial Neural Network produces an accuracy rate of 93.75%. Syahputra H. [4] has used 22 GLCM features for leaf image recognition. The recognition results obtained were 83.3% for three types of plants.

In this study, leaf feature extraction will be carried out using Gray Level Co-Occurrence Matrix (GLCM), Moment Invariant and Leaf Morphology. Furthermore, the introduction process will be handled using an artificial neural network classifier. Backpropagation can train the system before it is applied to recognize the image of the leaf that identified for its type [9]. Finally, In the system built, the accuracy of the results of the recognition will be compared with the three extraction methods used.

2. Methodology

The system is designed as shown in Figure 1 below:



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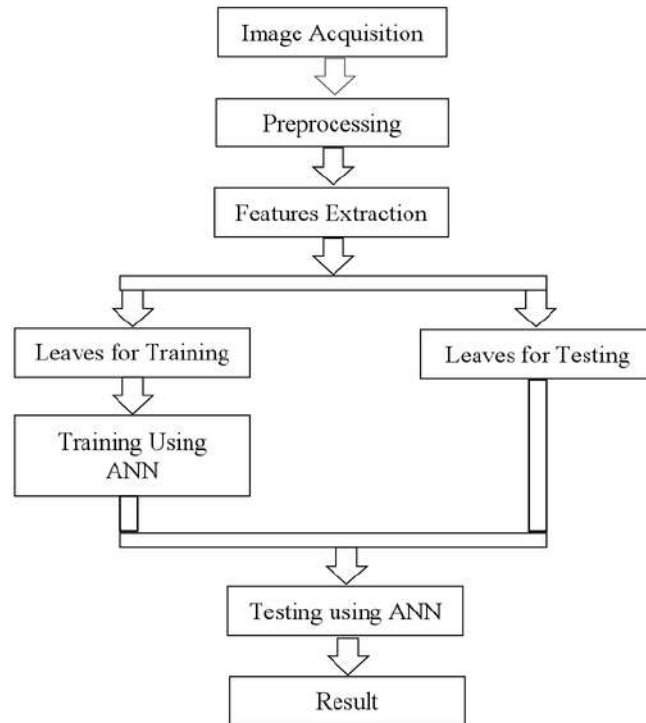


Figure 1. Scheme of research

2.1. Image Acquisition

In this study, 10 types of medicinal plants were used, which consisted of Bangun-Bangun, Binahong, Jarak, Kemuning, Mangkokan, Mengkudu, Pegagan, Sambiloto, Sambung Nyawa, and Sirih. The image of these leaves is taken as many as 60 images for each type of plant. All data will be pre-processed and extracted their features so that the properties of the leaf image were obtained, then divided into two data, 40 images to be trained using ANN backpropagation classifier and 20 to be tested or recognized.

2.2. Preprocessing

Pre-processing is performed to adjust the image so that the image is of better quality and the image does not lose valuable information in it. Image preprocessing is performed to obtain grayscale images and binary images that are used to detect the texture and shape feature values of the image. Preprocessing starts with resizing images, converting color images to grayscale and binary, improving the quality of grayscale images and segmentation.

2.2.1. Images Resizing. The acquired RGB image is 4608×3456 pixel. To accelerate and simplify the system process, the RGB image is resizing to 1/100 from the size of the initial image, so that the entire image becomes approximately 461×346 pixels.

2.2.2. Converting RGB Image to Grayscale and Binary. After resizing, the image converted to an image whose has a matrix that can be used to represent the texture and shape values of the image. Therefore, the resized RGB images are converted to grayscale and binary (see Fig. 2).

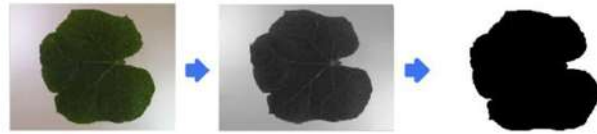


Figure 2. Image Converted to Grayscale and Binary

2.2.3. Quality Improved of Grayscale Images. To get a good texture value from the grayscale image, it is necessary to improve image quality. Image quality improvement serves to uniform the intensity that may be uneven when taking images so that the texture and characteristics of the leaf object can be seen clearly.

2.2.4. Images Segmentation. Image segmentation is to change the image background to black to getting 0 value in the matrix and to eliminate the noise that might be taken in the acquisition process. The segmentation process is carried out on grayscale and binary images (see Fig. 3).

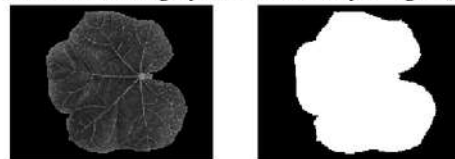


Figure 3. Grayscale image and segmented Binary image

2.3. Features Extraction

In this research, the recognition of medicinal plants is designed using three extraction methods, that is Gray Level Co-Occurrence Matrix (GLCM), Shape Morphology and Invariant Moment.

2.3.1. Gray Level Co-occurrence Matrix (GLCM) Extraction. GLCM is a matrix that represents the interpixel neighbor relationship in the image in various directions of orientation θ and spatial distance d . The GLCM matrix is one of the most popular and effective sources of natural texture analysis. The GLCM matrix of an image $f(x, y)$ is a two-dimensional matrix (x, y) where each element of the matrix represents the probability of occurrence along with the intensity level x and y at a certain distance d and angle θ . Five GLCM features used follow:

1. **Angular Second Moment (ASM)**

ASM represents the size of the image homogeneity.

$$ASM = \sum_x \sum_y (p(x, y))^2 \quad (1)$$

Where $p(x, y)$ is the value in row x and column y in matrix normalization.

2. **Contrast**

Contrast is a measure of the difference between the gray level of an area in an image. In a histogram, contrast shows the size of the spread of the image intensity value

$$Con = \sum_x \sum_y (x - y)^2 p(x, y) \quad (2)$$

3. **Correlation**

Indicates the size of the linear dependency of the intensity used to indicate the linear structure in the image.

$$Con = \frac{\sum_x \sum_y (x-y)^2 p(x,y) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (3)$$

4. *Inverse Different Moment (IDM)*

Demonstrating the level of image homogeneity with similar intensity values, relatively homogeneous images have large IDM.

$$Con = \sum_x \sum_y \frac{1}{1+(x-y)^2} p(x,y) \quad (4)$$

5. *Entropy*

Represent the size of irregularity in the texture shape of the image. If the image structure is regular, then the entropy value is large. On the contrary, if the entropy value is small, it means that the structure of the image is irregular.

$$E = -\sum_x \sum_y p(x,y) \log_2(p(x,y)) \quad (5)$$

2.3.2. *Shapes Morphology Features.* The shape feature is used to distinguish objects whose shapes are geometrically different. In the shape feature, the image used is a binary image. Some features of the form used are as follows [1]:

1. *Area and Perimeter*

Area (A) is the number of constituent pixels of an object. The perimeter (P) of an object is the length of the border of the image object.

2. *Compactness*

Compactness C of an object was measured through the analysis of dimensionless form factors with the following 2.6 equation:

$$C = \frac{P^2}{A} \quad (6)$$

Where C, A, and P are compactness, area, and perimeter respectively. Compactness is used to identify the shape and size of the same object, but with a different edge profile.

3. *Roundness*

The roundness (R) of an object is defined as:

$$R = \frac{4 \times \pi \times A}{P^2} \quad (7)$$

4. *Leaning*

Lean shape features are used to distinguish between wide and narrow objects (fat and thin). A Slim shape was measured by comparing the width and length expressed by the following equation [8]:

$$Leaning = \frac{\text{width}}{\text{length}} \quad (8)$$

2.3.3. *Invariant Moment Features.* Moment Invariant is a method of taking characteristics of an object. Characteristics taken can be in the form of position, area, orientation, and other characteristics. This method was introduced by Hu in 1962.

The basic equation of the moment an object is defined in equation 2.9:

$$m_{ij} = \sum \sum x^i y^j a_{xy} \tag{9}$$

The central moment μ is the moment corresponding to the center of the area. The central moment is defined in equations 2.10 to 2.14.

$$\mu_{ij} = \sum \sum (x - x')^i (y - y')^j a_{xy} \tag{10}$$

$$x' = \frac{m_{10}}{m_{00}} \quad \text{dan} \quad y' = \frac{m_{01}}{m_{00}} \tag{11}$$

$$m_{00} = \sum \sum a_{xy} \tag{12}$$

$$m_{10} = \sum \sum x_1 a_{xy} \tag{13}$$

$$m_{01} = \sum \sum y_1 a_{xy} \tag{14}$$

Then the normalized center moment has the following 2.15 equation:

$$\eta_{ij} = \frac{\mu_{ij}}{(\mu_{00})^{\lambda}}; \quad \lambda = \frac{(i + j)}{2} + 1 \tag{15}$$

Where:

η_{ij} = central moment

(x', y') = centroid citra with x' dan y' coordinate

The results of the normalized moment produced 7 results from the normalized moment, resulting in 7 moments of invariants which can be seen in the following equations 2.16 to 2.22 [10].

$$\phi_1 = \eta_{20} + \eta_{02} \tag{16}$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{17}$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2 \tag{18}$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2 \tag{19}$$

$$\begin{aligned} \phi_5 = & (3\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12}) \\ & [((\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2) + \\ & (\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - \\ & (\eta_{21} + \eta_{03})^2] \end{aligned} \tag{20}$$

$$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (21)$$

$$\begin{aligned} \phi_7 = & (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12}) \\ & [((\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2) + \\ & (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - \\ & (\eta_{21} + \eta_{30})^2] \end{aligned} \quad (22)$$

2.4. Backpropagation Neural Network

After the image passes through the extraction process with GLCM, Shape Morphology and Invariant Moment, image classification with Backpropagation Neural Networks is carried out. Backpropagation Artificial Neural Network is a multi-layer artificial neural network that changes the weight by way of backing from the output layer to the input layer. The goal is to train the network to get a balance of the ability to recognize the patterns used during training and the ability of the network to respond correctly to input patterns with the patterns used during training [7]. The input used is the result of the feature values of each feature extraction.

Backpropagation network training begins with building a backpropagation network architecture. Backpropagation network architecture is used to train the network until it is considered capable of being implemented in the testing process so that it produces output in the form of images that can be recognized correctly.

The training system is using the following backpropagation algorithm [9]:

Step 0: Initialize all weights with small random numbers

Step 1: If the termination condition has not been met, do steps 2 - 9.

Step 2: For each pair of training data, do steps 3 - 8.

Phase I: Advanced Propagation

Step 3: input unit receives a signal and passes it to a hidden unit on it

Step 4: Calculate all outputs in the hidden unit z_j ($j = 1, 2, \dots, p$)

$$\begin{aligned} z_net_j &= v_{j0} + \sum_{i=1}^n x_i v_{ji} \\ z_j &= f(z_net_j) = \frac{1}{1 + e^{-y_net_j}} \end{aligned} \quad (23)$$

Step 5: Calculate all network outputs in units y_k ($k=1, 2, \dots, m$)

$$\begin{aligned} y_net_k &= w_{k0} + \sum_{j=1}^n z_j w_{kj} \\ y_k &= f(y_net_k) = \frac{1}{1 + e^{-y_net_k}} \end{aligned} \quad (24)$$

Phase II: Backward Propagation

Step 6: Calculate the unit output factor δ based on errors in each output unit y_k ($k = 1, 2, \dots, m$).

$$\delta_k = (t_k - y_k) f'(y_net_k) = (t_k - y_k) y_k (1 - y_k) \quad (25)$$

δ_k is an error unit that will be used in changing the screen weight below (step 7).

Calculate the rate of change in weight w_{kj} (which will be used later to change weight w_{kj}) with the acceleration rate α .

$$\Delta w_{kj} = \alpha \delta_k z_j \tag{26}$$

Step 7: Calculate hidden unit factors δ based on errors in each hidden unit z_j ($j = 1, 2, \dots, p$)

$$\delta_{net_j} = \sum_{k=1}^m \delta_k w_{kj} \tag{27}$$

Hidden unit factor δ :

$$\begin{aligned} \delta_j &= \delta_{net_j} f'(z_{net_j}) \\ &= \delta_{net_j} z_j (1 - z_j) \end{aligned} \tag{28}$$

Calculate the rate of change weight v_{ji} (which will be used to change the weight v_{ji} later).

$$\Delta v_{ji} = \alpha \delta_j x_i \tag{29}$$

Fase III: Weight Changed

Step 8: Calculate all weight changes. Change of line weights that lead to the output unit:

$$w_{kj}(new) = w_{kj}(old) + \Delta w_{kj} \tag{30}$$

Change of line weights that lead to hidden units:

$$v_{ji}(new) = v_{ji}(old) + \Delta v_{ji} \tag{31}$$

3. Result and Analysis

The type of data used are 10 types of images of medicinal plant leaves, that is Bangun-Bangun, Binahong, Jarak, Kemuning, Mangkokan, Mengkudu, Pegagan, Sambiloto, Sambung Nyawa, and Sirih. With 40 images for system training and 20 images for testing or image recognition of medicinal leaves.

The introduction process was carried out with 4 different types of extraction, GLCM and Shape Morphology, GLCM, Shape morphology, and Moment Invariant. After the image obtained by its value based on the type of extraction performed, the value will be an input value in the backpropagation training process network. In the system training process, if the validation results show the MSE value is close to 0 (zero), then the system that is built is considered to have been implemented into the system [2]. In the training process for all systems shows the value is close to validation, so the network can be used to do recognition.

The results of the recognition of the image of medicinal plant leaves are from different extractions results can be showed as in Table 1 following.

Table 1. Results of recognition of the image of medicinal plant leave by using the four different extractions

Extraction	Hidden Layer Units	α	MSE	Accuracy
GLCM & Shape Morphology	10	0.01	0,072	86%

GLCM	100	0.01	0,001	97%
Shape Morphology	10	0.01	0,154	69%
Moment Invariant	10	0.01	0,102	79%

The results of recognition accuracy for each type of extraction used in detail based on the types of medicinal plants are as follows. Based on the results of accuracy, the system can recognize well the leaf in 3rd class, that is Jarak leaf. All systems that built with different types of extraction, the accuracy of Jarak in 3rd class is 100%. While the lowest is in class 10, sirih in last class that has an average accuracy of 71%. The high and low level of accuracy of the recognition results depends on the similarity of texture and leaf shape values in each type. If all data in the same type have the same characteristic value then it will be easily recognized correctly, if the characteristic value in the same type has diversity then the image will be wrongly recognized by another type that has the same value with that image.

While based on the type of extraction used, the highest level of recognition is generated by the system with GLCM extraction which reaches 97% and the lowest is produced by Shape Morphology which is 69%. This shows that the extraction value and the type of extraction used are very influential on the results of the accuracy of recognition. In this study, GLCM extraction is very good to be used to do image recognition because it can produce a high level of recognition.

4. Conclusion

Leaf Feature Extraction Using GLCM, Moment Invariant and Shape Morphology for Indonesian Medicinal Plants Recognition has been done successfully. Based on the test results, obtained 97% accuracy with GLCM features, 69% with Shape Morphological features, 86% with GLCM and Shape Morphological features and 79% with moment invariant features. The image classification system of medicinal plant leaves by using three types of feature extractions found that the system successfully recognized the types of medicinal plants with an average level of accuracy recognition of 100% on Jarak leaf and the lowest on sirih leaf by 71%. While based on the type of extraction used, the system shows that the extraction value and the type of extraction used are very influential on the results of the accuracy of recognition. GLCM extraction used in the system provides the best results with an accuracy rate of 97%.

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