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Automatic Identification of Herbal Medicines Based on Medicinal Plant Leaf Images Using the Scale Invariant Feature Transform (SIFT) Features

1st Anita Ahmad Kasim
Department of Information Technology
Tadulako University
Palu, Indonesia
nita.kasim@gmail.com

2nd Muhammad Bakri
Department of Architecture
Tadulako University
Palu, Indonesia
embakri@gmail.com

3rd Chairunnisa Lamasitudju
Department of Information Technology
Tadulako University
Palu, Indonesia

4th Ahmad Fachrozi
Study Program of Informatics
Tadulako University
Palu, Indonesia
ahmadfachrozi001@gmail.com

***Abstract*— Background: A few people prefer to consume medicinal plants compared to modern medicine. This is because modern medicine contains chemicals which over time can have a bad impact on the kidneys, and medicinal plants are also considered cheap treatments. Meanwhile, in our current environment, there are plants that grow and have certain benefits, but some people don't know whether these plants are herbal medicinal plants or not. By utilizing technology, people can find out about herbal medicinal plants based on the leaves by photographing them on an Android smartphone. Method: The method used to extract features from the leaf image is Scale Invariant Feature Transform (SIFT). Aim: This research aims to recognize leaves whose images have been photographed or uploaded. The system will identify herbal medicinal plants using the leaf image of the plant using the Scale Invariant Features Transform (SIFT) method. Result: Feature Extraction and Support Vector Machine (SVM). With this system, it is hoped that users will be able to identify herbal medicinal plants that may grow in the surrounding environment. Based on the description in the background above, the problem formulation in this research is how to identify herbal medicinal plants using leaf images using Android-based SIFT feature extraction. Conclusion: The results of the confusion matrix test explain that this system has an average accuracy of 77%, which means that this system is quite good at identifying leaf images, even though the error rate is quite high at 23%.**

Keywords—Medicinal Plant Leafs, SVM, SIFT

I. INTRODUCTION

The current role of digitalization can certainly be a supporting factor in the development of the world of health. There are many tools that help humans in carrying out tasks in the health sector that have been computerized, coupled with the role of several Artificial Intelligence (AI) or artificial intelligence created to make work easier. [1] The role of AI is very useful and is used to support health devices, such as AI which is used to detect internal diseases by several hospitals and which is used to detect DNA in several laboratories. Even though these features have been used and have given good results, there are still many other health fields that have not used Artificial Intelligence, even though it can be used for other purposes and can also be used for humans themselves.

Everyone needs to know about health because health is the most important factor for living creatures, especially humans. Health influences the productivity of human life, therefore health must be maintained as well as possible. If they are sick, people will look for ways to recover, one of which is with medicine. Medicines as objects or substances that can be used to treat, relieve, eliminate symptoms of disease, or change chemical processes in the body are definitely needed. There are several types of medicine, one of which is medicine derived from herbal plants, and to this day herbal medicine is still used to cure diseases.

Herbal medicine is an alternative that people use to heal and protect the body from disease. This is proven by the fact that many people still use herbal medicines as a means of healing and the discovery of extraordinary functions behind several herbal plants that make people use them. Currently, many people prefer to use herbal medicines from plants, apart from being easy to obtain, the reason people prefer herbal medicines is because they are natural medicines. Meanwhile, in our current environment there are certainly plants that grow and have certain properties, but some people don't know whether these plants are herbal medicinal plants or not and if they are medicinal plants, the properties of these plants are not yet known. Based on the problems described, the author intends to create a research entitled Identification of Herbal Medicinal Plants with Leaf Images Using Android-based SIFT Feature Extraction. The system will identify herbal medicinal plants using the leaf image of the plant using the Scale Invariant Features Transform (SIFT) method. Feature

Extraction and Support Vector Machine (SVM). It is hoped that users will be able to identify herbal medicinal plants that may grow in the surrounding environment[2].

The goal to be achieved in plants research is to produce a system that is able to identify herbal medicinal plants using leaf images using Android-based SIFT feature extractionin their research entitled Identification of Herbal Medicinal Plants Based on Leaf Images Using the Gray Level Co-occurence Matrix and K-Nearest Neighbor Algorithms. The aim of this research is to create a herbal medicinal plant recognition system that is capable of identifying and recognizing herbal medicinal plants. The information obtained can be in the form of digital images which are then analyzed and processed by the system. The system identifies images of leaves from herbal medicinal plants and recognizes a pattern or characteristic of the object. This research addresses the problem of the lack of information about herbal medicines for the public. The similarity between the research above and the research conducted by the author is that they both identify herbal medicinal plants using leaf images, but the difference is in the algorithm used, the research above uses the Gray Level Co-occurence Matrix and K-Nearest Neighbor algorithms while the author uses Scale Invariant Features Transform (SIFT) Feature Extraction and Support Vector Machine (SVM) [3].

Research on Plant Type Identification Using Leaf Images Based on Artificial Neural Networks. This research aims to identify plant types based on images from several leaf samples. The system identifies leaf images from several plants and recognizes a pattern or characteristic of the leaves and groups them into certain types of plants[4].

The similarity between the research above and the research conducted by these paper is that they both conducted research on leaf images. The difference is in research conducted is the algorithm used is Artificial Neural Network, while the author uses the Scale Invariant Features Transform (SIFT) Feature Extraction and Support Vector Machine (SVM) algorithms. Apart from that, the research above focuses on types of plants, whereas in this research the author only focuses on herbal plants.

The others work are researches about identified plant types based on extracting leaf morphological features using K-Nearest Neighbor[5]. The aim of the research is to classify and identify leaf objects based on training data. Before the classification stage, the image preprocessing stage and leaf edge image feature extraction are first carried out in order to obtain the correct input values for the plant type classification stage based on leaf morphological characteristics. The similarity between the research above and the research conducted by the author is that they both conducted research on leaf images. The difference is that in the research conducted, the algorithm used was Artificial Neural Network, while the author used the Scale Invariant Features Transform (SIFT) Feature Extraction and Support Vector Machine (SVM) algorithms. Apart from that, the research above focuses on types of plants, whereas in this research the author only focuses on herbal plants. Research on leaf identification has previously been carried out by researchers [6]–[13].

II. Proposed Method

This research has four stages, namely: Scale-space extrema, Keypoint Localization, Orientation Assignment and Local Image Descriptor. The first stage in computational search which is carried out at all scales and locations in the image. This serves to identify potential points that are invariant in scale and orientation and can be determined continuously at different viewpoints on the same object. The second stage For each candidate location obtained, a detailed model is required to indicate the location and scale. The third stage is determining this orientation, a Gaussian smooth L image is used which has a scale closest to the keypoint scale, and the final process is calculating the descriptor vector. Descriptors are calculated for each keypoint, this step is performed on the image closest to the scale for the keypoint scale. The proposed method shown in Figure 1.

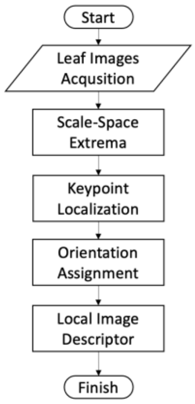

Figure 1. The Scale Invariant Features Transfer for Leaf Images Method

A. Scale-Space Extrema

Based on the classical paradigm, the image's stable point is located at the extrema of the image's Laplacian in the image's scale-space. This scale-space is a continuous scale function that represents a smoothing parameter σ, scale, and image convolution with a Gaussian function of increasing blur level σ. According to Lowe, to be able to determine a stable SIFT scale space, four octave levels and five levels of scale blur at each octave level are required. An illustration of scale space can be seen in Figure 2.

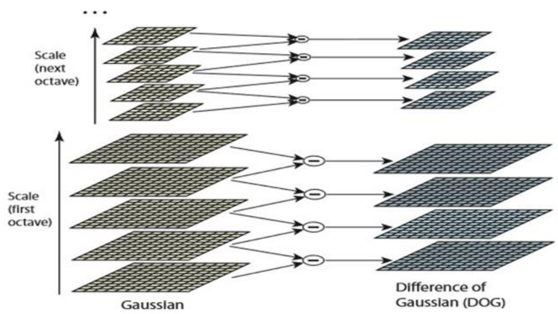

Figure 2. Illustration of Gaussian and Difference of Gaussian Scale Space

The image scale space is defined as the function $L_\sigma = L_{(x,y,\sigma)} =$, which results from the convolution of the Gaussian variable $G_\sigma = G_{(x,y,\sigma)}$ with the input image $I_{(x,y)}$. The digital image will be smoothed to obtain Gaussian Scale Space with equation (1).

$$L_\sigma = G_\sigma * I \quad (1)$$

where

$$G_\sigma = G_{(x,y,\theta)} = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

is a Gaussian function with integral I and standard deviation σ. The notation * is the symbol for the convolution operation. Based on the classical approach, the Laplacian of the Gaussian can be replaced by the Difference of Gaussian (DoG), $D_\sigma = D_{(x,y,\sigma)}$ at different scales separated by a constant multiplicative factor k, so that the DoG search will use equation (3).

$$D_\sigma = L_{k\sigma} - L_\sigma \quad (3)$$

k is a constant multiplicative factor with the value $k = \sqrt{2}$. Based on the equations (3), the difference equation can be specified as equation (4).

$$D_{(x,y,\sigma)} = \left(G_{(x,y,k\sigma)} - G_{(x,y,\sigma)}\right) * I_{(x,y)} - L_{(x,y,k\sigma)} - L_{(x,y,\sigma)} \quad (4)$$

B. Detecting Accurate Key Points (Extreme)/Keypoint Localization

For each candidate location obtained, a detailed model is required to indicate the location and scale. Therefore, keypoints here are selected based on their stability measures. Extrema detection (maximum and minimum values) is carried out by comparing the value of each pixel in the DoG scale space with the eight pixels around it and the corresponding 9 pixels in the DoG image before and after so that a total of 26 neighboring pixels can be compared. If the pixel value in question is greater or smaller than the values of the comparison pixels then the pixel coordinates are marked as extreme. After getting the extreme points, it is necessary to improve localization with subpixel accuracy using Taylor order second expansion from the difference of Gaussian scale space function, $D_{(x,y,\sigma)}$, so that the actual extremum position, z, is obtained using equation (5).

$$z = -\left(\frac{\partial^2 D}{\partial x^2}\right)^{-1} \frac{\partial D}{\partial x} \quad (5)$$

C. Orientation Assignment

In determining this orientation, a Gaussian smooth L image is used which has a scale closest to the keypoint scale. For each sample image $L_{(x,y)}$ magnitude $m_{(x,y)}$ and orientation $\theta_{(x,y)}$ are calculated using pixel differences. Magnitude is calculated in equation (6) and orientation in equation (7).

$$m_{(x,y)} = \sqrt{(L(x+1,y) - L(x-1,y)^2) + (L(x,y+1) - L(x,y-1)^2)} \quad (6)$$

$$\theta_{(x,y)} = tan^{-1} \frac{L(x,y+1) - L(x,y-1)}{L(x+1,y) - L(x-1,y)} \quad (7)$$

Where, m = magnitude/weight value; L = image resulting from Gaussian convolution x, y = coordinates; θ = orientation value; L = image resulting from Gaussian convolution and x, y = coordinates.

The histogram orientation is formed from the gradient orientation of the sample points in a region around the key point. The orientation histogram has 36 bins covering a 360 degrees orientation range. Each sample is added to a histogram weighted by the magnitude of the gradient and with a Gaussian weighted circular window with a scale of 1.5 times the scale of the key point. The peaks in the histogram orientation correspond to the dominant direction of the local gradient. The highest peak in the histogram is detected, and then any other local peaks that are within 80% of the highest peak are used to create a key point with that orientation. Therefore, for locations with multiple peaks of the same magnitude, there will be multiple key points created at the same location and scale but different orientations.

D. Local Image Descriptor

The final process is calculating the descriptor vector. Descriptors are calculated for each key point; this step is performed on the image closest to the scale for the key point scale. First create an orientation with 4x4 pixels with 8 bins for each key point. The histogram obtained in this orientation determination step calculates the magnitude and orientation values for samples in the 16x16 region around the key point. Magnitude is calculated with a Gaussian function with σ equal to one half the width of the descriptor. Then the descriptor becomes a vector of all these histogram values. Since 4x4=16 histograms with 8 bins each, the vector has 128 elements.

III. Result and Discussion

Primary data in this research was obtained at the image acquisition stage. Image Acquisition is the process of capturing or scanning an analog image to obtain a digital image. Several factors that need to be considered in the image acquisition process include the type of acquisition tool, camera resolution, lighting techniques, magnification or zooming, distance and angle of image capture. In this research, the author acquired images using a smartphone camera because the system will be based on Android. Secondary data in this research is in the form of journals, e-books and articles related to the leaf identification system.

After the data acquisition stage, the data is analyzed first. The data used in this research is leaf image data from herbal medicinal plants. Where this leaf image data will be the main data as an indicator for identifying herbal medicinal plants. This data becomes a reference for identifying herbal medicinal plants.

In software design, the steps taken include designing a herbal medicinal plant identification system with leaf images using the SIFT and SVM algorithms. Support Vector Machine is a state-of-the-art method for data classification. SVM classifies data that can be separated linearly using a hyperplane that has a maximum margin between data classes. The choice of maximum margin is based on an approach to minimize the risk of error.

Implementation testing of system accuracy was carried out using testing data and direct testing on the leaves of herbal medicinal plants found in the surrounding environment. System accuracy will be tested using a confusion matrix. Confusion matrix is a performance evaluation of an object-based classification model by estimating what is true or false.

This test was carried out to obtain recall, precision, error rate and accuracy values. Recall aims to measure the proportion of true leaf (TL) of leaf tuples that are correctly identified. Precision aims to measure the proportion of cases that are predicted to be leaf which are also true leaf in the actual data. Accuracy aims to add up correct prediction results. Error rate is used to add up incorrect prediction results. The following is a confusion matrix test for each class of the dataset. The accuracy result in this research can be seen in Table 1 and Table 2.

TABLE 1. CONFUSION MATRICES OF IDENTIFICATION OF HERBAL MEDICINES BASED ON MEDICINAL PLANT LEAF IMAGES USING THE SCALE INVARIANT FEATURE TRANSFORM FEATURES (BELIMBING WULUH)

		Predicted	
		Belimbing Wuluh (BW)	**Not Bukan Belimbing Wuluh (NBW)**
Actual	**Belimbing Wuluh (BW)**	T_{BW}=10	F_{BBW}=7
	Not Belimbing Wuluh (NBW)	F_{BW}=1	T_{BBW}=21

$$Recall = \frac{10}{10+1} \times 100 = 90\%$$

$$Precision = \frac{10}{10+7} \times 100 = 58\%$$

$$Accuracy = \frac{10+21}{10+1+21+7} \times 100 = 80\%$$

$$Error\ Rate = \frac{7+1}{10+1+21+7} \times 100 = 20\%$$

TABLE 2. CONFUSSION MATRICES OF IDENTIFICATION OF HERBAL MEDICINES BASED ON MEDICINAL PLANT LEAF IMAGES USING THE SCALE INVARIANT FEATURE TRANSFORM FEATURES (LENGKUAS)

		Predicted	
		Lengkuas (L)	**Not Lenkuas (NL)**
Actual	**Lengkuas (L)**	T_L=11	F_{NL}=5
	Not Lengkuas (NL)	F_L=2	T_{NL}=32

$$Recall = \frac{11}{11+2} \times 100 = 84\%$$

$$Precision = \frac{11}{10+5} \times 100 = 73\%$$

$$Accuracy = \frac{11+31}{11+32+5+2} \times 100 = 86\%$$

$$Error\ Rate = \frac{5+2}{11+32+5+2} \times 100 = 14\%$$

TABLE 3. THE ACCURACY RESULT IDENTIFICATION OF HERBAL MEDICINES BASED ON MEDICINAL PLANT LEAF IMAGES USING THE SCALE INVARIANT FEATURE TRANSFORM FEATURES

Class	***Confusion matrix***			
	Recall	***Precision***	**Accuracy**	***Error rate***
Belimbing Wuluh	90%	58%	80%	20%
Lengkuas	84%	73%	86%	14%
Nangka	1%	11%	70%	30%
Mimba	33%	15%	63%	37%
Sambiloto	0%	0%	70%	30%
Bayam	58%	37%	68%	32%
Bayam Malabar	92%	31%	74%	26%
Sawi	0%	0%	80%	20%
Sereh	25%	20%	70%	30%
Cabe rawit	0%	0%	90%	10%
Kunyit	0%	0%	95%	5%
Lemon	33%	27%	76%	24%
Miyana	0%	0%	77%	23%
Ficus	15%	40%	72%	28%
Ara suci	91%	59%	87%	12%
Kembang sepatu	0%	0%	72%	28%
Jarak pagar	0%	0%	60%	40%
Melati	11%	14%	60%	40%
::: :::				
Kelabat	57%	33%	69%	31%
Asam jawa	0%	0%	70%	30%
Averages	**28%**	**28%**	**77%**	**23%**

Based on table 3, it can be seen that the leaves with the highest accuracy are turmeric leaves, while the leaves with the lowest recognition accuracy are lime leaves and jasmine leaves. This is due to the irregular shape of the leaves so that in their classification they become objects that are difficult to recognize.

Testing of the SIFT and SVM algorithms was carried out using a dataset of 2006 data, by splitting 80% of the data as training data and 20% testing data, it was found that the leaf image identification process had a moderate level of accuracy. This is because there are several leaves that have almost the same characteristics and shape. Like Moringa leaves and fenugreek leaves which have almost the same structure and shape. The similarity of the leaves can be seen in Figure 3.

Figure. 3. The RGB of Kelor Leaf (left), The RGB of Kelabat Leaf (right)

Because there are similarities between several leaves, there are several leaf classes that are identified as other leaf classes. Apart from similarity in shape, the quality of the image taken also influences the identification results, there are several images in the dataset that are not sharp (blurry) so that this image class can be read as another image class. The background of the image must also be white to make the image read well, because some images have a background that is not white enough, causing the background to also be read as a feature of the image and be identified as another image.

The relationship between the four components of the confusion matrix test is that if the recall and precision values are low while the accuracy value is high, then the system is only able to identify some of the target data and some of it does not match the expected results and results in the error value getting bigger. If the accuracy and precision values are high while the recall value is low, then the system is only able to identify part of the leaf image identification process data that matches its class and the error value will be large. If the accuracy and recall values are high while the precision value is low, then the system is able to identify all data in the leaf identification process, but there will be data outside the target that will also be identified. However, if the accuracy, precision and recall values are high, the system can identify all data well according to the expected class, thereby making the error value smaller.

IV. Conclusion

Based on testing and analysis of the design of the Herbal Medicinal Plant Leaf Image Identification System with SIFT feature extraction, the following conclusions are:

1. This system is able to identify herbal medicinal plant leaves by utilizing SIFT feature extraction and classification with SVM.
2. The system can implement digital image processing for identifying herbal medicinal plant leaves with SIFT feature extraction and can be implemented on Android.
3. The results of the confusion matrix test explain that this system has an average accuracy of 77%, which means that this system is quite good at identifying leaf images, even though the error rate is quite high at 23%.

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