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Thai Herb Leaf Image Recognition System (THLIRS)

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ABSTRACT

There are many kinds of Thai herb species, so it very difficult to identify them all. The objective of this research was to build a computer system that could recognize some Thai herb leaves, using a process called the Thai herb leaf image recognition system (THLIRS). The system consisted of four main components: 1) image acquisition, 2) image preprocessing, 3) recognition and 4) display of results. In the image acquisition component, the system used a digital camera to take a leaf picture with white paper as the background. A one-baht coin was photographed beside the leaf in order to provide a scale for comparison. In the image preprocessing component, the system applied several image-processing techniques to prepare a suitable image for the recognition process. In the recognition component, the system extracted 13 features from the leaf image and used a k-nearest neighbor (k-NN) algorithm in the recognition process. In the result display component, the system displayed the results of the classification. The experiment involved 32 species of Thai herbs, with more than 1,000 leaf images. The system was trained with 656 herb leaf images and was tested using 328 leaf images for a training dataset and 30 leaf images for an untrained dataset. The precision rate of the THLIRS of the training dataset was 93.29, 5.18 and 1.53% for match, mismatch and unknown, respectively. Moreover, the precision rate of the THLIRS of the untrained data set was 0, 23.33 and 76.67% for match, mismatch and unknown, respectively.

Keywords: Thai herb heaf recognition, leaf features extraction, K-nearest neighbor algorithm, pattern recognition, image processing

INTRODUCTION

Thailand is an agricultural country with many kinds of herbs widely distributed in every part of the country. The Thai people use herb leaves for cooking and medicinal purposes. Nevertheless, there are only a few people who can recognize or identify specific kinds of Thai herbs because of the wide variation within a species. The objective of this research was to construct a computer system that could recognize some Thai herb leaves. The system was developed to extract some herb leaf features and apply an image processing technique to recognize them. In addition, people can use this system to search for the herb leaf name and its specifications using only a herb leaf picture.

There are about 250,000–270,000 plants species that have been named and classified in the world (Guo *et al.*, 2004). Therefore, it is not

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* Corresponding author, e-mail: itcpp@mahidol.ac.thNeural network technique

feasible for one person to know every kind of plant leaf. Many researchers have tried to identify plant leaves by applying several techniques that are briefly reviewed below.

Neural network technique

Hong and Chi (2003, 2006) applied neural network methods for vein pattern extraction to recognize leaf images. Jiazhi and He (2008) proposed neural network methods for recognizing digital images of plant leaves. Stephen *et al.* (2007) presented a leaf recognition algorithm for plant classification using a probabilistic neural network. Huang and Peng (2008) studied leaf shape and texture features combined with a probabilistic neural network to recognize 30 kinds of broad-leaved trees. Yun *et al.* (2005) proposed leaf vein extraction combined with a cellular neural network for plant recognition. Panagiotis *et al.* (2005) implemented a feed-forward neural network for the classification of plant leaves. Xiao *et al.* (2005b) used k-nearest neighbor classification and a probabilistic neural network to recognize plant leaves.

Fuzzy logic technique

Liqun (2008) used fuzzy statistics for grouping tobacco leaves. Yan *et al.* (2007) proposed fuzzy curves and surfaces to identify and diagnose cotton diseases using cotton leaf images.

Support vector machine

Jordi *et al.* (2008) implemented a support vector machine to recognize plant leaves. Wu and Chengwei (2006) used the support vector machine method to measure the damage degree of leaf miners.

Leaf shape matching

Wang *et al.* (2003) presented leaf image retrieval by using simple leaf shape features and the centroid-contour distance. Cholhong *et al.* (1998) used *Acer* spp. leaf shapes and polygon approximation to recognize *Acer* plant species. Ji *et al.* (2006) proposed a leaf shape matching method for plant species.

Moving center hypersphere classification

Guo *et al.* (2004) used the moving center hypersphere technique to classify plant leaves. Xiao *et al.* (2005a) proposed a moving center hypersphere to recognize leaf images.

Based on the previous work, the present research tried to extract more leaf features to increase the recognition precision and apply a simple matching algorithm to identify Thai herb leaves. The THLIRS extracts almost 13 leaf features and uses a simple k-nearest neighbor algorithm to recognize Thai leaves.

MATERIALS AND METHODS

System architecture overview

The THLIRS takes a leaf image and stores it in a computer system (Figure 1). The system then extracts several features from the leaf image such as the leaf color, leaf size, aspect ratio and roundness using image processing techniques. The THLIRS then uses all the leaf features to identify the Thai herb and display its properties.

System flowchart chart

The THLIRS flowchart starts with loading a leaf image into the system. Then, the system processes the image using nine

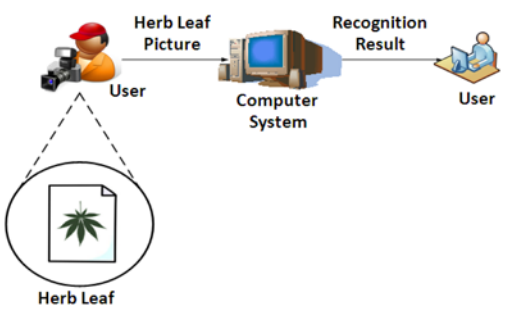

Figure 1 Framework of the THLIRS.

modules—namely, 1) image resizing, 2) black and white conversion, 3) image enhancement, 4) leaf and coin extraction, 5) cropping leaf image, 6) boundary tracking, 7) 13 features extraction, 8) recognition and 9) retrieve information. Finally, the system displays the recognition results. The THLIRS flowchart is shown in Figure 2 and the details of each module are described in more detail in the next section.

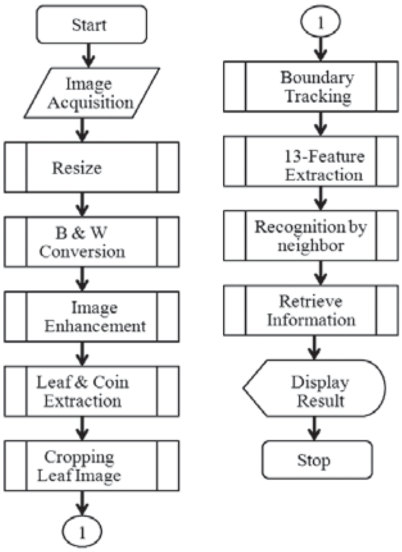

Figure 2 THLIRS flowchart.

System structure chart

Figure 3 shows the four main components of the THLIRS—namely, 1) image acquisition, 2) image preprocessing, 3) recognition and 4) display. The details of each component are described below.

a. Image acquisition

In the first stage, the THLIRS takes a picture of the leaf in a controlled environment. The leaf is placed on a white background such as white paper and the system also inserts the image of a one-baht coin beside the leaf to provide a scale for comparative purposes (See Figure 4).

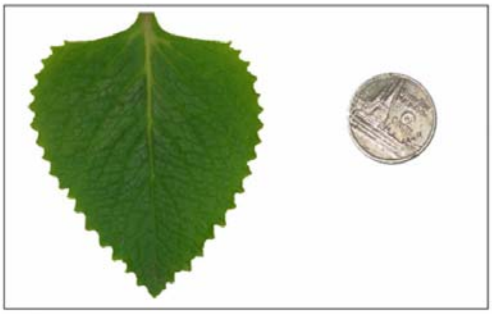

Figure 4 Leaf image compared with size of one-baht coin.

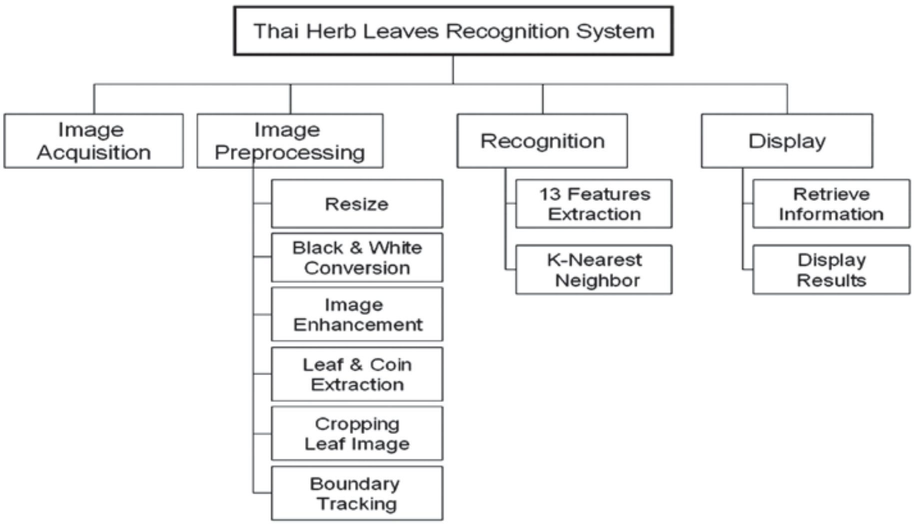

Figure 3 THLIRS structure chart.

b. Image preprocessing

In the second stage, the THLIRS applies six image preprocessing modules: 1) resize, 2) black-and-white conversion, 3) image enhancement, 4) leaf and coin location, 5) cropping leaf image and 6) boundary tracking.

1. Resize –the input images may have different sizes and the image size can affect the recognition results. Therefore, the system resizes every image to be 400 pixels in height and preserves its ratio.

2. Black and white conversion – to extract leaf features, the system needs to change a leaf-color image to a black-and-white image. First, the system converts the image to a grayscale image using Equation 1. Sample results of grayscale image conversion are shown in Figures 5(a) and 5(b).

$$G = 0.299*R + 0.587*G + 0.114*B \quad (1)$$

where G = gray, R = red, G = green and B= blue. Then, the system converts the grayscale image to a black-and-white image using a binarization technique. A sample of a black-and-white image conversion is shown in Figures 5(c) and 5(d).

3. Image enhancement – the system performs morphological operations to remove holes and reducing the noise in the black-and-white picture. A sample of image enhancement is shown in Figures 6(a) and 6(b).

4. Find leaf and extract coin – the system assumes that the leaf is the largest object in the image and the one-baht coin is the second largest object in the same image. At the completion of this module process, the system has identified both the leaf and coin objects in an image, as shown in Figure 7(a).

5. Cropping leaf image – the system separates the leaf image from the coin image for the leaf recognition process by cropping the leaf image in a bounding box, as shown in Figure 7(b).

6. Boundary tracking – the system defines the boundary of the leaf in terms of x-y coordinates. From a starting point, the system traces the boundary coordinates in a clockwise direction, as shown in Figure 8.

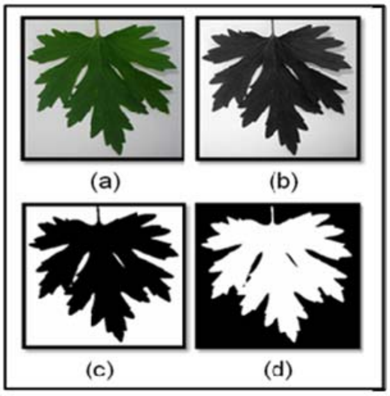

Figure 5 Sample of (a) grayscale image conversion; and (b) black-and-white image conversion.

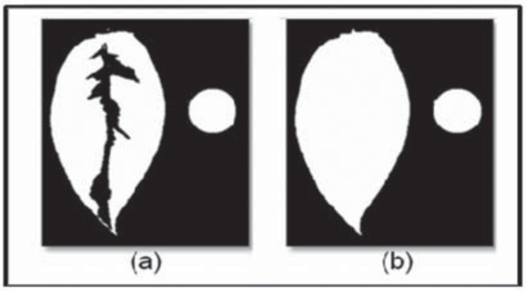

Figure 6 Sample of leaf image (a) before; and (b) after image enhancement.

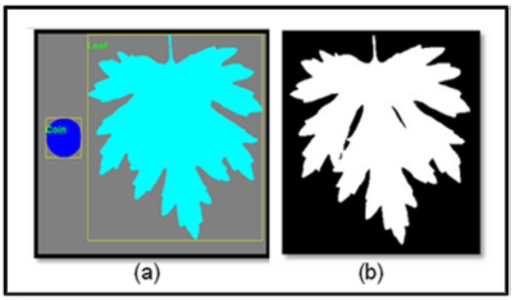

Figure 7 (a) Leaf and one-baht coin separation; (b) Cropping leaf image in a bounding box.

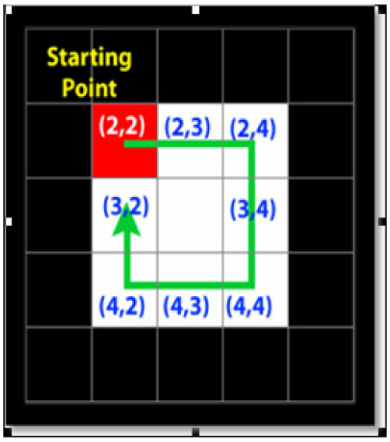

Figure 8 Leaf boundary tracking direction.

c. Recognition

In the third stage, the system is divided into two parts—namely, features extraction, and k-nearest neighbor classification.

1. Features extraction – features are the characteristics of a leaf that can be used in the leaf recognition process. The THLIRS uses seven main identifiers, which can be divided into thirteen leaf features. The thirteen leaf features are:

1.1 Leaf and coin ratio – is defined as the ratio of the height of the coin to the height of the leaf in the same picture (shown in Figure 8). It is calculated by Equation 2:

$$CLR = HC / HL \quad (2)$$

where CLR = coin to leaf ratio, HC = height of the coin (pixels), and HL = height of the leaf (pixels).

In Figure 9, the coin to leaf ratio (CLR) is equal to 0.25.

1.2 Aspect ratio – is defined as the ratio of the height to the width of the leaf in the same picture, which is calculated by Equation 3:

$$AR = HP / WP \quad (3)$$

where AR = aspect ratio, HP = height (pixels), and WP= width (pixels).

In Figure 9, the aspect ratio (AP) is equal to 400/350 = 1.14.

1.3 Roundness – measures the similarity of the leaf to a round object, which is calculated

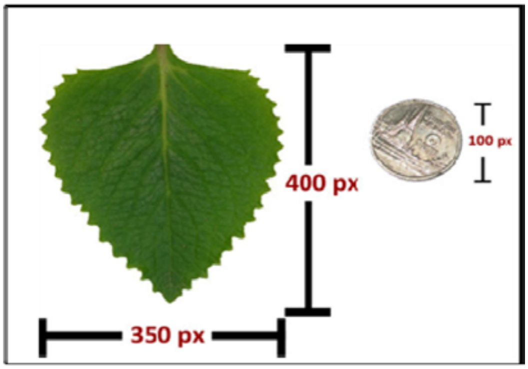

Figure 9 Leaf and coin ratio (px = pixels).

using Equation 4:

$$RN = 4\,\pi * A / B^2 \quad (4)$$

where, RN = roundness, A = area is the area of the leaf found by counting the number of white pixels in the leaf only and B = the approximate length of the leaf boundary. A roundness value of RN = 1 indicates a perfectly round object.

1.4 Ripple features – describes the fluctuation of the leaf boundary. The ripple image can be obtained by finding the differences between the leaf image and the average boundary of the leaf image. The average leaf boundary is calculated from the leaf boundary coordinates by finding the average of a range of boundaries defined by Equation 5:

$$R = LB / 10 \quad (5)$$

where R = range and LB = length of boundary.

Once the difference has been determined, the system filters out any narrow areas and remove any areas less than 10 pixels. The final image is called the ripples image, as shown in Figure 10(d). The ripple features are divided into two sub-features:

1.4.1 Ripples counting – the ripples are the remaining objects in the ripple image, as shown in Figure 10 (d). The result of counting the number of ripples is shown in Figure 11.

1.4.2 Ripples pixels counting – this process counts all the white pixels in all ripples.

1.5 Half-leaf area ratio – The THLIRS divides the leaf image into two equal areas by a

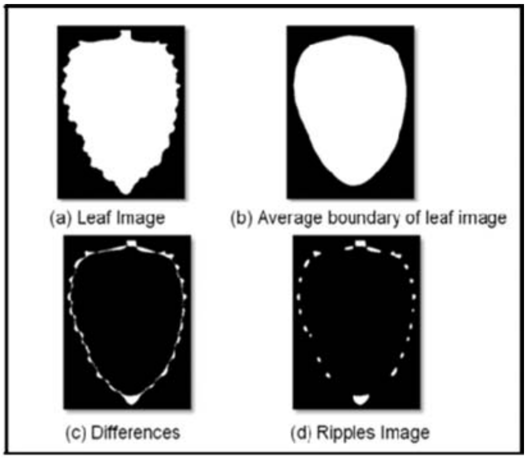

Figure 10 Ripple images (d) determined from difference (c) between the leaf image (a) and the average boundary of the leaf image (b).

Figure 11 Ripples counting result.

horizontal line (Figure 12) and uses the upper leaf area ratio and the lower leaf area ratio for two more leaf features.

1.5.1 Upper leaf area ratio – is calculated by dividing the upper leaf area by the upper image area. The upper leaf area is found by counting the number of white pixels in the upper leaf image.

1.5.2 Lower leaf area ratio – is calculated by dividing the lower leaf area by the lower image area. The lower leaf area is found by counting the number of white pixels in the lower leaf image.

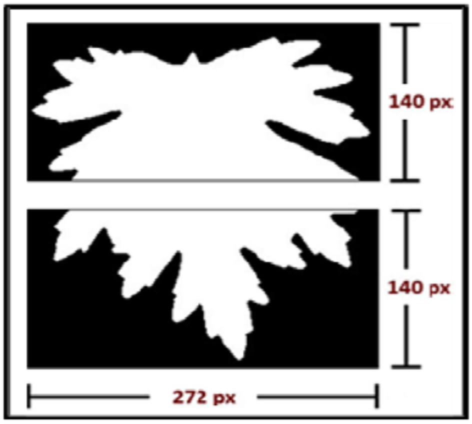

Figure 12 Upper (top) and lower (bottom) leaf area ratio features. (px = pixels)

Based on the half-leaf area ratio in Figure 12, the THLIRS calculates both area ratios:

Half-leaf area = 272×140 = 38,080 pixels
Upper leaf area = 22,848 pixels
Upper leaf ratio = 22,848 / 38,080
= 0.6
Lower leaf area = 15,232 pixels
Lower leaf ratio = 15,232 / 38,080
= 0.4

1.6 Color features – the THLIRS transforms the RGB color space to an L*a*b* color space. Taking into account only the leaf pixels, the system finds the average L*, a* and b* values for three more leaf color features by applying Equations 6 to 11:

$$X = k_1R+k_2G+k_3B \tag{6}$$
$$Y = k_4R+k_5G+k_6B \tag{7}$$
$$Z = k_7R+k_8G+k_9B \tag{8}$$
$$L^* = 116(Y/Y_n)1/3 -16 \tag{9}$$
$$a^* = 500[(X/X_n)\ 1/3 -(Y/Y^n)\ 1/3] \tag{10}$$
$$b^* = 200[(Y/Y_n)\ 1/3 -(Z/Z_n)\ 1/3] \tag{11}$$

where

R, G, B = the gray pixel in three components (red, green and blue);
X, Y,Z = the tri-stimulus values in the Commission Internationale de l' Eclairage (CIE1931) system;
k_1–k_9 = constants (relating to the standard white and the three primary colors);

X_n, Y_n, Z_n = tri-stimulus values of standard white color;
L* = average value of the luminance;
a*, = average value of the chromaticity channel a
b* = average value of the chromaticity channel b.

The result of the leaf L*a*b color features is shown in Figure 13.

1.7 Vein Features – utilizes Sobel edge detection using the grayscale leaf image with threshold values 0.05, 0.03, and 0.01. The result from excluding the boundary using the AND operation with the eroded leaf image is a shown in Figure 14.

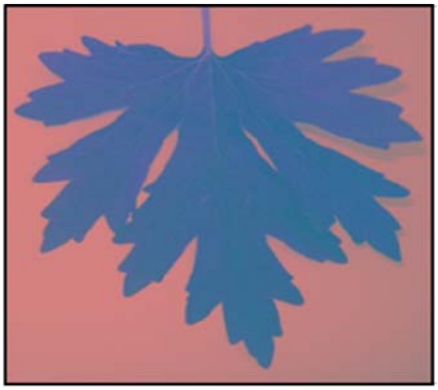

Figure 13 Leaf L*a*b color image.

The THLIRS counts the remaining pixels and divides this value by the area of the leaf. This reflects vein intensity and how clearly the venation can be seen. The leaf vein features can be divided into three more sub-features:

1.7.1 Threshold at 0.05 – is the threshold of the gradient image at 0.05, excluding the boundary and counting the number of white pixels.

1.7.2 Threshold at 0.03 – is the threshold of the gradient image at 0.03 excluding the boundary and counting the number of white pixels.

1.7.3 Threshold at 0.01 – is the threshold of the gradient image at 0.01 excluding the boundary and counting the number of white pixels.

The results of vein features detection using thresholds of 0.05, 0.03 and 0.01 are shown in Figures 15(a) to 15(c), respectively.

2. K-Nearest Neighbor Classification

Using the k-NN algorithm, an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k-nearest neighbors. Neighbors are taken from a set of objects whose class is known. Position vectors in a multidimensional feature space represent each object. Object identification was based on a training data set containing 656 leaf images in the system.

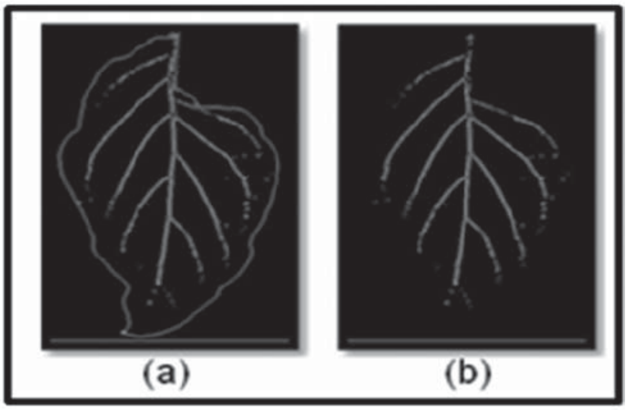

Figure 14 Result (b) from applying Sobel detection after excluding the boundary to a leaf (a).

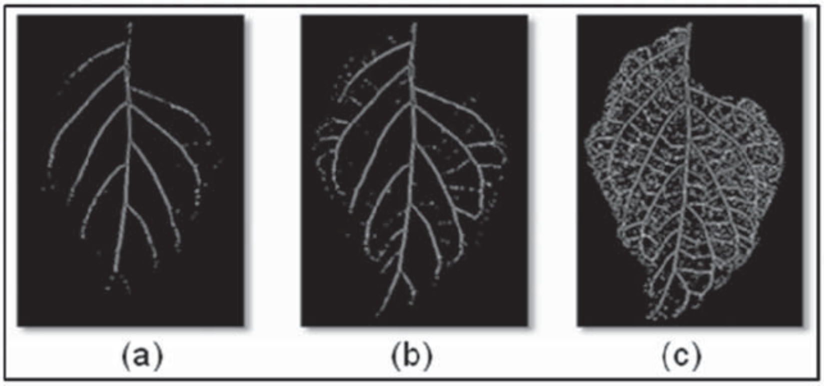

Figure 15 Vein pixel detection with threshold values of (a) 0.05; (b) 0.03; and (c) 0.01.

The Euclidean distance was used to measure the distance between every feature of a sample and every feature of each of the training objects. The THLIRS uses the thirteen features.

The THLIRS uses a value of K = 6, which restricts the classification to the classes of the six nearest objects. The system uses the nearest neighbor algorithm to solve a tie between equally voted classes, so that if there are two classes with the same vote, the sample is assigned to the same class as that of the nearest object.

When the nearest object has a distance value of more than 1.15, the sample is classified as class 0, indicating an unknown class.

d. Display

The final module displays the result using two processes—namely, retrieve information and display results.

1. Retrieve information: The system uses the thirteen features to compare the herb leaf images with leaf information from the system database.

2. Display results: The system shows the results of retrieved information in the user interface screen (Figure 16).

Figure 16 User interface screen showing 1) original image box; 2) recognition image box; 3) property text box; and buttons to 4) browse image; 5) recognize; 6) get data; and 7) run test.

User interface screen

The THLIRS used MATLAB 7.6.0 (R2008a) to develop a user screen as shown in Figure 16. There are two image boxes, displaying the original image box (Figure 16 label number 1) and the recognition image box (Figure 16 label number 2). Below both image boxes, there is a property text box (Figure 16 label number 3) displaying all the properties from the leaf recognition result. There are four buttons to the right:

Browse image – opens a leaf image to be recognized (Figure 16 label number 4)

Recognize – recognizes the loaded leaf image (Figure 16 label number 5)

Get data – extracts the features of all the leaves in the image store in a database, and then builds a training set and a test set (Figure 16 label number 6)

Run test – performs data testing (Figure 16 label number 7).

RESULTS AND DISCUSSION

The accuracy of the system based on 32 species of Thai herb leaf is shown in Tables 1 and 2. The present study divided the leaf images into two datasets—namely, a training dataset and an untrained dataset. The training dataset consisted of 328 leaf images and the untrained dataset consisted of 30 leaf images. The precision rate of the THLIRS of the training dataset was 93.29, 5.18 and 1.53% for match, mismatch and unknown, respectively. Moreover, the precision rate of the THLIRS of the untrained data set was 0, 23.33 and 76.67% for match, mismatch and unknown, respectively.

A comparison between the THLIRS and the other leaf recognition systems is provided in Table 3. The eight systems were compared using five criteria: researcher, recognition method, leaf testing species, leaf testing dataset and accuracy. The accuracy depended not only on the recognition method but also on the leaf species and number of samples in the dataset. The number of leaf species and the number of samples in the dataset in every system in Table 3 are both very low when compared with the number of leaf species in the world. Moreover, more time and more recognition techniques are required to improve the recognition accuracy, using for example, herb leaf texture and an “e-nose” to analyze the smell of the herb leaf. However, at this primary stage, it is hoped that the system described in the present study can help doctors, medical technicians and other people to recognize some species of Thai herb leaf.

CONCLUSION

In this paper, the THLIRS fulfilled the research objective by extracting seven main leaf features for the recognition of Thai herb leaf samples. The THLIRS used 32 species of Thai herbs to test the system. The precision rate of the THLIRS of the training dataset was 93.29, 5.18 and 1.53% for match, mismatch and unknown, respectively. Moreover, the precision rate of the THLIRS of the untrained data set was 0, 23.33 and 76.67% for match, mismatch and unknown, respectively.

Table 1 Training dataset precision rates.

Scientific name	Number tested	Match	Mismatch	Unknown
Graptsophyllum pictum	10	9	1	0
Piper betel L.	10	9	0	1
Graptophyllum pictum (L.) Grif. cv. Gloden	10	10	0	0
Citharexylum spinosum L.	10	7	3	0
Albizia myriophylla Benth.	10	5	5	0
Robusta coffea canephora Pierre ex Froehner	10	9	1	0
Solanum eriathum D. Don	11	10	1	0
Gyhura samentosa DC.	12	11	1	0
Leonurus sibiricus Linn.	10	10	0	0
Cinnamomum camphora (L.) Presl	10	9	0	1
Manikara hexabdra (Roxb.) Dubard	10	9	1	0
Ixora ebarbata Craib.	10	10	0	0
Excoecaria bicolor Hassh.	10	9	1	0
Quisqualis indica L.	10	10	0	0
Datura fastuosa L.	10	9	1	0
Datura metel L. var. *fastuosa* (Bernh.) Danert	10	10	0	0
Ipomoea batatus (L.) Lam.	10	10	0	0
Carissa cochinchinensis Pierre	10	10	0	0
Coleus amboinicus Lour.	10	9	0	1
Gynura divaricata DC.	12	11	0	1
Piper nigrum L.	10	10	0	0
Quassia amara L.	11	11	0	0
Clinacanthus nutans (Burm.f) Lindau.	10	10	0	0
Ipomoea pes-caprae (L.) R.br.	10	10	0	0
Spilanthes acmella (Linn) Murray	10	10	0	0
Iresin herbstii Hook.	10	9	0	1
Ardisia elliptica Thunb.	10	9	1	0
Eupatorium stoechadosmum Hance	10	10	0	0
Gendarussa vulgaris Nees.	11	10	1	0
Cinnamomum porrectum (Roxb.) Kosterm.	10	10	0	0
Cestrum diumum L.	11	11	0	0
Cocculus lasrifolius DC.	10	10	0	0
Total	328	306	17	5

Table 2 Untrained dataset precision rates.

Scientific name	Number tested	Match	Mismatch	Unknown
Aglaonema crispum	5	0	0	5
Alternanthera aessilis DC.	5	0	2	3
Codiaeum varicgatum	5	0	0	5
Polyscias fuilfoylei (L.) Harms	5	0	0	5
Hibiscus rose-sinenisis	5	0	0	5
Nelumbo nucifera	5	0	5	0
Total	30	0	7	23

Table 3 Comparison of THLIRS with other leaf recognition systems.

Researcher	Methods	Species	Dataset	Accuracy
Guo *et al.* (2004)	Moving Median Center	17	n/a	86.00%
Stephen *et al.* (2007)	Probabilistic Neural Networks (PNN)	10	1800	90.31%
Huang and Peng (2008)	PNN	30	2100	98.30%
Xiao *et al.* (2005b)	PNN	20	n/a	91.18%
	1 Nearest Neighbor Classifier	20	n/a	93.17%
	5-Nearest Neighbor Classifier	20	n/a	85.47%
Liqun (2008)	Support Vector Machine (SVM)	1	1712	94.62%
Jordi *et al.* (2008)	Fuzzy Logic & SVM	16	1200	87.14%
Wu and Chengwei (2006)	SVM	1	300	97.40%
Present research	K-Nearest Neighbor Classifier	32	328	93.29%

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