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Full Length Research Paper

Thai botanical herbs and its characteristics: Using artificial neural network

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This paper proposed an explicit supervising technique with artificial neural network (ANN) which is associated with typical Content-based image retrieval (CBIR) systems. The main purpose of implementing this CBIR system with a unique supervising technique is for the system to apprehend various parts of Thai Botanical Herbs in the retrieving processing. This essential step prevents users from herbal usage misconception, and the lack of proper knowledge may lead to faulty exploitation of botanical herbs in Thailand. The input image or query image for our CBIR system is an image data of botanical herb features. The implementation of ANN supervision provides four kinds of training to the retrieval system which consists of 35, 50, 70, and 100% image section training of the original image. The weight, color histogram and edge pattern are set manually in order for these data to be supervised with back propagation technique. The retrieving results manifested a 91% precision and 50% recall with our implemented technique for 50% training. With all the assumptions and procedures, the implemented herbal CBIR system can facilitate several botanical herb users in terms of proper knowledge and misconception.

Key words: Artificial neural network, back propagation, Thai herb image, supervised retrieval.

INTRODUCTION

One of Thailand's largest merchandise apart from rice is botanical herbs. To promote good health and human well-being, botanical herbs or Thai spices are included as the main ingredients in several ethnic cuisines as well as medical ingredients. Some botanical herbs can become the panacea if they are processed and used correctly, while faulty process or lack of appropriate knowledge and misconception may promote abnormal side effects with excruciating pain and in some cases are fatal. This is because the characteristics of plants are very identical and there are various kinds of plant species that share mutual heredity but obtain different functional properties. Only few can recognize and distinguish one from the other. Global discovery shows that there are about 250,000 to 270,000 plants species that have been appropriately named and classified (Guo et al., 2004). Therefore, it is not feasible for individuals to notice botanical characteristics and distinguish one from the other. Many researchers have tried to identify plant leaves by applying several techniques. Since, Verayuth et al. (2009) proposed three strategies used on a prototype search engine for Thai herbal information:

1. Improving the efficiency of the Thai word segmentation which is used by Thai herbal search engine,
2. A set of synonyms of these technical terms in both Thai and English is built for helping users from several keywords of the same term and,
3. A set of keywords from herbal usages can be combined with the name keyword.

Later in 2010, they had developed a platform for building a web community for collecting the intercultural knowledge. Recently, Chomtip et al. (2011) proposed a computer system that could recognize some Thai herb image. The system was developed to extract some herbal leaf features and apply an image processing technique to recognize them. However, the scope and methodology of research associated in this field is still of great challenge for researchers to explore the techniques that can

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accurately define and extract different herbal leaf-structure features. In order to discriminate as much error and botanical structure misconception that may occur as possible, we propose a preprocessing data approach for training artificial neural network to supervise the retrieval process.

The objectives of this research is to implement the principles of image data, to facilitate our retrieval model and compare the system's efficiency by feeding query images of different scales.

RELATED WORKS

The advantage of herbal information image

Herbal information is a special type of information dealing with medicinal herbs. Some topics such as name identification still remain problematic. For example, 'Dracaena loureiri Gagnep' is a scientific phrase which globally describes a kind of botanical herb called Chan dang, in Thai. The medicinal property of the hard wooden part is known for fever relieve. In some parts of the country, it is expressed by different names or titles depending on where that region of the country is located, e.g., Chan pha (northern part), and Lakka chan (central part) (Smitinand, 2001). The lack of knowledge about the origin of specific botanical herb information has led to several difficulties and misinterpretation. Therefore, scientific names are the common phrase to express herbal heredity (Wu et al., 2007). According to Verayuth (2009), the evaluation survey of botanical herbs information center has indicated that image retrieving models for herbal features have accurately assisted several active users in terms of providing effective and direct information regarding users' interpretation.

Content based image retrieval for herb

Whether supervised or not, herbal CBIR systems are implemented from the mediocre concept of typical CBIR systems. George et al.'s (2002) research was on incorporating shape into histogram for CBIR. Later, Apostol et al. (2004) proposed a robust similarity retrieval algorithm which rescales and translates objects within an image called WALRUS (WAveLet-based Retrieval of User-specified Scenes). Until, Shi et al. (2007) had proposed a technique for improving the retrieval performance of the image. Young et al. (2008) had proposed a content-based image retrieval method based on an efficient combination of multi-resolution color and texture features. Then Verayuth et al. (2010) had developed a platform for building a web community for collecting the intercultural knowledge. Recently, Chomtip et al. (2011) proposed a computer system that could recognize some Thai herb images. The system was developed to extract some herbal leaf features and apply an image processing technique to recognize them. From all related assumptions and relevant research, we have implemented a supervised CBIR system for botanical herb images with one type of artificial neural network algorithm called back propagation.

Herb images recognition using 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 broadleaved 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. Chen et al. (2005) also implemented a fuzzy logic derivation of neural network models with time delays in subsystems.

Later, Lin et al. (2009) used linear regression technique to improve the generalization performance of RBF neural networks. Chen and Chen (2010), however, have also applied neural network controllers on the basis of GA-based for nonlinear systems. In this same year, Li et al. also contributed their work on nonlinear structural vibration suppression using dynamic neural network observer and adaptive fuzzy sliding mode control. Recently, Chen and Jayaswal (2011) have both proposed a neural network approach for controlling system. Finally, Su et al. (2012) have contributed their work on an optimized noise cancelling in gray images with cellular neural networks.

ARTIFICIAL NEURAL NETWORK MODELING AND VALIDATION

For over the last decade, the study of artificial neural networks (ANN) was one of the two major branches of artificial intelligence; the other branch was expert systems. A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects: the knowledge is acquired by the network through a learning process; and inter-neuron connection strengths, known as synaptic weights, are used to store the knowledge.

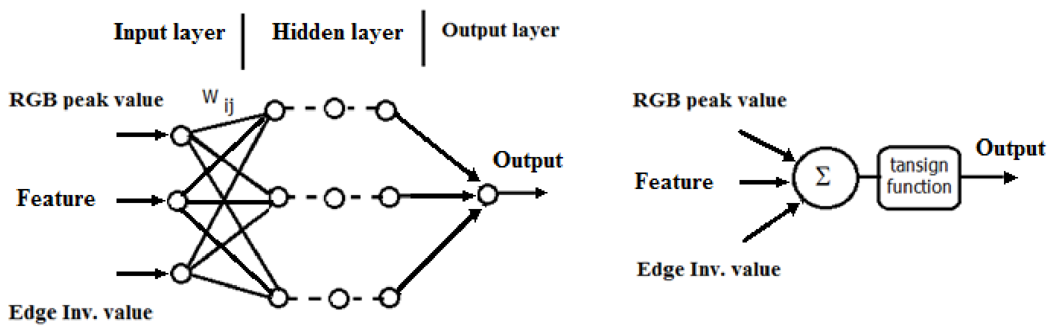


Figure 1. Show schematic diagram of typical multilayer fee forward neural network and a single model.

Artificial neural network models may be used to store as alternative methods in predictions (Kalogurou, 2000). A schematic diagram of typical multilayer feed forward neural network architecture is shown in Figure 1. The network usually consists of an input layer, some hidden layers and an output layer.

In its simple form, each single neuron is connected to other neurons of a previous layer through adaptable synaptic weights. Knowledge is usually stored as a set of connection weights. Training is the process of modifying the connection weights, in some orderly fashion, using a suitable learning method. The network used a learning mode, in which an input is presented to the network along with the desired output and the weights are adjusted so that the network attempts to produce the desired output. The weights, after training, contain meaningful information whereas before training they were random and had no meaning. The most popular learning algorithms are Back-propagation (BP) and its variants (Rumelhart et al., 1986). The training set has to be a representative collection of input–output examples. BP training is a gradient-descent algorithm. It tries to improve weights along its gradient. The error is expressed by the root-mean-square (RMS) values, which can be calculated by:

$$E = \frac{1}{2}[\sum_p \sum_i | t_{ip} - O_{ip} |^2]^{\frac{1}{2}} \qquad (1)$$

Where E is the RMS error, t the network output (target), and O the desired output vectors over all pattern (p). An error of zero would indicate that the networks are well trained. In brief, BP training is performed by initially assigning random values to the weight terms (w_{ij}) in all nodes. Each time a training pattern is presented to the ANN, the activation for each node, α_{pi}, and is computed. After the output of the layer is computed, the error term, δ_{pi}, for each node is computed backwards through the network. This error term is produced of the error functions, E, and the derivative of the activation function and, hence, is a measure of the change in the output layer node, and for the case of the logistic sigmoid activation, the error term is computed as:

$$\delta_{ij} = (t_{pi} - \alpha_{pi})\alpha_{pi}(1 - \alpha_{pi}) \qquad (2)$$

For a node in hidden layer

$$\delta_{pi} = \alpha_{pi}(1 - \alpha_{pi})\sum_k \delta_{pk} w_{kj} \qquad (3)$$

In the latter expression, the k subscript indicates a summation over all nodes in the downstream layer. The j subscript indicates the weight position in each node. Finally, the δ and α term for each node are used to compute an incremental change to each weight term via,

$$\Delta w_{ij} = \varepsilon(\delta_{pi} \cdot \alpha_{pi}) + m \cdot w_{ij}(old) \qquad (4)$$

The term ε is referred to as the learning rate; it determines the size of the weight adjustment for each training iteration. The term m is called the momentum factor. It is applied to the weight change used in the previous training iteration, w_{ij} (old). Both of these constant terms are specified at the start of the training cycle and determine the speed and stability of the network.

Retrieving botanical herbs by implementing ANN in CBIR system

The flow diagram in Figure 2 shows the steps and procedures of our Herbal CBIR system. Like traditional CBIR systems, herbal retrieving systems require a query image at the input (Iq) to compare with the information from our database (Ii). If Iq > Ii, the system will compute RGB histogram peak and edge using Sobel mask of the *Ii* image. Then inverse the vector values before supervising with ANN. On the contrary, if Iq < Ii, the system will separate supervising spatial into 100 cell before entering the computation process for RGB histogram peak and edge with Sobel mask. Once more, these vectors are inverted before the system can supervise with ANN. Group 1 from the diagram illustrates the maximum amount or peak of the RGB histogram. The second group

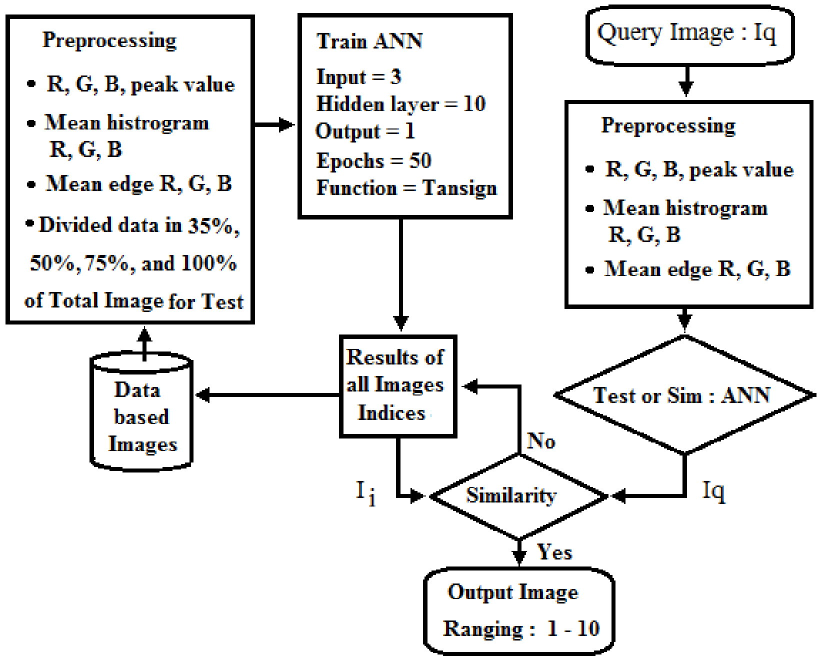


Figure 2. Flow diagram of herb image retrieval using ANN.

displays the acquired mean values of RGB histogram from the image features.

Finally, group 3 manifests the mean RGB histogram of the edge. In the supervising section, these three groups will deliver their input values to the ANN. The ANN consists of 3 inputs, 10 hidden layer values, 1 output layer, and a tangent sigmond function. After supervising the data, each index value of the image are kept and rearranged iteratively throughout the entire database. We begin the retrieval procedure by considering the right loop, which the pre-processing step allows the query image to identify the data. The data are then divided into three different groups, as displayed on the left loop. Testing our ANN back propagation algorithm is the next critical step to determine our CBIR system. The simulation solutions are then compared with the supervised similarity values that we received from the database. Relevant feedbacks are compared with r_{corr}, the correlated coefficient. If r_{corr} of that particular data is equivalent to 1, the image will be sorted at the dominant position, the first position. The results manifested on the interface are displayed in descending order of 10 data in accordance with the value of r_{corr}.

System supervising with ANN

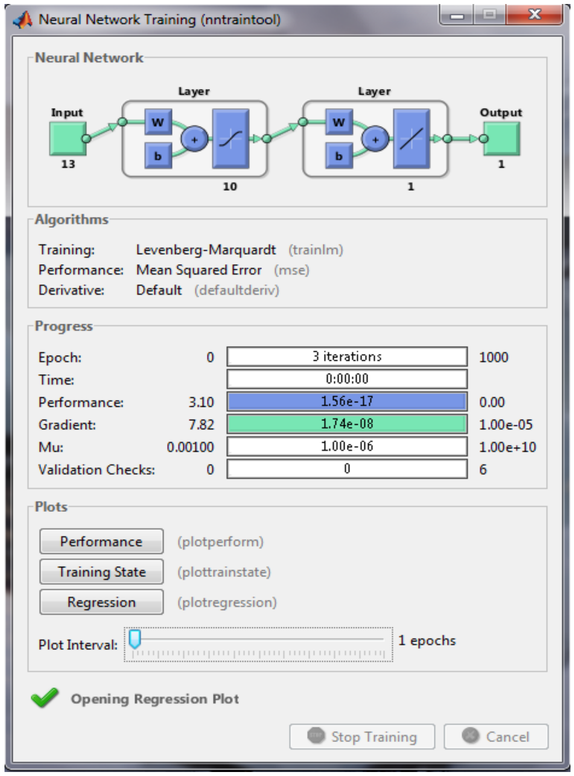
The data from our query image consists of three components; histogram RGB peak, mean value of histogram RGB and inverse edge. There are ten hidden layers in the artificial neural network. The error is arranged explicitly at 10^{-5}, lowest. There are 1000 epochs for the iteration. Training ANN is set in accordance with trainlm and the output layer as tansig function. The experimented paradigm implemented a 50% of the original image supervising and testing the system is displayed in Figure 3a and b, respectively. The supervising data are dispersed into 4 options; 35, 50, 75, and 100%. The first option, 35% training, splits the ratio of black cell per white cell as 1:3. While, 50% training has fixed the ratio at 1:2. Reversely, the ratio of black cell per white cell is 3:1 for 75% training. Finally, 1:1 is equivalent to 100% training. The reason we disperse the cell into 100 units is because the system will facilitate a smaller image. For instance, if our query image is of smaller size, 100 units dispersion can assist the retrieval system in terms of recognition.

System simulation and relevant feedbacks

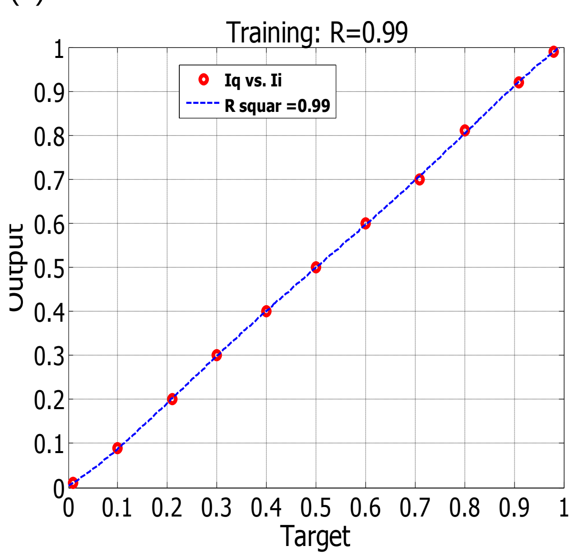
The simulation of this artificial neural network delivers its results as indices of the query image. Once these indices are compared to the database, relevant feedbacks will be displayed. The coefficient of correlation (r_{corr}) is the comparison of resolution between two images as shown in Equation 5, where the total of (r_{corr}) should be equivalent to 1. The explicit paradigm of the simulation is manifested in Figure 4a to c.

Image processing

The overall comparison will then be solved by the



(a)



(b)

Figure 3. Some results of train process and validation of the output data and query image: a) training process; b) testing or simulation results of ANN.

coefficient of correlation or r_{corr}. The correlation r_{corr} is one of the most common and most useful statistics. A correlation is a single number that describes the degree of relationship between two variables. In this paper, the correlation r_{corr} is a correlation between query image and retrieved images. When *I* is a query image and *J* is a retrieved image. They are reduced to the matrices of the same size. The correlation r is defined as follows:

$$r_{corr}(I,J)=\frac{\sum_m\sum_n(I_{mn}-\bar{I})(J_{mn}-\bar{J})}{\sqrt{(\sum_m\sum_n(\mathrm{Im}n-\bar{I})^2)(\sum_m\sum_n(J_{mn}-\bar{J})^2)}} \tag{5}$$

Where $\bar{I}$ is the average of matrix element *I*; $\bar{J}$ is the average of matrix element *J; m* is the row number of the pixel; *n* is the column number of the pixel. Similarity measures are computed as Equation 6

$$S \;=1-r_{corr}(I,J) \tag{6}$$

Color saturation can be evaluated by two coefficients called entropy and purity, in Equations 7 and 8.

$$E(c_j)=\frac{1}{\log c}\sum_{k=1}^{c}\frac{c_{j,k}}{c_j}\log\frac{c_{j,k}}{c_j} \tag{7}$$

$$p(c_j)=\frac{1}{|C_j|_{k=1,..c}}\max|c_{j,k}| \tag{8}$$

Where c_j, *k* is the c_j clusters that are the member of *k*. $|c_j|$ is the member of cluster *j*.

Finally, the two most well known coefficients to determine the retrieval efficiency, precision and recall, is calculated as follows:

$$\text{Recall}=\frac{Number\ of\ relavant\ image\ retrieved}{The\ total\ number\ of\ relavant\ image\ in\ databased} \tag{9}$$

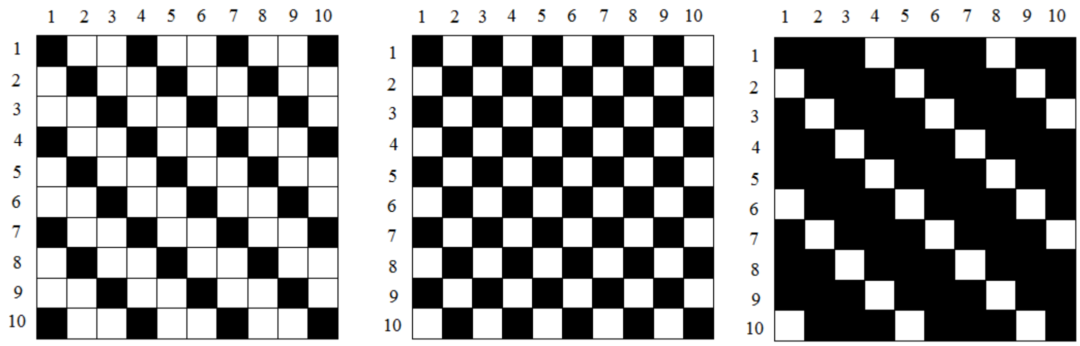
$$\text{Precision}=\frac{Numberofrelavantimageretrieved}{The\ total\ number\ of\ image\ retrieved} \tag{10}$$

EXPERIMENTS

The environment of our experiment consist of CPU core 2 duo – 7200, clock speed 2,8 GHz, RAM 3 G byte, window 7, and MATLAB version 7.11. The images used in this experiment is a total of 100 Thai botanical herb images, which were divided into 10 main herbs namely, tamarind, emblica, sparrow brinjal, plate brush egg plant, bergamot, horse radish tree, ebony tree, star fruit, blue pea, and ringworm bush.

RESULTS

The GUI in Figure 5 is designed to facilitate users for the retrieval system. The upper frame includes the command



(a) (b) (c)

Figure 4. Discrimination cells on an image for training, (a) 35%, (b) 50%, and (c) 75%.

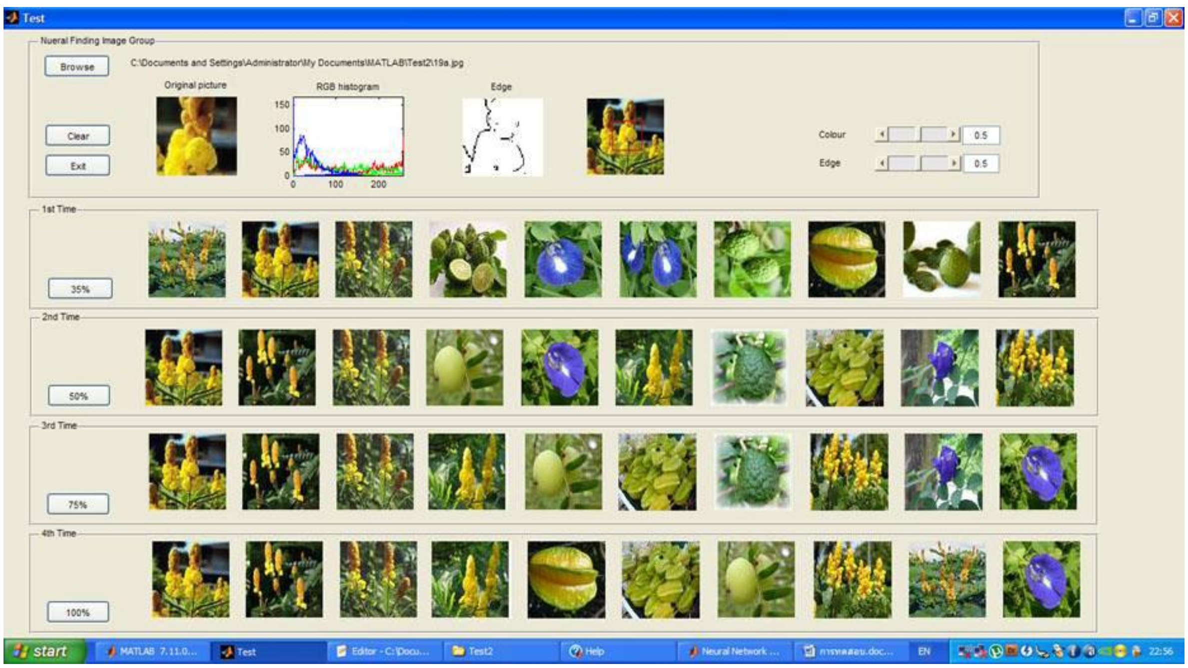


Figure 5. The application of GUI -Thai Herb image Retrieval using ANN.

button of “Query”, “clear”, “exit”, and “weight”. The “browse” button handles an event where data such as original image, histogram, edge, and output image appear after selecting the function button of 35, 50, 75 and 100%, respectively.

The second frame onward manifests the ANN associated assessment of the system. In 35% ANN supervision, the retrieving results displays 4 out of 10 relevant feedbacks. However, the perspective result has yet displayed in the first position. For 50% ANN supervision, half of the output images are considered as relevant feedbacks. In supervising 70% to the system, the output displays half accurate relevant feedbacks in a descending order, in which the position shows a more precise arrangement once compared with 50% supervision. The final frame expresses the results of 100% supervision. Although the result in this frame illustrates 5 out of 10 relevant feedbacks, the arrangement order is located at a more précise descending order than those of 70% supervision.

Table 1 manifests the retrieval results in ascending order, which the results can be statistically compared among 35, 50, 70, and 100% sub-images. The correlation denotes the retrieval similarity at 0.81, 0.92, 0.98, and 0.99, respectively. The figures indicate that higher resolution images also obtain higher similarity measures as well.

The measured precision is approximately 78, 91,

Table 1. The comparison of Herbal retrieving efficiency.

Image size (%)	Correlation; R^2	Precision (%)	Recall (%)	Entropy	Purity
35	0.81	78	40	0.40	0.50
50	0.92	91	50	0.30	0.75
75	0.98	95	60	0.25	0.80
100	0.99	99	65	0.20	0.85

95 and 99%, respectively. While the recall values denote 40%, 50%, 60%, and 65% retrieval efficiency, respectively. The results above indicate a 99% accuracy and 65% retrieval efficiency in terms of our retrieval model, which includes 500 Thai herbal images and query images of 100% in size (the full image). While lower entropy denotes better clustering quality, higher purity indicates more sufficient clustering quality.

Conclusion

In conclusion of this paper, we have proposed a CBIR system which implements a back propagation in ANN supervision method to determine accurate Thai botanical herbs. With the support of ANN, the system obtains a specific visual memory of Thai botanical herbs characteristics from the database. For instance, the system can recognize certain features the query herb from its color and patterns. The weight of these herbal images is internally fixed. With the supervision support of back propagation, even a smaller sized image can obtain an accurate feedback at the output. It is also essential to set the weight ratio between the color and pattern at 0.5 per 0.5. This is because, the set values was proven to provide the highest accuracy to the retrieval system, eventually.

In addition, images of higher resolution would probably provide a more precise arrangement for the relevant feedbacks. The experiment in this case has prioritized our expectation in terms of herbal CBIR system. For several decades, vague information and misconception have caused several harms to patients engaged with medicinal use. Lack of proper knowledge has made the interpretation of each individual to remain ambiguous. This herbal CBIR system is implemented to assist these lacks for amateur herbal users, as well as providing accurate information for proper usage. We also hope that our model can be further implemented in the future.

For instance, the system can provide a faster processing speed remaining active relevant feedbacks or feasibly retrieve image by the supervising with the smallest image resolution. From the assumption aforestated, our experiment has sufficiently reached our expectation that it will veraciously facilitate the extensive knowledge and misconception of herbal manipulation and exploitation in many ways.

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