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Plant Identification Based on Leaf Shape and Texture Pattern Using Local Graph Structure (LGS)

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ABSTRACT

Plant identification is the process of matching a specimen plant to a known plant group. Most of the people identify plants visually (morphologically). The natural key systems use morphological characteristics that can be compared with known databases to find the plants' genus. Characteristics observed to include general character, structures of stems, roots, leaves and flowers. People who are not intimately familiar with particular species require assistance in their identification. In this context, we proposed an approach called local graph structure to identify and classify the plant species based on their leaf shape and texture pattern. The experimental results have shown a significant level of accuracy of the plant species identification.

INTRODUCTION

Plants are basically identified according to their morphological features such as leaves, structures of stems, roots, flowers, and general character. Identifying plants using such keys is a very time consuming task and has been carried out only by trained botanists. In addition to this time intensive task, there are several other drawbacks in identifying plants using these features such as the unavailability of required morphological information and use of botanical terms that only experts can understand. Even reference books such as Tumbuhan Liar (2008), Rempah Ratus (2008) and Buah (2007) by Ong Hean Chooi use pictures to identify the plant species; these books are currently available in Bahasa Melayu and therefore of less use to tourists.

A number of studies have been done on plant species identification by Chiang *et al*. (2011), Kadir *et al*. (2011), Edi *et al*. (2011), Gao *et al*. (2010), Backes *et al*. (2009), Zulaikha (2009), Pahalawatta (2008) and Bruno *et al*. (2008). It should be mentioned here that a couple of research works have been done by Ibtisam(2011), Khairy *et al*. (2009), Reham *et al*.(2013), Rahim *et al*. (2013), Gado (2013), Hassan *et al*. (2012), Hanan *et al*. (2011) and Mazen (2012) on medicinal and aromatic plants which have the great importance and benefits for the society.

There are many unique species of plants which are of great interest not only to botanists but also to other people as well. In the markets, there are many unique plants which tourists do not recognize, neither in the marketplace nor in the plants' native habitat. Plants such as these should form the basis of our identification system.

A substantial amount of work has been done on leaf shape based plant classification and recognition. Wang *et al*. (2008) extracted seven Hu geometric moments and sixteen Zernike moments to represent leaf shape and the average correct classification rate archived up to 92.6%. Wu *et al*. (2007) used Probabilistic Neural Network (PNN) with image and data processing techniques to extracted 12 commonly used digital morphological features, which were orthogonalized into 5 principal variables. The technique accuracy greater than 90%. Du *et al* (2006) used shape matching technique and employed Douglas-Peucker approximation algorithm to extract leaf shape features. This paper is organized into five sections. Section I gives a brief introduction about the plant identification. In section II described about the proposed methodolgy, section III described about experiments and the expermetal outcomes and the final conclusions are drawn in Section IV.

Proposed Methodology:

We have collected some of the Malaysian plant leaf images from Melaka botanical garden and Agricultural Research Institutions. We have collected 300 leaf images of plants using the colour Digital Camera Cannon 5D Mark II , having resolution of 22 Mega pixels.

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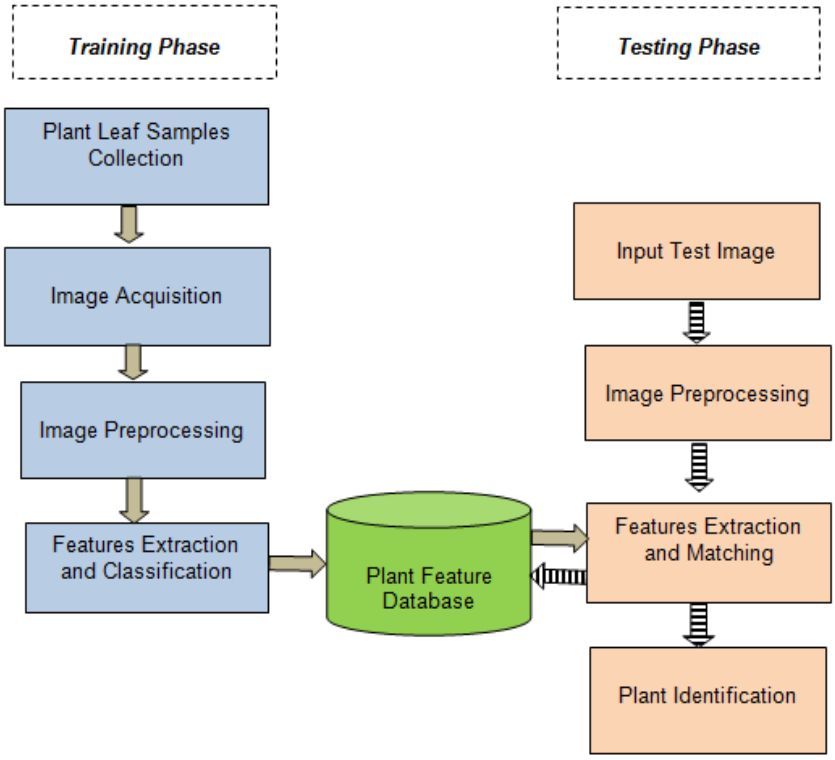

Fig. 1: Proposed Model for Plant Identification

Image Acquisition:

We have collected leaf images of 50 plant species. The leaf images acquired using high resolution digital camera. There are a number of sample leaf images are shown in Fig. 2.

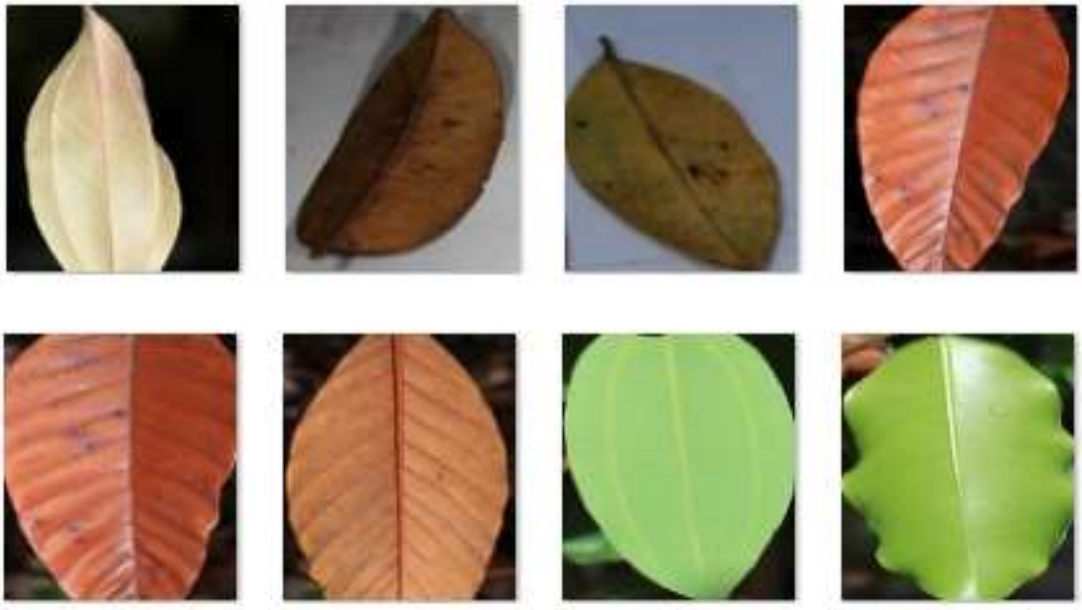

Fig. 2: Samples of leaf images acquired using high resolution digital camera

Image Pre-processing:

In this step, the raw leaf images converted from rgb to grayscale for features extraction.

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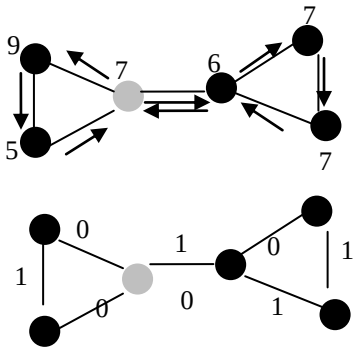
Feature Extraction and Classification:

In this step, all features of the leaves extracted using Local Graph Structure (LGS) algorithm, then calculated the Histogram for training samples and stored the Histogram features into the plant feature database. Finally, extracted the features of testing samples and then classified them by using correlation-coefficient to calculate the distance between the corresponding Histograms.

The idea of Local Graph Structure (LGS) comes from a dominating set for a graph G = (V, E) is a subset D of V such that every vertex not in D is joined to at least one member of D by some edge. The domination number γ (G) is the number of vertices in a smallest dominating set for G (Eimad *et. Al*, 2011).

LGS works with the six neighbors of a pixel, by choosing the target pixel C as a threshold, then start by moving anti clockwise at the left region of the target pixel C, If a neighbor pixel has a higher gray value than the target pixel (or the same gray value) then assign a binary value equal to 1 on the edge connecting the two vertices, else assign a value equal to 0. After finish on the left region of graph stops at the target pixel C and then move in a horizontal way (clockwise) to the right region of the graph and apply the same process till get back to the target pixel C.

(a)



(b)

Binary: 01010110

Decimal: 86

Fig. 3: Local Graph Structure (a. Direction, b. binary)

To produce the LGS for pixel (x_d, y_d) a binomial weight 2^p is assigned to each sign $s(g_d - g_n)$. These binomial weights are summed:

$$LGS(x_d, y_d) = \sum_{K=0}^{7} s(g_d - g_n)2^p \quad (1)$$

where $s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$

Where $p = 7.\ \ p = 7, 6, ...0.$

LGS Algorithm:

1. *Start moving from the target pixel in anti clockwise direction to the first neighbour.*
2. *If the move from large vertex to small vertex we assign a value = 1 to that edge.*

Else we assign a value to that edge.

3. *Loop until get back to the target pixel.*
4. *Then move to the right side of the graph and compare the target pixel with its neighbor in the right side.*
5. *Assign the target pixel to the next pixel on the right hand side of the target pixel.*
6. *Move a clock wise and apply the same as in step 2.*
7. *At the end, get back to the original target pixel which assigned 2 values.*

Plant Identification

Based on the extracted features which have been classified by using correlation-coefficient to calculate the distance between the Histograms and then identify the exact plant species using their correlation value.

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Experiments And Results:

In the initial experiment of plant leaf processing using LGS, can be seen in Fig 5, is an example of new generated image from original image Fig. 4 using LGS, a histogram of the LGSs for original image and a new generated one are illustrated in Fig 6 and Fig 7 consequently, histogram of LGSs image representing the distribution of 256 patterns across the leaf image. The advantage of LGS; Firstly it is a local measure, so LGS in a certain region will not be affected by the illumination conditions in other regions. Secondly it is a relative measure, and is invariant to any monotonic transformation such as shifting, scaling, or logarithm of the pixel-values. Therefore, it can be invariant to a certain range of illumination changes.

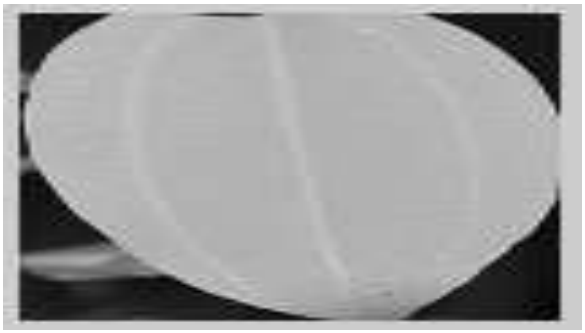

Fig. 4: Example of an original leaf image

Fig. 5: Example of new generated leaf image from original image using LGS

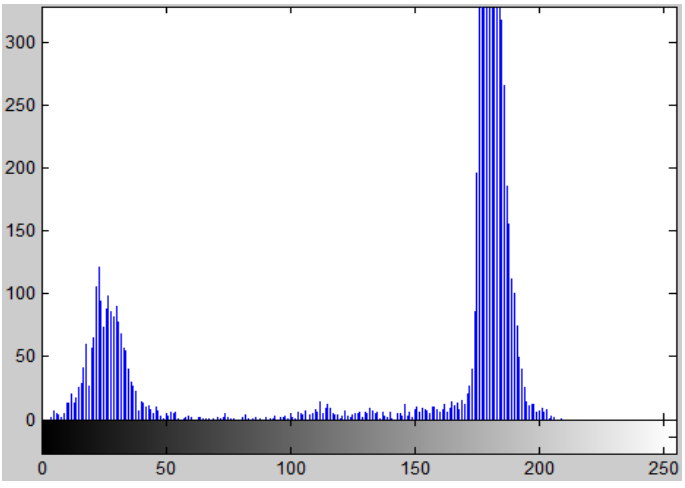

Fig. 6: Histogram of an original image

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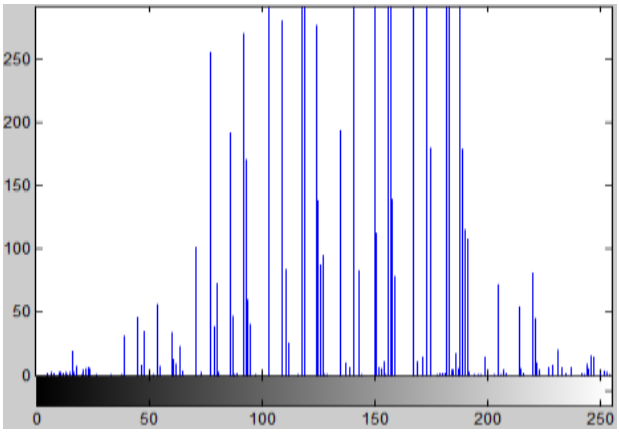

Fig. 7: Histogram of new generated image using LGS

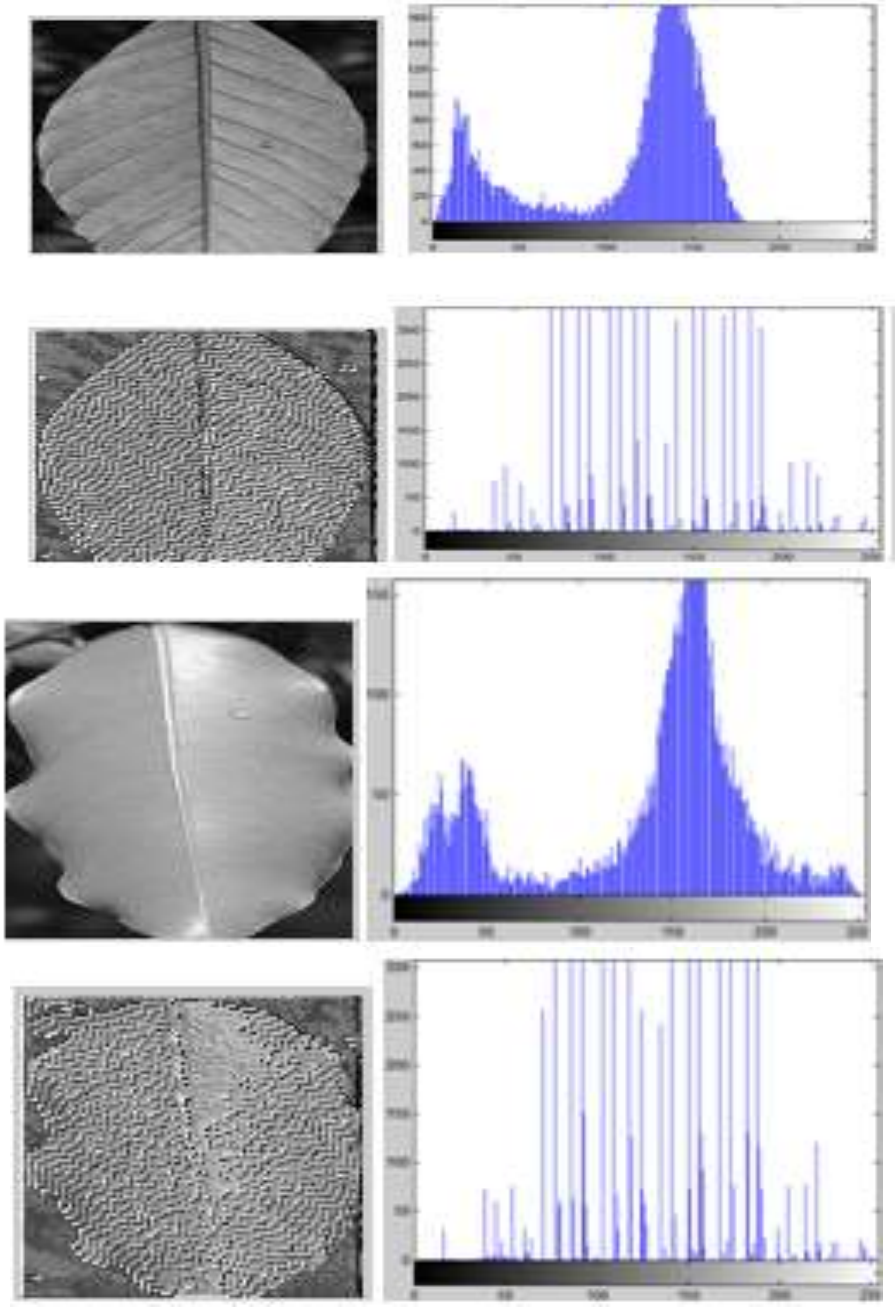

Fig. 8: Examples of original images with their corresponding Histograms and new generated images from original images using LGS along with their corresponding Histograms.

In our experiments, we have tested our proposed method using our own plant database. The database consists of 300 images. The images were captured with the subjects in a straight, frontal position, and with acceptance for some sloping and regular change of up to 20 degrees.

To assess the performance of the proposed LGS method on leaf recognition. 5 subjects have taken for our experiments, 4 images for training and the remaining 1 image for testing. First, LGS is applied to generate the histograms for the entire training sets. Consequently, LGS is also applied to generate the histograms for testing samples as well. Then calculate the matching between the histograms of the training images and the corresponding histograms of test images by applying the correlation functions..

The recognition rates obtained from the experiment with LGS is shown in Table 1. The experimental results showed that LGS is robust with respect to variations of illumination. We believe that the main explanation for the better performance of the local graph structure over other texture descriptors, it takes in consideration the relationship between the pixels that form the local graph of the target pixel C and consideration tolerance to monotonic gray-scale changes.

Table 1: Recognition Rate

Method	LGS
Recognition Rate	99%

The similarity and overall results for the proposed method are shown in Table 2 and 3, respectively.

Table 2: Similarity Rate

Subjects	Testing Image	Similarity (with Training) LGS
IMG1	1	0.998085110527295
IMG 2	1	0.997743662023461
IMG 3	1	0.976487569942248
IMG 4	1	0.984459108806954
IMG 5	1	0.998942694967835

Table 3: Overall Recognition Rate

Overall	LGS
Recognition Rate	83.3%

Conclusions:

The features of local graph structure are derived from a general definition of texture in a local graph neighborhood. The advantages of LGS over other local methods it's invariant to illumination changes, computational efficiency, and fast so that it can be easily applied in real-time system. LGS assigns weight for target pixels by considering not only the relationship of one pixel to its neighbours but also the relationship between the pixels that form the local graph of the target pixel; this feature is unique to LGS and lead to improve the image appearance and subsequently the recognition performance. In our experiments, the proposed approach is used for the identification of Malaysian plants using Local Graph Structure (LGS) algorithm based approach. We applied local graph structure to identify and classify the Malaysian plant species based on their leaf shape and texture pattern. From the experimental results, we obtained a maximum of 99% of plant recognition rate. The overall recognition rate is 83.3%, which is considered to be a significant level of accuracy of the plant species identification.

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