"myHerbs": A MOBILE BASED APPLICATION FOR HERBAL LEAF RECOGNITION USING SIFT

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Abstract

Herbs are plant with exquisite or sweet-smelling properties that been widely used since ancient times and are still used until today. Herbs generally refers to the leafy green, which are some of them have the same appearance, color and shape. Due to that, most of the ordinary people have trouble in recognizing the herbal species because of the similar features and appearances of the herbs leaf. In addition, the complexity of the structure of the herbs leaf itself contributes to the difficulty in recognizing its species. Other than that, botanist also had spent a lot of time to examine herbal species and classify them into group. Hence, this study proposed an automated mobile-based application for herb leaf recognition, "myHerbs. This study covers two species of the local herbs. The species of the herbs used in this study are Basil (Selasih) and Centella (Pegaga). All images used in this study are self-collected. Scale Invariant Feature Transform (SIFT) algorithm is used for extracting features from the herbs leaf and Fast Library for Approximate Nearest Neighbors (FLANN) algorithm is used for the classification purpose. 55 images have been evaluated for the testing purpose and the accuracy rate of 74.55% is achieved. The outcome of this study is believed to help the botanist and people in recognizing herbs species. In addition, it also contributes to the exploration and implementation of learning algorithm in mobile-based application.

Keyword: Basil, Centella, FLANN, herbs leaf recognition, mobile-based application, SIFT

Introduction

Malaysia is a multi-racial country that is rich in many traditional practices. One of the traditional practices that still practiced by locals is using herb leaves. Herb leaf is widely used in many daily routines including for the purpose to ease health conditions, to improve wellness, in cooking and many more. On the other side, usage of herbal medicines is increasingly important and gaining attention in the public (Kennedy & Seely, 2010). Knowledge about herb leaf is also important in life which it can be used whenever necessary. However, it is infeasible for the ordinary people when walking in the jungle to identify the names of the plant using visual inspection (Jeon & Rhee, 2017).

As well as the variety usage of the herbs leaf itself, it is very challenging to recognize the herbs leaf manually. It is due to the herbs leaf exhibits different characteristics from one species to another. Similarly, some of the herbs species may portray almost similar looks characteristic resulting the challenge in manual recognition. In addition, manual recognition of herbs leaf can be also troublesome and sometimes time consuming (Ibrahim et al., 2018). Hence, this lead to the attention of many researchers to explore the automatic plants identification but it is hard to satisfy the requirement of individual species (Imah et al., 2018).

In general, plants can be recognized based on many parts from the plant itself including from the flower, leaf and other parts on it. However, flower on the plant does not exhibits all the time due to many factors such as the weather. Leaf do exists throughout the year and it is visible (Ibrahim et al., 2018). Other than that, leaf is availabe in a big amount compared to others parts or features from the plant and leaves retain such unique physiognomies thru geometric features and venation architecture on the surface of the leaves. These physiognomic based discriminations have spawned curiosity in the minds of researchers to devise machine-based plant. Hence, leaf can be used to recognized the plant species**. Figure 1** shows the varieties herbs leaf shape.

Figure 1 The varieties of herbs leaf shape

Interest in recognizing plants based on the herbs leaf has grown tremendously since back. Roundness or compactness and aspect ratio of the leaf are the most used geometrical features to describe the leaf. Roundness or compactness of a leaf is defined as a ratio between area of the leaf and square of perimeter of the leaf while aspect ratio is the measurement between length and width of the leaf (Chaki et al., 2015; Chaki et al., 2018). Other available geometrical features are including convex hull, rectangularity and solidity.

Based on these varieties of the available geometrical features on the leaf, many techniques have been applied in building a robust automatic leaf recognition system. Scale Invariant Features Transforms (SIFT) is one of the widely used technique in extracting key-points in representing features of the leaf (Aslina et al., 2013; Lowe, 2004; Lavania & Matey, 2015). For the classification purpose, among of the established classifier in the literature are Convolutional Neural Network (CNN) (Visalini & Ramamoorthy 2020), Support Vector Machine (SVM) (Venkataraman & Mangayarkarasi, 2016; Aslina et al., 2013) and K-Nearest Neighbors classifier (Suresha et al., 2017; Turkoglu & Hanby, 2019). Hence, this study proposed a mobile application for herbs leaf recognition using Fast Library for Approximate Nearest Neighbors FLANN algorithm and SIFT features and Similarity measurers using Eulicdean distance.

Materials and Methods

This section describes the methodology used in this study. There are there main stages proposed in the methodology which are pre-processing, processing and post-processing. **Figure 2** shows the flow chart of the proposed application.

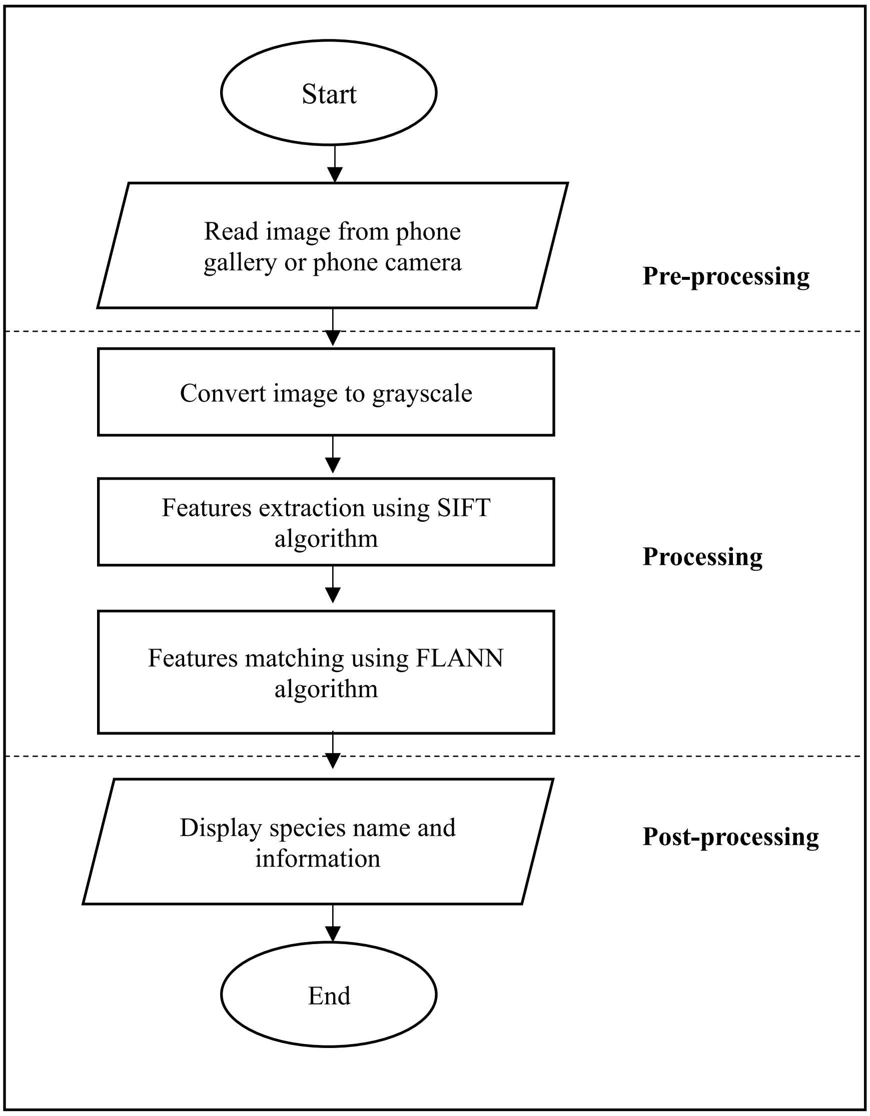

Figure 2 Methodology of the study

Pre-Processing

The proposed application starts with the pre-processing stage. In this stage, input image can be read from a phone camera or by browsing existing images in the phone gallery. Next, input image is resized to all standard size, which is 500 pixels x 500 pixels. Following, the input image is converted to grayscale image. The choice to perform grayscale conversion is it helps to simplify the algorithms and to reduce the computational cost. **Figure 3** illustrates sample of the two species of herbs used in this study which are Basil and Centella. While, **Figure 4** depicts the results from the grayscale conversion process.

Figure 3 Sample of Basil and Centella herb leaf

Figure 4 Comparison between input image before and after grayscale conversion

Features Extraction using SIFT

Shape features are extracted from the herbs leaf using the Scale Invariant Feature Transform (SIFT) algorithm. SIFT is robust in durable to transformation of geometrical and robust to noise (Aslina et al., 2013; Lowe, 2004). SIFT key-points of herbal leaf will be drawn to show the most point to that particular lead and give the nearest shape to the reality. SIFT algorithm works according to four steps from Lowe (2004). Firstly, Step 1 computes the scale-space extrema detection. This step performs the scale-space peak selection for finding the potential location of the features. It computes the difference of Gaussian over all scales and all location. Equations 1 and 2 show the implementation of Gaussian convolution.

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y) \tag{1}$$

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} \tag{2}$$

From Equations 1 and 2, $L(x,y,\sigma)$ is the scale space of an image, $G(x,y,\sigma)$ is the Gaussian and $I(x,y)$ is the image. Steps 2 and 3 involve key-point localization and orientation assignment respectively. Equation 3 computes the derivatives of DoG from the image. Equations 4 and 5 show the implementation of orientation assignment for Step 3.

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \tag{3}$$

$$m(x, y) = \sqrt{(L(x, y+1) - \mathrm{L}(x-1, y))^2 - (L(x, y+1) - L(x, y-1))^2} \tag{4}$$

$$\theta(x, y) = tan^{-1}((L(x, y+1) - L(x, y-1)) \,/\, (L(x+1, y) - L(x-1, y))) \tag{5}$$

In Step 3, orientation assignment aims to assign a consistent orientation to the key-points based on local image properties. The key-points descriptor, can then be represented relative to this orientation, achieving invariance to rotation. An orientation histogram of 36 bins is composed with the selected highest peak from the histogram (Lowe, 2004). Subsequently, Step 4 involves key-points descriptor based on the histogram built. **Figure 5** shows the SIFT key-points detected on the herb leaf.

Figure 5 SIFT key-points detected on the herb leaf

Based on **Figure 5,** all the SIFT key-points detected on the herb leaf are highlighted. The detected key-points are point (pt), size, angle, response, octave and class id. **Figure 6** shows sample of these values.

KeyPoint [pt={1722.8262939453125, 25.411706924438477}, size=1.9256233, angle=238.03386, response=0.0145231355, octave=5046783, class_id=-1]
KeyPoint [pt={993.4808959960938, 88.27037811279297}, size=2.075293, angle=130.28304, response=0.020969968, octave=10486271, class_id=-1]
KeyPoint [pt={1424.01513671875, 117.53390502929688}, size=2.179775, angle=278.43643, response=0.015845004, octave=14025215, class_id=-1]
KeyPoint [pt={1424.01513671875, 117.53390502929688}, size=2.179775, angle=82.68323, response=0.015845004, octave=14025215, class_id=-1]
KeyPoint [pt={119.32344818115234, 393.6947937011719}, size=2.103483, angle=334.03772, response=0.021856535, octave=11403775, class_id=-1]
KeyPoint [pt={119.32344818115234, 393.6947937011719}, size=2.103483, angle=196.85168, response=0.021856535, octave=11403775, class_id=-1]
KeyPoint [pt={119.32344818115234, 393.6947937011719}, size=2.103483, angle=160.92422, response=0.021856535, octave=11403775, class_id=-1]
KeyPoint [pt={119.32344818115234, 393.6947937011719}, size=2.103483, angle=122.73018, response=0.021856535, octave=11403775, class_id=-1]
KeyPoint [pt={119.32344818115234, 393.6947937011719}, size=2.103483, angle=33.910156, response=0.021856535, octave=11403775, class_id=-1]
KeyPoint [pt={990.5068969726562, 415.53765869140625}, size=2.1504343, angle=258.62494, response=0.020361504, octave=13042175, class_id=-1]

Figure 6 Sample of key-points data extracted from features extraction

Feature Matching using FLANN

Next, feature matching is performed to identify the herbal species type that is query by the user. Fast Library for Approximate Nearest Neighbors (FLANN) is used as the method to identify the herbal species. FLANN is one of the best feature matching which can performing fast approximate nearest neighbor searches in high dimensional spaces (Muja & Lowe, 2009). It contains a collection of algorithms that work best for nearest neighbor search and will select the best algorithm with the most optimal parameters based on the given input image. **Figure 7** illustrates the species match the query while **Figure 8** illustrates the output display upon the recognition of the herb species.

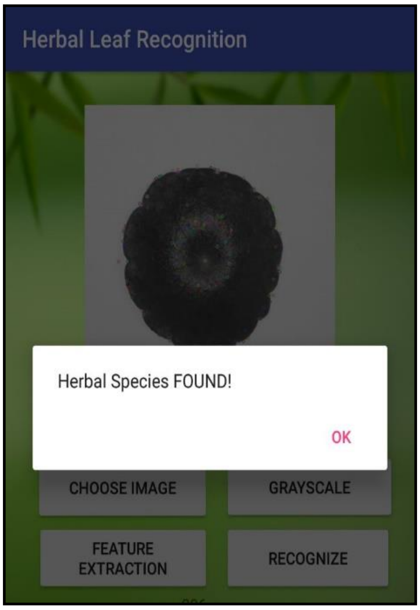

Figure 7 Sample of key-points value detected from herb leaf

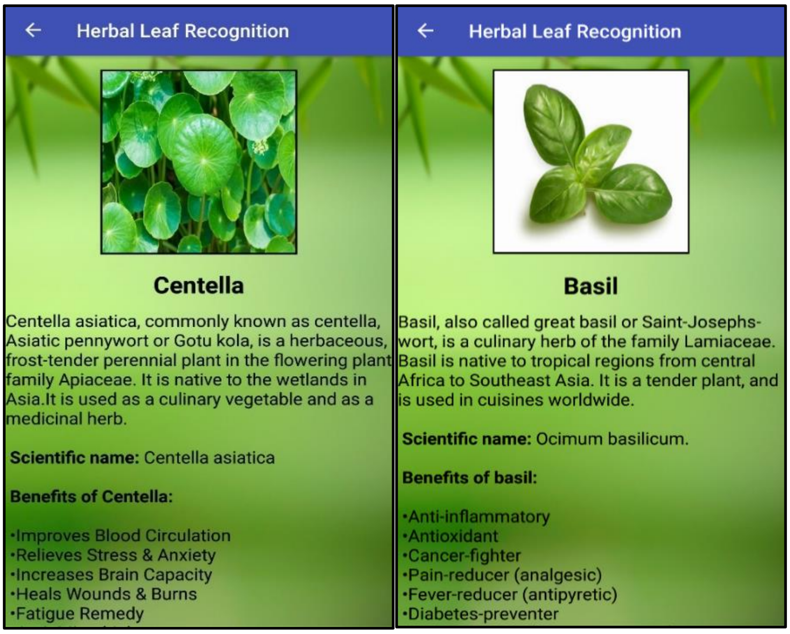

Figure 8 Species name and information are displayed

Post-Processing

This section discusses on validation process involving the testing conducted in this study. Functionality testing and accuracy testing were conducted to test the performance of the application. For the functionality testing, all the test cases are pass accordingly. Meanwhile, for the accuracy testing, 55 images are tested on the application. The overall performance of the application is computed based on the accuracy formula as stated in Equation 6. On the other hand, Equations 7 and 8 measure the sensitivity and specificity correspondingly.

$$Accuracy = \frac{Number\ of\ TRUE\ images}{Total\ Number\ of\ Testing\ Images}\ x\ 100\% \tag{6}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{7}$$

$$Specificity = \frac{TN}{TN+FP} \tag{8}$$

Accuracy measures the overall performance of the testing. On the other hand, sensitivity measures the proportion of the correct predicted positive classes while specificity measures the proportion of the negative classes that have correctly classified (Wong & Lim, 2011; Abdul & Anthony, 2008). Based on Equation 7, TP and FP populates the True Positive and False Negative result respectively. On the other hand, TN and FP in Equation 8 defines True Negative and False Positive recognition result respectively.

Result and Discussion

This study proposes “myHerbs”, a mobile-based application for recognizing herbs leaf. This study only covers two types of local herbs leaf including Basil (selasih) and Centella (pegaga). **Table 1** shows the sample results of 10 tested images.

Table 1 Sample result of 10 tested images

Input Image	Key-points	Good Matches Point (%)	Ground Truth	Actual Result	Accuracy Result
Image 1	876	89	Centella	Centella	True
Image 2	358	23	Basil	Centella	False
Image 3	102	80	Basil	Basil	True
Image 4	98	70	Basil	Basil	True
Image 5	399	36	Basil	Centella	False
Image 6	221	75	Basil	Basil	True
Image 7	500	12	Centella	Basil	False
Image 8	1002	90	Centella	Centella	True
Image 9	1429	70	Centella	Centella	True
Image 10	534	10	Centella	Basil	False

According to **Table 1**, Centella herb’s key-points value is between the range of 600 to 1500. Meanwhile, the key-points value for Basil herb is in the range of 95 to 260. If good matches points of the test images obtained 70% similarity, then the type of the herb will be classified.

The application is tested using 55 test images. **Table 2** shows the construction of the confusion matrix based on the testing conducted. The positive class for this study is the Basil (selasih) species and the negative class is the Centella (pegaga) species. Based on the results tabulated in **Table 2**, TP value achieved is 22 and the TN value achieved is 19. FN value and FP value achieved are 1 and 13 respectively. On the other hand, overall performance of the application is 74.55% as mention in **Table 3** as follows.

Table 2 Confusion matrix

Type of Herbs Leaf		**Predicted Type**	
		Basil (Selasih)	**Centella (Pegaga)**
Actual Type	Basil (Selasih)	22 (TP)	13 (FP)
	Centella (Pegaga)	1 (FN)	19 (TN)

Table 3 Result achieved

Number of Testing Images	**Number of Accuracy Result (TRUE)**	**Accuracy (%)**
55	41	74.55

Based on the result in **Table 3**, the overall accuracy achieved is 74.55%. It shows the developed application is able to perform good classification. However, the challenges are remain in distinguishing the robust key-points in recognizing the herbs species. Hence, the robust features are important for the recognition task consequently.

On the other side, the sensitivity and specificity rate obtained for this application are 0.957 and 0.594 respectively. From **Table 2**, its shows, the TP value achieved is 22 and the TN value is 19. Hence, this TP and TN value yields to the high sensitivity rate, 0.957 as achieved. It is concluded that this application is able to perform excellent recognition for both of the positive class (Basil) and negative class (Centella) in term of the sensitivity value. However, this application obtained only 0.594 for the specificity value which indicates it has fair performance in term of the specificity since the FP value obtained in **Table 2** is high. It is also noted that the number of testing images should be increased for optimizing the result achieved.

Conclusion

As a conclusion, this study proposed the implementation of SIFT algorithm and FLANN algorithm in a mobile-based application and achieved an accuracy of 74.55%. It is also stated that this study achieved both the sensitivity and specificity achieve of 0.957 and 0.594. However, it is believed that the hybridization or integration of any existing techniques for both feature extraction and classification can improve the accuracy result in future. In addition, this study hopes to expand the number of herbs species to be recognized in future.

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Conflict of interests

All authors in this paper declare there is no conflict of interests.

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