HerbApp: A Mobile-Based Application for Herbal Leaf Recognition Using Image Processing and Regularized Logistic Regression Classifier

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Abstract— Imaging technology has taken off at its significant level in the last decades. It has been used in different areas of research such are those that tackle plant recognition. In fact, there has been considerable body of work that performs analysis on leaf images, but most of them focus on plant or leaf identification. In this study, we present HerbApp, a mobile-based application that serves as a convenient tool in discriminating herbal from non-herbal plants to develop awareness among people on the significance of the plants whether or not it has been known publicly. Different characteristics and features of plants are used to perform pattern recognition and data analysis. From the captured leaf image, we perform segmentation process based on Localized Active Contour (LAC) model and extract features, which are used to build a classifier for leaf classification using Regularized Logistic Regression (RLR). Experiments show that our approach provides efficient results.

Keywords—Leaf Recognition; Herbal Leaf Recognition; Herbal And Non-Herbal Discrimination; Medicinal Leaf Recognition; Image Processing; Regularized Logistic Regression; Data Mining; Local Active Contour Model; LAC-Based Segmentation.

I. INTRODUCTION

Plants have been used for centuries for many different and innumerable uses including its vital role in the therapeutic world wherein the medicinal properties it contains are very beneficial. Some of the several advantages of traditional medicine include being affordable and easy to access [1]. Plants that are classified as herbal are processed and made into medicines or it can be freshly-picked boiled. They are used for therapies and common sickness such as cough, colds, and allergies. It marked its way for the reason of its easy availability, based knowledge passed from generation to generation and its low-cost availability because it can be found in all places where soil is fertile and accessible by sunlight.

Visually classifying a plant if it is herbal or non-herbal, is not a simple task for a non-botanist and a non-taxonomist. When it comes to reliability or accuracy, expert determination is said to be the best option. However, even an expert requires some considerable amount of time for the process. Compared to other methods, such as cell and molecule biology method, classification based on leaf image is the foremost choice for leaf plant classification [2]. Recognition is also deemed reliable, next to expert determination. Thus, there is a great need to come up with an application that discriminates from herbal to non-herbal plants.

Literature shows that there has been considerable number of work that tackles leaf recognition and identification but none of them tackles discrimination of herbal from non-herbal leaves. Leafsnap [3], for example, allows users to identify tree species simply by taking a photograph of the plant's leaves. The current version of Leafsnap has covered 184 tree species of the Northeastern side of the United States. It uses a visual recognition system for automatic plant species identification. The recognition process include: leaf/non-leaf classification, color-based segmentation, extraction and comparison. Leafsnap is only available for an iOS mobile operating system and only shows the most likely candidate to the captured image wherein the users will make the final identification. Plant Leaf Recognition using Neural Networks (LeafRApp) [4] is a desktop application which recognizes a plant from an input image file using the plant leaf's shape. The following are the techniques used in the LeafRApp: (1) A hybrid of two modelling techniques is used to extract features from the leaf; (2) Moment-Invariant method is used to extract the first four moments of the image; (3) Centroid-Radii method, which is employed to extract 36 radii with the image's centroid; and (4) Canny Edge Detection technique is utilized in extracting the edges of the leaf images, which undergoes a pattern recognition process using Multilayer Perceptron. LeafRApp is a desktop application which is similar to Leafsnap, which also produces a possible match from its plant leaf database within the percentage of its matching cut off and then presented to the user according to its proximity to the leaf plant image. However, canny edge detection is vulnerable to noise disturbances [5]. Input leaf images may contain noise due to illumination, which result to many false edges detected.

Our work is similar to knowItHerbal [6], which is an android-based herbal leaf identifier that helps the user recognize an herbal plant which is found only in the Philippines. The study utilized the Oriented FAST and Rotating BRIEF (ORB) algorithm for the processing of the image. Nevertheless, it is difficult to judge the accuracy of the system in terms of herbal leaf identification based on the datasets used as it was not disclosed by the authors. Instead, only the results of the User's Acceptability Test (UAT) were presented.

MedLeaf [7], on the other hand, is a new mobile application for medicinal plants identification based on leaf image. The application runs on Android operating system. It has two main functionalities: (1) to identify medicinal plants; and (2) to search for documents of medicinal plant. It uses the Local Binary Pattern to extract leaf texture and Probabilistic Neural Network to classify the image. In this research, there were thirty (30) images of Indonesian medicinal plants species used and each species consists of 48 digital leaf images. Nonetheless, it utilized the leaf textures only as their parameters or features, which are in turn the basis for medicinal leaf recognition with an accuracy of 56.33%.

Analysis of plants would depend on their different characteristics. From these characteristics, classification of plants is made easy. There are varieties of ways to identify a plant. The traditional methods commonly used are expert determination, recognition, comparison and use of keys and similar devices. These methods have different advantages of their own. In particular, it is known that the exact way to extract plant features is to involve plant recognition based on leaf images. Leaves are easier, accessible and abundant compared to the other plant morphological structures such as flowers, barks or fruits. In almost all automatic leaf plant identification, shape of the leaves is the most common feature used for identification as it is claimed to be the most discriminative feature of a plant's leaf [8]. Two features, which are widely used for plant recognition based on leaf image is the color and shape.

In the color-based conventional study, a simple color similarity between two images can be measured by comparing their color histogram. Also, in the shape based-conventional study, they used region and contour-based simple features [9]. Essentially, shape, color and texture features are common features involved in several applications. However, some researchers only used a specific part of those features [10]. The plant's leaf is normally green in color. But there are various shades of color for a single plant. Moreover, the variety of shades for a single plant appears because changes in water volume, nutritional value, an atmospheric change in environment occurs. Based on this, it has been recognized that the color feature has low reliability to identify a specific plant [11]. Accordingly, when the color is considered, it is undeniable that the recognition performance is limited due to the leaf's color which is easily affected by its environment.

In this paper, we proposed a herbal leaf recognition application based on the shape and texture features of a leaf of a plant. We leverage Localized Active Contour (LAC) model [12] for leaf segmentation, necessary in automating the extraction of features or parameters; and subsequently classifying the leaf/plant using regularized logistic regression.

II. METHODOLOGY

A. Herbapp: An Overview

Our application performs herbal leaves recognition. We capture leaf images of a leaf using our herbApp application and download them in the user's mobile phone. The application works very well with leaf images taken in a plain background possibly white and with a reasonable illumination of light so that in getting its edges, shadows and other nuisances could not distort the features to be extracted.

herbApp runs on Android mobile operating system and works on server side and client side. Fig. 1 shows the system architecture of the mobile application. On the client side, a leaf is placed in a paper with white background and a digital image is obtained via smart phone camera. The captured leaf image is then sent to the server for classification. The server runs the pre-processing, segmentation and feature extraction on the image sent before the classifier predicts its classification (i.e. herbal or non-herbal). The result of the classification is sent back to the client via smart phone.

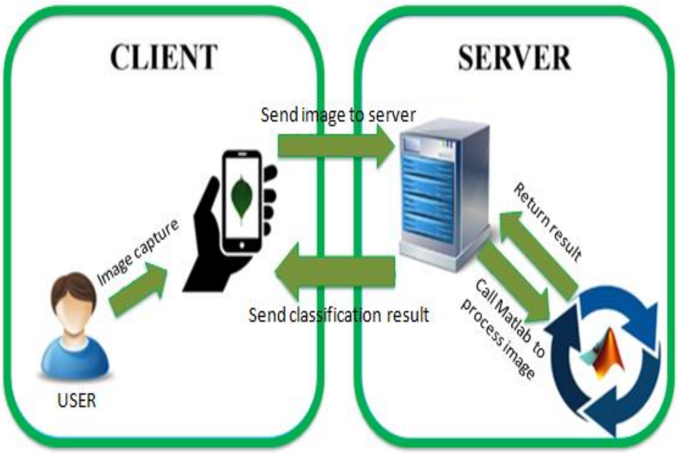

Fig. 1 System Architecture

B. Framework of Herbapp

Our work discriminates herbal from non-herbal leaves by applying data mining based on the features and parameters extracted from the captured leaf image. Leaf images of a plant may be collected and stored in the image database giving the user an option to let the application perform the batch analysis or by individual leaf immediately after it has been captured. **Fig. 2** presents the framework of herbApp. The process starts by taking the leaf image or retrieving leaf images that have been stored in the database. This is followed by image pre-processing and feature extraction, which are necessary for herbal leaf recognition.

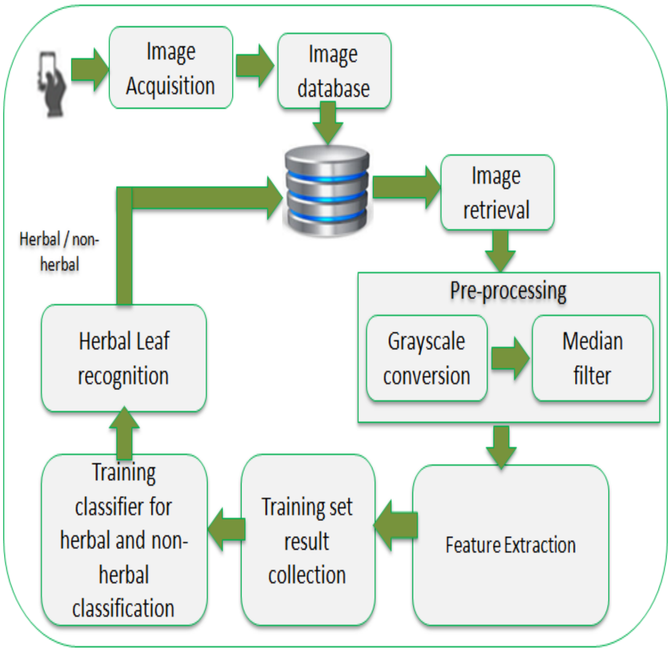

Fig. 2 Framework of the Proposed Herbapp Mobile-Based Application

B.1 Image Acquisition

The process starts with the user capturing an image of a leaf using our herbApp application downloaded to the user's smart phone. The leaf images or still photos should be taken in a plain white background and with a reasonable illumination of light so that in getting its edges, shadows and other nuisances could not distort the features to be extracted.

B.2. Image Pre-processing

The leaf image will then undergo the pre-processing phase to remove any noise before the actual analysis of the image data and the conversion of the image into numerical values. Pre-processing is performed to eliminate the noise and correct the distorted or degraded data of the leaf image to have a more authentic representation of the leaf and to increase its classification accuracy.

There are many pre-processing techniques that can be used to enhance, filter, smoothen and remove the noise of an image. Initially, the conversion of the image from the original Red-Green-Blue (RGB) format to a grayscale format and noise removal with a digital filtering technique called the median filter will transpire. The median filter is a typical pre-processing step to improve the results of later processing and it is used in digital image processing because, under certain conditions, it preserves edges while removing noise which is a huge contribution to have accurate results later on. The result is presented in Fig. 3.

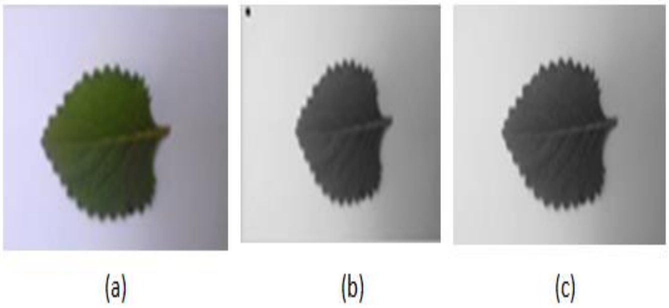

Fig. 3 Pre-Processing Results. A) Original RBG Image; (B) Grayscale Image (C) Result After Employing Median Filter

B.3. Image Segmentation

At this stage, the leaf image undergoes the segmentation process in order to get the Region of Interest (ROI). The ROI is a portion of an image that you want to filter or perform some other operation on. ROI can be defined by creating a binary mask, where it defines the region. The segmentation process is a necessary method because sometimes the images do not only include the leaf region; it may also include the stem. Since we are only focused in getting the leaf region, we aim to keep only the leaf region and discard the unnecessary parts of the captured images.

In getting the leaf region, an initial experimentation has been done which aims to compare the result of the Sobel Edge Detection and the Localized Active Contour (LAC). Sobel Edge Detection performs a 2-D spatial gradient measurement on an image and emphasizes regions of high spatial frequency that correspond to edges. It is normally used to find the approximate absolute gradient magnitude at each point in an input grayscale image. LAC on the other hand, utilizes image gradients in order to identify object boundaries. This type of highly localized image information is adequate in some situations, but has been found to be very sensitive to image noise and highly dependent on initial curve placement. One benefit of this type of flow is the fact that no global constraints are placed on the image. Thus, the foreground and background can be heterogeneous and a correct segmentation can still be achieved in certain cases. Empirical results show that LAC [12] does have an appealing quality that generates closed contours, which can be very useful in separating the outer boundaries of an object from the background [5, 13-14]. Thus, it is presumed that LAC will be superior among the standard edge detection tools (Canny, Prewitt, etc.). Nevertheless, to further compare LAC with some other standard tools, we also utilized Sobel Edge Detection and compared its performance with LAC. For example, in Fig. 4, two leaf images were captured by an 8mp camera phone wherein the first image was captured poorly combined with a shadow near the stem, whereas the second image was captured with the right light of illumination with no shadows lurking. As observed, LAC is more efficient to use than the Sobel Edge Detection. In getting the ROI, the binary masking is statistically set to 400 iterations.

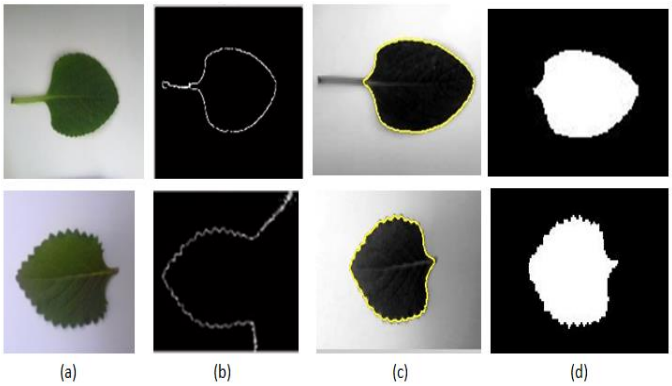

Fig. 4 Segmentation Results. A) Original RBG Image, (B) Using Sobel Filter, (C) Using LAC Model, (D) Binary Form of the Results

B.4. Feature Extraction

Once the leaf region has been identified after segmentation, leaf feature extraction takes place. The leaf extraction takes into interpretation of the shape and texture feature. Figures 5 and 6 show the geometric and morphological features of a leaf, respectively.

B.4.1. Shape Features

The shape features to be extracted is from the digital morphological features of the binary format of the leaf image. Sub-features under the shape feature include: (1) aspect ratio; (2) rectangularity; (3) eccentricity; (4) diameter; (5) narrow factor; (6) perimeter ratio; and (7) irregularity

The *aspect ratio* - is the ratio between the maximum length and the minimum length of the minimum bounding rectangle (MBR).
Rectangularity - is defined as the ratio between the region-of-interest (ROI) area and the MBR area

Eccentricity - the ratio of the length of the main inertia axis of the ROI (EA) and the length of the minor inertia axis of the ROI

Diameter- the longest distance between any two points on the margin of the leaf

Narrow Factor- it is defined as the ratio between diameter and physiological length

Perimeter Ratio -it is defined as the ratio between perimeter and sum of physiological length and physiological width

Irregularity - irregularity or dispersion is defined as ratio between the radius of the maximum circle enclosing the region and the minimum circle that can be contained in

Fig. 5 Five Basic Geometric or Morphological Features

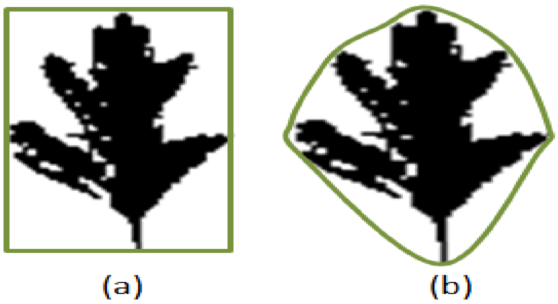

Fig. 6 Some of the Morphological Features (a) Minimum Bounding Rectangle (MBR) (b) Convex Hull

B.4.2. Texture Features

The texture features are extracted using the Gray-level Co-occurrence matrices (GLCM) [15-16]. The GLCM is one of the many texture feature extraction techniques and is one of the most popular means of texture analysis. The matrices are designed to measure the spatial relationships between pixels. The method is based on the belief that texture information is contained in such relationships. The following are some of the sub-features of the texture feature include: contrast, homogeneity, correlation, energy, entropy, dissimilarity, inverse difference, autocorrelation, sum of squares, sum of variance; sum entropy, information measures of correlation, maximal correlation coefficient, and inverse difference moment normalize.

B.5. Training Set and Result Collection

After several leaf features are extracted, the values corresponding to each feature will then be collected and trained. To determine the best classifier to employ in our application, we use three (3) on the same dataset. These include the Decision Tree (DT); Naïve Bayes (NB); and Regularized Logistic Regression (RLR). Consequently, the best classification method will be utilized for herbal and non-herbal classification.

III. RESULTS AND DISCUSSION

In our experiment, 140 leaf images were utilized, all of which are from publicly available leaf database which can be downloaded such as flavia and imageClef; and leaf images of medicinal plants found in Philippines. The images come in different size (e.g. 640 x 480 resolution), which are converted to 96 x 127 resolution during the image processing. Twenty-one (21) parameters or features used for classification. All features extracted are stored in a vector and is saved in an ".m" file and an excel file purposely for training and testing the model. In acquiring additional images, the user captures an image of a leaf using the herbApp application downloaded in the user's mobile phone. The application works very well with leaf images taken in a plain background possibly white and with a reasonable illumination of light so that in getting its edges, shadows and other nuisances could not distort the features to be extracted.

In discriminating herbal from non-herbal leaves, we employed Decision Tree (DT), Naive Bayes (NB) and Regularized Logistics Regression (RLR); and compared the results in terms of the measures of evaluation (e.g. precision, recall, specificity and accuracy); and consequently utilized the best classifier for an efficient herbApp application. Since the size of the database was not very large, we adopt the k-fold cross-validation test scheme. 10-fold cross-validation has become the standard method in practical terms. Tests have also shown that the use of stratification somewhat improves the results. Thus, the standard evaluation technique in situations only have a limited data is available is 10-fold cross-validation [8]. Since our dataset is limited, we took the N-fold cross-validation test scheme.

To test the accuracy of this system, we use the N-fold cross validation. Cross validation is a method applied to a model and a data set in an effort to estimate the out of sample error. It has become quite popular because of its simplicity and utility. In N-fold cross validation, the data set is randomly partitioned into n-partitions, we then fit its model to a data set consisting of n-1 used as training data, while a single subsample is retained as the validation data for testing the model and use the remaining portion for validation. We estimated the out of sample error using the portion of data left out of the fitting procedure and repeated it n-times and their estimation for the out of sample error is the average over the n-validation runs. For example, to evaluate the accuracy of the classification, the n-fold cross validation is utilized where N=10, which can be referred to as a 10-fold cross validation. The 10-fold cross validation indicates that the training and testing sets are performed 10 times by partitioning the dataset into 10 mutually in iteration exclusive subsets or what we call "folds" in which a subset in our case is 10% of our data is reserved as the test set and the remaining partitions which is 90% are collectively used to trained and produce a model. In each fold, we leave one fold out as our test set and use the remaining 9 folds as our training set (e.g. in the first round, fold 1 is the validation set, in the second round fold 2 is the validation set, in the third round, fold 3 is the validation and so on and so forth). In each fold, the 9 folds will serve as the training set that aims to learn a model. Since it's a 10-fold cross validation, we do the procedure for 10 repetitions.

Accuracy is perhaps the most intuitive performance measure. It is simply the ratio of correctly predicted observations. Using accuracy is only good for symmetric data sets where the class distribution is 50/50 and the cost of false positives and false negatives are roughly the same. It can be attractive at first because it is intuitively easy to understand. However, it is advised not to rely on it too much because most data sets are far from symmetric [9]. Based on the experiments conducted, Regularized Logistic Regression (RLR) appears to be superior among other classification methods as shown in Table 1. It presents a comparison of the performance of the three (3) classification methods using the measures of evaluations, which include the accuracy, precision, recall and specificity.

	Decision Tree	Naive Bayes	Regularized Logistic Regression
Accuracy	86.0%	79.6%	88.3%
Precision	86.9%	81.2%	90.0%
Recall	90.3%	84.6%	89.2%
Specificity	88.4%	85.6%	92.6%

Table 1: Comparison of the Performance of the Three Classification Methods for Herbal and Non-Herbal Discrimination.

As shown in the table, the probabilistic approach using the RLR yields a highest specificity (or true negative rate) of 92.6% score and is consistent to be superior over other methods in terms of accuracy and precision rate. While Decision Tree (DT) yields a little bit higher result in recall or sensitivity (or true positive rate) measure of 90.3% (i.e. 5.7% and 1.1% higher than NB and RLR, respectively), the study is more concerned on the specificity in which RLR prevails. This is because, considering the essence of the problem we are addressing, we are particularly avoiding the FP (False Positive) results or a non-herbal plant predicted as an herbal plant as it has a critical implication. For instance, a non-herbal plant (e.g. non-medicinal, toxic, dangerous leaves, etc.), when wrongly predicted as herbal plant can relatively cause danger to human health. Thus, looking at this significant implication, the study is much focused on the specificity measure rather that sensitivity. Hence, we employ RLR in running our herbApp.

The Herbapp Application

Figures 7 to 9 presents some sample screen shots of the herbApp application. The process starts by installing our herbApp application and connecting to the server's IP address as presented in Fig. 7.

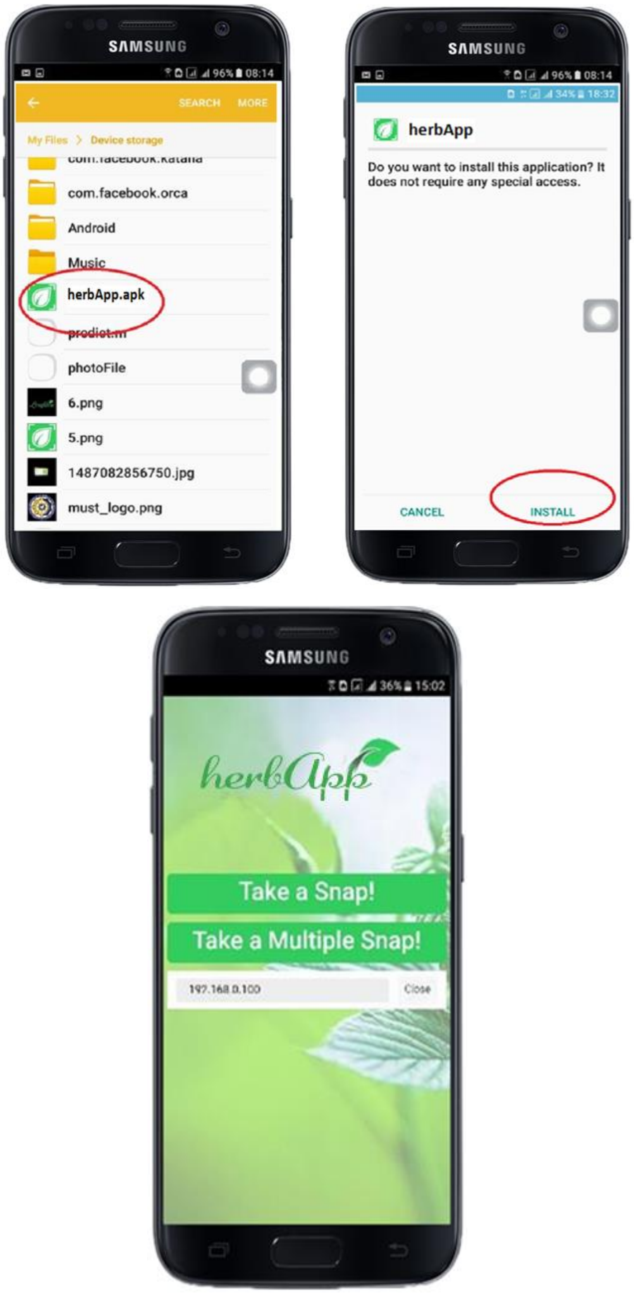

Fig. 7 Sample Screen Shots of Herbapp's Installation Process

Once, installed and the application is ready to use, the user has an option, either to take an image one at a time by choosing "Take a snap" button and see the results immediately or take multiple images ("Take a multiple snap button"), save or upload them for processing later. Fig. 8 shows some samples of screen shots.

When the user clicks the "Take a snap" button, it will lead him to a window to take an image one at a time then see the result immediately or take multiple images and upload them. That is, the user can either capture a leaf image (i.e., to press the button with a camera icon) or upload a leaf photo from his gallery (i.e., to press the button with a folder icon). When the user chooses the other option which is to "capture an image" button, it will lead him directly to his camera's phone and clicks OK if it's good to go and Retry to capture again.

Fig. 8 Sample Screen Shots of Herbapp's Herbal Leaf Recognition

A loading icon will then appear, and when processing is done, a message alert will then appear showing the leaf classification as evaluated by the system. When a user presses the "Take a multiple snap" button, it will lead you to an interface shown in

Fig. 9. With this, the user can capture a leaf image (i.e.; by pressing the button with a camera icon). The user may click “OK” if it’s good to go and “RETRY” to capture again. The user has an option either to press the “Upload” to send the images to the server for processing or “See the Results” button to get the classification result.

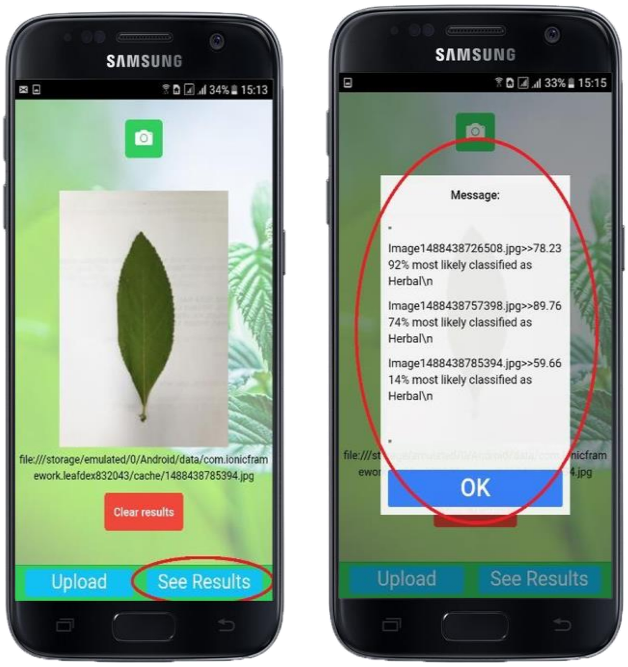

Fig. 9 Sample Screen Shots of Herbapp’s Leaf Recognition Using Multiple Uploads

IV. CONCLUSION

In this paper, we present a novel approach to perform leaf classification (i.e. herbal or non-herbal). herbApp Android-based application was developed that can discriminate herbal from non-herbal leaves. Our approach provides efficient results in recognizing herbal from non-herbal leaves. Experiments show that employing LAC model appears to be superior over other edge detection tools in segmenting leaf image prior to recognition stage. Thus, it significantly contributes to the efficiency of the results in discriminating herbal or medicinal from non-herbal or non-medicinal leaves.

The main difficulty of this work, however, is finding leaf imageset or datasets that are located within Philippines. Most of the leaf images used was from the publicly available dataset, which are mostly from the U.S. Shape and texture can be considered excellent features to identify a plant. However further researches with large amount of dataset, experiments and investigations are needed to further support and confirm the claim. Other feature extraction methods should also be tested to verify the consistencies of the results. Nevertheless, our approach has significant number of merits that are necessary to help other researchers whose endeavors are in line with this area as well as to serve as an excellent stepping stone for increasing efficiency of herbal leaf identification and its corresponding names and usage for practical use.

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