Computer Assisted Plant Identification System for Android

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***Abstract*—Plant leaves provide sufficient features to distinguish them among other species. Identification of plants using leaf images is a classic problem in digital image processing. Usually those image processing systems use shape based digital morphological features for leaf identification task. Even there are number of studies on leaf based plant identification, very few of them are for mobiles. In this paper we describe a leaf image based plant identification system using SIFT features combining with Bag Of Word (BOW) model and Support Vector Machine (SVM) classifier. The system is trained to classify 20 species and obtained 96.48% accuracy level. Based on the results, we developed an Android application communicates with the server and gives users the ability to identify plant species using photographs taken of plant leaves using the smart phone.**

Keywords—plant identification, image processing, leaf features

I. Introduction

Shape and venation of plant leaves provide sufficient features to distinguish them among other species. Professionals who are engaging with botany, use plant leaves for plant identification purposes. The practical usage of botanical field guide emerge on those users who are involved with applied botany such as researchers, university students and even general public. However carrying heavy paper based botanical guides to the field is a burden. To eliminate the problem many studies have been carried out on plant identification systems using different approaches such as extracting contour based features and venation based features etc. on leaf images. Today there is a rapid increase of number of Android powered smart phones in use and it is easy to carry these tiny devices in to field and they are equipped with sufficient processing power for speed internet access. But there are very few mobile plant identification application dedicated to smart phones. Leafsnap [1] is the first product came out to the market to identify plants of Northeastern USA using leaf images for iPhone users. In our work we implemented a plant identification system for Android mobile, using scale, orientation, illumination and camera view point invariant leaf features extracted using Scale Invariant Feature Transform (SIFT) algorithm combining with BOW model for feature vector dimensionality reduction and SVM as the classifier. We eliminated low contrast features based on contrast threshold. Our method achieved better accuracy comparing to other existing methods. And the whole system is easy to implement and fast responsive.

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The rest of this paper is organized in the following way. In section II we describe some related works. Section III describes the overall architecture of the system, flow of system training, classifier generating process, SIFT feature extraction and the Android implementation. In section IV data preparation and evaluation of the system is described. Finally section V presents our concluding remarks.

II. Related Work

A number of studies have been done on computer assisted classification and identification of plant leaves. For the first time, Petry and Kuhbauch [2] proposed a discrimination model for identifying weed species using digital morphological features. In the past few years many studies dealing with leaf classification have been published because of the importance of the research area.

We could find number of approaches when working with leaf based plant identification. In order to build robust leaves representation, most crucial leaf features used were leaf shape and the vein structure. Concerning shape based leaf descriptors, Xiang et al. [3] proposed method of plant species recognition based on extracted digital morphological features (DMF) from leaf contours. They have used 15 DMFs including aspect ratio, circularity, rectangularity, form factor, sphericity, ratio of convexity, area, eccentricity and perimeter ratio of convexity, etc. Then moving median centers (MMC) hypersphere classifier was adopted to classify feature vectors. Similar approach was suggested by Stephen Gang Wu et al. [4]. They proposed a plant leaf classification algorithm based on 12 digital morphological features computed on basic features extracted from a leaf image like diameter, physiological, length, physiological width, leaf Area and leaf perimeter. To reduce the dimensionality of feature vector they have used principle component analysis (PCA) and then used probabilistic neural network (PNN) for classification of feature vectors.

Another leaf shape based plant identification method was proposed by Shuang et al. [5] They suggested polygonal approximation using accelerated Douglas Peucker approximation algorithm as compression method because extracted leaf contours exhibits too many resolvable points. Since extracted features were not invariant to scale, rotation and translation they suggested invariant attributes sequence representation. Then modified dynamic programming algorithm was adopted for invariant feature matching. Sofiene et al. [6] proposed a method using combination of two shape based descriptors. Firstly descriptors for leaf margin or the contour and secondly spatial relations between the Harris points (salient points) and the leaf contour points.

Yeni et al. [7] proposed a method using Combination of digital Morphological features with Color Moments Features and Local Binary Pattern Variance (LBPV). They implemented PNN to classify feature vectors.

Using venation of a leaf image for plant identification has been addressed in many studies [8], [9], [10], [11], [12]. Vein structure of a leaf is unique to a species. So combining leaf shape descriptors with venation can be used to obtain accurate and robust leaf descriptors. Lee and Hong [8] proposed a way of describing leaf direction using projected histogram of venation in the horizontal and vertical directions to measure the distribution of the leaf vein. They decided the leaf direction using vertical projections. First they took the difference of gray scale image and the image created performing morphological open operations. Then they converted difference image in to binary image to extract leaf venation. In [9] authors proposed to use number of ramification of the main vein to measure the complexity of venation. Vein extraction method was proposed in [10] using independent component analysis (ICA). They first patches of leaf image using FastICA algorithm to learn a set of linear basis functions. Then these linear basis functions were used as the pattern map to venation extraction. In [11] and [12] authors proposed a method to represent main venation using curvature scale scope corner detection method on the venation image. However extracting venation features accurately is a difficult task sometimes this may need well captured venation images of leaves.

A number of studies have been done using Fourier descriptors. Leaf recognition using amplitude-frequency feature by performing Discrete Fourier transform on ordered sequence computed by extracting serial points of the leaf contour was proposed by Yang and Wang in their study [13]. In another study Neto et al. [14] used Elliptic Fourier (EF) harmonic functions generated on leaf boundary. They used PCA to eliminate the Fourier coefficients with the low discriminatory power. Unlike study in [13] they parameterized the leaf contour by angles not by the distance.

Some authors used leaf descriptors using histograms of oriented gradients (HOG) features. Xiao et al. [15] used HOG to represent leaf shape. For dimensionality reduction of the feature vector they have used Maximum Margin Criterion (MMC). Xia et al. [16] used a similar method as [15] except they have used some configuration changes with crucial variables in the original HOG algorithm to achieve robust feature descriptors which are invariant to illumination, shadow etc.

While most of the studies were on building general purpose leaf classification algorithms there are some studies dedicated to build leaf identification algorithms for mobile users [1], [17], [18]. In [1] authors suggested a leaf recognition application (Leafsnap) for mobile using Histograms of Curvature-Based Shape Features (HoCS). They used nearest neighbor matching over HoCS features. This is the first and most popular application in the market, however this application is only for iPhone users. Nguyen and Le suggested a leaf classification method in their study [17] for Android users combining Speeded Up Robust Features (SURF). To reduce dimensionality of extracted features BOW model is used. Then SVM classifier was used to classify extracted feature vectors. Knight at el. [18] proposed an automatic plant classification for Android mobile using digital morphological features and using MMC hypersphere classifier. They used angle code histogram (ACH) to compute angles of adjacent contour segments. In our study we used leaf features extracted using SIFT algorithm.

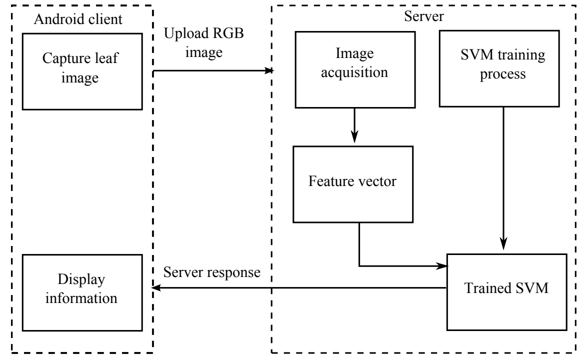


Fig. 1. Overall architecture of the system.

III. Methodology

A. *Overall Architecture of The System*

Our system is based on the client server architecture as shown in Fig. 1.

Server involves in two main activities. Firstly training of the SVM and generate the classification feature vectors and save it in the server file system. Secondly acquire photographs uploaded by Android client and generate feature vector. This vector is used by the trained SVM for identification of the plant.

From the client side, user takes a photograph of leaf against simple white background using an Android smart phone. Then this photo is uploaded to the server application. After identification process, server responses to the client with the plant species and few information about the plant. The client application will display the information to the user. Following sections describe methods we used to generate the classification vectors and leaf image identification.

B. *SVM Training Process*

SIFT descriptors in combination with Bag of Feature model is used to generate the classifier. The classifier generating process can be described in four major steps. In the first step SIFT descriptors from each leaf image of the training dataset are extracted. BOW model which is an unsupervised learning method as a dimensionality reduction method of the data space is used. In the second step system use BOW method to cluster all the features extracted in to feature bags and builds the vocabulary. Third step is to generate BOW histograms considering all the images in the training data set where each bin of the histogram contains the number of SIFT features nearest to the respective feature bag. After completing this step each and every image in the training data set has a histogram. As the fourth step we pass all the histograms as classification feature vectors to the SVM and then create and save the classifier which contains feature vectors, in the server storage.

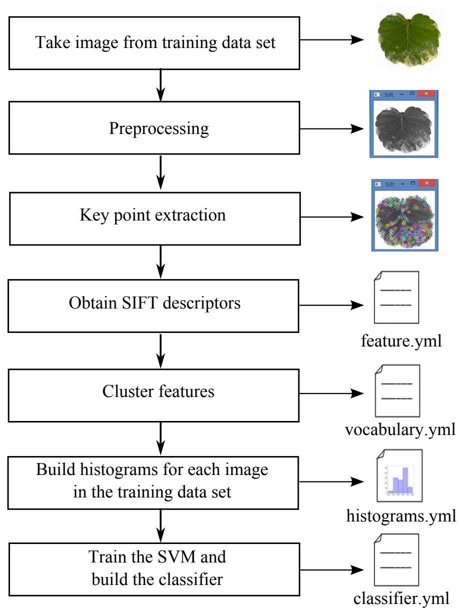


Fig. 2. Methodology of creating the classifier.

We used yml files to store data. The flow of the implemented method is shown in Fig. 2. Clustering features and histogram creating processes are shown in Fig. 3.

a) Sample leaf images of train data set.
b) Obtained SIFT feature points.
c) Computed feature descriptors of key points.
d) Cluster feature descriptors.
e) Create and train the Bag of Features, build the vocabulary.
f) Take sample image from train data set.
g) Extract SIFT key points.
h) Compute SIFT descriptors for each key point.
i) Match feature descriptors with the vocabulary.
j) Compute the histogram.

C. Preprocessing

Before extracting SIFT feature points we converted RGB image in to gray scale image. To convert values of Red, Green and Blue components of a pixel to gray scale value we used Equation 1.

$$gray = 0.299.R + 0.587.G + 0.114.B \tag{1}$$

R, G and B represent the corresponding color of a pixel respectively.

D. Key Point Extraction and Generating Descriptors

We used SIFT algorithm proposed by David G. Lowe [19]. Which is highly involving algorithm in CBIR (content based image retrieval).

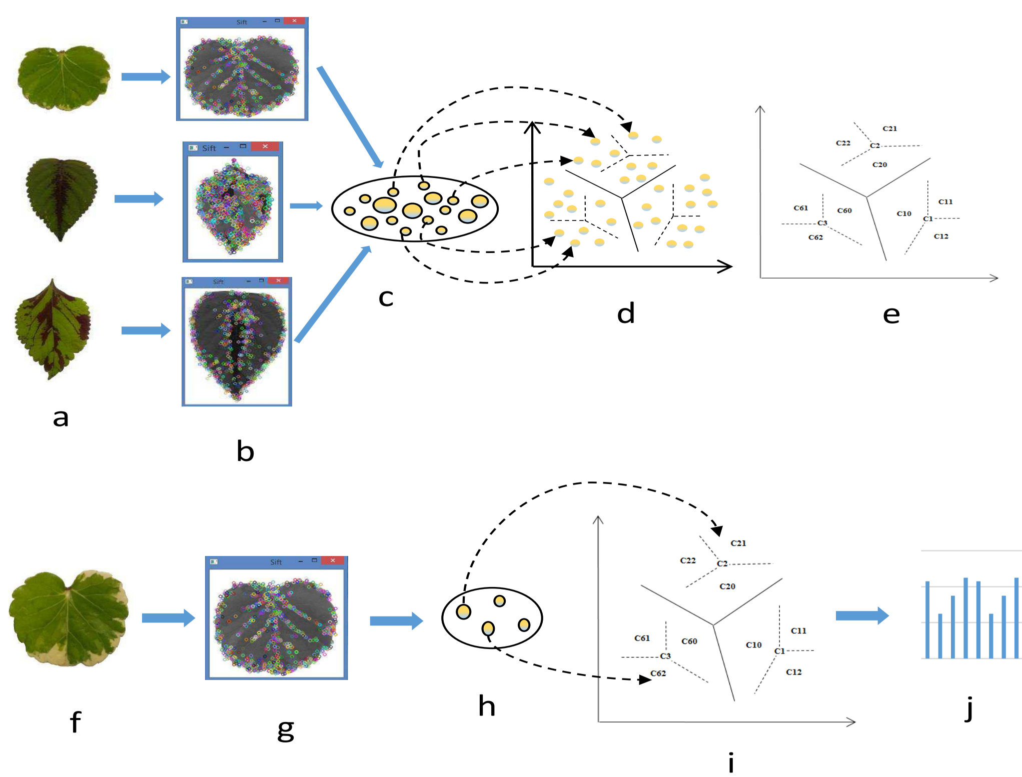


Fig. 3. Generating classification feature vectors.

SIFT features are scale, rotation, illumination and camera view point invariant so rather than using contour based features in our study we used SIFT features to make robust leaf classification method. According to the study [19] the SIFT algorithm can be described in following steps.

1) Scale-Space Extreme Detection: Scale space of an image is a function of $L(x, y, \sigma)$, produces by the convolution of a variable-scale Gaussian, $G(x, y, \sigma)$ with an input image, $I(x, y)$:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \tag{2}$$

Where * is the convolution operation in x and y, and

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e - (x^2 + y^2)/2\sigma^2 \tag{3}$$

To detect stable key points in the scale space efficiently, difference-of-Gaussian function is convolved with the image $D(x, y, \sigma)$. Lowe [19] used two nearby scales which separated by constant multiplicative factor k.

$$D(x, y, \sigma) = (G(x, y, k\sigma) - D(x, y, \sigma)) * I(x, y) \tag{4}$$

$$= L(x, y, k\sigma) - L(x, y, \sigma) \tag{5}$$

2) Key Point Localization: Key points from candidate points are selected based on the stability of the candidate key point. Stable key points are selected by locating maxima and minima in the DOG images coarsely. Each candidate key point is checked against with 26 neighbor pixels including above and below images in the scale space to find local maxima and minima. To locate sub pixel area Taylor expansion is used.

$$D(X) = D + \frac{\partial D^T}{\partial X} X + \frac{1}{2} X^T \frac{\partial^2 D}{\partial^2 X} X \tag{6}$$

3) Orientation Assignment: For each image sample $L(x, y)$ around a key point gradient orientations, (x, y), and gradient magnitudes, $m(x, y)$, are computed using Equation 7 and 8 respectively.

$$\theta(x, y) = \tan^{-1}((L(x, y+1) - L(x, y-1))/((L(x+1, y) - L(x-1, y))) \tag{7}$$

$$m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2} \tag{8}$$

Then a histogram is created for each image sample which has 36 bins (contains 10 degrees). Gradient directions are collected to each bin proportional to the gradient magnitude at the key point.

4) Key Point Descriptor Generation: SIFT feature is a unique finger print used to identify a key point. First a 16x16 (pixels) window around the key point is taken and this is broken into sixteen 4x4 windows. Gradient magnitudes and orientations for each 4x4 window is calculated and orientations are collected into an 8 bin histogram. Amount added to the each bin of histogram is depend on gradient magnitude and the distance from the key point. Gaussian weighting function used for this purpose. For each key point the feature vector is size of 4x4x8 = 128.

E. Cluster Features

We needed a way of reduction of dimensionality of extracted features in order to reduce the computational cost. In this work we used BOW model coming from natural language processing (NLP) [20]. We cluster all collected SIFT features from training data set in to several clusters using k-means clustering method. Cluster centers act as visual words.

F. Build the BOW Descriptor Histogram.

We represent each image in the training data set as a histogram. Histogram has feature clusters as bins and we collect SIFT features in to appropriate bin. These histograms are used as feature vector for SVM classifier.

G. Train the SVM and Generate the Classifier.

A multi class linear Support Vector Machine is used for classification of the histograms. After the training process, a classifier file is generated and saved in the server storage.

H. Android Implementation

We developed an Android client application which consumes the leaf recognition algorithm running on the server. The client and the server exchange information and communicates each other over the internet using SOAP based web service as shown in Fig. 4.

We used Dll (dynamic link library) application invoke through the web service to make communication between the OpenCV implementation of the image processing algorithm and the web service.

After receiving uploaded image, leaf identification algorithm first represents image as a histogram with the aid of the vocabulary crated in the training process. Then that histogram is passed as the input vector for the SVM prediction. SVM compares the input vector with the classified features and reruns identified type. Android client receives the information through the internet.

Server has a web UI shown in Fig.5 (a). Where we can directly see results. Fig. 5 (b) and (c) Shows some screen photos of the Android client application.

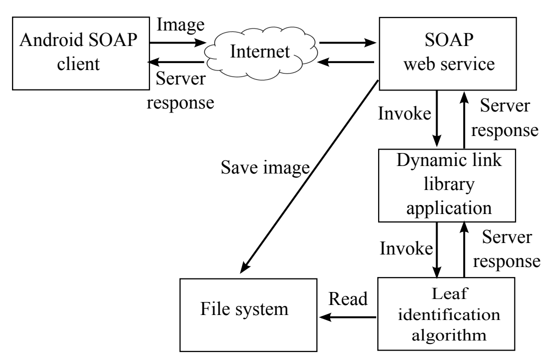
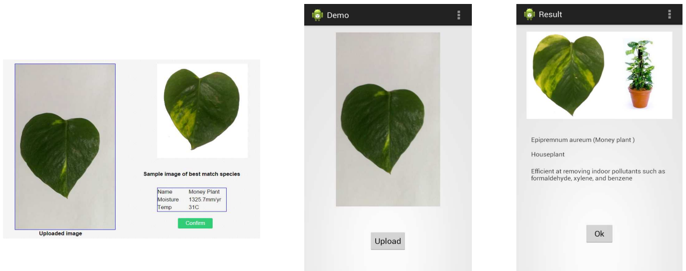


Fig. 4. Client server interaction.



(a) (b) (c)

Fig. 5. Some screen captures of the system. (a) Web UI (b) Photograph captured by user. (c) Identification result shown to the user, scientific name and common name etc.

Fig. 6. Used leaf images.

IV. Experimental Results

In order to train and test the proposed system we used 700 leaf images coming from 20 plant species as shown in Fig. 6. We used 35 images from each species. Among those 20 species, images belong to 14 species were extracted from Flavia data set [4] and images for the remaining 6 species were created by us. All these images were captured against a simple white background and resized to 240 * 180 pixels.

We divided the data set in to two as 25 images from each species all together 500 images for training the system and 10 images from each species collectively 200 images used to test the accuracy. We recorded numbers of correct identifications.

The accuracy is computed as the ratio between the correct recognitions and number of test samples. We obtained an average accuracy of 96.48% for our data set. We compared the accuracy of our system with other systems in Table I, based on DMF and PNN [4], SURF with SVM [17], HOG with SVM [21] and FFD with k-NN [22].

Based on the above results, our method has the highest accuracy because SIFT features are very robust in object detection.

V. Conclusion

In this paper we introduced a way of plant identification through a photograph of leaf taken and uploaded by an Android mobile. The classification framework use SIFT features in combination with BOW model and SVM classifier. SIFT features are used because they are invariant in scale, rotation, camera view point and illumination. BOW model is used to reduce the high dimensionality of the data space. SVM is adopted as the classifier because it has simple structure, comparatively fast speed on training and it is easy to implement. Histograms of SIFT features against feature bags are used as the input vector for SVM. Our system can automatically identify leaf images coming from 20 different plant species.

TABLE I. Comparison of accuracy

Method	Accuracy
DMFs PNN [4]	90.31%
SURF SVM [17]	95.94%
Method proposed in [23]	71.4%
SVM+HOG [21]	84.68%
FFD+ kNN [22]	95.66%
Our method	96.48%

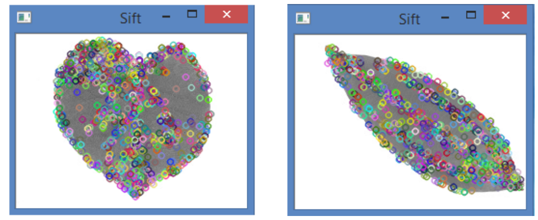


Fig. 7. SIFT descriptors are lying along the contour and veins.

According to the experimental results our system is workable with an accuracy of 96.48% on 20 kinds of species. We gained higher accuracy mainly because we used leaf images against simple white background and SIFT descriptors are detected mostly on leaf contours and veins as shown in Fig.7 and SIFT features are more robust in feature detection, also BOW model choose most representative SIFT features.

So we can say SIFT features with BOW method can effectively use for computer assisted leaf identification purpose. We show that compared to the other methods, our approach is efficient in plant recognition and it is easy to implement.

To improve the usability of the system, in the future we wish to integrate a leaf non-leaf classification algorithm with the system, to verify the uploaded image before preprocessing. We need to optimize the speed of system training process by using Message Pass Interface (MPI) to parallelize the clustering process with the use of multiple execution cores. Other than that we need to test our system on complex data sets and hope to train for more Sri Lankan species and test with end users.

References

[1] N. Kumar, P. N. Belhumeur, A. Biswas, D. W. Jacobs, W. J. Kress, I. C. Lopez, and J. V. Soares, "Leafsnap: A computer vision system for automatic plant species identification," in *Computer Vision–ECCV*, 2012, pp. 502–516.

[2] W. Petry and W. Kuhbauch, "Automated discrimination of weed species with quantitative image analysis," *Journal of Agronomy & Crop Science*, vol. 163, pp. 345–351, 1989.

[3] J.-X. Du, X.-F. Wang, and G.-J. Zhang, "Leaf shape based plant species recognition," *Applied mathematics and computation*, vol. 185, no. 2, pp. 883–893, 2007.

[4] S. G. Wu, F. S. Bao, E. Y. Xu, Y.-X. Wang, Y.-F. Chang, and Q.-L. Xiang, "A leaf recognition algorithm for plant classification using probabilistic neural network," in *IEEE International Symposium on Signal Processing and Information Technology*, 2007, pp. 11–16.

[5] J.-X. Du, D.-S. Huang, X.-F. Wang, and X. Gu, "Computer-aided plant species identification (capsi) based on leaf shape matching technique," *Transactions of the Institute of Measurement and Control*, vol. 28, no. 3, pp. 275–285, 2006.

[6] S. Mouine, I. Yahiaoui, A. Verroust-Blondet *et al.*, “Plant species recognition using spatial correlation between the leaf margin and the leaf salient points.” in *ICIP 2013-IEEE International Conference on Image Processing*, 2013.

[7] Y. Herdiyeni and M. M. Santoni, “Combination of morphological, local binary pattern variance and color moments features for indonesian medicinal plants identification,” in *International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, 2012, pp. 255–259.

[8] K.-B. Lee and K.-S. Hong, “An implementation of leaf recognition system using leaf vein and shape,” *International Journal of Bio-Science and Bio-Technology*, vol. 5, no. 2, pp. 57–66, 2013.

[9] Q. Wu, C. Zhou, and C. Wang, “Feature extraction and automatic recognition of plant leaf using artificial neural network,” *Advances in Artificial Intelligence*, vol. 3, 2006.

[10] Y. Li, Z. Chi, and D. D. Feng, “Leaf vein extraction using independent component analysis,” in *SMC’06. IEEE International Conference on Systems, Man and Cybernetics*, vol. 5, 2006, pp. 3890–3894.

[11] J. Park, E. Hwang, and Y. Nam, “Utilizing venation features for efficient leaf image retrieval,” *Journal of Systems and Software*, vol. 81, no. 1, pp. 71–82, 2008.

[12] J.-K. Park, E. Hwang, and Y. Nam, “A venation-based leaf image classification scheme,” in *Information Retrieval Technology*, 2006, pp. 416–428.

[13] L.-W. Yang and X.-F. Wang, “Leaf image recognition using fourier transform based on ordered sequence,” in *Intelligent Computing Technology*, 2012, pp. 393–400.

[14] K. Singh, I. Gupta, and S. Gupta, “Svm-bdt pnn and fourier moment technique for classification of leaf shape,” *International Journal of Signal Processing, Image Processing and Pattern Recognition*, vol. 3, no. 4, pp. 67–78, 2010.

[15] X.-Y. Xiao, R. Hu, S.-W. Zhang, and X.-F. Wang, “Hog-based approach for leaf classification,” in *Advanced Intelligent Computing Theories and Applications with Aspects of Artificial Intelligence*, 2010, pp. 149–155.

[16] Q. Xia, H.-D. Zhu, Y. Gan, and L. Shang, “Plant leaf recognition using histograms of oriented gradients,” in *Intelligent Computing Methodologies*, 2014, pp. 369–374.

[17] Q.-K. Nguyen, T.-L. Le, and N.-H. Pham, “Leaf based plant identification system for android using surf features in combination with bag of words model and supervised learning,” in *International Conference on Advanced Technologies for Communications (ATC)*, 2013, pp. 404–407.

[18] D. Knight, J. Painter, and M. Potter, “Automatic plant leaf classification for a mobile field guide,” *Rapport technique, Université de Stanford*, 2010.

[19] D. G. Lowe, “Distinctive image features from scale-invariant keypoints,” *International journal of computer vision*, vol. 60, no. 2, pp. 91–110, 2004.

[20] Z. S. Harris, “Distributional structure.” *Word*, 1954.

[21] N.-H. Pham, T.-L. Le, P. Grard, and V.-N. Nguyen, “Computer aided plant identification system,” in *International Conference on Computing, Management and Telecommunications (ComManTel)*, 2013, pp. 134–139.

[22] P. Novotnỳ and T. Suk, “Leaf recognition of woody species in central europe,” *Biosystems Engineering*, vol. 115, no. 4, pp. 444–452, 2013.

[23] Y. Ye, C. Chen, C.-T. Li, H. Fu, and Z. Chi, “A computerized plant species recognition system,” in *Proceedings of International Symposium on Intelligent Multimedia, Video and Speech Processing*, 2004, pp. 723–726.