Using mobile image recognition system for nonwood species identification in the field*

Noor Ahmed Shaikh[1], Ghulam Ali Mallah[1], İsmail R. Karaş[2], Abdullah E. Akay[3]**

[1]*Shah Abdul Latif University, Department of Computer Science, Khairpur Mirs, PAKISTAN*

[2]*Karabük University, Faculty of Engineering, 78050 Karabük, TURKEY*

[3]**Bursa Technical University, Faculty of Forestry, 16310 Bursa, TURKEY*

Abstract

Non-wood forest products (NWFPs) provide important source of income for millions of households world-wide especially for those in rural areas. Especially nonwood plants are main source of income for rural people in many parts of the world. These plants are also consumed by local people for health, nutrition and many other needs. In order to ensure benefits of NWFPs, it is important to identify nonwood plants and determine their population distribution. However, plant identification by using manual method is a complex task to fulfill especially in varying conditions in the field. The leaves are often used to identify plant species based on their visible characteristics. Image recognition systems have been developed to identify plant species by using leaf image. Comparing manual plant identification systems, image recognition systems are easier and, in most cases, more accurate alternatives. In recent years, some mobile applications have been developed to assist people to identify plants by taking pictures of their leaves using smart phones. In this study, it was aimed to investigate the capabilities of the most common mobile image recognition systems in identification of plant species based on leaf images.

Keywords: Image recognition, Mobile applications, Plant identification, Nonwood species

1. Introduction

Non-wood forest products in general are essential for the daily life of both rural and urban populations [1]. The term non-wood forest product (NWFPs) is often used for "goods of biological origin other than wood derived from forests, other wooded land and trees outside forests" [2]. In Pakistan, forested lands cover an area of 4.37 million hectares, which is about five percent of the country's total area. These forests provide variety of NWFPs such as food products, medicinal plants, industrial products, fibers, and silk cocoons [3]. Especially food products and medicinal plants are considered as the major source of income for rural people [4].

Because of the rich variety of environment, Pakistan has large number of medicinal plants in the forested lands. Some of the commercially important medicinal plants are listed in Table 1. Besides, there are number of nonwood plants used as food products including roased seeds of *Pinus gerardiana*, kernels of walnut (*Juglans regia*), gurgura (*Reptonia buxifolia*), deela (*Capparis aphlla*), pelu (*Salvadora oleoides*), jujube (*Zizyphus* spp.), sumal (*Berberis lycium*), guch (*Viburnum nervosum*), wild fig (*Ficus glometra*) and mulberry (*Mows alba*) [5].

In order to estimate overall potential of nonwood plants, it is important to identify nonwood plants and determine their population distribution through field surveying. However, plant identification by using manual method can be a complex task due to varying conditions in the field. The visible structures of the leaves are generally used to identify plant species [6]. There are three main structures of the leaf; 1) the leaf base which is the point joining the stem to the leaf, 2) the stalk which is a section joining the base to the lamina, and 3) the lamina which is the wide part of the leaf [7].

Computer vision methodologies and image recognition techniques have been developed to identify plant species automatically. By using advanced algorithms and procedures in digital image recognition, it has become possible to identify plants by using leaf image [7]. The image recognition task is completed in three stages including pre-processing, feature extraction, and classification [Figure 1].

In recent years, some mobile applications have been developed to assist people to identify plants by taking pictures of their leaves using smart phones. One of the first plant identification systems was developed for the iOS users and it was able to work with only tree species [8]. Pl@ntNet was another example of early systems that was developed to identify more than 4100 plant species based on their photographs. Wu [9] developed this plant identification system for Android users based on descriptors extracted from plant leaf image.

In this study, the capabilities of the most recent mobile image recognition systems developed for identification of plant species were presented. The possibilities of generating population distribution map for plant species by using GPS feature on smart phones were also evaluated.

Table 1. Commercially important medicinal plants collected from forests in Pakistan [4]

Name	Botanical name	Part used	Estimated extracted quantities annually (tons)
Mushk-e-Bala	*Valeriana wallichii*	Roots	300-400
Persoshan (maiden hair fern)	*Adiantum capillus*	Whole plant	100-125
Anjabar	*Polygonum amplexicule*	Roots	40
Unab	*Zizyphus vulgaris*	Fruits	30-40
Hub-al-as (Munru)	*Myrtus communis*	Fruits and leaves	40-45
Banafsha	*Viola serpens*	Flowers	30
		Leaves	40
Suranjan-e-Telkh	*Colchicum luteum*	Corms	12
		Seeds	2
Ban Kakri	*Podophyllum emodi*	Rhizomes and roots	30-60
Kamila	*Mallotus philippensis*	Fruits	4-5
Mamekh	*Paeonia emodi*	Rhizomes	18
Afsantine	*Artemisia maritima*	Leaves/ shoots	100-150
Ajwain	*Carum copticum*	Seeds	200
Chiraita	*Swertia chirata*	Twigs	30
Wirch	*Acorus calamus*	Roots	10
Darhald or Meda Chob	*Berberis lycium*	Wood	600
		Roots	120
Khurasani	*Hyocyamus niger*	Seeds	2
Ajwain Khaksir	*Sisymbrium irio*	Seeds	50
Ajwain	*Carum copticum*	Seeds	200
Zeera Siah	*Carum carvi*	Seeds	10
Bermi Booti	*Centella asiatica*	Whole plant	12
Meetha Teela or sufaid Mori	*Aconitum chasmanthum*	Roots	4
Atis	*Aconitum hetero phyllum*	Roots	2
Kaniz (Yam)	*Dioscorea deltodea*	Rhizome	230
Angoor shefa (Belladona)	*Atropa acuminata*	Whole plant	10
Barg-u; Azra (Foxglove)	*Digitalis purpurea*	Whole plant	10
Bhaikar	*Adhatoda vasica*	Leaves	20
Bhang	*Cannabis sativa*	Whole plant	20
Panir Dodi	*Withania coagulans*	Fruit	125
Asgand	*Withania sominfera*	Roots	32
Amaltas	*Cassia fistula*	Pods	150
Baid Mushk	*Salix alba*	Bark	10
Jangli piaz Scilla	*Urginea indica*	Bulbs	6
Indrayan (Colocynth)	*Citrulus colocynthus*	Fruits	12
Asmania	*Ephedra nebrodemsis*	Twigs	780
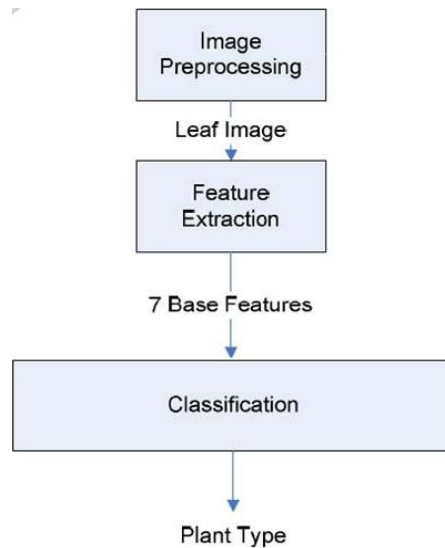
Figure 1. The main stages of image recognition task [7]

2. Materials and Methods

2.1. MedLeaf

MedLeaf is a plant recognition system that was developed to identify medicinal plants based on combinations of leaf features such as shape, color and texture. The system is an Android application with two main functionalities; 1) medicinal plant identification and 2) document searching of medicinal plant. To identify the plant species, leaf image captured from the gallery or by camera phone is first displayed on the mobile screen, and then MedLeaf automatically identifies the medical plant species (Figure 2). In the second main function of MedLeaf, Local Binary Pattern was used to extract leaf texture and then Probabilistic Neural Network was used to classify the image (Figure 3) [10].

Figure 2. User interface of the first main function in MedLeaf system [10]

**Figure 3.** User interface of the second main function in MedLeaf system [10]

The accuracy of medicinal plant identification function based on leaf texture was found as 56.33%. The performance of the application was also evaluated by 20 users based on a questionnaire which consisted of following points [11]:

- Visibility of system status
- Match between system and the real world
- User control and freedom
- Consistency and standards
- Error prevention
- Recognition rather than recall
- Flexibility and efficiency of use
- Aesthetic and minimalist design
- Help users recognize, diagnose, and recover from errors
- Help and documentation

The results from the questionnaire indicated that 35% of user are satisfied with the results of medicinal plant identification functionality, while 50% were quite satisfied, and 15% were not satisfied. In terms of document searching functionality, the results showed that 40% of user were satisfied, while 60% were quite satisfied.

2.2. Fully Aautomatic leaf-based plant identification

A fully automatic plant identification application, which works based on plant leaf images was developed for Android devices (Figure 4). The application consists of four main steps; petiole detection and removal, leaf orientation normalization, modified kernel descriptor (KDES), and Support Vector Machine (SVM) based classification [12].
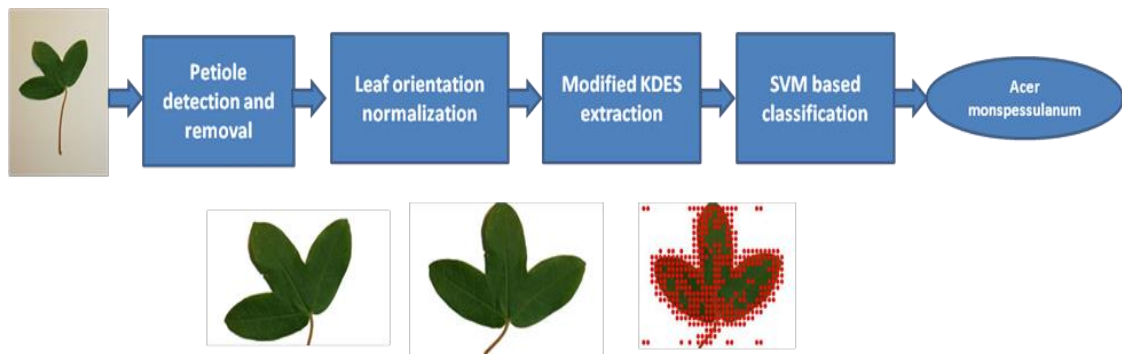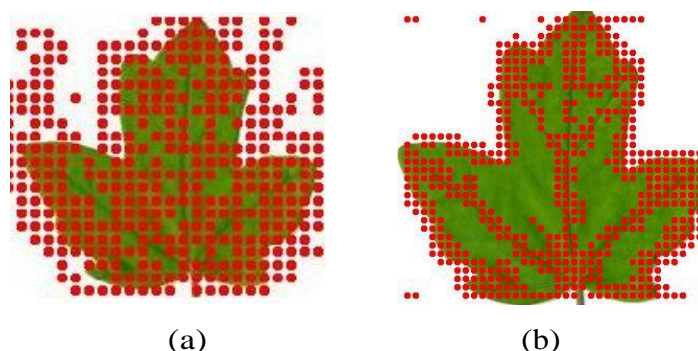
Figure 4. Methodology of leaf-based plant identification application [12]

Based on the image generated by after Watershed algorithm segmentation method, the petiole detection was built based on statistic experiments. Then, the image of the leaf without the petiole was generated on the background with white pixels (Figure 5). In order to prevent identification errors in case of rotation-variant features due to leaves captured with different orientations, the process of leaf orientation normalization as applied based on the theories of image moment (Figure 5). KDES was used to extract a specific type of features under a hierarchical structure: pixel-level features, patch-level features, and image-level features. This study proposed the improvements for patch-level feature extraction and image-level feature extraction steps. And, the results of the improvement are indicated in Figure 6.

(a)   (b)   (c)
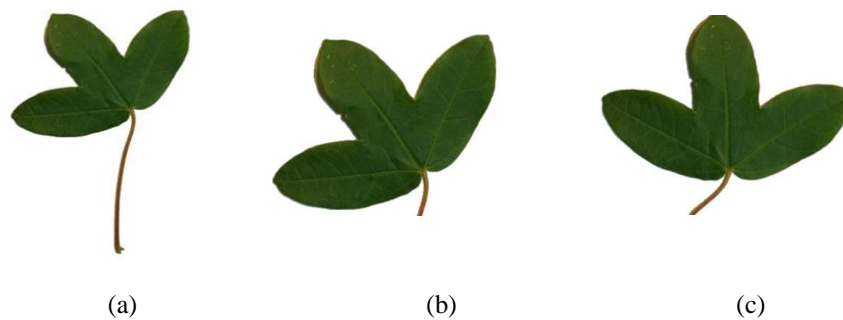
Figure 5. A leaf of *Acer monspessulanum* before petiole cutting (a), after petiole cutting (b), and after orientation normalization (c) [12]

(a)   (b)

Figure 6. A leaf image of *Acer monspessulanum* species before (a) and after (b) the improvements [12]

Based on the leaf-based plant identification method, Vietnamese medicinal plant search system was developed and deployed on Android devices (Figure 7). The system has two important functions: text-based search and image-based search. The user can type the medicinal plant of interest or take the plant image to use leaf-based plant identification method.
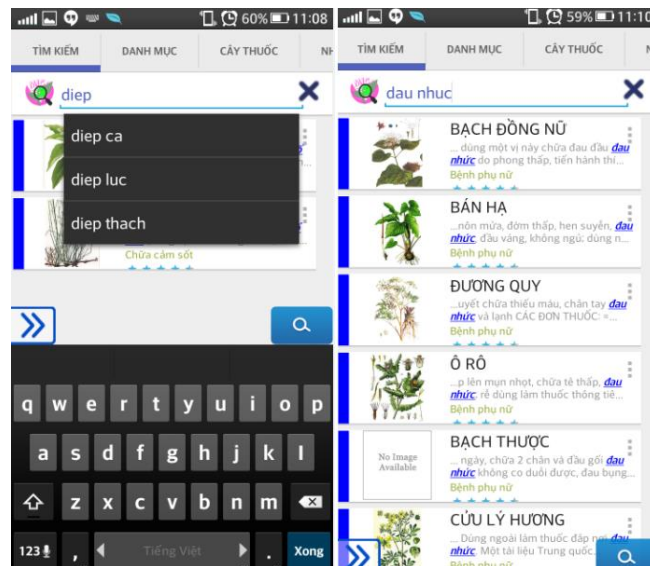
Figure 7. The interface of the Vietnamese medicinal plant search [12]

2.3. Deep learning for plant identification

Deep learning architectures are formed by multiple linear and nonlinear transformations of input data for yielding more discriminative representations [13]. The BJFU100 dataset was generated by collecting natural scenes using mobile devices. The dataset contains 10,000 images of 100 ornamental plant species in Beijing Forestry University campus [14]. A 26-layer deep learning model that consists of 8 residual building blocks was designed for largescale plant classification in natural environment. Deep residual networks with residual units have shown good accuracy and convergence behaviors on several largescale image recognition tasks, such as ImageNet [15] and MS COCO [16].

The model implementation was conducted based on the open source deep learning framework. Compared with manual classification method, deep learning model was found to be much easier. A series of experiments were conducted on BJFU100 dataset to find the best deep residual network (ResNet). The comparison of test accuracy among the proposed ResNet26 model and the original ResNet models were shown in Figure 8. It was found that the model achieved a recognition rate of 91.78% on the BJFU100 dataset. Thus, deep learning is a promising technology for smart forestry applications.
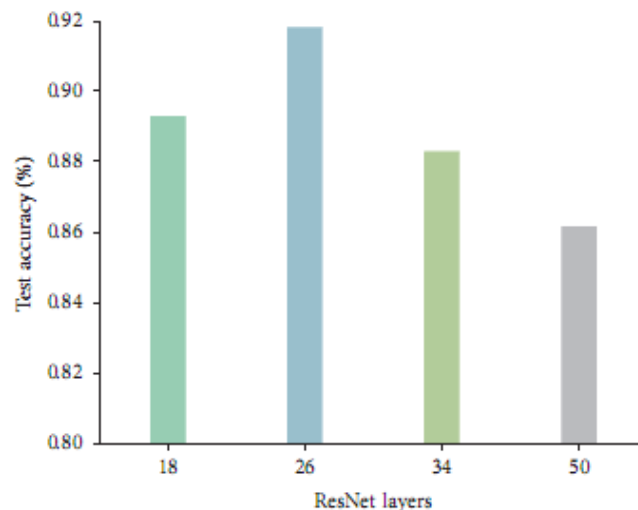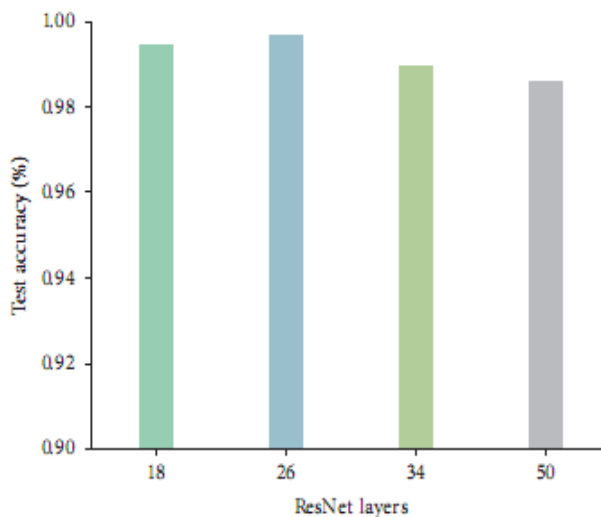

Figure 8. Test accuracy of the ResNet18, ResNet26 model, ResNet34, ResNet50 [14]

46

A series of experiments were performed on the publicly available Flavia [17] leaf dataset to test capabilities of the ResNet26 model (Figure 9). In the testing process, 80% of the dataset were selected randomly for training and 20% for testing purposes. The training algorithm was the same as that used in the BJFU100 dataset. The test accuracy of each model was shown in Figure 10. The test accuracy for ResNet18, ResNet34, and ResNet50 was 99.44%, 98.95%, and 98.60%, respectively. On the other hand, the proposed ResNet26 model reaches up to 99.65% accuracy. Thus, results indicated that deep learning is the promising technology for large-scale plant classification in natural environment.

**Figure 9.** Example images of the Flavia dataset [14]   **Figure 10.** Test accuracy of the ResNet models [14]

2.4. Plant recognition by using machine learning techniques

A fully automated method for the medicinal plant recognition was developed by using machine learning techniques [18]. A database of medicinal plants which are available on the tropical island of Mauritius was created using a smartphone with Android system. For the database, 30 images of different leaves were taken from 24 different plant species. The petiole of each leaf was removed manualy, placed on a white paper, and then being photographed in 1024x600 pixels size (Figure 11). The application consists of three main steps; automatic pre-processing steps, feature extraction, and derived features.

In the pre-processing stage, the image first was converted to the HSV format and then split into its different color channels to remove the shadow on the image. A median blur filter with a window size of 25 was used to reduce noise effect in the image. Then, Otsu thresholding method was implemented to convert the image into a binary image with only black and white pixels (Figure 11). Based on images in Figure11, a number of base features were extracted: length, width, area of the bounding box, area of leaf, perimeter of leaf, hull area, hull perimeter, number of vertices, horizontal and vertical distance maps, 45° radial map and the original RGB values of each pixel.
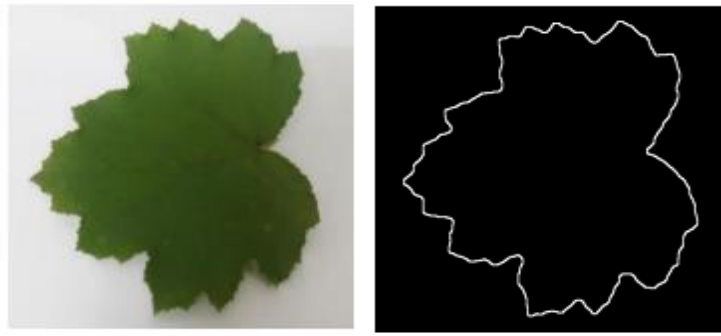
Figure 11. Original Giant Bramble leaf (left) and binary image of leaf (right) [18]

Figure 12 shows the bounding box & contour line and area & diameter of a giant bramble leaf. The length and the width of the leaf was computed using the bounding box, while the perimeter was obtained from the contour line. Figure 11 also shows the convex hull used to compute the hull perimeter, the hull area, and the number of vertices in the leaf.
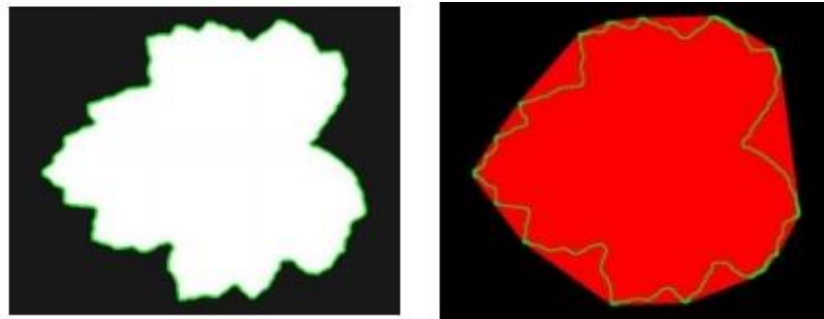
Figure 12. Bounding box & contour (left) and area & perimeter of hull (right) [18]

Figure 13 shows the vertical distance maps where the image was divided into 24 equal strips to find where each vertical line intercepts the contour line of the leaf. Then, the distances between the intercepts were computed. Figure 14 shows the horizontal distance maps in which the image was divided into 24 equal strips. To avoid overfitting, only 12 alternate values were used for both directions. The radial distances were computed likewise as shown below in Figure 15.

Fianally, a number of derived features were calculated using the base features which were extracted directly from the image. Since ratios were independent of the actual size of the image in pixels, they were more suitable for comparison. To assess the recognition rate five different machine learning classifiers were used. As a result, the Random Forest classifier achieves the best performance with an accuracy of 90.1%, while the Multilayer Perceptron produced the second best accuracy at 88.2%.
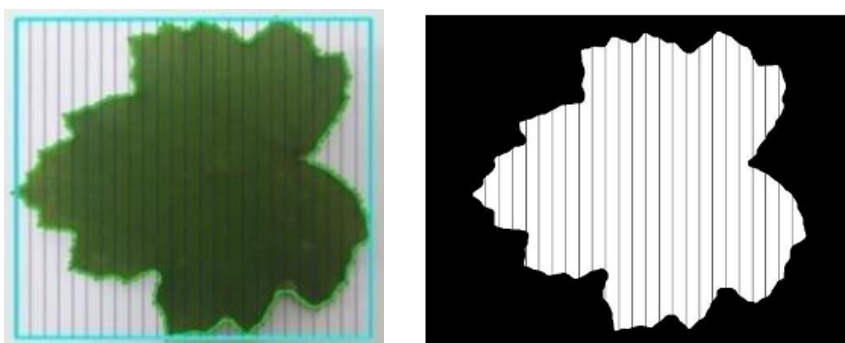
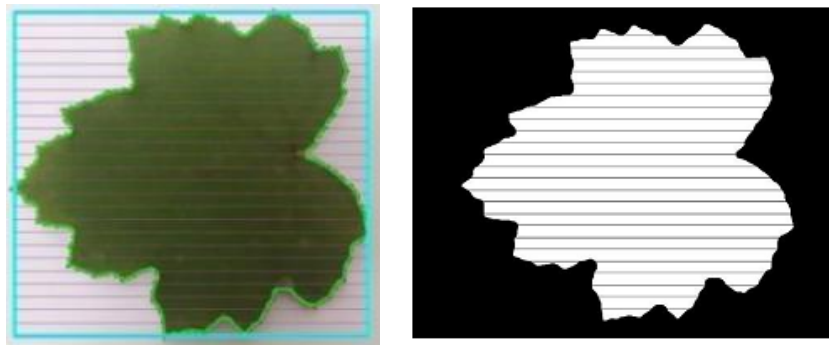**Figure 13.** Vertical distance maps [18]

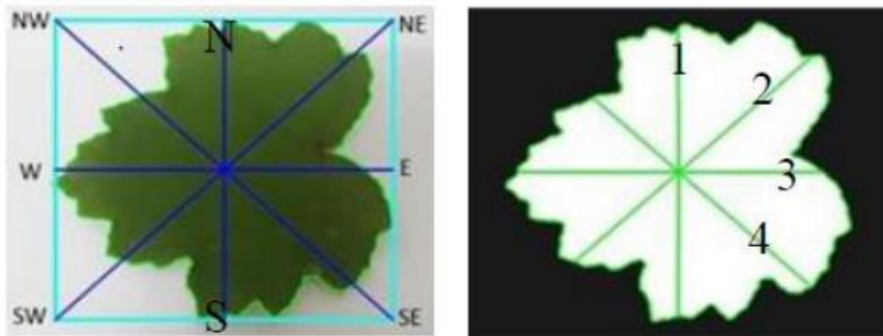**Figure 14.** Horizontal distance maps [18]

Figure 15. Radial maps [18]

3. Conclusion

The identification of plant species by using manual method is a not an easy task, especially in difficult conditions in the field. Computer-assisted image recognition systems have been developed to identify plant species by using leaf image. Image recognition systems are much easier and more accurate techniques when compared to manual identification systems. In recent years, mobile applications for smart phones have been also developed to assist people to identify plants by taking pictures of their leaves. In this study, the capabilities of the most common mobile image recognition systems in identification of plant species based on leaf images were presented. The first one was MedLeaf which is a plant recognition system that was developed to identify medicinal plants based on combinations of leaf features such as shape, color and texture. The second system was a fully automatic plant identification application which was developed for Android devices. Third was a deep learning architectures which were formed by multiple linear and nonlinear transformations of input data for yielding more discriminative representations in plant identification. And the last one was a fully automated method for the medicinal plant recognition which was developed by using machine learning techniques. It can be concluded that mobile computer system for the recognition of plant species can assist to improve the knowledge on medicinal plants, help taxonomists to develop more efficient identification techniques and contribute significantly in the protection of endangered species.

References

[1] Chupezi, T.J. , Ndoye, O., Tchatat M. and Chikamai. B. (2009). Processing and Marketing of Non-wood Forest Products: Potential Impacts and Challenges in Africa. *Discov. Innov.*, 21:60-65.

[2] Dembner, S.A. and Perlis, A. (1999). Non-wood Forest Products and Income Generation. Vol. 50.

[3] Durst, P.B., Ulrich, W. and Kashio, M. (1994). Regional office for Asia and the Pacific (RAPA) food and agriculture organization of the United Nations. Vol. 28. pp. 151-161.

[4] Iqbal, M. (1991). Non-timber forest products: their income-generation potential for rural women in North West Frontier Province (Pakistan). International Labour Organization and Government of NWFP. Peshawar.

[5] RAPA, (1987). Forest based rural enterprises in Pakistan. Regional Office for Asia and the Pacific (RAPA), Food and Agricultural Organization of the United Nations. Bangkok. 88 p.

[6] Salada, L.L., Hickey, K. and Salada, T. (1995). Comparing manual plant identification systems, Hort Technology, 5(2):159.

[7] Bylaiah, V. (2014). Leaf recognition and matching with Matlab. MSc Thesis, san Diego State University, 42 p.

[8] Neeraj, K. (2012). Leafsnap: A computer vision system for automatic plant species identification. ECCV 2012, pp. 502–516.

[9] Wu, G. (2007). A leaf recognition algorithm for plant classification using probabilistic neural network, in signal processing and information technology. IEEE International Symposium on Signal Processing and Information Technology, 15-18 December, Giza, Egypt.

[10] Prastiva D.S. and Herdiyeni, Y. (2013). International Journal on Advanced Science, *Engineering and Information Technology*. 3(2):5-9.

[11] Ridwan, A. (2007). Pengukuran usability aplikasi menggunakan evaluasi heuristic. *Jurnal Informatika Komputer*, 12(3):220-222.

[12] Le, T., Tran, D. and Hoang, V. (2014). Fully automatic leaf-based plant identification, application for Vietnamese medicinal plant search. SoICT '14, December 04 – 05, Hanoi, Vietnam.

[13] Bengio, Y., Courville, A. and Vincent, P. (2013). Representation learning: a review and new perspectives, *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 35(8):1798–1828.

[14] Sun, Y., Liu, Y., Wang, G. and Zhang, H. (2017). Deep Learning for Plant Identification in Natural Environment" Computational Intelligence and Neuroscience Volume 2017, Article ID 7361042, 6 p. https://doi.org/10.1155/2017/7361042.

[15] He, K., Zhang, X., Ren, S. and Sun, J. (2016). Deep residual learning for image recognition in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR '16), pp.770-778, Las Vegas, Nevada, USA.

[16] Dai, J., He, K. and Sun, K. (2016). Instance-aware semantic segmentation via multi-task network cascades, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR '16), pp.3150-3158, Las Vegas, Nevada, USA.

[17] Wu, S.G., Bao, F.S., Xu, E.Y., Wang, Y.X., Chang, Y.F. and Xiang, Q.L. (2007). A leaf recognition algorithm for plant classification using probabilistic neural network. IEEE International Symposium on Signal Processing and Information Technology, 15-18 December, Giza, Egypt.

[18] Begue, A., Kowlessur, V., Mahomoodally, F., Singh, U., Pudaruth, S. (2017). Automatic Recognition of Medicinal Plants using Machine Learning Techniques, *International Journal of Advanced Computer Science and Applications*, 8(4):166-175.