Review on Automatic Plant Identification Using Computer Vision Approaches

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Abstract. Plants are crucial resources on the Earth for ecological living habitat. However, the rapid loss of plant species has alerted the globe with the rising awareness of biodiversity conservation. The need of plant identification provides an essential biologist information for plant research and development. It has brought significant impact on environmental conservation and exploration. Nevertheless, it requires species identification skills, high time consumption on study the species and usage of specific botanical terms. The knowledge of plant identification is not only for botanist and plant ecologists, but it is also useful for society, from professionals to the general public. The challenges of plant identification is the complexity of gaining plant species knowledge. Currently, with relevant technologies (digital cameras, mobile devices and remote access to databases) and computer vision techniques, it have created an automated plant identification to ease the society in plant identification. The aim of this paper is to document an analysis and comparison of studies between two types computer vision approaches for plant species identification and the features, i.e., shape, texture, colour, margin, and vein structure. It is useful to researchers in the fields for ongoing researches and comparable analyses of applied methods.

1. Introduction
Plants contribute to human lives and major sources of food, medications and etc. However, biodiversity is declining rapidly throughout the world [1]. Direct and indirect human activities are the main reason of the current rate of extinction [2]. For future biodiversity conservation, have a proper knowledge of the identity and the geographic distribution of plants is essential. Hence, fast and precise of plant identification is important to conserve biodiversity. In a traditional identification process, botanist required to understand and identify different plant characteristics as identification keys. The usage of identification need to answers a series of questions about one or more attributes of the plant and continuously focusing on the most discriminating characteristics and narrowing down the set of candidate species until the desired species [3]. However, using this traditional plant species identification to determine of plant species is totally impossible for the general public and even tough and challenging for those professionals that work with botanical such as farmers, landscape architects,
conservationist and even botanists themselves had hard time on identify because it requires a substantial botanical expertise.

The situation is further exacerbated by the increasing shortage of skilled taxonomists [4]. The declining and partly nonexistent taxonomic knowledge within the general public has been termed “taxonomic crisis” [5]. Due to the high declination of biodiversity and limitation of taxonomists, researchers develop manifold efficient methods towards plant identification. With relevant technologies, such as digital cameras, mobile devices and remote access to databases and computer vision techniques like image enhancement, image compression, and image analysis that created an automated plant identification in order to ease the society. Image-based methods seem as good approach for species identification [4]. Users can take an image of a plant in the field using any mobile device with built-in camera. With an installed plant recognition application, it able to identify the species or receiving a list of potential species that is similar to the species if it unable to identify as single species.

Computer vision consists of two approaches which are features extraction and deep learning approaches. Using features extraction such as SVM and k-NN implemented into plant identification process and using deep learning approaches (CNN) to improve the accuracy of the classification. The objectives of this paper are reviewing research done in field of automatic plant species identification using two different approaches, features extraction and deep learning approach. The contribution of this paper is that plant identification works with their remarkable accuracies on classification and dataset which available globally. Section 2 is review the dataset used by two approaches. Section 3 contains plant identification using feature extraction approach and Section 4 is plant identification using deep learning approach.

2. Review of Plant Dataset

Dataset are based on utilized images that fall into 2 categories: scans and photos. Datasets used in the studies are Swedish Leaf, ICL, FLAVIA, FLOWERS28&102, PlantCLEF, TARBIL, ImageCLEF 2013 and Oxford-102 flower. Swedish leaf dataset [6] is considered challenging due to its high interspecies similarity of 15 Swedish tree species with 75 leaves per pieces collected by Linkoping University and the Swedish Museum of Natural History as part of a joined leaf classification project.

Flavia dataset [7] contains 32 species and sampled on the campus of Nanjing University and Sun Yat-Sen arboretum, Nanking, China. The leaf images only contain blades with petioles with plain background. ICL dataset captured at Hefei Botanical Garden by group of Intelligent Computing Laboratory at Institute of Intelligent Machines, China. All the images are plain background and leafstalks have been cut off before scanned or photographed. Dataset contains 220 plant species.

Oxford Flower 102 dataset [8] contains 102 flower classes that commonly occurring in the United Kingdom. The dataset gathered from various websites, with some supplementary images from their own photographs. Each image is rescaled so that the smallest dimension is 500 pixels. FLOWERS 28 and FLOWERS 102 dataset obtained from the Visual Geometry group at University of Oxford. The Oxford 17 dataset are added with few more flower classes and renamed it to FLOWERS 28. ImageCLEF (2013) dataset [9] collected 1000 plant species from West Europe. It consists plain and natural background of images that cover different organs of the individual plants rather than focus their leaves. PlantCLEF 2015 is improvised version of ImageCLEF (2015) by adding 50 species on the dataset. TARBIL dataset is focused on agricultural plants. It consists 16 plants that obtained through Turkish Agricultural Monitoring and Information Systems (TARBIL) project.

3. Plant Identification Using Feature Extraction Approach

Features are the plants characteristics that been extracted such as shape, color, texture and leaf. All these features will be used by descriptors (Fourier Descriptors-FD, Histogram Oriented gradients-
HOG) to describe the plants identity. Classifiers used the information from descriptors to recognize the species of the plant. First part of the results belongs to supervised learning or classification method with feature and descriptor used by authors to identify types of plants. The datasets that been used for classification are Swedish leaf dataset, ICL dataset and FLAVIA dataset.

For Swedish leaf dataset, [10] [11] [12] [13] applied k-nearest neighbor (k-NN) classifier and followed by simple 1-NN to perform classification and observe their methods. Fuzzy k-nearest neighbors classifier was proposed in order to improve the robustness and discriminability of classification. Fuzzy k-NN able to consider congeneric number and the similarity between the k-NN and the unknown sample.

**Table 1.** Comparison of classification accuracy on the Swedish leaf dataset containing twelve species

| Descriptor | Feature | Classifier       | Accuracy | studies |
|------------|---------|------------------|----------|---------|
| GF         | Texture | Fuzzy k-NN       | 85.75    | [10]    |
| SC         | Shape   | k-NN             | 88.12    | [11]    |
| FD         | Shape   | k-NN             | 89.60    | [12]    |
| HoCS       | Shape   | Fuzzy k-NN       | 89.35    | [10]    |
| TAR        | Shape   | k-NN             | 90.40    | [13]    |
| HOG        | Shape   | 1-NN             | 93.17    | [14]    |
| MDM-ID     | Shape   | k-NN             | 93.60    | [12]    |
| IDSC       | Shape   | 1-NN             | 93.73    | [14]    |
| IDSC       | Shape   | SVM              | 93.73    | [15]    |
| IDSC       | Shape   | k-NN             | 94.13    | [12]    |
| TOA        | Shape   | k-NN             | 95.20    | [13]    |
| TSL        | Shape   | k-NN             | 95.73    | [13]    |
| TSLA       | Shape   | k-NN             | 96.53    | [13]    |
| LBP        | Shape   | SVM              | 96.67    | [15]    |
| 1-IDSC     | Shape   | 1-NN             | 97.07    | [16]    |
| MARCH      | Shape   | 1-NN             | 97.33    | [17]    |
| DS-LBP     | Shape+  | Fuzzy k-NN       | 99.25    | [10]    |
| PDMSL      | Texture | k-NN             | 94.00    | [18]    |
| DBCSR      | Shape   | MAP              | 99.50    | [19]    |
From table 1, Deformation Based Curved Shape Representation (DBCSR) had the best result with 99.50%. DBCSR able to get high accuracy for it considers curves shapes as elements of finite dimensional matrix. Besides, the dataset only consists of nonlinear elastic deformations and distance metric based on uniform sampling. Dual-scale decomposition and local binary descriptors (DS-LPB) method is the second best classification rate of 99.25% and the third best result belong to MARCH which obtained 97.33%.

| Table 2. Comparison of classification accuracies on the ICL dataset |
|---------------------------------------------------------------|
| Description | Feature | Classifier | Accuracy | Studies |
|-------------|---------|------------|----------|---------|
| FD          | Shape   | 1-NN       | 60.08    | [17]    |
| TAR         | Shape   | 1-NN       | 78.25    | [17]    |
| IDSC        | Shape   | 1-NN       | 81.39    | [17]    |
| IDSC        | Shape   | k-NN       | 83.79    |         |
| GF          | Texture | Fuzzy k-NN | 84.60    | [10]    |
| MARC H      | Shape   | 1-NN       | 86.03    | [17]    |
| HoCS        | Shape   | Fuzzy k-NN | 86.27    | [10]    |
| MDM         | Shape   | Fuzzy k-NN | 88.24    | [10]    |
| IDSC        | Shape   | Fuzzy k-NN | 90.75    | [10]    |
| SIFT, SC    | Shape+ Vein | k-NN | 91.30    | [34] |
| EnS and CDS | Shape+ Texture | SVM | 95.87    | [33] |
| DS-LBP      | Shape+ Texture | Fuzzy k-NN | 98.00 | [10] |
| RSSC        | Texture | k-NN       | 92.94    | [35]    |

Table 2 shows results gained based on 220 species in ICL dataset and authors mostly used Fuzzy k-NN and 1-NN. K-NN and SVM classifiers were proposed in ICL dataset. DS-LBP with Fuzzy k-NN classifier gained the best result in ICL dataset with 98.00%. EnS and CDS with SVM had 95.87% placed as second best result and RSSC is the third best result with 92.94%. DS-LBP produced high accuracy because it consists of two phases. First phase is decomposed into several subbands with an adaptive lifting wavelet scheme and second phase filtered each subband using a group of variable-scale Gaussian filters [10]. It combines shape and texture as features. According to authors [136], the ICL dataset contains many species with similar shapes that cause higher drop on classification accuracies on shape-based feature.

Table 3 showed that various classifiers were used: Naïve Bayes (NB), decision tree (DT), random forest (RF), neuro fuzzy classifier (NFC), multi-layered perceptron (MLP), Riemannian metrics, artificial neural network with back-propagation (BPNN), and probabilistic neural networks (PNN). Naïve Bayes classifiers are highly scalable, requiring number of parameters linear in the number of
variables in a learning problem. Decision Tree classifier is flow-chart like structure where each internal node denotes a test on an attribute, each branch represents the outcome of a test and each leaf node holds a class label. Random Forest classifier is ensemble learning method that operate by constructing a multitude of decision trees at training time and outputting the class. Neuro fuzzy is hybrid of fuzzy and neural networks.

Table 3. Comparison of classification accuracies on the FLAVIA

| Feature                  | Descriptor                  | Classifier | Accuracy | Studies |
|--------------------------|-----------------------------|------------|----------|---------|
| Shape                    | Hu moments                  | SVM        | 25.30    | [20]    |
| Shape                    | HOG                         |            | 84.70    |         |
| Shape                    | SIFT                        |            | 87.50    | [21]    |
| Shape + vein             | SMSD, $A_{ven}/A_{leaf}$    | PNN        | 90.31    | [22]    |
| Shape                    | SMSD                        |            | 70.09    |         |
| Shape                    | PFT                         | k-NN       | 76.69    | [23]    |
| Shape                    | SMSD,FD                     |            | 84.45    |         |
| Color + shape            | SMSD,FD,CM                  | k-NN, DT   | 91.30    |         |
| Shape                    | SMSD                        | PNN        | 91.40    | [24]    |
| Shape + vein             | SMSD, $A_{ven}/A_{leaf}$    | SVM (k-NN) | 94.50 (78.00) | [25] |
| Shape                    | SIFT                        | SVM        | 95.47    | [26]    |
| Shape                    | SURF                        | SVM        | 95.94    | [27]    |
| Shape                    | SMSD, FD                    | BPNN       | 96.00    | [28]    |
| Shape + color + texture + vein | SMSD, CM, GLCM, $A_{ven}/A_{leaf}$ | SVM | 96.25 | [29] |
| Shape                    | SMSD                        |           | 87.61 (82.34, 80.26, 72.89) | [30] |
| Shape + color            | SMSD, CM                    | RF (k-NN, NB, SVM) | 93.95 (92.46, 88.77, 86.50) | 96.30 (94.21, 89.25, 92.89) | [30] |
| Shape + color            | SMSD, CM, CH                |           |         |         |
| Shape                    | SMSD                        | NFC        | 97.50    | [31]    |
| Texture                  | GF, GLCM                    | NFC (MLP)  | 81.60 (87.10) | [32] |
| Shape + texture          | CT, Hu moments, GF, GLCM    |           | 97.60 (85.60) |         |
| Shape + texture          | EnS and CDS                 | SVM        | 97.80    | [33]    |
| Shape                    | ST                          | k-NN       | 47.00    | [19]    |
| Shape                    | TSLA                        |            | 69.93    |         |
| Shape                    | DBCSR                       |            | 94.11    |         |

Multi-layered perceptron is a class of feedforward artificial neural networks that consist of at least three layers of nodes and each nodes uses a nonlinear activation function except input nodes.
Riemannian metric is defined several geometric notions on Riemannian manifold. ANN are computing systems vaguely inspired by biological neural networks. ANN with backpropagation able to calculate a gradient that is needed in the weights to be used in the network. The lowest classification rates were obtained from Hu moments [20] with 25.30%. The highest accuracy 97.80% obtained by EnS and CDS approach and second highest 97.60 that combine shape and texture feature with NFC. Another NFC approach with only shape feature gain third place with 97.5%. DBCSR failed to get high accuracy because the dataset contains rotation and scaling of images. EnS and CDS method used shape and texture as features. It extracted shape using representation of center distance sequence and texture by intersecting cortical model.

Table 1-3 shows that more researches had been done on shape as feature and produce wide range of accuracy (25% -99%). Shape and Texture as feature show a incredible result in accuracy. All papers that used both shape and texture as feature had accuracy above 95% to 99%. Although author [29] used shape, color, texture and vein produce the accuracy is just 96%, it is unjustified the result that shape and texture is sufficient as feature for it is lack of research towards the four features.

4. Plant Identification Using Deep Learning Approach

Table 4 and 5 results are belonging to ANN model used by authors for plant identification. The dataset used in the studies are based on FLOWERS-28 and FLOWERS-102, PlantCLEF, TARBIIL, ImageCLEF (2013) and Oxford 102. In Table 4, there are Inception-v3, Xception and OverFeat and RHF. Rankings (Rank-1 to Rank-5) show the top 5 retrieved plants by ANN model. Inception-v3 is top player in rank 1 accuracy with 92.41% and 93.41%. Xception is second best accuracy in rank-1 with 90.18 and 90.60. RHF that used leaf-flower feature obtained 89.80%. There are some changes in accuracy when compare in Rank-5. OverFeat ruled the FLOWERS28 with 99.11 while Inception-v3 and Xception had 98.66%. However, FLOWERS102, Inception-v3 remained top accuracy with 97.68%. RHF using Leaf and flower feature had 98.40% as highest accuracy compared to other features.

| Dataset          | Model         | Rank-1 accuracy | Rank-5 accuracy | studies |
|------------------|---------------|-----------------|-----------------|---------|
| FLOWERS28        | Inception-v3  | 92.41           | 98.66           | [36]    |
|                  | Xception      | 90.18           | 98.66           |         |
|                  | OverFeat      | 85.71           | 99.11           |         |
| FLOWERS102       | Inception-v3  | 93.41           | 97.68           | [36]    |
|                  | Xception      | 90.60           | 96.58           |         |
|                  | OverFeat      | 73.05           | 90.58           |         |
| PlantCLEF        | RHF           |                 |                 |         |
| (En-Le)          | 76.6          | 94.6            |                 | [37]    |
| (En-Fl)          | 81.2          | 94.4            |                 |         |
| (Le-Fl)          | 89.8          | 98.4            |                 |         |
| (Br-Le)          | 78.4          | 93.8            |                 |         |
| (Br-Fl)          | 81.4          | 95.4            |                 |         |
| (Br-En)          | 58.6          | 83.8            |                 |         |
Convolution Neural Network (CNN) model used in TARBIL dataset depicted 97.47% which is highest accuracy among other model in Table 5. M. A. Hedjazi et al. [39] focused on the AlexNet by tuning some parameter. AlexNet3 is considered fine tune and gained the highest accuracy 96.46% while original AlexNet only produced 86.75% in DS1 which dataset only with plain background. DS2 is the dataset mixed with cropped background and uncropped background. AlexNet3 obtained 71.17% while AlexNet only 58.57%.

Table 5: Comparison of Dataset and Model accuracies

| Dataset        | Model                | Accuracy | Studies |
|----------------|----------------------|----------|---------|
| TARBIL         | CNN                  | 97.47    | [38]    |
| ImageCLEF-DS1  | AlexNet              | 86.75    | [39]    |
| ImageCLEF-DS2  | AlexNet3-fine tune   | 96.46    |         |
|                | AlexNet              | 58.57    |         |
|                | AlexNet3-fine tune   | 71.17    |         |
| Oxford-102 flower | MobileNet-224          | 70.6     | [40]    |
|                | GoogleNet            | 69.8     |         |
|                | VGG 16               | 71.5     |         |
|                | AlexNet              | 57.2     |         |

In Oxford-102 flower dataset, the author introduced MobileNet and compare with GoogleNet, VGG16 and AlexNet. VGG16 obtained 71.50% and proposed MobileNet-224 is 70.60%. However, the compilation time for VGG16 is higher compare to MobileNet-224. Through the observation, deep learning approaches have high accuracy in recognition like features extraction. AlexNet is the most popular model use in plant identification for it is easy to adjust or tuning parameters. Deep learning approach in plant identification is a good approach for it works as descriptor and classifier and able to auto-adjust weight in algorithm that reduce processing time.

5. Conclusion
Features extraction approach has the highest accuracy compare to deep learning approach. Those using shape as the features have higher accuracies in recognition of the plant. The deep learning approaches are trainable and automated approaches that also able to produce high accuracies on recognition. AlexNet is one of the deep learning approaches that widely used in the plant identification by the researchers. More studies towards deep learning approaches for plant identification in these recent years. Future trend will be on deep learning approach for its trainable and automated feature extraction and description process by learning from training dataset and by develop a robust classification model. Challenges for researchers in deep learning approaches are huge in term of data collection, high performance and time consumption in order to be useful for public.

References
[1] Pimm SL, Jenkins CN, Abell R, Brooks TM, Gittleman JL, Joppa LN, Raven PH, Roberts CM, Sexton JO (2014) The biodiversity of
species and their rates of extinction, distribution, and protection. Science 344(6187).

Murphy GE, Romanuk TN (2014) A meta-analysis of declines in local species richness from human disturbances. Ecol Evol 4(1):91–103

Wäldehen J, Mäder P. “Plant Species Identification Using Computer Vision Techniques: A Systematic Literature Review.” 2017, Arch Computat Methods Eng (2018) 25: 507

Gaston KJ, O’Neill MA (2004) Automated species identification: why not? Philos Trans R Soc Lond B Biol Sci359(1444):655–667

Dayrat B (2005) Towards integrative taxonomy. Biol J Linn Soc 85(3):407–415

Lu Yu, Lichao Zhang, Joost van de Weijer, Fahad Khan, Yongmei Cheng, C. Alejandro Porrata, “Beyond Eleven Color Names for Image Understanding”, Machine Vision and Applications, 29(2): 361–373, 2018

Stephen Gang Wu, Forrest Sheng Bao, Eric You Xu, Yu-Xuan Wang, Yi-Fan Chang and Chiao-Liang Shiang, A Leaf Recognition Algorithm for Plant classification Using Probabilistic Neural Network, IEEE 7th International Symposium on Signal Processing and Information Technology, Dec. 2007, Cairo, Egypt

Nilback, M-E, and Zisserman, A., “A Visual Vocabulary for Flower Classification”, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2006

Goeau H., Bonnet P., Joly A., Bakic V., Bartehlney D., Boujenaa N., Molino J-F., “The ImageCLEF 2013 plant image identification task”, ImageCLEF 2013 working notes, Valencia, Spain, 2013

Wang X, Liang J, Guo F (2014) Feature extraction algorithm based on dual-scale decomposition and local binary descriptors for plant leaf recognition. Digit Signal Process 34:101–107

Ling H, Jacobs DW (2007) Shape classification using the innerdistance. IEEE Trans Pattern Anal Mach Intell 29(2):286–299

Hu R, Jia W, Jing H, Huang D (2012) Multiscale distance matrix for fast plant leaf recognition. Image Process IEEE Trans 21(11):4667–4672

Mouine S, Yahiaoui I, Verroust-Blondet A (2013b) Plant species recognition using spatial correlation between the leaf margin and the leaf salient points. In: 2013 20th IEEE international conference on image processing (ICIP), pp 1466–1470

Xiao XY, Hu R, Zhang SW, Wang XF (2010) Hog-based approach for leaf classification. In: Proceedings of the advanced intelligent computing theories and applications, 6th international conference on intelligent computing (ICIC’10). Springer, Berlin, pp 149–155

Ren XM, Wang XF, Zhao Y (2012) An efficient multi-scale overlapped block LBP approach for leaf image recognition. In: Proceedings of the 8th international conference on intelligent computing theories and applications (ICIC’12). Springer

Yang LW, Wang XF (2012) Leaf image recognition using fourier transform based on ordered sequence. In: Huang DS, Jiang C, Bevilacqua V, Figueroa J (eds) Intelligent computing technology, lecture notes in computer science, vol 7389. Springer, Berlin, pp 393–400

Wang B, Brown D, Gao Y, Salle JL (2015) March: multiscalearch- height description for mobile retrieval of leaf images. Inf Sci 302(0):132–148

Q. Wang, J. Zhao, M. Li, C. Cao and Y. Lei, “Preserving discriminant manifold subspace learning for plant leaf recognition,” 2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), Changsha, China, 2016, pp. 1744-1749

G.G. Demisse, D. Aouada and B. Ottersen, “Deformation Based Curved Shape Representation,” in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 40, no. 6, pp. 1338-1351, 1 June 2018

Pham NH, Le TL, Guad P, Nguyen VN (2013) Computer aided plant identification system. In: 2013 International conference on computing, management and communications (ComMan- Tel), pp 134–139

Lavania S, Matay PS (2014) Leaf recognition using contour based edge detection and sift algorithm. In: 2014 IEEE international conference on computational intelligence and computing research (ICCIC), pp 1–4

Wu S, Bao F, Xu E, Wang YX, Chang YF, Xiang QL (2007) A leaf recognition algorithm for plant classification using probabilistic neural network. In: 2007 IEEE international symposium on signal processing and information technology, pp 11–16

Prasad S, Peddjoji S, Ghosti D (2013) Mobile plant species classification: a low computational approach. In: 2013 IEEE Second international conference on image information processing (ICIIP), pp 405–409

Hossain J, Amin M (2010) Leaf shape identification based plant biometrics. In: 2010 13th International Conference on Computer Vision and Pattern Recognition, 2010

C. A. Priya, T. Balasaranavan and A. S. Thanamani, “An efficient leaf recognition algorithm for plant classification using support vector machine,” International Conference on Pattern Recognition, Informatics and Medical Engineering (PRIME-2012), Computer Technology, Tamilnadu, 2012, pp. 428–432

Hsiao JK, Kang LW, Chang CL, Lin CY (2014) Comparative study of leaf image recognition with a novel learning-based approach. In: 2014 Science and information conference (SAI), pp 389–393

Nguyen QK, Le TL, Pham NH (2013) Leaf based plant identification system for android using surf features in combination with bag of words model and supervised learning. In: 2013 International conference on advanced technologies for communications (ATC), pp 404–407

Aakif A, Khan MF (2015) Automatic classification of plants based on their leaves. Biosyst Eng 139:66–75.

Ghasab MA, Khamis S, Mohammad F, Fariman HJ (2015) Feature decision-making ant colony optimization system for an automated recognition of plant species. Expert Syst Appl 42(5):2361–2370

Caglayan A, Guclu O, Can A (2013) A plant recognition approach using shape and color features in leaf images. In: Petrovino A (ed) Image analysis and processing ICIAP 2013, lecture notes in computer science, vol 8157. Springer, Berlin, pp 161–170
[31] Chaki J, Parekh R, Bhattacharya S (2015b) Recognition of whole and deformed plant leaves using statistical shape features and neuro-fuzzy classifier. In: 2015 IEEE 2nd international conference on recent trends in information systems (ReTIS), pp 189–194

[32] Chaki J, Parekh R, Bhattacharya S (2015a) Plant leaf recognition using texture and shape features with neural classifiers. Pattern Recognit Lett.

[33] Wang Z, Sun X, Ma Y, Zhang H, Ma Y, Xie W, Zhang Y; “Plant recognition based on intersecting cortical model,” In: 2014 International joint conference on neural networks (IJCNN), 2014 pp 975–980

[34] Wang Z, Lu B, Chi Z, Feng D (2011) Leaf image classification with shape context and sift descriptors. In: 2011 International conference on digital image computing techniques and applications (DICTA), pp 650–654

[35] Prasad, S., Peddou, S.K. & Ghosh, D, “An adaptive plant leaf mobile informatics using RSSC,”. Multimed Tools Appl 76: 21339, SpringerLink 2017

[36] I. Gogul and V. S. Kumar, "Flower species recognition system using convolution neural networks and transfer learning," 2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN), Chennai, 2017, pp. 1-6.

[37] T. Do, H. Nguyen, T. Nguyen, H. Vu, T. Tran and T. Le, "Plant identification using score-based fusion of multi-organ images,” 2017 9th International Conference on Knowledge and Systems Engineering (KSE), Hue, 2017, pp.191-196

[38] H. Yalcin and S. Razavi, "Plant classification using convolutional neural networks,” 2016 Fifth International Conference on Agro-Geoinformatics (Agro-Geoinformatics), Tianjin, 2016, pp. 1-5

[39] M. A. Hedjazi, I. Kourbane and Y. Genc, "On identifying leaves: A comparison of CNN with classical ML methods,” 2017 25th Signal Processing and Communications Applications Conference (SIU), Antalya, 2017, pp. 1-4

[40] N. R. Gavai, Y. A. Jaknade, S. A. Tribhuvan and R. Bhattad, "MobileNets for flower classification using TensorFlow," 2017 International Conference on Big Data, IoT and Data Science (BID), Pune, 2017, pp. 154-158