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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. ReThe 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 inter-species 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

Figure 1: Features extraction through descriptors and classifiers

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]
I-IDSC	Shape	1-NN	97.07	[16]
MARCH	Shape	1-NN	97.33	[17]
DS-LBP	Shape+ texture	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

Descriptor	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]
MARCH	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_{vein}/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_{vein}/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_{vein}/A_{leaf}	SVM	96.25	[29]
Shape	SMSD	RF (k-NN, NB, SVM)	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)	[30]
Shape + color	SMSD, CM, CH	RF (k-NN, NB, SVM)	96.30 (94.21, 89.25, 92.89)	[30]
Shape	SMSD	NFC	97.50	[31]
Texture	GF, GLCM	NFC (MLP)	81.60 (87.10)	[32]
Shape + texture	CT, Hu moments, GF, GLCM	NFC (MLP)	97.60 (85.60)	[32]
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, TARBIL, 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.

Table 4: Comparison of Dataset and Model with Rank-1 and Rank 5 accuracy

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			[37]
	(En-Le)	76.6	94.6	
	(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	

*En – Entire, Le – Leaf, Fl –flower, Br—Branch

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]
	AlexNet3-fine tune	96.46	
ImageCLEF -DS2	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.

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