Artificial Intelligence for Automated Plant Species Identification: A Review

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***Abstract*—Plants are very important for life on Earth. There is a wide variety of plant species and their number increases each year. The plants identification using conventional keys is complex, takes time and it is frustrating for non-experts because of the use of specific botanical terms/techniques. This creates a difficult obstacle to overcome for novices interested in acquiring knowledge about species, which is very important to develop any environmental study, like climate change anticipation models for example. Today, there is an increasing interest in automating the species identification process. The availability and omnipresence of relevant technologies, such as digital cameras, mobile devices, pattern recognition and artificial intelligence techniques in general, have allowed the idea of automated species identification to become a reality. In this paper, we present a review of automated plant identification over all significant available studies in literature. The main result of this synthesis is that the performance of advanced deep learning models, despite the presence of several challenges, is becoming close to the most advanced human expertise.**

***Keywords*—Plants identification; species; artificial intelligence; machine learning; deep learning**

I. Introduction

Species diversity of vascular plants is relatively important on the scale of global biodiversity. There are no less than 390000 distinct species known around the world. This number is very approximate, insofar as there is at least an equivalent number of taxa cited in the literature but in fact only falling under simple synonymies. This clearly shows the difficulty that exists in the determination and taxonomy of plants. Species identification is the essential step to properly identify biodiversity and better act in terms of conservation.

Among techniques used in biosystematics to diagnose discriminant characters, that allow us to differentiate taxa and draw practical keys of determination, absolutely herbariums remain an indispensable tool for the botanist daily work. Indeed, research in botanical taxonomy cannot be considered without the presence alongside us of a rich herbarium with collections of references and specimen's types that provide basic information very important for systematic research.

In general, botanists use various methods that involve memory and observation. They may have implicit knowledge of morphology and variability of species, as a result of experience and learning. Other elements may also be involved in the identification process and especially in the wild field, for example, botanists must take into account abiotic factors, edaphic characters, climate and seasonal change that influence the morphology, appearance and distribution of species. These elements also provide useful information for identification. In addition to morphology, taxonomists can use a range of characters or taxonomic arguments including anatomy, palynology, chromosomes, biochemistry and molecular systematics to estimate the actual evolution of the species, to define it and to place it in its correct taxonomic rank.

In practice, each species has its own evolutionary history marked by genetic, ecological or morphological changes. There are several differences between species in morphology, ecology, reproductive system, interfertility, pollination, disease resistance, genes and many other traits. Systematics comes to find the product of this evolutionary history. To do this, taxonomists base themselves, in addition to morphology, on a set of characters or taxonomic arguments, in particular: odor, chromosomes, anatomy, molecular and biochemistry, to estimate the real evolution of species, grouping them into entities called taxa, to also give them scientific names according to the international code of botanical nomenclature and classify them, according to precise determination keys, in their correct taxonomic ranks starting with Kingdom then Phylum, Class, Order, Family, Gender and finally Species (Fig. 1).

In addition, there is the constraint in term of the specialized training required by the discipline and in particular the language of botany and its works (Flores, checklists, synopsis, monograph, etc.). That is why despite its importance, plant taxonomy remains a barely known and available notion to the majority of biologists. Indeed, defining taxa is a very complex task requiring a serious biosystem study based on the confrontation of several techniques.

This demanding situation by scientific, material and human needs push botanists to think about the idea where plants can be an object perfectly adapted to an automatic recognition system, able to make decisions about the belonging of a presented plant to any of the learned species [1][2]. In fact, accelerating the identification process and making possible for everyone is highly suggested, especially if we consider the continuous loss of plant biodiversity day after day. More than sixteen years ago, authors of [3] have argued that the developments of artificial intelligence and digital image processing would make automatic species identification from digital images real in the near future. Today, artificial intelligence, omnipresent mobile technologies and the emergence of smart phones make it possible to propel technological applications and make the idea of automatic species identification close to reality.

In this paper, we will categorize and present the different proposed approaches for automated plant identification, then we will discuss and answer questions like: how far can automated systems be from human expertise? Can they completely take the place of botanists and provide accurate results even for difficult groups that require more than just image observation? What is the best methodology currently and how can it be optimized? Are there still other alternatives?

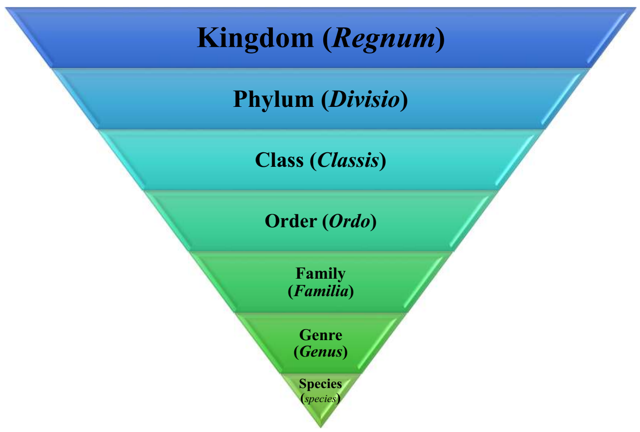


Fig. 1. The Seven Main Taxonomic Ranks Recognized by the International Code of Botanical Nomenclature (ICBN). Names in Italic are Latin Names.

It should be noted here that for our search strategy of papers that deal with the automated plant identification issue using AI, we have searched the Web of Science database to find relevant articles and books up to April 2022. The systematic search of the published literature was conducted using several keywords related generally to AI and plant identification.

The rest of the paper is organized as follows. In Section II, we will review automated plant identification categories / approaches. Our discussion is provided in Section III. Finally, we conclude the paper in Section IV.

II. Literature Review

The term of Artificial Intelligence (AI) was proposed and used for the first time by the late American programming expert John McCarthy in 1956, and it meant the ability to perform intelligent tasks by machines, especially tasks that mimic human intelligence.

Now that artificial intelligence techniques have developed and its uses have expanded, the definition of artificial intelligence can be developed as making computer system able of performing tasks that normally require simulating human intelligence, such as visual perception, pattern recognition, speech recognition, decision-making and translation between languages.

The use of artificial intelligence techniques has expanded in the last decade very significantly, and this is due to many reasons, the most important of which are: the power of modern computers (i.e., evolution of hardware) and their very large capabilities, which made the possibility of implementing very complex algorithms, that were not previously able to solve. We cannot ignore as well the spread of sensors connected to the web service that transfer huge quantity of data in a fast way. These sensors are also a huge source of data that are very necessary to improve the functioning of the AI techniques.

We can divide the artificial intelligence according to the amount of intelligence that the machine has reached into three categories:

- **Artificial Narrow Intelligence**: It means that computers perform one specific task with high efficiency and high repetition capacity that exceeds the ability of humans to accomplish, but at the same time it has not yet reached the level of human intelligence. Indeed, all that we see now of applications and devices are of this type.

- **Artificial General Intelligence**: It means that machines reach a level of intelligence that simulates human intelligence. It is possible that we will see its first "complete" applications during the few coming years, and absolutely the reason for not reaching this level yet is that we still do not know the details of many aspects of the human brain.

- **Artificial Super Intelligence**: It means that machine intelligence surpasses the human intelligence. It is absolutely not clear when humanity can reach that, but we can hear already scientists today warn of and fear that machines will control humans with this level of intelligence.

In this paper, we are talking exactly about the "Artificial General Intelligence" techniques. We can distinguish here two main categories: 1) Machine Learning (ML) techniques and Deep Learning (DL) techniques. To be simple, we can say that the main difference between Machine Learning and Deep Learning is that ML models get progressively better, and they always need human intervention to give them an outline of how they learn from the data, while deep learning models learn itself, without relying on human intervention. For example, if a ML algorithm is taught to open a gate when it hears the word *"open"*, the algorithm will respond only when it hears that word. If the model receives data such as *"I am unable to enter"* then Machine Learning techniques will not respond, however Deep Learning algorithms can infer that the meaning is the same, and then respond and open the door.

Technically speaking, in the context of automated plant identification (Fig. 2), generally all proposed AI techniques or systems use *plant images* as an input and the output, after several processing operations (i.e., feature extraction + classification), will be of course the identification result of the entered plant (i.e., the species or any other taxonomic rank). For all systems, we can consider two stages, the *training* stage where the system will learn about all available plants, then the *identification* stage where the system will be able to give answers about entered plants. In the next two subsections, We will give more details about the difference between Machine Learning and Deep Learning techniques and we will present all significant approaches proposed in literature for each category.

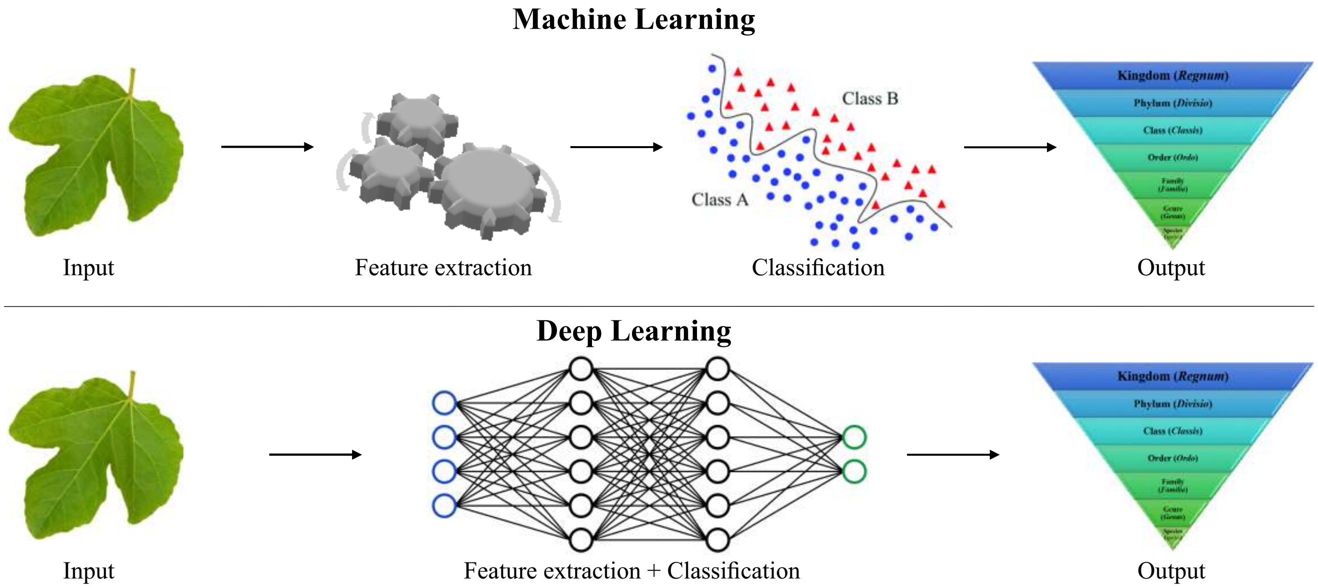


Fig. 2. The Main Modules of Machine Learning and Deep Learning Techniques.

A. *Machine Learning Techniques*

Speaking about automated plant identification using ML techniques (Fig. 3), we can say that during the *training* stage, all Machine Learning techniques apply, on the input images of all learned plant species, several classical feature extraction techniques, like PCA [4], to create plant *templates* (most of the time are “numerical vectors”) that will be stored in the system database. Then, during *identification* stage, users can submit any test plant image to the system, this last will apply the same feature extraction technique of the training stage then will match the query template with all stored templates in the system database, matching can take place using some classical classifier like SVM [5]. It should be noted that the majority of proposed ML techniques in literature add a pre-processing step on input images before applying the feature techniques to enhance data quality (i.e., to remove noisy information and keep the most useful data for learning and identification). In the next paragraphs of this sub-section, we will present the most significant works of this category according to an ascending chronological order.

In the context of the first edition of the PlantCLEF challenge, authors of [6] have used a dataset containing almost 5436 images belonging to 71 species of the French Mediterranean region. The dataset images are subdivided into three categories: scans, pseudo-scans and digital photos. Authors of this study focused on the identification of tree species from leaf images, with the aim of associating the correct tree species to each test image. The best results were obtained on scans and pseudo-scans, with accuracy equals to 53.8% and 68.5% respectively, while identification using digital images has not exceeded 52%.

As a continuation of the 2011 PlantCLEF challenge, the number of plant species in [7] has been increased from 71 to 126 and so the number of data has reached 11572 images subdivided always into three categories: scans, pseudo-scans and photos. The scores are globally lower than those obtained during the 2011 campaign, of which the best for scans, pseudo-scans and photos are successively: 58%, 51% and 45%. During the same year, a technique that use the fuzzy local binary pattern and fuzzy color histogram as extracted features and a probabilistic neural network (PNN) for classification task has been proposed in [8]. A dataset of 2448 leaf images, obtained from medicinal plants in Indonesian forests, has been used for the experimentation. Authors have achieved a classification accuracy of 74.5%.

During the third edition of the PlantCLEF challenge, [9] moved towards the use of organ images for the identification of tree and grass species and not only their leaves. The number of used species in this challenge edition is about 250 with a total of 26077 photos belonging to two categories: SheetAsBackground (i.e., photos of leaves taken in front of a uniform background) and NaturalBackground (i.e., natural photographs in the wild). The results obtained are slightly higher than those obtained during the 2012 challenge, and as expected the results for NaturalBackground are significantly lower than for SheetAsBackground due absolutely to the noisy backgrounds. In the same year, the authors of [10] have proposed an approach that uses the fractal dimensional features of leaf shape and vein patterns for the feature extraction step. A KNN classifier [11] is used for comparison. Authors achieved an identification accuracy of 87.1%. Using the same Flavia dataset, but this time with only 930 images belonging to 31 species, [12] have obtained an accuracy of 97.6%, using a neuro-fuzzy classifier (NFC) with a 44 element texture vector and a 3-element shape vector. [13] achieved almost a similar accuracy of [12] using only the shape features frequencies of 1865 leaves taken from the Flavia dataset. The features are extracted using the Fourier transform followed by a traditional dimensionality reduction technique like Principal Component Analysis (i.e., PCA) technique for example. Then the selected features are submitted to test several classification models:

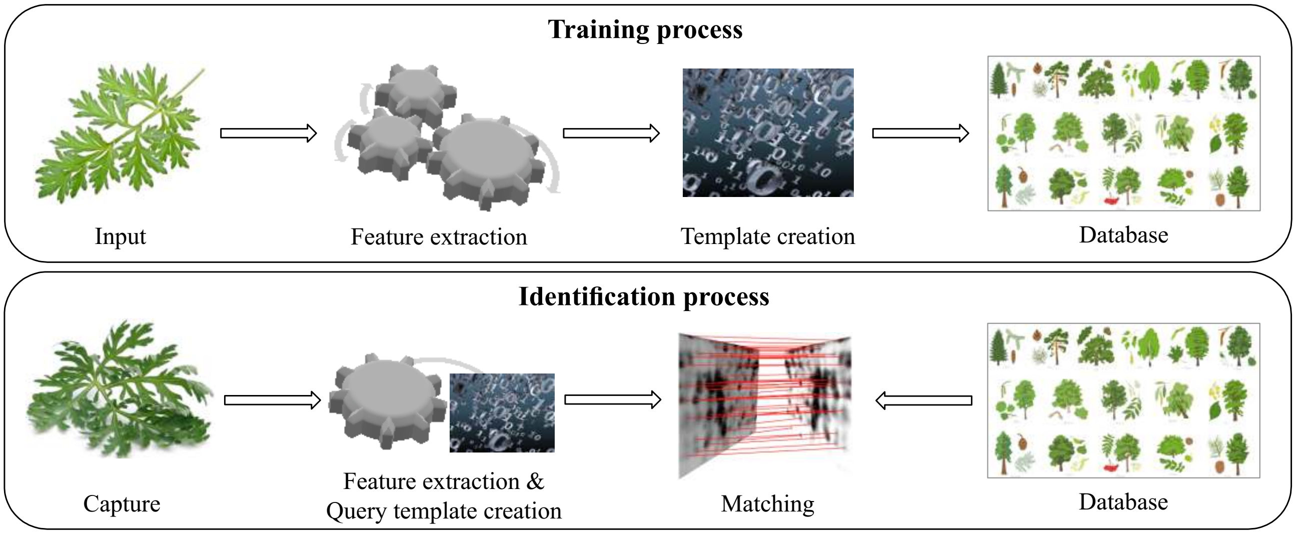


Fig. 3. The Main Steps of Machine Learning Techniques.

Pattern Net (feedforward neural network), Random forest, Rotation forest, Bayes Network, Model trees, Naive Bayes and C4.5 decision tree. The highest accuracy was achieved using the Pattern Net model with the vectors in the PCA space. Always during 2015, [14] developed an algorithm based on 817 leaf images of 14 tree species. This algorithm uses an artificial neural network (ANN) with backpropagation. An input vector of morphological features and Fourier descriptors (FDs), was fed into the ANN, resulting in a classification accuracy of 96% for their own dataset. To verify its effectiveness, they tested their algorithm on the Flavia and ICL datasets and achieved an accuracy of 36% for the both databases. For the fourth edition of the PlantCLEF challenge [15], the task of species identification has focused on observation and not on images, which means that the same person takes several photos of detailed views of different organs during the same day using the same camera under the same lighting conditions of the same plant. The constructed dataset for this challenge contains 113205 images of 1000 species. Experiments have showed that systems that combine different views of the same plant observation have proved a higher accuracy compared to those that use single images, up to 66.7%.

The authors of [16] have created two datasets with the same species: a clean one and a noisy one. They used the histogram of curvature on scale (HCoS) and local binary pattern variance (LBVP) algorithms to extract contour and texture features. Authors have claimed that the accuracy levels of the two datasets are very close, and they conclude that images taken directly without preprocessing can produce satisfactory results. [17] authors were the first team that uses images of old herbarium specimens of 26 tree species to classify them into categories. Using the support vector machine (SVM) after preprocessing, normalization and character extraction, they obtained an accuracy of 73.23% using a test set (I) that contains 24 species, and an accuracy of 84.88% using a test set (II) containing 17 species.

In [18], authors have used a set of leaf images of 24 different medicinal plant species collected from Mauritius. They extracted several features of each leaf such as: length, width, perimeter, color, number of vertices and shell area. A number of classifiers such as: KNN, naive bayes, SVM, neural networks and random forest were tested, of which the random forest classifier achieved the highest accuracy of 90.1%. [19] have focused on three Ficus species with similar leaf shapes. They used two classification models: an artificial neural network (ANN) and a support vector machine (SVM). Based on the morphological characteristics of the leaves, both models achieved the same accuracy of 83.3%.

The authors of [20] have lunched their experiments on 1125 leaf images of 15 Swedish species. Pre-processing was done using Gaussian filtering mechanism, then color and texture features were extracted and finally the classification was executed using a multi-class support vector machine. They obtained an accuracy of 93.26%. Finally, the team of [21] have used the ICL dataset to test a method that performs classification by automatically extracting shape features. The classification is then performed using a back propagation neural network. This experiment has achieved an accuracy of 96% for the test images and 99% for the training image.

Table I provides a comparison of all studies based on Machine Learning techniques. We will discuss the results of this comparison in Section III.

B. Deep Learning Techniques

We can say that the concept of Deep Learning is a discipline of Machine Learning which in turn is a discipline of Artificial Intelligence. The Deep Learning is the field concerned with the study of Artificial Neural Networks (i.e., ANN) that simulate neural networks in the human brain. As we know, the basic processing unit in the human brain is the neuron, and the artificial neuron in the DL techniques

TABLE I. SUMMARY OF STUDIES BASED ON MACHINE LEARNING TECHNIQUES

	Features	Dataset	Accuracy (%)
Goeau et al. (2011) [6]	Shape	5436 images (71 species)	52
			53.3
			68.5
Goeau et al. (2012) [7]	Shape	11572 images (126 species)	45
			51
			58
Herdiyeni and Wahyuni (2012) [8]	Texture, color	2448 images (51 species)	74,5
Goeau et al. (2013) [9]	Shape, color, texture	26077 images (250 species)	60.7
			39.3
Du et al. (2013) [10]	Shape, curvature, veins	2422 images (30 species)	87,1
Chaki et al. (2015) [12]	Shape, texture	930 images (31 species)	97,6
Siravenha and Carvalho (2015) [13]	Shape	1865 images (32 species)	97,5
Aakif and Khan (2015) [14]	Shape	817 images (14 species)	96
Go¨eau et al. (2015) [15]	Shape, texture, color	113205 images (1000 species)	66.7
C.-Rojas and M.-Montero (2016) [16]	Curvature, texture	2345 images (184 species)	87.2
Unger and Merhof (2016) [17]	Shape, veins	260 images (26 species)	73.23
			84.88
Begue et al. (2017) [18]	Shape, color, shell area	720 images (24 species)	90.1
Kho et al. (2017) [19]	Shape	54 images (3 species)	83.3
Kaur and Kaur (2019) [20]	Texture, color	1125 images (15 species)	93.26
Amlekar and Gaikwad (2019) [21]	Shape	No details are available!	96

corresponds to it. An assembly of artificial neurons is known as an Artificial Neural Network. The discipline of Deep Learning emerged as an extension and development of Machine Learning when traditional ML algorithms were unable to perform some complex tasks (e.g., learning from large datasets such as different sound waves and high resolution images dimensions).

Generally, as shown in Fig. 4, DL techniques consist of a multi-layer structure where the layer on the left end is the input layer, the layer on the right is the output layer, and in the middle are several hidden layers responsible for processing. Each layer consists of some *neurons*, *weights* and *activation functions*. Indeed, unlike the traditional Machine Learning algorithms that require a lot of human intervention to adjust and improve, the deep learning algorithms requires a lower level of human intervention in optimizing the algorithm's results, because they learns and improve from their mistakes on their own thanks to their special architectures. However, these last make DL techniques require a lot of time and high computing power to learn from huge data set to build a viable model.

Speaking about automated plant identification using DL techniques (Fig. 4), we can say that during the *training* stage, unlike ML methods, the set of images of all species will be used as inputs in a recursive way to train the system. In fact, the weights will be adjusted until an optimal model is built for identification. Then, during identification stage, users can submit any test plant image to the trained model that will extracts features and perform the matching to give an identification result.

Depending on the network architecture, we can define several categories of DL methods, like: Multi-Layer Perceptron (i.e., MLP), Recurrent Neural Networks (i.e., RNN) and Convolutional Neural Networks (i.e., CNN). For example, MLP networks are *fully connected layers* where each neuron in a layer often communicates with all the neurons in the layers that precede it. For RNN networks, they are suitable for applications that must take into account the relationship between data and the temporal context, such as speech recognition for example. RNN networks solve this problem by remembering what has been learned from previous inputs, so that the past state can be learned and used with the current input. For CNN networks, they mostly deal with two-dimensional matrices, which are most time likely images. We can say that in the context of automated plant identification, CNN are is the most used category of DL techniques.

In the context of the fifth edition of the PlantCLEF challenge [22], it was the first time where participants introduced the use of the deep leraning techniques, plant identification task was based on the use of a dataset that contains 113205 images representing plant organs and whole plants as well, covering 1000 woody and herbaceous species. 94 groups of participants have tried to use CNNs and only eight of them have submitted successfully their models. The highest classification accuracy was 72.4%. Always during 2016, in order to provide information on weeds for the good management of agricultural fields, [23] have trained and tested a convolutional neural network using a database that contains 10,413 images of 22 weed species. These images were taken from six datasets that present variations in terms of lighting, resolution and soil type. The developed CNN has provided an accuracy of 86.2%. In other work, [24] proposed to use the CNN for plant identification based on the morphological characters of the leaf veins of three legume species. After segmentation of the veins and extraction of the central spot to eliminate all possible influences of leaf shape, two scenarios (S1 and S2) were studied. In the first one only one image per sample was provided to train the CNN model, while in the second one three resized images (100%, 80% and 60%) were used as input to the CNN. They obtained almost similar average accuracy: 92.6% for S1 and 96.9% for S2.

The PlantCLEF challenge of 2017 [25], was organized on a dataset that contains 10000 plant species and 1.1 million

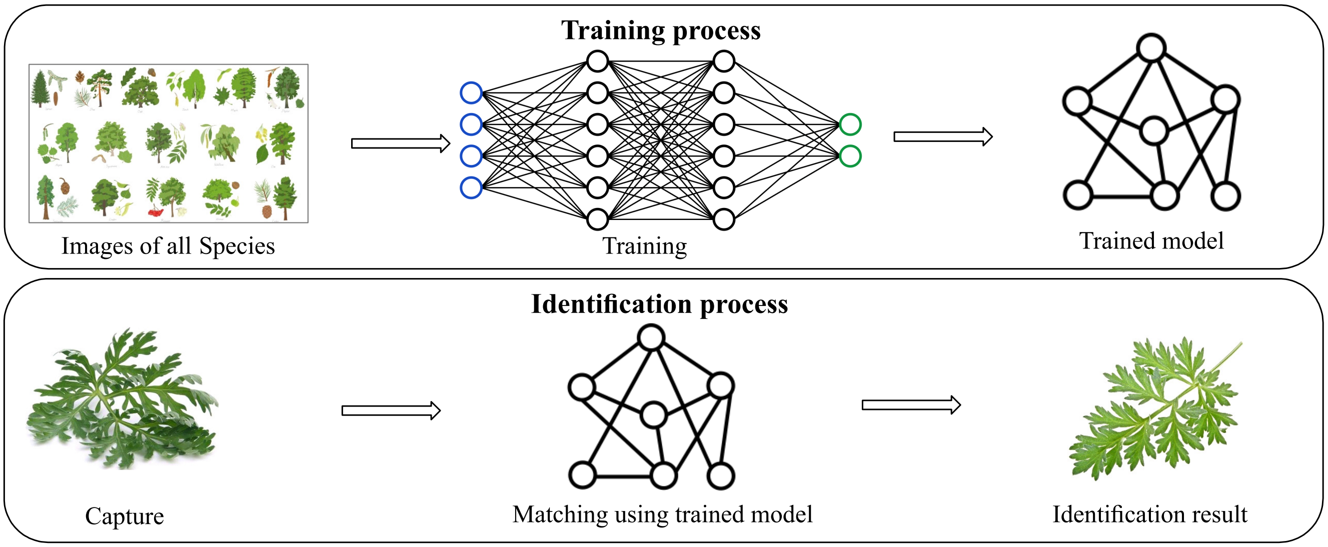


Fig. 4. The Main Steps of Deep Learning Techniques.

image in total. This was the first evaluation at this scale in the world where the test data to be analyzed was a large sample of raw query images. This dataset is divided into two sub-datasets: 1) the first one is huge and built using noisy web crawlers collected via the web; 2) the second one is smaller than the first sub-dataset and built using reliable training package verified by experts. The results obtained are almost similar, with systems using the reliable training set achieving almost 84% and systems processing a noisy training set exceeding 80%. While the systems that use both datasets achieved astonishing results of up to 92%. During the same year, [26] developed a plant identification system based on a Convolutional Neural Network called *LeafNet*. To evaluate it, they used three datasets: LeafSnap [27], Flavia [28] and Foliage [29]. On the LeafSnap dataset they obtained an accuracy of 86.3% for the top-1 and 97.8% for the top-5. Using the Flavia dataset, they obtained an accuracy of 97.9% for the top-1 and 99.99% for the top-5. Finally, for the Foliage dataset they obtained an accuracy of 95.8% for the top-1 and 99.6% for the top-5. Based on leaf features, [30] have used a Convolutional Neural Network to identify the most relevant features for a correct classification. They used two datasets: D1 and D2 with the same species, except that in the first one the images represent leaf shape as a classification feature, while in the second one venation and divergence between different venation orders are considered as selected features. They have obtained an accuracy of 98.1% for D1 and 99.5% for D2. In other work, [31] have proposed a 26-layer ResNet model for plant identification in a natural scene. They have use the BJFU100 dataset where images are taken using mobile phone cameras. It contains 10000 images of 100 plant species. The proposed model has achieved an accuracy of 91.78%. Always during 2017, [32] were the first team that has tested the classification of plant species using a large number of herbarium leaves and a Convolutional Neural Network. They have used five datasets: two of them (i.e., Herbarium255 and Herbarium1K) contain images of herbarium sheet images of leaves token from iDigBio; two others (i.e., CRLeaves and PlantCLEF 2015) contain images of leaves taken by a digital camera; and the last one is the ImageNet database [33] which is used to train the CNN model. They have conducted a series of experiments to evaluate the effectiveness of herbarium leaves alone for plant species identification and to see if the combination with plant photos in the wild field is relevant in terms of accuracy. The best results are obtained when combination is considered. For example, the top1 accuracy of the H1K herbarium sheets is 72.6% and the accuracy of the H1K sheets combined with ImageNet is 79.6%.

Same team [34] has tested several Deep Learning models to identify plant species using herbarium leaves. The identification task in this work take place not only at the species level, but also at other taxonomic levels such as genus and family. They used the Herbaria1K dataset and ImageNet (for pre-training of the Deep Learning model). The tested architectures are the Flat Classification Model (FCM), the Multi-Task Classification Model (MCM) and the Hierarchical Classification Model (TaxonNet). They obtained in general almost similar results using the different architectures. For FCM, they obtained 63.02% for the species; 70.51% for the genus and 75.55% for the family. For MCM the results are 64.32%, 75.95% and 88.17% for species, genus and family respectively. TaxonNet showed an accuracy of 62.39% for species, 76.23% for genus and 86.92% for family. The family classification was still the best of the three which is evident since the number of classes will be less in this scenario of test. In the same year, [35] have used a deep Convolutional Neural Network consisting of 19 layers in combination with linear SVM for plant classification using the database of the PlantCLEF 2015 edition that contains images of different plant organs. They obtained better results, up to 90.20%, compared with other models that use the same database.

In addition to plant identification using images, Convolutional Neural Network models have also been developed to identify and diagnose plant pathologies. In this context, [36] has developed a CNN model to detect plant diseases using images of diseased and healthy leaves. The author has used an open database of 87848 images of 25 species containing in a set of 58 combination classes (Plants, Diseases). He obtained an accuracy of 99.53%. [37] have tested several pre-trained Convolutional Neural Network architectures using the PlantVillage dataset [38] for plant disease identification. The tested architectures are: AlexNet [39], DenseNet-169 [40], Inception v3 [41], ResNet-34 [42], SqueezeNet-1.1 [43] and VGG13 [44]. The results obtained are globally high with an accuracy of up to 99.76%.

In the same context, [45] have developed a plant pathology identification model based on a Deep Convolutional Neural Network composed of 9 layers. Authors have used an open database contains 39 combination classes (Healthy Plant / Diseased Plant). The proposed model was trained using 55636 images and tested using 1950 images. Data augmentation methods [46] such as image flipping, rotation to scale, etc., were used. An accuracy of 96.46% was obtained. The result obtained shows that the use of augmentation methods can improve the performance of CNN models. To identify large-scale plants in a natural environment, [47] have tested a five-layer deep Residual Neural Network using a database that contains 185 classes of leaf images taken from the Columbia University, the University of Maryland and the Smithsonian Institution. They achieved an accuracy of 93.09%. In the 2019 edition of the PlantCLEF challenge, [48] have extended the challenge to flora in data-poor countries such as the Amazon rainforest. The results obtained illustrate the difficulty of species identification using a single image. The top accuracy of human experts ranges from 15.4% to 67.5%. However, the best automated system achieves an accuracy of 32% which can be explained by the fact that there is generally much diversity in tropical regions and by other reasons that we will discuss in the Section III. Always during 2019, [49] have carried out a series of experiments that compare five Convolutional Neural Network models, one of which was developed individually and the remaining four are transfer learning models. Four publicly available plant datasets were used for experimentations: Flavia, Swedish Leaf [50], UCI Leaf [51] and PlantVillage. The obtained results show that the transfer learning approaches perform better than the developed model for all datasets. For example, using the UCI Leaf dataset, the end-to-end model accuracy is 76.15%, while it reached up to 90.56% in a transfer learning model.

To answer this question: “among the images of plant leaves and flowers, what kind of perspectives contain more characteristic information and allow a high accuracy of identification?”, the study of [52] was conducted. They developed an image capture system to create observations of flowering plants. Each observation contains images of whole plants, front and side views of flowers, top and back views of leaves. The collected data set includes 101 species that are morphologically similar. They have used a Convolutional Neural Network to perform experiments. They obtained top-1 accuracies ranging from 77% (whole plant) to 97% (when merging all features). Flowers achieved the highest accuracy of 88%. The fusion between flowers and leaves gives an accuracy of 96%. In other work during 2019, [53] have studied automated plant classification at the genus and family level. They have tested a CNN model using a dataset that contains 1000 images of representative species of the Western European flora belonging to 516 genera and 124 families. The classification accuracy of the trained species increased from 82.2% at the species level to 85.9% and 88.4% at the genus and family level. While the accuracy decreases considerably to 38.3% and 38.7% at genus and family level for untrained species.

We can say that the 2020 edition of PlantCLEF challenge [54] is entirely different from all previous editions. It is based on a large collection of over 60000 herbarium sheets of 1000 species from the Guiana Shield region of South America. A valuable asset of this collection is that many herbarium sheets are accompanied by a few photos of the same specimen in the field. For the test set, they used field images from different sources, including Pl@ntNet and Encyclopedia of Life. The metrics used for the evaluation of the task are classification accuracy and Mean Reciprocal Ranking (MRR) which is calculated according to the following equation:

$$MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{Rank_i} \tag{1}$$

where $|Q|$ is the total number of specie occurrences in the test set.

Authors of [54] claimed that the highest accuracy is MRR= 0.18 for ITCR PlantNet Run 10, followed by MRR= 0.17 for ITCR PlantNet Run 9. Always during 2020, [55] have organized a sub-competition hosted on the Kaggle platform to encourage the development of an automated species identification algorithm using herbarium leaves. 22 teams have participated with 254 models for species identification of Melastomataceae. They have used a large collection of photographed herbarium specimens for experiments (46469 specimens representing 683 species). Four models out of 254 obtained the highest accuracies exceeding 88% of correct identification.

For the 2021 edition of PlantCLEF challenge [56], we can say that the training dataset is based on the same visual data used during the previous challenge of 2020. Indeed, the 2021 task was particularly challenging, focusing on species rarely photographed in the field in the northern tropical Amazon. PlantCLEF 2021 introduces also new data related to five “traits” covering exhaustively all the 1000 species of the challenge. Traits are very valuable information that can potentially help to improve prediction models. Indeed, it can be assumed that species which share the same traits also share to some extent common visual appearances. The five most exhaustive traits (“plant growth form”, “habitat”, “plant life form”, “trophic guild” and “woodiness”) were verified and completed by experts of the Guyanese flora, so that each of the 1000 species have a value for each trait. The main evaluation measure for the challenge was the MRR.

Finally, to build an reliable system, the authors of [57] have proposed an efficient method of behavioral similarity developed through three models based on deep learning. To train their models, they have used the MalayaKew dataset that includes 44 classes of plant species and the FLavia dataset that contains 32 plant species. The results obtained for all the proposed models using the two datasets are respectively 99.67% and 99.81%.

Table II provides a comparison of all studies based on Deep Learning techniques. We will discuss the results of this comparison in Section III.

TABLE II. SUMMARY OF STUDIES BASED ON DEEP LEARNING TECHNIQUES

	Dataset	**Accuracy (%)**
Dyrmann et al. (2016) [23]	10413 images (22 species)	86,2
Goeau et al. (2016) [22]	113205 images (1000 species)	72,4
Grinblat et al. (2016) [24]	15 images (3 species)	92.6
		96.9
Barré et al. (2017) [26]	LeafSnap (7719 images of 185 species)	86.3
	Flavia (60 images of 32 species)	97.9
	Foliage (120 images of 60 species)	95.8
Goeau et al. (2017) [25]	1.1 million images of 10000 species	92
Lee et al. (2017) [30]	MalayaKew (2816 images of 44 classes)	98.1
		99.5
Sun et al. (2017) [31]	10000 (100 species)	91.78
C.-Rojas et al. (2017) [32]	Herbier255 (11071 images of 255 species)	79.6
	Herbier1K (253733 images of 1204 species)	
C.-Rojas et al. (2018) [34]	Herbier1K, ImageNet (1 Million arbitrary hand-annotated images)	$\left.\begin{array}{l}63.2\\64.32\\62.39\end{array}\right\}$ for specie $\left.\begin{array}{l}70.51\\75.95\\76.23\end{array}\right\}$ for genus $\left.\begin{array}{l}75.55\\88.17\\86.92\end{array}\right\}$ for family
Zhu et al. (2018) [35]	113205 (1000 species)	90.2
Ferentinos (2018) [36]	87848 (25 species)	99.53
Brahimi et al. (2018) [37]	PlantVillage (54323 images of 14 species)	99.76
G. and J. (2019) [45]	55636 images of 13 species	96.46
Bodhwani et al. (2019) [47]	27000 images of 185 leaf classes	93.09
Goeau et al. (2019) [48]	434251 images of 10000 species	32
Kaya et al. (2019) [49]	Flavia, PlantVillage	90.56
	UCI Leaf (443 images of 40 species)	
	Swedish Leaf (1125 images of 15 species)	
Rzanny et al. (2019) [52]	9090 images of 100 observations (no data about species)	97.1
Seeland et al. (2019) [53]	500000 images of 1000 species	82.2 for specie
		85.9 for genus
		88.4 for family
Joly et al. (2020) [54]	60000 images (1000 herbarium species)	MRR = 0.18
Ambrose et al. (2020) [55]	46469 images of 683 species	$\geq$ 88
Goeau et al. (2021) [56]	60000 images of 1000 species	MRR = 0.18
		MRR = 0.158
KBeikmohammadi et al. (2022) [57]	MalayaKew (2816 images of 44 classes)	99.67
	Flavia (60 images of 32 species)	99.81

III. DISCUSSION AND FUTURE DIRECTION

It should be noted that while several results are discussed separately here, they are interrelated in many ways. Therefore, this discussion tends to overlap in some parts.

Before discussing any of the results of Section II, we can immediately draw these six observations: 1) Most of results do not give a clear and sure view on the indicators that can improve the accuracy of plant identification. 2) There is no better approach for automated plant identification (with a priority of DL techniques compared to ML approaches); and the current available identification systems are not yet mature enough for a large-scale deployment. 3) There are no common protocols of test, no common performance indicators or metrics and no common databases used and shared between all proposed approaches, which make any comparison of results not fair or even wrong. 4) No information are given about the taxonomy of each family / genus / specie which is very important to specify the degree of resemblance between classes (i.e., intra- and inter- subject variations) that gives as well an idea of the complexity of any identification task. 5) Recent automated plant identification systems might be in the way to surpass the ability of the human expert botanists. 6) Most of proposed systems are developed by computer science experts and only very few of botanists.

For our first observation, we believe that the clearest results that we can get are:

- **Image type and identification accuracy**: We can say that the systems analyzed during the first edition of PlantCLET challenge [6] have provided good classification scores, especially using scans and pseudo-scans categories, while using digital photos performance has been degraded. Thus, the evidence conclusion here is that the images type influences the identification accuracy. The same observation can be drawn from the results of the 2012 edition [7], even that the difficulty of the challenge has increased and that the technological progress made by the participants has not compensated for the increased difficulty.

- **Feature extraction and identification accuracy**: We can say that for Machine Learning techniques, the improvement and the fusion of several methods of feature extraction / selection can improve identification accuracy. For example, the improvement of classification accuracy in [8] was due to the effective fusion between the FLBP and the FCH methods. The same result can be confirmed in [9] where most of approaches focused on the extraction of shape, texture and color. In the same context, [18] added more characters to be extracted such as length, width, perimeter, number of vertices, and hull area to get better results.
- **Image view and identification accuracy**: Always for Machine Learning techniques, we believe that observing different plant organs, using different views of the same plant specie, which is a current practice of botanists, can improve the identification accuracy. This is slightly confirmed in [15] where systems that combine different views of the same plant observation showed higher accuracy compared to systems that use single images.
- **Image pre-processing and identification accuracy**: We believe that adding a pre-processing of images before feature extraction can improve performance. This can be confirmed in the experiments of [16] and [17] who obtained good scores even if the used herbarium images were old, thanks to the added pre-processing step.
- **CNNs and identification accuracy**: Without any doubt, performance of automated plant identification systems has started to increase concretely since the 2016 PlantCLEF challenge [22]. Knowing that the database used during this edition is the same one used in the previous edition, the proposed systems gave higher scores in 2016. These systems were based on Convolutional Neural Networks. This definitely confirms the supremacy of Deep Learning approaches over the Machine Learning methods previously adopted for plant identification. In addition, all CNNs systems can use a huge database with a very high number of images. These last can be noisy, collected via the web, taken by digital cameras or cell phones and do not undergo any pre-processing step.
- **Taxonomic levels and identification accuracy**: The idea of moving to the classification at higher taxonomic levels has also given good performance whether in the experiment of [34] or that of [53]. The main idea to note here is that the higher the taxonomic level, the more relevant the classification accuracy becomes.
- **Species diversity and identification accuracy**: The remarkable decrease in the results of the 2019 challenge [48] dedicated to regions lacking data. This can be explained by the fact that there is generally much more diversity in tropical regions compared to temperate regions, already studied in the previous challenges, for the same reference areas. In addition, tropical plants in high forests are much less accessible to humans who have much more difficulty in improving their knowledge of these ecosystems. The decline in results is continuing despite attempts to improve data in 2020 [54] and 2021 [56] challenges, the tasks were particularly difficult, focusing on rarely photographed species in the field from data deficient regions (while CNNs require huge number f images per class for the training step).

For our second observation, as we have said before, performance of automated plant identification systems has started to be increased with the first uses of Deep Learning techniques in the 2016 PlantCLEF challenge [22], which means already that DL techniques have proven a superiority compared to ML techniques. However, we believe that all current available identification systems are not yet mature enough for a large-scale deployment.

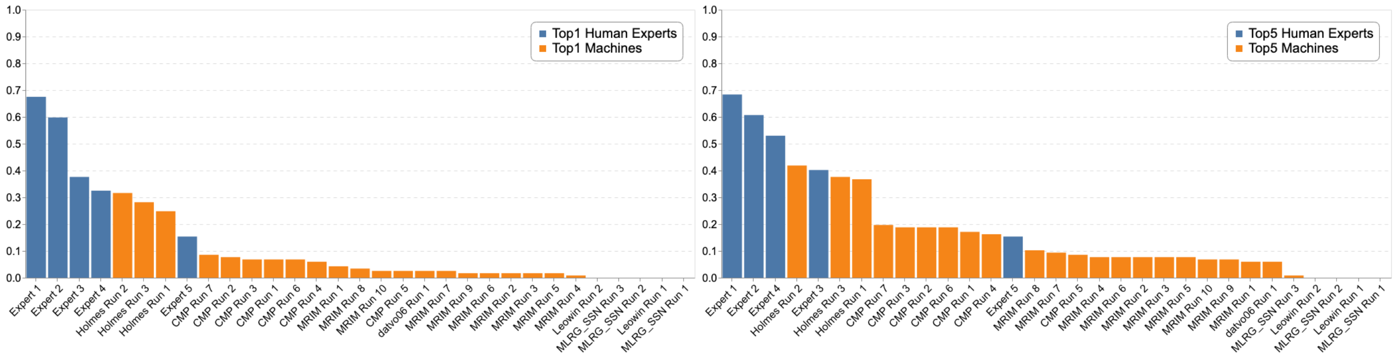
For the third observation, we believe that, before giving any judgment about the best approach or the good practices to follow to improve accuracy of automated plant systems, the community of research of this field must establish a common evaluation protocol to make researches able to compare their results. In this context, we think that even the basic metrics of evaluation, like the ROC curve and the Error Equal Rate (ERR), are not used by all proposed technique of literature. In addition, we believe as well that a common database must be built to make the the use of the common evaluation protocol fair and correct as well. The best example in this context to be followed is the Fingerprint Verification Competition (FVC) [58]. This is an international competition that has been organized by academic laboratories to evaluate fingerprint verification algorithms developed by both academics and industry. Several databases (i.e., FVC2000, FVC2002, FVC2004 and FVC2006), which are acquired with various types of sensors while increasing difficulty, were provided to the participants to allow them to test and compare their techniques according to a predefined test protocol[2]. The proposed protocol / databases are used until now by all researchers in fingerprinting field. We believe that the same strategy must be adopted for automated plant identification.

For our fourth observation, we can say that the majority of works in literature do not give any information about the taxonomy of each family / genus / specie in the used dataset, such information is very important for any identification system to define the degree of resemblance between classes and therefore define the difficulty of the database. All that confirm again the need to build common databases of test while taking in consideration the complexity of identification that is related to the chosen plant for every database.

For the fifth observation, we think that the current automated plant identification systems might be in the way to surpass the ability of the human expert botanists. This can confirmed especially in the results of the 2019 PlantCLEF challenge [48] and in Fig. 5 taken from the same challenge. We can notice also that the results of automated systems improves well in the Top 5 scenario compared to human experts, which means that if we are looking for a tools to minimize the list of candidate plants during a classic systematic identification (top

[1] https://www.imageclef.org/PlantCLEF2019

[2] https://biolab.csr.unibo.it/fvcongoing/UI/Form/Home.aspx



(a) Top 1 accuracy

(b) Top 5 accuracy

Fig. 5. Results of Automated Plant Identification Systems vs the Human Experts (Taken from [1]).

10 or top 20 list for example), absolutely automated systems can be this very useful / fast tool.

For our last observation, we have noticed that the majority of proposed systems are developed by computer science experts and only very few of botanists which is absolutely not a good practice to build successfully a robust automated system. This prove why all works of literature have a huge lake of taxonomic information about tested plant species. We believe that All teams of work on this challenge must contain computer scientist and botanist to optimize the design and results of automated plant identification systems.

IV. Conclusion and Perspective

In this paper, we present a review of automated plant species identification issue over all significant available studies in literature. The main result of this synthesis is that the performance of advanced deep learning models is becoming close to the most advanced human expertise. However, we have to mention that several fundamental challenges are remaining to be solved to achieve the design of an efficient system. This is exactly the objective of our future works. First, we have a plan to propose an efficient evolution protocol to be used with any plant identification system. Second, we will publish several databases (with different level of difficulty) for tests while giving all needed taxonomic information, including a national database of Moroccan toxic plants species. Third, we will test our first identification system (as a personalized architecture of Convolutional Neural Network) using the Moroccan toxic plants database since the complexity of this last will be low because the degree of similarity is weak due to the high diversity of families / genus of Moroccan toxic plants. Finally, we will perform and optimize our system using harder databases with high degree of similarity.

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