A New Deep Learning System for Wild Plants Classification and Species Identification: Using Leaves and Fruits

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A New Deep Learning System for Wild Plants Classification and Species Identification: Using Leaves and Fruits

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Abstract. Many studies are based on the study of plant classification and their identification using its leaves, and there are many studies to identify plants using its fruits. Most of these studies are based on the leaves of the plant in general as well as the fruits in general as well. In this research, we present a new tool using artificial intelligence to classify and identify wild plants through the leaves of these plants, or by using their fruits, or by using both leaves and fruits together. This tool has proven an excellent result compared to similar tools in the same field. More than one AI model was applied to three datasets, lower plants dataset (LPDS), upper plant dataset (UPDS), and fruit plant dataset (FPDS). The aim of this study is to use machine learning methods to serve in the plant taxonomy and identification. The wild plant's dataset was gathered in its natural habitat in Egypt. The developed convolution neural network model (AlexNet CNN), the Random Forest (RF), and the support vector machine (SVM) techniques were contrasted in the species classifications. The highest degree of accuracy achieved was 98.2% by using the developed CNN model.

Keywords: Plant taxonomy · Deep learning · Support vector machine · Random forest

1 Introduction

Botanists, especially plant taxonomists, after collecting plant samples from the fields, the first step before starting work on plant samples is to identify plants in terms of family, genus and species. Taxonomists use flora books and also comparisons with herbarium

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samples to obtain an accurate and correct identification of plant samples and this process is delicate and a little cumbersome. Recently, some programming scientists have implemented a set of applications and websites to identify plants using artificial intelligence algorithms to facilitate this process for scientists and those interested in botany as, PlantNet, PlantDetect Lite, Plant D, PlantSnap Pro and Picture This. Botanists used morphology, anatomy, genomic analysis, and photochemistry to identify and classify plants, among other methods. The first is through the plant's morphological characteristics, especially the flower. When the flowering stage is unavailable, the fruit characters are useful for species identification and separation [1]. In recent years, Deep Learning has demonstrated the highest machine learning efficiency, and its image rating has skyrocketed. Several linear and non-linear layers make up a standard deep learning system. The term "deep" refers to the multiple layers of deep stacking. Deep learning approaches' progress is largely dependent on the development of devices that can manage large amounts of data and network architecture. Convolutional neural networks CNN, in particular, have recently achieved the highest image classification success and are commonly used in modern deep learning techniques [2]. To identify and classify plants, recent studies of image recognition and taxonomy approaches have been used. These techniques used texture and color-based features to perform classification. Aspect ratio, kurtosis, skewness, energy, correlation, sum variance, entropy, and compactness are some of these characteristics. The computing power is disproportionate. The major drawback of these traditional methods is the lengthy computation time needed for handcrafted feature extraction. All conventional approaches have been replaced by machine learning techniques in recent years. The convolution layers are concerned with the digital filtering techniques, that are used to highlight or extract the most noticeable features. The pooling mainly concerned lowering the volume of the feature maps received from the convolution layer, decreasing the overfitting of the maps in the network layers, and reducing the computations.

Most of the implemented applications depend on datasets for cultivated plants, not wild plants. One of the main objectives of the current study is to work on the wild plant's dataset, this research aims to create a system to help the scientists to identified plant specimens using only images. This system can be considered a kernel of an electronic herbarium for wild plants.

2 Review of Related Literatures

In this section, we will list the recent studies related to plants image classification based on the leaf and the fruits.

Using the large and deep learning method, a model that integrates a linear and a deep learning models to solve fine-grained plant image classification challenge [2].

The CNNs had five convolutional layers at the time, but ensemble systems outperformed them in terms of true deep learning. Another method used handcrafted visual features and qualified SVM classifiers for various view styles [3]. Using the ImageNet model and dataset released in [3], a new model to classify plant images using the convolution neural network architecture [4]. The study [5] present three models, Alexnet, DLeaf, and AyurLeaf; the AyurLeaf CNN model is evaluated and compared to AlexNet, Leaf, and fine-tuned AlexNet versions using two classifiers, CNN and SVM with accuracy 96.76%. Plant taxonomy is the study of how various species of plants are categorized.

In comparison to other transfer learning strategies, the study found that transfer learning improves the performance of deep learning models, especially models that apply deep features and use fine-tuning to provide better performance [6], the research applies deep learning features SVM and LDA to four publicly accessible plant datasets using two deep learning models, Alexnet and VGG16 (Flavia, Swedish Leaf, UCI Leaf, and Plantvillage). The study [7] present the extension work to [8] with an adaptive algorithm that relies on a deep adaptive Residual Neural Network to deal with the identification of multiple plant diseases in real-world acquisition environments, where numerous modifications have been proposed for early disease detection using a Residual Neural Network, including several enhancements to the augmentation scheme and tile cropping. The study [9] presents D-Leaf, a modern CNN-based approach that was proposed. After pre-processing the leaf images, the three pretrained Convolutional Neural Network (CNN) models: pre-trained AlexNet, fine-tuned AlexNet, and D-Leaf. Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest-Neighbour (K-NN), Nave-Bayes (NB), and CNN are five machine learning methods which used to extract and identify the features. The accuracy of these techniques is 90–98% on three publicly available datasets: MalayaKew, Flavia, and Swedish Leaf Dataset. [10] present the three neural network architectures, Inception v3, ResNet50, and DenseNet201 to improve the performance of plant species classification, used a variety of augmentation operations to increase the dataset diversity further, using dataset holds 256.288 samples and the noisy set 1.432.162. These samples are for 10.000 different plants, as well as a robust Orchid family plant database built for algorithm evaluation. The study [11] present a pre-trained AlexNet was fine-tuned, which resulted in the 4th place. The study [12] providing a detailed empirical guide showing that residual networks are easier to refine and can achieve precision by increasing depth substantially, also test performed on the residual nets with a depth of 152 layers in the ImageNet dataset, but with lower complexity, on the ImageNet test range, an ensemble of these residual nets achieves a 3.57% error. The model was pre-trained with ImageNet and fine-tuned with the PlantCLEF database, using an Inception Convolutional Neural Network (CNN) model-based network. They merged the outputs of five CNNs, which were fine-tuned with randomly selected sections of the database. The optimization of hyperparameters, on the other hand, was not completed [13]. The study [14] design A multi-input convolutional neural network for large scale flower grading and achieves 89.6 after data augmentation. The study [15] presents a method for extracting distinctive invariant features from images that can be used to perform reliable matching between different views of an object or scene. The study [16] propose model that use different training epochs, batch sizes and dropouts. Compared with popular transfer learning approaches, the proposed model achieves better performance when using the validation data. After an extensive simulation, the proposed model achieves 96.46% classification accuracy. The study [17] present overview on the plant species recognition methods and features extraction using leaf image. The study [18] provide a data article for a dataset that holds samples of images of healthy citrus fruits and leaves. The study [19] the pre-processing, feature extraction, and categorization into one of the species. Several morphological parameters such as centroid, major axis length, minor axis length, solidity, perimeter, and orientation are retrieved from digital pictures of various leaf categories with an accuracy rate of 95.85%

In the study [20], builds an unique multiscale convolutional neural network with attention (AMSCNN) model for plant species detection, with a maximum accuracy of 95.28%.

3 Description of the Implemented Techniques

Taxonomy and family classification of plants are difficult to decipher. There have been several studies on the classification and recognition of plant images. We used a matrix of multiple models with multiple plant parts in this study. On the lower leaf, upper leaf, and fruit images, CNN developed model, Random Forest with parameter optimization, and SVM are used. Deep Learning has shown the best outcomes of machine learning. Convolutional neural networks (CNN) have recently achieved the greatest success in image recognition and are commonly used in most advanced deep learning techniques. Most recent studies have focused on using deep learning to classify images.

Support Vector Machine: The main objective of the SVM is to find the hyperplane that can separate the data most efficiently and most accurately. In both classification and regression, the support vector machine (SVM) is used.

In a linear SVM, the given data set is represented as a p-dimensional vector that can be separated by a maximum of p-1 planes. These planes divide the data space or define the boundaries between data classes in classification and regression problems [21].

Deep Learning: VGGNet, LeNet, GoogLeNet, and AlexNet are the most common CNN architectures used in current state-of-the-art Deep Learning research to solve various Computer Vision problems such as Image Classification, Object Recognition. AlexNet is a CNN model that has been pre-trained using images from the ImageNet dataset. It can distinguish 1000 different animals. There are five convolutional layers, three completely linked layers, and a softmax classification layer in this model [22]. Mathematical formula for a convolution layer:

$$Conv(I, K)x, y = \sum_{i=1}^{nH} \sum_{j=1}^{nW} \sum_{k=1}^{nC} (Ki, j, kIx + i - 1, y + j - 1, k)$$

where: I: image, K: filter, nH: the size of the Height, nW: the size of the Width, nC: the number of Channels.

Random Forest: Random Forest is a powerful and scalable that classify as the supervised learning of the machine learning algorithms that creates a "forest" by growing and combining more than one of the decision trees that are compiled to enhance the prediction. It can be used to solve problems involving classification and regression.

4 Empirical Studies

4.1 Description of Dataset

- Reviewed all images of (lower leaf, upper leaf, and fruit) and ensured that the image is clear.
- Ensured that all images are uniform in length.
- Distortion cleaning.
- Standardized the image features.

4.2 Dataset Analysis

The dataset is 51 original images for 17 species belonging to two families, is not useful in the training of the CNN model. We use the augmentation to increase the dataset to 3954 images for 51 species belong to two different families. The image dimensions are 224 ×224, divided into 3164 for training and 790 images for testing, as shown in Table 1. Eight for the first family (Apiaceae), and nine images from the second family (Brassicaceae) as shown in Fig. 1, and Fig. 2 respectively. In our work we used different four plants species in identification testing, which does not train by our system.

Table 1. Plant dataset information.

Family name	No. of plants	Fruit images	Lower leaf images	Upper leaf images	Total
Apiaceae	8	608	608	608	1824
Brassicaceae	9	710	710	710	2130
Total	17	1318	1318	1318	3954

Fig. 1. The image of family Apiaceae used for the dataset (1- Lower leaf, 2- Upper leaf, and 3-fruit).

One of the contributions in the current study is preparing this dataset, because the current study is the first machine learning and AI experiments applied on this dataset. The dataset consists of three parts; the first is lower leaf images, the second is upper leaf images and the third is the fruits images. All images related to two plant families as shown in Table 1.

Fig. 2. The image of family Brassicaceae used for the dataset (1- Lower leaf, 2- Up*per leaf, and 3- fruit).*

4.3 Feature's Extraction

Features are parts or patterns of an object in an image that help to identify it. The HOG (Histogram of Oriented Gradients) descriptor is one of commonly used global explored in the object detection group. It is based on the idea of counting the number of times a gradient orientation appears in a particular localized region of an image [23]. We extract the Histogram of Oriented Gradients (HOG) for the plant's images, and compute a HOG by using python package (SKIMAGE) that working on:

- Global image normalization
- Computing the gradient image
- Computing gradient histograms
- Normalizing across blocks
- Flattening into a feature vector
- Combine color and hog features.

HOG descriptors are not tied to a specific machine learning algorithm.

In the current study we have developed the features extraction process based on the CNN model.

5 Proposed Models and Results

More than one AI model was applied to three datasets, lower plants dataset (LPDS), upper plant dataset (UPDS), and fruit plant dataset (FPDS). The AlexNet CNN (Convolution Neural Network) model developed and implemented to extract the fruit and the leaves features, classify each plant to its family, and use the trained model to identify the plant and to classify it to the belongs family. The current study propose the system for family classification and species identification based on the developed CNN model as shown in Fig. 3:

- Developed CNN
- SVM (Support Vector Machine)
- Random Forest.

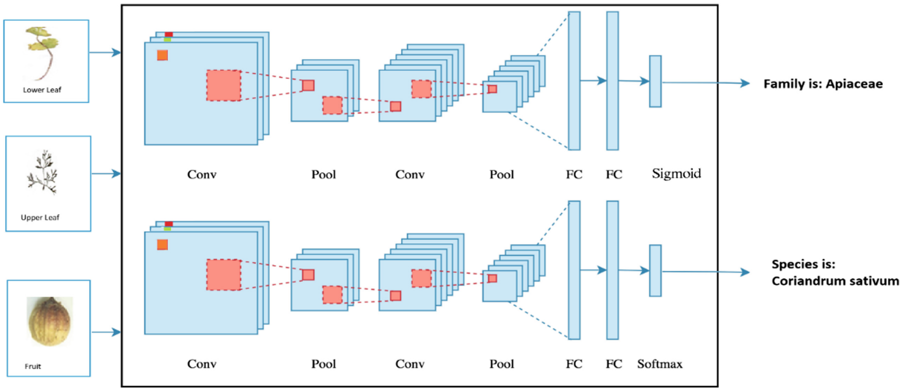

Fig. 3. Proposed System Architecture based on developed CNN.

5.1 Families Classification (Binary Classification)

In this section we implemented different deep learning models of binary classification to classify the plants into two families (Apiaceae and Brassicaceae) with validation on these models.

First Experiment Description. The dataset described in Table 1 is the input for the first developed CNN model, the model architecture consists of 11 layers. In this experiment the three datasets (LPDS, UPDS, and FPDS) applied and the accuracy is near to 99% as shown in Fig. 4, also the loss is near to zero. This result is individual for each dataset type standalone the result is binary and classify two families based on supervising training, as shown in Fig. 4, the accuracy of fruit and lower leaf are better than the accuracy of upper leaf and the best result with the fruit.

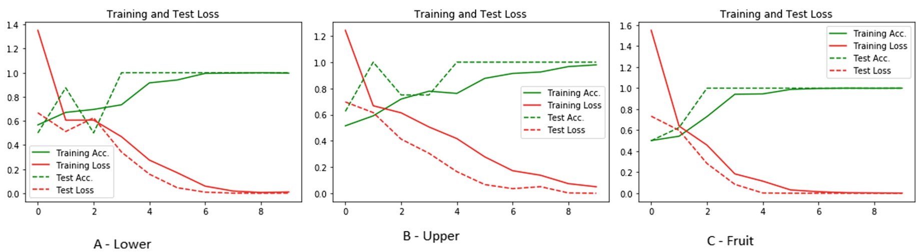

Fig. 4. Single Input CNN Model Accuracy (binary classification)

Second Experiment. The dataset described in Table 1 is the input for the first CNN model, the model architecture consists of 11 layers. The input layer are three images (lower, upper, and fruit) each one has dimension (200, 200).

In this experiment the three datasets (LPDS, UPDS, and FPDS) applied and the accuracy is near to 99% as shown in Fig. 5, also the loss is near to zero. This result is based on the three images added to the inputs parallel, the result is binary and classify two families based on supervising training. The accuracy is stable and better than the first experiment.

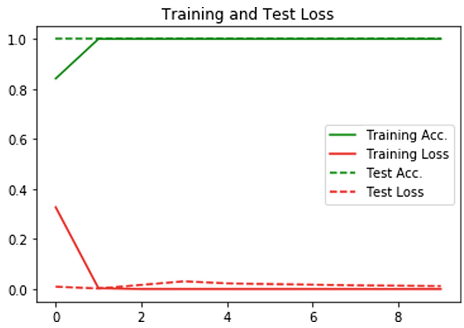

Fig. 5. Three-inputs CNN Model Accuracy (binary classification)

The results of a comparison of different binary classifiers applied on the dataset are shown in Fig. 6, the best accuracy is 99.7% by using the Random Forest method.

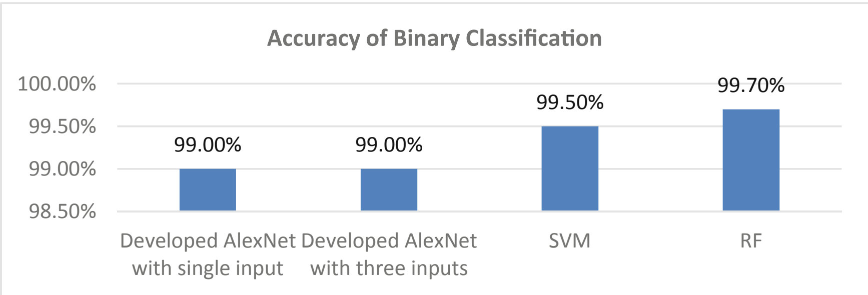

Fig. 6. Comparison of Binary Classification Accuracy

5.2 Species Identification (Categorical Classification)

The categorical classification problem is very important to build the digital library of plants. In this section we implemented the same deep learning models with changing in the output cost functions and number of classes to classify the plants into seventeen plant of the same families.

Third Experiment. In this experiment we applied the same model implemented in the first experiment with changing the number of classes in the output layer to 17 class (Number of plants in the two families), with change the objective function from sigmoid to the activation function calculation, that classify the 17 plant, Softmax function comes to solve categorical classification problem its responsible for the final prediction layer, and with using categorical entropy in loss calculation. We applied this experiment using two dataset size and modifying the developed AlexNet CNN hyperparameters using KERAS python package as shown in Table 2.

Table 2. Developed CNN hyper parameters.

Parameter	Value
Loss	Categorical cross entropy
Learning rate	0.0001
Activation function	Softmax
rho	0.9

The results from this experiment are the classification probabilities for 17 plants using categorical entropy in loss calculation. As shown in Fig. 7 the accuracy and loss for each training and testing of three datasets (LPDS, UPDS, and FPDS) with small dataset samples is very bad, the average of validation accuracy is 6% and the average of validation loss is 282%.

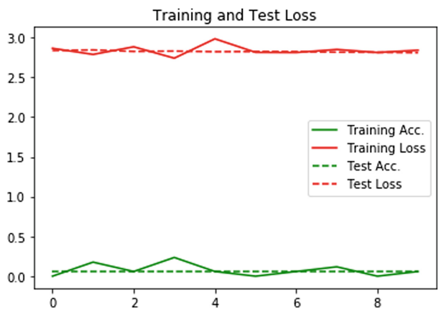

Fig. 7. CNN Plant Categorical Classification of 17 plants without augmentation.

Fourth Experiment (SVM). In this experiment, we were used the SVM method with the parameter's optimization. The best parameters are {'C': 10.0, 'gamma': 1e−08} with a score of 1.00 and using the SKLEARN package from python language. The results from this experiment we were used the SVM method with the parameter's optimization, the testing accuracy of 30% from the dataset is 96.7%.

Fifth Experiment (Random Forest). SKLEARN Python package was used to implement the RF (Random Forest) select the optimal parameters, and to evaluate the accuracy as shown in Table 3.

Random forest method applied to classify 17 plants, 1106 samples the results of important features are shown in Fig. 8, and the testing accuracy of 30% from the dataset is 93%, 96%, and 96% respectively for the fruit, lower, and upper.

Table 3. Random forest parameters

	Max depth	None
Random forest	Min. samples leaf	1
	Min. samples split	2
	Random state	None

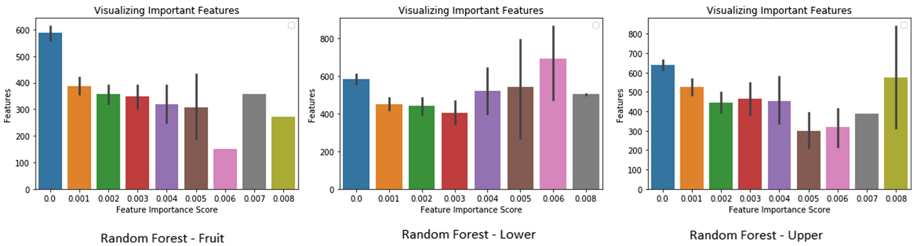

Fig. 8. Random Forest visualizing the important features of 17 plants.

The results of a comparison of different methods implemented on the dataset are shown in Fig. 9 the best accuracy is 98.2% by using the developed CNN model.

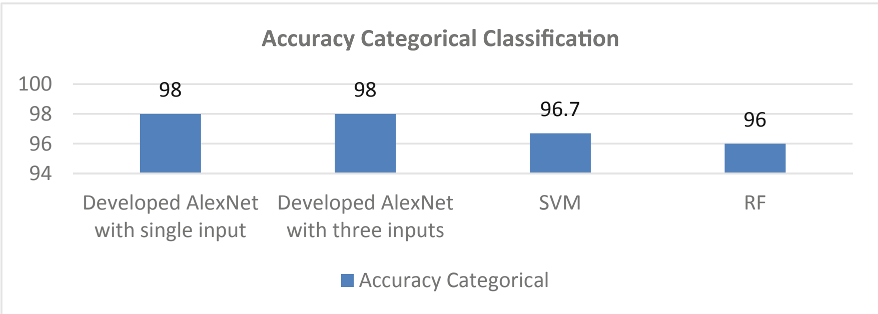

Fig. 9. Comparison of categorical classification accuracy

6 Conclusion and Recommendation for the Future Work

The purpose of the current study was to implement machine learning based tools to serve a plants taxonomy. The wild plants dataset collected from its natural locality in Egypt. The techniques that were compared in the family classifications (binary classification) were the developed convolution neural network (CNN), support vector machine (SVM), and the Random Forest. The highest level of accuracy obtained was 99.7% achieved with the random forest method RF with the two samples classification, while support vector machine (SVM), and CNN obtained 99.5%, and 99% accuracy, respectively. The challenges in the species classification (categorical classification) not in the families, and we obtained the excellent results in this area. The techniques that were compared in the categorical classifications were the developed convolution neural network (CNN), support vector machine (SVM), and the Random Forest. The highest level of accuracy obtained was 98.2% achieved with the developed CNN with the 17 plants samples classification, while support vector machine (SVM), and RF obtained 96.7%, and 96% accuracy, respectively.

In the future, we recommend increasing the samples and implement the digital library using website and mobile application to increase the wild plants samples and to facilitate the biological researchers in the plant taxonomy.

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