Automated Plant Identification with CNN

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Abstract - *In both botanical taxonomy and computer vision, plant image recognition has become a transdisciplinary priority. We use convolutional deep neural networks to identify the types of plants photographed in the image and to explore various factors that affect the performance of these networks. Determining plant species from field observations requires a large botanical specialist, which puts more than the reach of many nature lovers. Discovery of traditional plants is virtually impossible for the general public and is a challenge even for professionals who deal with daily crop problems such as conservationists, farmers, foresters, and architects. Even for botanists themselves, the species identification is often difficult task. This change enhances the accuracy of the model significantly. This model is tested in a leaf set of Flavia leaf sets. The results of the identification phase show that the proposed CNN model is still effective in leaf recognition with an optimal accuracy of more than 88.22%.*

Key Words*: *Deep learning, leaf classification, convolutional neural networks.

1. INTRODUCTION

Plants are vital to the preservation of natural resources. Plant species identification gives useful knowledge on plant classification and traits. Because it requires an individual's visual perception, manual interpretation is not precise. It is simple to sample and capture digital leaf photos, which include textural elements that aid in determining a certain pattern. The venation and form of a leaf are the most crucial features to distinguish across plant species. As information technology advances, tools such as image processing, pattern recognition, and others are used to identify plants based on the description of leaf shape and venation, which is a critical concept in the identification process. It is tough to keep track of changing leaf properties throughout time. As a result, a dataset must be created as a reference for a comparable study. Because of their appealing characteristics and year-round availability, leaves are included in most plant identification procedures. Automatic plant image recognition is the most promising option for closing the botanical taxonomic gap, and it has gotten a lot of interest from botany and the computing community. As machine learning technology progresses, more sophisticated models for automatic plant identification have been developed. Millions of plant photographs have been obtained thanks to the popularity of cellphones and the launch of PlantNet mobile apps. In real-world social-based ecological surveillance, invasive exotic plant monitor, ecological science popularization, and other applications, mobile-based automatic plant identification is critical. Improving the efficacy of mobile-based plant identification algorithms [2] has piqued the interest of researchers.

In computer vision, despite many attempts [3 - 8] (with computer vision algorithms), crop identification is still considered a challenging and unresolved issue. Leaf snap an automated plant identification system that identified using integral measure to compute functions of the curvature at the boundary, plants based on curvature-based shape aspects of the leaf. The plant recognition process is largely divided into the following steps shown in Figure 1.

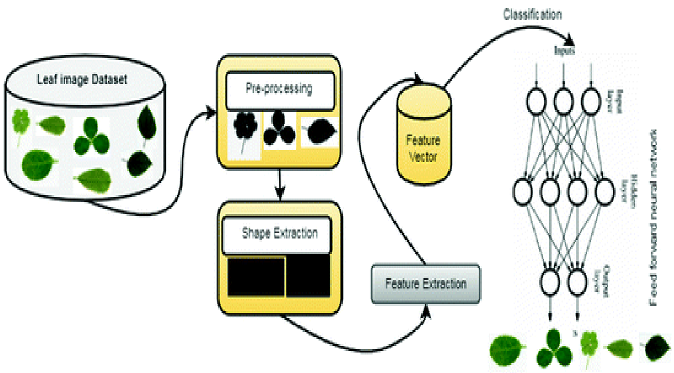

Fig -1 [1]: Steps of an Image-Based Plant Classification Process

Image Acquisition: The purpose of this step is to obtain an image of plant species to perform pre-processing and classification operations.

Pre-processing: The pre-processing process detects the image as inserted and produces a modified image as output, which is suitable for the action to remove the feature. Previous processing usually includes tasks such as sound removal, image enhancement, and separation. It improves the availability of plant species.

Feature Extraction: Feature removal is an important step in identifying plant species. Refers to extracting image information from the control groups. Feature releases can be divided into global and local features. Earth features mean representation of elements that define all image information, such as shape, texture, and color elements. Local features refer to the part of the image within a particular region.

Classification: In the separation step, all output elements are connected to the feature vector, which is then separated. Advanced methods use classification algorithms, such as k-Nearest Neighbor (k-NN), Decision Tree (DT), Vector Support Machine (SVM) and Artificial Neural Networks (ANN) .The efficiency of all methods. Much depends on the factors described earlier. Graphical engineering itself is a complex process that requires changes and recalculation of each problem or set of related data.

With the development of neural networks, neural network architecture has been used as an effective solution to extract high-quality features from data. Deep Convolutional Neural Network structures can accurately visualize structures that cannot be summarized while conserving modern features of raw data. This is useful for dividing or guessing. In more recent times, the Convolutional Neural Network (CNN) has emerged as a functional framework for defining features and identities in image processing. CNN can learn the basics automatically and integrate them systematically to define basic concepts to identify patterns. While using CNN one does not have to do differently the time-consuming engineering features. The customization of the method makes it a practical and useful method for the various problems of the application of isolation and recognition.

2. LITERATURE SURVEY

Recently, a few modern methods have used depth learning-based methods for identifying plant species. Deep learning-based approaches use in-depth learning algorithms such as convolutional neural networks (CNN) to extract features as well separate leaf pictures.

J Wei Tan, S.W. Chang, S. Abdul-Kareem, H. J. Yap, and K.T. Yong [9] proposed a CNN-based approach called DLeaf. Pictures of the leaf of the plant are pre-processed and extracted features using three CNN models namely pre-trained AlexNet, well configured AlexNet, and D-Leaf. Five machines Classes are used for classification as SVM, ANN, k-NN, NB and CNN. In the process of processing, the captured images are converted to the marked file format (TIFF) and sounds are removed using Adobe Photoshop. The image is redesigned into a square dimension and so on resized to 250x250 adjustment. Sobel edge detection method is used in the area of interest (ROI). Because all these images are converted from RGB to grayscale, background image classification was processed again skeletonized to find a pure vein architecture. After preliminary processing, feature removal was performed using CNN models as mentioned earlier and the feature is extracted using a common morphological method called vein features extracted from the image separated by measuring morphological vein features. Testing shows CNN's method is better than the usual morphological method. Proposed D-Leaf feature issuance with ANN as a classification gives a test of 94.88% accuracy.

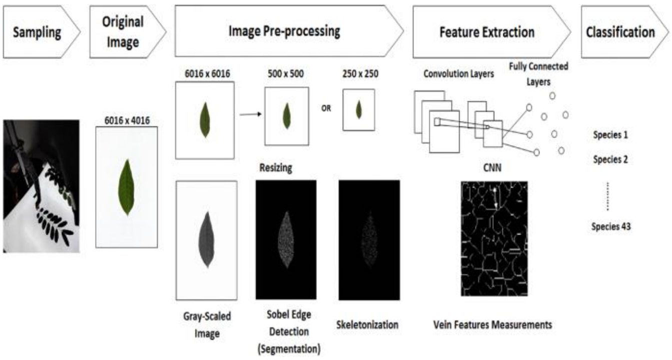

Fig -2: Deep Learning for Plant Species Classification

Truong Quoc Bao, Nguyen Thanh Tan Kiet, Truong Quoc Dinh and Huynh Xuan Hiep [10] proposed two solutions for classification leaf by using image processing combined with a shallow architecture and a deep architecture to classify the image leaf. We must find parameters by hand or by hand-designed feature extraction when recognizing shallow architecture. We use HOG features for recognition of the result in Table 3. With recognition, deep architecture combined with the effect of horizontal reflection and rotation augmentation of datasets further improves the results. Shallow architecture's accuracy is determined on the image's input size as well as the length of the feature vector. Deep architecture with the same input image excitation, has the feature vector is shorter and they are found by the model itself for greater accuracy. The results show that the proposed architecture for CNN-based leaf classification closely competes with the latest extensive approaches on devising leaf features and classifiers. Comparisons of the results were compiled in Wäldchen and Mäder [11] with the method of leaves recognition on the Swedish and Flavia data sets. From experiment results with Swedish and Flavia data sets, we can confirm that the CNN-based neural network depth model, which we propose, works very well on classification problems of leaves based on the shape of veins. This finding verifies the CNN depth geometry model's usefulness and simplicity for real-world issues with enormous data. Building the model and finding the right parameters is all that is required for the recognition procedure. The effectiveness of the classification process has improved, and recognition is no longer as reliant on discovering and recognizing visual features, which is a time-consuming and labor-intensive procedure.

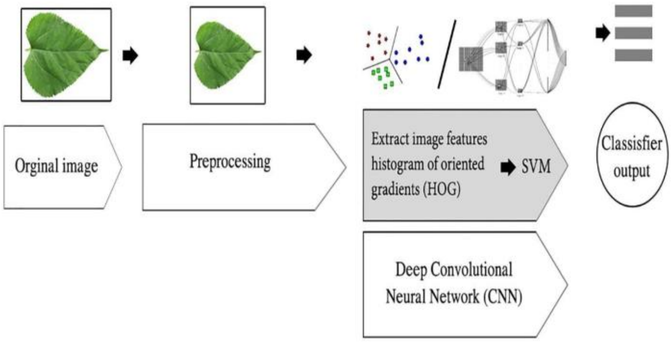

Fig -2: Scheme Implementation.

In this work, the grayed stages were compared with a deep convolutional network.

S. A. Riaz, S. Naz, and I. Razzak [12] introduced the plant diagnostic method using a multipath deep convolutional network. In the training phase, the images are pre-processed, extracted features from the pre-processed image and classified. In the testing phase, the images not used for training are processed and tested by feeding them into a neural network. The proposed architecture is displayed in Fig. 4 containing multiple CNN blocks, max pooling layers, flat and soft layer - maximum size separation of images of input plants. Each block contains three convolutions, one batch normalization, one max-pooling layer and a single thick layer. Features released in one block are combined with features from the second block. The soft-max layer separates plant species. This study uses the two data sets LeafSnap and MalayaKew and achieved 99.38% accuracy and 99.22% respectively.

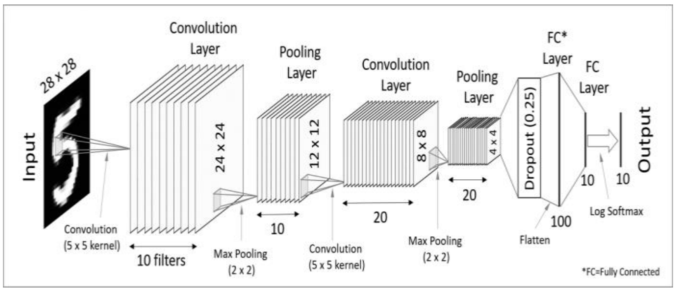

Fig -2: INFOPLANT: Plant Recognition Using Convolutional Neural Networks

3. PROPOSED METHOD

The prediction loss minimization method is commonly used to train deep neural networks.

Convolutional Neural Network

Convolutional neural network is an effective detection method, which has been developed recently. In past years, which garnered widespread attention. Now, CNN has become one of the most efficient methods in the field of pattern classification and, more recently, have been used more widely the field of image processing (Krzyzewski et al., 2012; Lecan [13], Bengio, & Hinton, 2015)[14], and It can reach better performance than traditional methods (Chatfield, Lempitsky, Vedaldi, and Zisserman, 2011). Through extensive verification. A CNN consists of one or more pairs of convolutional and maximum pooling layers. A convolutional layer applies a set of filters that process smaller Local parts of the input where these filters are repeated along the entire input space. Max pooling produces a low-resolution version of activating the convolutional layer activation of the top filter from different locations within the specified window. It adds translation changes and tolerances for minor differences in position of objects parts. Higher layers use more extensive filters that operate on lower resolution inputs Process the more complex parts of the input. The top fully connected layers are finally combined Input from all positions to classify the overall input. This hierarchical organization produces good results in image processing tasks.

Convolutional neural network structure

- Convolution layer: The convolution procedure extracts several information from the input. The first layer of convolution produces low-level features such as edges, lines, and corners.

- Nonlinear layers: A nonlinear "trigger" function is used by neural networks in general and CNNs in particular, to signify different identification of likely features on each hidden layer. CNNs may use a variety of specific functions such as rectified linear units (ReLUs) and continuous trigger (nonlinear) functions to efficiently implement this nonlinear triggering. ReLU uses the function y = max (x, 0), so the input and output size of this layer are the same. It increases the nonlinear properties of the decision function and of the overall network without electing the receptive fields of the convolution layer. In comparison to the other nonlinear functions used in CNNs (e.g., hyperbolic tangent, absolute or hyperbolic tangent, and sigmoid), the advantage of a ReLU is that the network trains many times faster. ReLU functionality is illustrated in Fig. 6.

- Factor adjustment reduces the mixing / sample layer. Strengthens the resistance of elements to noise and distortion.

Fully Connected Layers : These layers add up the weighted sum of the previous layer's characteristics, indicating the exact mix of "ingredients" needed to get a given intended output result. In the case of a fully connected layer, all the elements of all the features of the previous layer get used in the calculation of each element of each output feature.

Table -1: The Proposed CNN Architecture

Attribute	L1		L2		L3	L4	L5
Type	Conv	MaxPool	Conv	MaxPool	Conv	Conv	
Filter size	8 × 8	7 × 7	5 × 5	6 × 6	2 × 2	3 × 3	SoftMax
Stride	2	2	2	2	1	1	
No. of filter	100	100	250	250	100	100	
Output size	61 × 61	28 × 28	13 × 13	4 × 4	3 × 3	1 × 1	

Training is done using a set of 'labeled' input data in a wide variety of input patterns that represent tags with their intended output response. Training uses general purpose methods to repeatedly determine medium and final weights features of neurons. Figure 5 shows the training process at block level

The proposed CNN architecture

CNN formats vary in the type of images and especially when the size of the input images different. In this paper, the size of the input images is estimated to be 128 × 128 pixels. After each Conv layer, ReLU activation function is used and for each compilation layer, the MaxPooling method is used. Fully connected layers are defined as flexible layers with a 1 × 1 filter size as is common in MatConvnet (Vedaldi & Lenc, 2015) The last layer has n units corresponding to n. and a leaf set of data sets. After all the layers, the SoftMax losses are fixed. There are 5 layers including: [Conv - ReLu – Max pool] → [Conv - ReLu - Max pool] → [Conv - ReLu] → [Conv → FC] → Softmax.

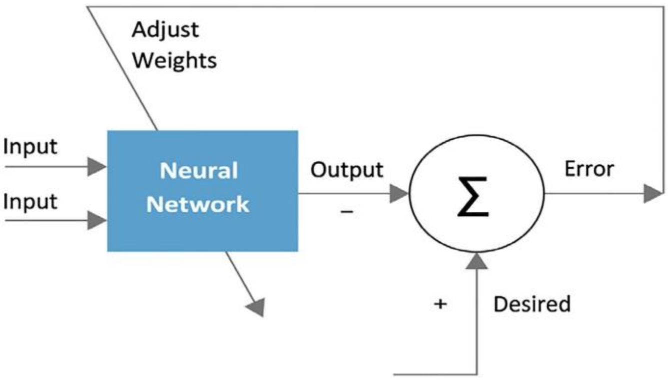

Fig -5 [15]: Training of Neural Networks.

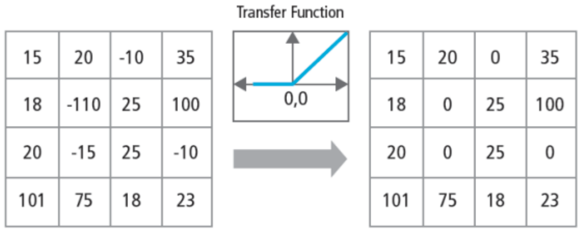

Fig -6: Pictorial Representation of Relu Functionality

The Final Layer has n units corresponding to n and category of leaf data sets. After all layers, a SoftMax layer is placed.

4. EXPERIMENTS AND RESULTS

Experiment data sets

In order to test the performance of the partition system, we have selected two standard sets:

- Swedish leaf data set: Swedish leaf data set taken as part of joining a leaf-splitting project between Linkoping University and the Swedish Museum Of Natural History (Soderkvist, 2001). The data set contains images of a single leaf and examines the empty base of 15 Swedish tree species, with 75 leaves per species (1125 photos in total). This data set is considered to be very challenging due to its height similarity of different species.

- Flavia Data Set: This data set contains 1907 leaf images of 32 different types and 50-77pictures of each type. Pictures of leaves found by scanners or digital cameras on an empty back. The individual leaf images contain only the blades, without petioles.

Augmentation data

Due to the limitations of most models due to insufficient data. Augmentation records is a powerful answer. Increase the number of training photos by creating three copies of each image after careful thought and rotation. So, each of the original images creates three image enhancements. The data divided for testing is shown in Table 2.

In this study, model input data is scanned or taken from tree leaves, and makes a training model. The screening process is as follows:

- Standardized image size: image resizes 128 × 128px to fit input network. To resize images to the desired size of 128 × 128 pixels, the first images are size so that their size is equal to 128, and then smaller combined with 0 pixels.

- . Image Partition: Each category is categorized as shown in Table 2 for testing objectives.

Initialization parameter: Reading level: set to 0.00007 (greater than the fastest combination network but not very good error rate, which is smaller than the network of slow connections).The above constants are selected primarily based on experimental effects for the proposed model with the aid of trial and error method. The amount of time it takes to train is determined by the computer's GPU or CPU resources.

Table -2: Partition Data

Data set	Number layers	Number Samples	Train		Val	Test
			60%	Augmentation data	20%	20%
Swedish	15	1125	900	3600	225	225
Flavia	32	1907	1145	4580	381	381
Flavia + Swedish	47	5825	2045	8180	606	606

Experiment results

The experiment results are aggregated into each test data set and detail in Table 2.

With the CNN model, data sets are divided into 80%, 20% and 20% as training, validation and sequential test sets, followed by extension training. Input data is 128 × 128, layer L4 (Table 1) is a vector of 1 × 100 aspect ratio with Softmax function.

Table -3: Experiment results of CNN model.

CNN Model		
Rate Train/Val/Test 60-20-20	Augmentation data	Accuracy test set CNN
Swedish (15 layers)	No	96.15
	Yes	98 . 22
Flavia (32 layers)	No	93.8
	Yes	95 . 5
Swedish + Flavia	No	94.17
	Yes	95.6

The experiment outcomes are summarized in Table 3 for each test data set.

5. CONCLUSION

Especially in this field, the effective use of in-depth learning in the agricultural sector reported, mainly to plant identification from the leaf. The main result is that we gained improved accuracy using a standard in-depth reading model. The proposed method will replace the first image channel and remove the leaf arterial data and augmentation to reduce overload by resizing and rotating images. It is often argued that neural networks do not provide any new perspective on a learning problem, as they fall into the category of black box models. However, due to the simple viewing method, it can be shown that images of patterns in the veins can be helpful in thought-provoking work.

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