

Observation on Therapeutic Plant Identification based on Deep Learning Technique



A. Pravin, C. Deepa

Abstract: *Plants have been used for medicinal purposes long before recorded history. It plays a major role in medicines, food, perfumes and cosmetics industries. By knowing the herbal plants and its usage it can be used for above applications. In this digital era, people don't have adequate knowledge to identify various herbal plants which are used by our ancestors for long time. Presently, the identification of herbal plants is purely based on the human perception or knowledge. There may be probability of human error occurring. In order to have an efficient herb species classification, there must be a complete model which should be automatic and convenient recognition system. This paper is reviewing the different leaf classification methodologies based on deep learning algorithms. The main aim of this research paper is to conclude the advanced technique for the leaf identification.*

Keywords : *Leaf identification, machine learning, deep learning algorithm, herbal plants, Plant recognition system.*

I. INTRODUCTION

Medicinal plants are a vital source for recent chemical compounds with possible remedial effects. The plant parts include leaf, stem bark, flower, fruit, root and rhizomes are used as a single drug or ingredient of formulation of Indian traditional medicines like Ayurveda, Siddha etc., since ages. Numerous plants synthesize substances are helpful for the human and animal health.

In present scenario, the World Health Organization (WHO) encourages the developed countries to use herbal medicines. Since, it would be increasingly recognized that there are fewer or even no side effects of natural products. Now, the use of herbs has significantly risen in Western nations, including locations like India and China. At least 2,000 species of MAP (Medicinal and Aromatic Plants) are traded commercially in Europe, of these 1,200 to 1,300 are being native to Europe (Open Course Ware). So, the computer-based plant identification or classification method can use distinct floral features beginning at a very easy stage such as: shape and color of the leaf, flower and fruit type, branching style, root type, seasonality, perspective, to very complex structure such as cell and tissue, genetic structure. At present there are many high quality camera devices and smart phones are capable of pictures, making the system even

more usable. Most leaves of the plant are of two dimensions in nature and have significant characteristics that can be helpful in classifying different plant species. For classification purposes, there are collections of suitable numerical attributes of characteristics to be removed from the object of concern. Research over the past few years into the use of moments for in- and non-invariant object characterization assignments has acquired significant attention [8], [9]. For many years, the mathematical notion of moments has been around and it is used in a lot of different areas from mechanics and statistics to recognition of patterns and comprehension of pictures. So, examining and recognizing the large number of plant species is not practical for a normal person and, moreover, it is highly cost-effective. The method is therefore necessary to overcome mistakes created by identification schemes of standard plant species based exclusively on human knowledge. Requirement of better plant species recognition system is in great demand and several researches have been made by some authors which are discussed in the next section. The Section I is an introductory part of this review paper where the importance of leaf identification is stated. The section II is continued with the general procedure for the leaf classification process. The Section III elaborates the various research work carried over for the leaf classification. The section IV is providing the review of various deep learning processes. The section V provides the results obtained from the various leaf detection processes. The conclusions as well as directions are given in the section VI.

II. STEPS INVOLVED IN CLASSIFICATION PROCESS

The method of classification is performed by the various sub processes [11]. Initially, a database of leaf images is built consisting of leaf sample images with their respective information of the plant. There is a shortage conventional leaf picture dataset which can be used to classify plants and therefore the scientists usually build the database. The first stage in the classification of plant leaves is the acquisition of images, which involves to pluck a leaf and capture the digital picture of a leaf with a digital camera [6], [7]. Leaf's image is preprocessed in the second step to improve the key characteristics. The step consists of gray conversion, segmentation of images, binary conversion and smoothing of images. The objective of preprocessing images is to enhance image information so it is possible to remove undesirable distortions and enhance the picture characteristics appropriate for further processing [6], [7].

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*Correspondence Author(s)

A. Pravin*, Research Scholar in Computer Science, Sri Ramakrishna College of Arts and Science (Formerly SNR Sons College), Coimbatore, India. Email: pravinsaga@gmail.com

Dr. C. Deepa, Associate Professor in Information Technology, Sri Ramakrishna College of Arts and Science (Formerly SNR Sons College), Coimbatore, India. Email: deepa_pkd@rediffmail.com

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Color picture image of the leaf is transformed into gray image due to variety of atmospheric and seasonal modifications causes' low reliability of the color element. Therefore, working with grayscale image is better. Once the picture is transformed to a gray scale, it is divided from the background and transformed to binary and smoothes the grayscale image. The significant characteristics are obtained in the next step and are compared with the dataset image. The picture image of input is classified by the plant whose picture of the leaf has the highest matching score by a classifier that provides the input leaf data. The general classification process is shown in the figure 1. Each plant leaf classification method follows the similar method as outlined in this chapter, but differs only in the classification phase. Several classification methods that are selected based on the morphological characteristics obtained are invented. In many applications, shape, color and texture are popular characteristics. Some researchers, however, only consider some of these characteristics. But for many researchers, Vein and contour characteristics are also an interesting area of studies.

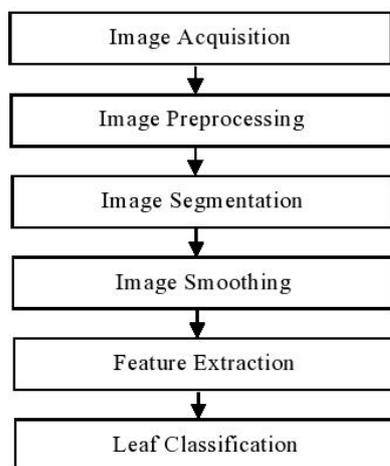


Figure 1: Leaf Classification process

Researchers used different classification methods to classify the leaves of crops for higher accuracy, taking into account several morphological characteristics. Most scientists currently target the texture of plant leaves as the most significant element in plant classification.

III. RELATED WORK

Y.G Naresh et al. [1] proposed medicinal plant classification: A symbolically represented method using modified LBP. The symbolic method for plant leaves classification is based on texture characteristics using Modified Local Binary Patterns (MLBP) to obtain texture characteristics from medicinal plant species. Ji-Xiang Du et al. [2] proposed recognition of a leaf picture set based on a multiple range that creates issues by classifying the picture set of the leaf when each set includes pictures of the same class. A set of local linear models used the clustering procedure to convey a manifold. Then the distance is calculated between local designs that come from the various multipliers that have been built. The final issue is transmitted in order to incorporate the distance between subspace sets. Vijayalakshmi et al. [3] proposed PSO and FRVM based kernel: detection of automatic leaf type by texture, shape and

color characteristics. Texture, shape and color characteristics are classified. For feature extraction, the GLCM and LBP systems are introduced. At last, the Vector Machine Fuzzy Relevance is used to characterize the sort of leaves. Compared with other work, the experimental study showed better outcomes such as 99.87 percent accuracy, sensitivity and specificity. Mohammad Ali Jan Ghasab et al. [4] proposed optimization of decision-making ant colony for automated recognition of plant species. Automatic recognition of various species is done by using the ant colony optimization (ACO) as a feature decision making algorithm through their leaf images. The pictures of the leaf extract a number of features such as form, morphology, texture and color to create a search space for a feature. Support Vector Machine (SVM) uses the chosen characteristics to classify the species. Aimen Aakif et al. [5] proposed automatic leaf-based classification of crops. In three separate stages, a plant is identified (i) pre-processing (ii) extraction of feature (iii) classification. These characteristics become the artificial neural network (ANN) input vector. The algorithm consists of 817 specimens of leaves from 14 separate fruit trees and provides more than 96% accuracy. Jyotisma Chaki et al. [12] proposed recognition of plant leaves using neural classifier texture and shape characteristics. A new approach for characterizing and acknowledging plants leaves texture and shape combinations. Leaf texture is designed by Gabor filter and gray level co-occurrence matrix (GLCM) and leaf shape is recorded with a pair of curvelet transform coefficients and invariant moment. Because these characteristics are generally susceptible to the alignment and scaling of the leaf picture, the preprocessing phase before extraction of the feature is implemented to correct various translation, rotation and scaling variables. There are two classifiers such as feed forward back propagation multi-layered perceptron (MLP) and neuro-fuzzy controller (NFC) were implemented to study the efficiency of the proposed methods and applied for 31 classes of leaves.

G. Larese et al. [13] proposed automatic legumes classification with images of the vein of the leaf. A process for segmentation and classification of real-time images are based solely on their vein analysis. Three legume species are considered for this work and automation aimed at recognizing legume species. Unconstrained hit or miss transform and adaptive thresholding are used to perform segmentation. Several morphological characteristics are calculated using Support Vector Machines (SVM) on the segmented venation and classifier.

IV. REVIEW OF VARIOUS DEEP LEARNING APPROACHES

A. Matrix-Based Convolutional Neural Network (M-bCNN)

There is a demand of an efficient algorithm to discriminate correctly between one category and the other. Therefore, the algorithm's representational capacity requires to be reinforced in order to learn about robust domain-specific discrimination effectively.

A combined convolution neural network (CNN) representing the matrix-based convolutionary neural network (M-bCNN) to tackle this challenge was proposed by Zhongqi Lin *et al.*, [14]. Its characteristic is the convolutionary kernel matrix, for those convolutionary layers are organised in parallel matrix method and embedded with Drop Connect, Exponential Linear Unit (ELU), Local Response Normalization (LRN), etc. The M-bCNN for good grained image classification the illness of the wheat leaves is suggested in an effort to take advantage the achievement of CNN for classification of objects. The purpose of the convolutional kernel matrix is to improve the representational capacity of the model in order to study a domain-specific discrimination to handle with good grained classification. The model is shown in Figure 2 as MbCNN-CKM-3 for its kernel matrix of 3X3. As can be seen from figure 2, M-bCNN-CKM-3 primarily includes four layers of convolution (Conv₁, Conv₂, Conv₃, Conv₄), three Max Pooling layers (S₂, S₄, S₇), three 3X3 convolutional kernel matrixes (CKM-3₅, CKM-3₆, CKM-3₇), and three fully-connected layers (F₈, F₉, F₁₀). Specifically, CKM-3₅, CKM-3₆, and CKM-3₇ are responsible for enhancing model depth and ability to represent. Each has nine convolution layers of 3X3 (Conv(1,1), Conv(2,1), Conv(3,1) ; Conv(1,2), Conv(2,2), Conv(3,2) ; Conv(1,3), Conv(2,3), Conv(3,3)) and each layer contains 96 3X3 convolution kernels.

B. Dual Path Convolutional Neural Network (DP-CNN)

In [15], Meet P. Shah *et al.*, proposed a dual-path profound convolution neural network (CNN) to (i) study joint characteristic representations for leaf pictures, exploit their shape and texture features, and (ii) enhance the features for the classification assignment. The proposed architecture of the CNN consists of two paths, first for studying shape-dependent features and next for studying texture features. These routes later join together in a multilayer perceptron to combine supplementary shape and texture data for ideal leaf image classification. Two distinct pictures regenerated for a leaf picture input, i.e. the leaf picture and the texture patch, which are input to the CNN model's two routes. The initial picture of the leaf is first matched with a common coordinate frame by recording the picture of a template leaf under a similarity transformation. Then the image of the leaf is merely the whole picture of the leaf resized to 144,192 pixels, which mainly captures data of the form. The input of texture-patch is obtained by 2x extension of the given leaf image, sharpening and next cropping of the main area of the leaf to obtain a 144x192 pixel size patch ; this primarily captures details of the texture and venation of the leaf. The CNN extraction function element consists of convolutionary and max-pooling layers. A batch normalization (BN) layer follows each convolution layer. The activation used in all layers is the rectified linear unit (ReLU), with the exception of the final layer. From both pathways, the concatenate characteristics learned to create the leaf's joint shape-texture representation. This joint depiction contributes to the classification of a multilayer perceptron.

C. Fine-tuned AlexNet model

Jing Wei Ta *et al.*, [16] suggested a novel CNN-based technique called D-Leaf in this study. The preprocessed leaf

pictures and the characteristics are extracted from three distinct models of the Convolutional Neural Network (CNN), which are pretrained AlexNet, AlexNet and D-Leaf. These characteristics are then categorized by five methods of machine learning which are Support Vector Machine (SVM), Artificial Neural Network (ANN), NaïveBayes (NB) and CNN. For benchmarking purposes, a standard morphometric technique calculated the morphological readings from segmented veins by using Sobel method. This study consisted of four primary steps: sampling, pre-processing of images, extraction of features and classification. Foremost, they gathered the leaf samples and obtained pictures. Based on the CNN and Sobel edge detection strategy, the leaf pictures are preprocessed and given into the feature extraction phase to obtain significant data from the leaves. Finally, the extracted characteristics were trained and categorized using different techniques of machine learning.

V. SIMULATION RESULTS OF DEEP LEARNING APPROACHES

A. Results of M-bCNN

In [14], the main advantage of proposed at a small rise in computational demands compared to simple networks, M-bCNN is important gains in information streams, neurons, and connection channels. The tests showed that the successful performance of the M-bCNN model is in competition with the current good grained image classification of wheat leaf illnesses. The scheme offers strong proof that convolutionary kernel matrix is generally a viable and helpful concept, providing a fresh route for identifying crop diseases. In this research, images of winter illnesses of wheat leaf were used as technical specimens of good grains for their powerful resemblance to subordinate varieties in different instances. Currently, there is no publicly accessible large-scale picture collection of wheat leaf illnesses. Thus 16,652 excellent fidelity pictures from number of plantation of wheat fields in the province of Shandong were gathered and allocated as the original dataset image. Then an obtained dataset with 83,260 pictures was built using five extension techniques. The original and expanded sets of images were used as samples for training and experimentation. This is the foremost large-scale high-resolution picture sets of winter wheat leaf illnesses accessible to the best of our understanding. 70% of the pictures in every category are randomly chosen as samples for training before the training starts and the persisting 30% are used as validation specimens. Because the enhanced data set is already balanced, the inter-class equilibrium can be ensured by this sampling method. The writers used confusion matrix, also called as error matrix in supervised learning method, which shows obviously the real and predicted classes in each column and row. In addition, the accuracy, recall, and F1 scores across various classes are used to directly assess the classifier model's performance. The scheme generated 91% as the greatest level of precision in the detection of leaves.

B. Results of Dual path CNN

The results presented in [15] show that the dual-path designed structure, allowing every track specializing in one of the supplementary shape and texture characteristics, is suitable than the unipath strategy. In addition, the texture-patch depend on CNN that disregards shape data is the least among CNN methods and even unpleasant than our handmade miscellaneous shape context, highlighting the usefulness of shape characteristics in the classification of leaves. The findings demonstrate the advantages of robust function learning with CNNs, e.g. dual-path and unipath-CNN, overall handmade characteristics.

C. Results of Fine-Tuned AlexNet Model

The information was divided into training and test set with a ratio of 80:20 for performance evaluation. Every model was performed once and for 10 times over feature extraction to achieve optimum efficiency. A pretrained model –AlexNet was used to extract features from the layer FC7 followed by four classifiers. For the extraction of features, a finely tuned AlexNet has been introduced and the characteristics extracted for trained and tested with five classifiers. CNN models had good performance than conventional morphometric computations (66.55%). The characteristics obtained from the CNN are well equipped with the ANN classifier.

The comparisons of accuracy in the stated three CNN methodologies are listed in the following table 1. The accuracy is very high in the DP-CNN [15] and the table also depicts about the importance and reliability of convolutional neural network because all the CNN algorithms are producing above 90% as accuracy.

Table- I: Comparison of Accuracy

	M-bCNN [14]	Dual path CNN [15]	Fine-tuned AlexNet Model [16]
Accuracy (%)	91%	95.67%	93.31%

^a. Sample of a Table footnote. (Table footnote)

VI. CONCLUSION

With the introduction of Computer Vision (CV), Machine Learning (ML) and Artificial Intelligence (AI) methods, progress has been made in the development of robust models to empower, accurately and promptly identify plant leaves disease. It has been acknowledged over the past few years that Deep Learning (DL) has been used primarily in agriculture. The greatest advantage of convolutional neural networks is they can learn appropriate features by themselves automatically. This paper is reviewed three different convolutional neural network algorithms M-bCNN[14], Dual path CNN[15] and Fine-tuned AlexNet model[16] for the medicinal leaf identification. After studying the results of these three algorithms, it is observed that the DP-CNN [15] was producing the highest accuracy of 95.67%. Moreover, it is important to note that, the accuracy of these convolutional algorithms are producing more than 90% accuracy in classification. This high accuracy is due to the precise features extraction in those convolutional algorithms.

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AUTHORS PROFILE



A. Pravin was born in Nagercoil, Kanyakumari of Tamil Nadu is a graduate from Bishop Ambrose College, Coimbatore in the year (2010). He completed his post graduation degree in Master of Science in Information Technology and Master of Philosophy in Computer Science from Sri Ramakrishna College of Arts and Science (Formerly SNR Sons College), Coimbatore. He started his professional career in 2012 as a Assistant Professor in Bishop Ambrose College, Coimbatore. Then in 2015 he worked as a teacher in Computer Science at Belfield Matric Hr Sec School, Nagercoil. He joined Ruben College of Arts and Science, Thadikkaranonam as Head of the Department of Computer Science in 2017. His areas of interest are Networking, Data Mining and Web Technology.





Dr. C. Deepa was born in Elappully, Palakkad, India is a graduate in Bachelor of Science in Physics from University o Calicut, Kerala and has completed her post graduation degree in Master of Computer Application and Master of philosophy in Computer Science and Ph.D in Computer Science from Bharathiar University, Coimbatore, Tamilnadu, India. Dr.C.Deepa, is now an Associate Professor in Information Technology, Sri Ramakrishna College of Arts and Science, (Formerly SNR Sons college) Coimbatore, Tamilnadu, India She has got 16+ years of experience in teaching and research and is a research supervisor for both M.Phil and Ph.D. She had authored a book and his published paper in many International Journals. She is a member for Board of Studies and reviewer for International Journals. Formerly she was the Head of the Department for Computer Science and Application at Nehru College of Arts and Science, Tamilnadu, India where she has organized and headed many activities for the Department and college. Dr. C.Deepa was an invited speaker for WGC-2018 held at Singapore and is a recipient of Best Women Researcher Award from IOSRD, Best Research Paper Award from SNR Sons College, Best Paper Presentation awarded in ICACCS-2013.