PLANT LEAF RECOGNITION USING CONVOLUTIONAL NEURAL NETWORKS

Shahid Hussain Wani[1], Er. Shaminder Singh[2]

[1]*M. Tech Student, Department of Computer Science and engineering, Desh Bhagat University, Mandi Gobindgarh, Punjab India.*

[2]*Assistant Professor, Department of Computer Science and Engineering, Desh Bhagat University, Mandi Gobindgarh, Punjab India.*

Email- wanishahid999@gmail.com

Abstract—This research paper presents the Plant Leaf Recognition Using Convolutional Neural Networks. Leaves are very important or significant part of the plant which actually identifies and classify the plants. Classification of the plant by their leaf biometric features is commonly performed task of trained botanist and taxonomist. To perform this task, they need to perform various set of operations. Because of this the task of classification of plants manually is time consuming. There are many biometric features of leaves of the plants for classification. Here the various features of leaves of the plant species are extracted for plant classification. A classifier named as a Convolutional Neural Network (CNN) is trained to identify the exact leaf class. It is done to achieve high effectiveness with less computational intricacy.

Keywords— Plant leaf recognition, Convolutional Neural network (CNN), image acquisition, image pre-processing, Feature extraction, leaf classification.

I. INTRODUCTION

Plants are the important resources of nature on earth which offers tremendous benefits to human life. Computer helped plant recognition is still very exceptional task in computer vision due to the presence of various recognition models and approaches. There is vast number of plant species all round the world. It was estimated in 2004 that there are about 250,000–270,000 plants species that have been named and classified in the world [6]. After that in 2013 Caner [5] pointed out that about 310 000-420 000 plant species are identified and many more still unknown. Most of the plant species are at the risk of extinction [7, 8]. So, it is vital to classify plant species which have wide applications in medical, botany, food sector and agriculture [5, 9]. A computerized plant identification system can be utilized for quick characterization of plant species without requiring the mastery of botanists [1]. Botanists and researchers require an automatic computer aided tool for identifying species of plants so that their task become easy instead of searching plant encyclopaedia. Moreover, automatic computerized plant classification systems are based on 2-D images which become appropriate for 3-D complex structured plant flowers, seedlings and morph of plants [2]. One of the approaching research territories is the essential for the development of automatic plant recognition system such as Computer Aided Plant Leaf Recognition (CAP-LR) [3, 4]. Such systems give results within few seconds by recognizing correct type of leaf species.

Artificial Intelligence has seeing a stupendous development in conquering the hindrance between the capacities of people and machines. Analysts and aficionados alike, work on various parts of the field to cause stunning things to occur or happen. One of numerous such regions is the zone of Computer Apparition.

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an information picture, allocate significance (learnable loads and inclinations) to different angles/ objects in the picture and have tendency to differentiate or separate one from the other. The pre-processing required in a ConvNet is much lower when appeared differently in relation to other calculations or algorithms. While in primitive strategies filters are hand- built, with enough preparing, ConvNets have the ability to gain proficiency with these filters/attributes.

II. REVIEW LITERATURE

Literature review is a systematic survey concentrated on a research work, attempting to recognize, evaluate, select and synthesize all high-quality research proofs and contentions related to that work. The literature is conducted regarding classification plant leaves.

In 2005 X. Wang et al. [10] presents the strategy for plant leaf recognition dependent on shape highlights utilizing Hyper Sphere classifier. Eight sort of shape highlights are determined like rectangularity, eccentricity, circularity and so on and seven moment invariants are taken to train the system. This proposed system classifies more than 20 classes of plant leaves and gives accuracy rate up to 92.2 %. Then Stephen Gang Wu et al. [11] in 2007 employs probabilistic neural network for classification and image processing techniques for doing pre-processing of leaves. 12 features were extracted which are orthogonal into 5 principal variables which constitutes the input vector of the PNN classifier. As compare to other approaches, this system proved to be efficient and easy in implementation with 90.312% accuracy. But the only work is done on the geometrical and morphological features. Accuracy rate can be increased by taking more features of plant leaves. Moreover, PNN classifier takes long training time. Further a new feature that is texture is included by Lei Zhang et al. [12] along with geometrical features which were absent in the previous work. Self-Organizing Feature Map (SOM) neural network performs well in case of complex problems such as multi-class pattern recognition, high dimension input vector and large quantity training data. But SOM classifier is able to identify some specific plant species. Plant leaves with complex background and illumination are not properly recognized by this classifier.

Jiazhi Pan and Yong He [13] describes that with the combined approach of image processing operations and neural networks which is widely used to distinguish weeds from plant leaves. Radial basis function neural network is fast, effective and obtained total accuracy of 80%. But still problem adopted was simple in nature, which can be possible with other algorithms also. However, it fails in multifaceted weather and lighting situations. He suggested designing hybrid approach of image processing with neural networks. After that A. Kadir et al. work on foliage plants and uses additional color feature which were absent in previous researches. Probabilistic neural network (PNN) classifier gives average accuracy of 93.0833% for 60 kinds of foliage plants. He concluded that kurtosis parameter consideration gives better performance for Flavia data than Foliage data. So decision to take kurtosis parameter is difficult task and more work is needed to improve the accuracy. Jyotismita Chaki and Ranjan Parekh [14] proposed a hybrid feature vector of Moment Invariant (M-I) and Centroid Radii model is fed into neural network classifiers. Good accuracy range is obtained as compare to literature survey reported. Accuracy can be improved by taking more shape, color-based techniques and hybridization of them.

A review report had been given by James S. Cope et al. [15] on various morphometrics, leaf features and image processing techniques. He discussed real time systems in agriculture which actually makes use of plant identification systems. He said that no single strategy is appropriate for classification. He suggested solutions to overcome challenges and to improve accuracy in plant species classification by taking small number of species samples. Next, Abdul Kadir et al. [16] had given improved performance of leaf identification system as compare to previous system. The system uses more shape, color and texture features as compare to taken by Stephen Gang Wu [19]. Due to which high accuracy rate is achieved by PNN classifier i.e from 92.2% to 95.7500%. However, it is difficult to understand structure of PNN and takes long training time. Some other alternatives can be thought of to obtain high accuracy.

Another work was carried out by Hang et al. [22] by taking plant leaf shape and texture features as major concern. SVM classifier performed well as compare to the previous methods for classification of plant species but occurrence of redundancies and its complex nature affect its performance.

Mohamad Faizal Ab Jabal et al. [17] surveyed the literature on plant classification techniques and suggested three classifiers i.e PNN, LDA and GRNN. He had given recommendations for taking into account more external factors and real-life samples for leaf recognition. Testing of selected classifiers would be done on large data set. Shayan Hati and Sajeevan [18] described various image processing techniques which are used to extract leaf features such as aspect ratio, width ratio, apex angle, base angle, moment ratio and circularity. Under his research 534 leaves of 20 kinds were taken. Out of which 400 leaves were trained and 134 testing samples were recognized with 92% accuracy. An integrated approach of distributed hierarchical graph neuron (DHGN) and K-nearest neighbor (KNN) classifier for plant pattern recognition is introduced by Anang and Asad [21]. DHGN ensures low complexity and minimum processing time. But KNN known as lazy classifier was used for final classification of pattern. Any other classifier would be chosen for better recall accuracy.

III. CNN ARCHITECTURE

Convolutional Neural Networks (CNN) is one of the deviations of neural network systems utilized vigorously in the field of Computer Vision. It originates its name from the sort of hidden layers it comprises of. The hidden or concealed layers of a CNN regularly comprise of convolutional layers, pooling layers, fully connected layers, and normalization layers. Here it essentially implies that as opposed to utilizing the ordinary activation capacities, convolution and pooling capacities are utilized as activation capacities.

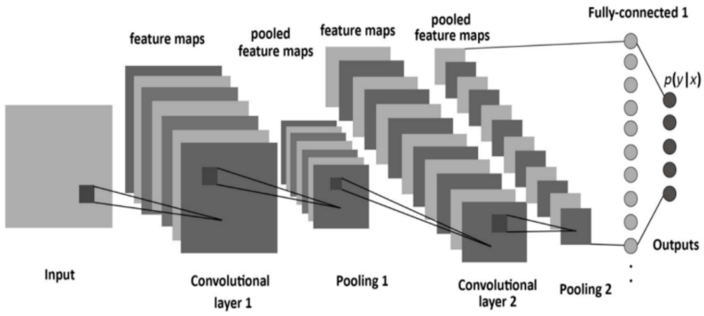

Fig. CNN Architecture

CNN receives the image as a matrix of pixel values. A sequence of convolution, maxpooling and normalization is done in several layers of CNN and is finally regularized.

A. CONVOLUTION: it takes in an information signal and applies a channel over it, basically multiplies the information signal with the kernel to get the changed or modified signal.

Scientifically, a convolution of two capacities f and g is characterized as

$$(f * g)(i) = \sum_{j=1}^{m} g(j) \cdot f(i - j + m/2)$$

In case of Image processing, it is simpler to envision a kernel as sliding over a whole picture and along these lines changing the estimation of every pixel all the while.

B. POOLING: Pooling lessens the spatial measurements (Width x Height) of the Input Volume for the following Convolutional Layer. It doesn't influence the profundity measurement of the Volume. The change is either performed by taking the most extreme incentive from the qualities perceptible in the window (called 'max pooling'), or by taking the average of the qualities or values. Max pooling has been supported over others because of its better execution qualities.

C. NORMALIZATION: Normalization turns all the negative values to 0 so that a matrix has no negative values. A stack of images becomes a stack of images with no negative values.

D. REGULARIZATION: Regularization is an indispensable feature in pretty much every cutting-edge neural system execution. To perform dropout on a layer, you haphazardly set a slice of the layer's qualities to 0 during forward spread. Dropout powers a counterfeit neural system to gain proficiency with various autonomous portrayals of similar information by on the other hand arbitrarily debilitating neurons in the learning stage.

There are a few pre prepared Convolutional Neural Networks that has gain popularity and ResNet-50 is one of them. Here in this theory work we use pre prepared Convolutional Neural Network ResNet-50 for characterization of plant leaves. ResNet-50 has been prepared or trained in image net dataset. image net dataset has one thousand item classifications and 1.2 million preparing or training pictures. The system is 50 layers profound (deep) and can arrange pictures into 1000 article classifications, for example, keyboard, mouse, pencil, and numerous creatures. Thus, the network has learned rich component portrayals for a wide scope of pictures. The system has a picture info size of 224-by-224. ResNet is short name for residual network (as the name of the system shows, the new phrasing that this system presents are residual or lingering learning).

IV. METHODS AND MATERIALS

Our system, Plant Leaf Recognition Using Convolutional Neural Networks undergoes series of steps to recognize the plant accurately from the image of the leaf captured. First, the image is acquired, then it is pre-processed to remove noise and extract features more clearly. At last we use Convolutional Neural Network (CNN) for image classification and the predicted result is displayed along with the name of the plant class.

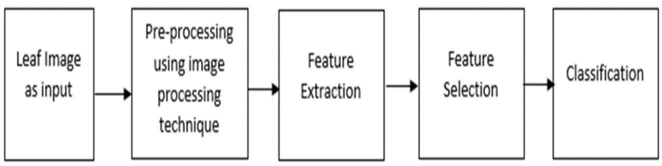

Fig 1.1 Classification System

A. DATA COLLECTION: Linkoping University has been working on leaf recognition and has therefore created a dataset consisting of 15 leaf categories and more than 1125 images. The leaves mainly come from Sweden. Downloads or more information can be found. This database is very attractive since at least 75 images of the same category are present, which is essential for a good recognition at a large scale.

B. IMAGE ACQUISITION: The first step of the system is image acquisition. The image of a leaf of the plant to be recognized is captured and fed to the system. Since our system is currently a desktop app, we have to locate the image via the user interface. The raw image is processed before it is sent to CNN.

C. IMAGE PRE-PROCESSING: Pre-processing is used to get the outer shape of the image from the colored image of the leaf and to remove any kind of external noises present in an image. The main idea of pre-processing is to enhance the image niceties so that features are clearly found for further processing.

The steps involved are described below.

a. Converting to gray scale: The colored image was converted to gray scale image. For various applications of image processing, gray scale image is sufficient for us to identify significant edges or other features so the image was converted to gray scale.

b. Sharpening the Image

The gray scale image was sharpen to enhance image features like edges, boundaries, or contrast to make the image extra supportive for display and analysis.

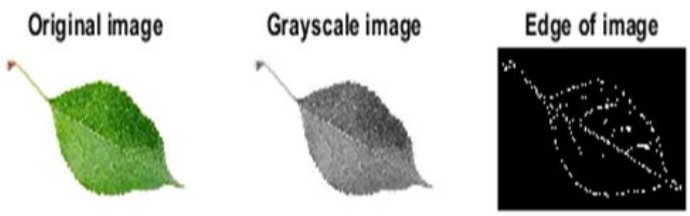

Fig 2: Image Pre-processing

D. IMAGE SEGMENTATION

Image segmentation is a usually utilized strategy in digital picture processing and investigation to partition an image into numerous parts or locales, regularly dependent on the attributes of the pixels in the picture. Image segmentation could include isolating foreground from background, or grouping areas of pixels dependent on similitudes in color or shape. For instance, a typical utilization of Image segmentation in medicinal imaging is to identify and mark pixels in a picture or voxels of a 3D volume that represent a tumor in a patient's brain or in any different organs.

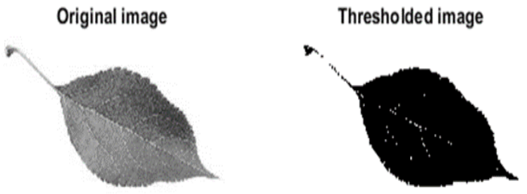

Fig 3: Gray Level thresholding

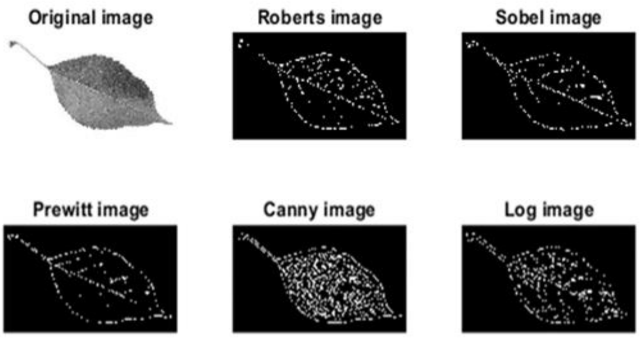

Fig 4: Edge Detection

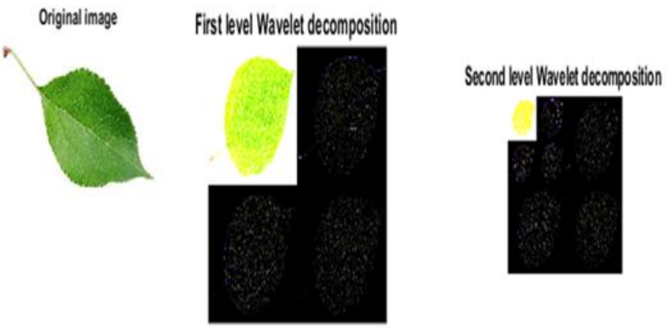

Fig 4: Discrete Wavelet Transformation

E. IMAGE CLASSIFICATION

We utilized CNN for image classification. CNNs are biologically motivated models enlivened by research by D. H. Hubel and T. N. Wiesel. They proposed a clarification for the manner by which mammals outwardly see their general surroundings utilizing a layered design of neurons in the cerebrum, and these thus motivated specialists to endeavour to create comparable pattern recognition instruments in PC vision.

A Convolutional Neural Network (CNN) is an amazing AI strategy from the field of deep learning. ResNet-50 pretrained CNN has been utilized in this proposal work. CNNs are prepared utilizing huge accumulations of different pictures. From these huge accumulations, CNNs can learn rich feature portrayals or representations for a wide scope of pictures. These component portrayals regularly outflank hand-crafted highlights, for example, HOG, LBP, or SURF. A simple method to use the intensity of CNNs, without putting time and exertion into preparing or training, is to utilize a pretrained CNN as a feature or component extractor.

In this thesis work, pictures from a Swedish Leaf Dataset are arranged into categories utilizing a multiclass linear SVM trained or prepared with CNN highlights extracted from the pictures. This way to deal with picture category classification pursues the standard routine with regards to training or preparing classifier utilizing highlights extracted from pictures. For instance, the Image Category Classification Using Bag of Features precedent uses SURF includes within the pack of highlights structure to train or prepare a multiclass SVM. The distinction here is that as opposed to utilizing picture highlights, for example, HOG or SURF, highlights are extracted utilizing a CNN.

F. FEATURE EXTRACTION

After pre-processing, in pattern recognition, the important and essential task is to measure the properties of an object because objects have to be detected based on these computed properties. In the feature extraction step, the task is to describe the regions based on chosen representation, e.g. a region may be represented by its boundary and its boundary is described by its properties (features) such as color, texture, etc. The various features are:

Area: Area represents number of pixels in the leaf region. Binary form of our leaf image has black background and white leaf. In this image, number of white pixels represents the area of the leaf.

Major Axis: Major axis is denoted as a line, which lies between apex and base of the leaf.

Minor Axis*:* Minor axis of the ellipse that has the identical normalized second central moments as the leaf region.

Perimeter: Perimeter is the distance around the boundary of leaf region.

Convex Hull*:* Convex hull represents the least convex polygon that encapsulates the leaf region.

Minor Axis Length Ratio of Major Axis Length: This feature is denoted as ratio of minor axis length to major axis length. It is reverse of the aspect ratio that is used in the literature.

Eccentricity: A scalar esteem which indicates the eccentricity or unpredictability of the ellipse that has indistinguishable second- moments from the region. The eccentricity or unpredictability is the proportion of the separation between the concentrations of the ellipse and its major axis length. The esteem extends somewhere in the range of 0 and 1.

Entirety: Entirety of a leaf is determined utilizing the accompanying recipe, (Convex area - Area) / Area.

Extent: Extent of a leaf indicates the proportion of pixels in the region or locale to pixels in the littlest rectangle shape containing the region. In Fig.6 (b), the zone of the littlest rectangle shape (appeared grey pixels) containing the locale is 99 and the area of the region is 56. In this manner, extent of the region is 56/99.

Equivalent diameter: Equivalent measurement determines the width of a circle with a similar territory as the region. A region's comparable width, DE can be determined utilizing the recipe,

$$DE = \sqrt{(b\ X\ Area/\pi)}$$

Shape Based Features	Features		
			
1. Leaf Name	Alnus Incana	Fagus Silvatica	Betla Pubescens
2. Area	5.463	4.363	2.561
3. Perimeter	6.362	3.981	2.313
4. Major Axis	3.791	2.918	2.281
5. Minor Axis	1.994	1.693	1.502
6. Equivalent diameter	2.38	2.103	1.816
7. Eccentricity	0.5935	0.503	2.873
8. Convex Area	8.69	5.503	2.873
9. Extent	0.8332	0.9272	0.9649
10. Euler Number	0.9816	0.9935	0.9934

V. RESULTS AND DISCUSIONS

Classification involves two stages, training and testing using any classifier. In training phase, classifier is trained using feature values and its respective target values. This trained classifier is then used to classify test images.

In this work total 1125 leaf images of Swedish Leaf Dataset are used and which has been divided into 15 catagories out of which 75 images are Acer leaf images, 75 images are Alnas incana leaf image, 75 images are Betula Pebescens, 75 images are Fagus sylvatica, 75 images are Populus, 75 images are Populus tremula, 75 images are Quercus, 75 images are Salix alba, 75 images are Salix aurita, 75 images are Salix sinerea, 75 images are Sorbus aucuparia, 75 images are Sorbus intermedia, 75 images are Tilia, 75 images are Ulmus carpinifolia and 75 images are Ulmus glabra leaf images. For training phase 20 Acer, 20 Alnas incana, 20 Betula Pebescens, 20 Fagus sylvatica, 20 Populus, 20 Populus tremula, 20 Quercus, 20 Salix alba, 20 Salix aurita, 20 Salix sinerea, 20 Sorbus aucuparia, 20 Sorbus intermedia, 20 Tilia, 20 Ulmus carpinifolia and 20 Ulmus glabra leaf images are used.

For testing phase 12 Acer, 12 Alnas incana, 12 Betula Pebescens, 12 Fagus sylvatica, 12 Populus, 12 Populus tremula, 12 Quercus, 12 Salix alba, 12 Salix aurita, 12 Salix sinerea, 12 Sorbus aucuparia, 12 Sorbus intermedia, 12 Tilia, 12 Ulmus carpinifolia and 12 Ulmus glabra leaf images are used. In order to test the efficiency one can, collect additional pictures of leaves present in the database and see if the system recognizes them. But to have significant results another set of suitable test images would have to be found. So, a ground truth evaluation of the database has been conducted.

$$Accuracy(\%) = \frac{\text{Total number of images correctly classified} * 100}{Total\ number\ of\ images\ used\ for\ testing}$$

Here we use 180 images for testing and more than 177 images has been classified correctly so, the recognition rate or accuracy is 98.33%.

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VIII. CONCLUSION

The aim of this thesis work was to create a new method called Plant Leaf Recognition using Convolutional Neural Networks which is capable to classify leaf images using CNN model. ResNet-50 a pre trained CNN that has been used in our thesis work to identify the correct species of leaf from different classes with the recognition rate of more than 98.33%.

Although performance of the system is good enough but still in future research, we will attempt to recognize leaves attached to branches, in order to develop a visual system that can replicate the method used by humans to identify plant types.

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X. BIOGRAPHY

SHAHID HUSSAIN WANI is pursuing M. Tech CSE (Computer Science Engineering) from Desh Bhagat University, Punjab India. He has published research papers in various fields like DISTRIBUTED DATA MINING USING MULTI AGENT DATA, UBIQUITOUS DATA MINING, CLOUD COMPUTING-TECHNOLOGIES, VOICE CONTROLLED WHEELCHAIR USING ANDROID TECHNOLOGY, ARTICLE 370 AND ITS IMPLEMENTATIONS, REVIEW: PLANT LEAF RECOGNITION USING ARTIFICIAL NEURAL NETWORKS etc.