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Image based Automated Identification of the Plant Species Diversity from the Western Ghats Region Using Machine Learning and CNN Based Deep Learning Techniques using Leaf Dataset

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Abstract

It becomes crucial to conserve the floral diversity of a region, as the rate at which the flora is diminishing is alarming, leading to biological degradation worldwide. Conservation is the key; to conserve one has to have a thorough knowledge of the species and also skills to identify them, which is acquired by years of rigorous training, active involvement and practice. Whereas, advancement in the field of computer vision has promoted automated plant species identification with favourable results. The paper presents the creation of a dataset with 95 plant species which are rare and endangered from the western ghats region. The leaf Images of these plant species were captured to create the dataset. The paper further discusses the use of various image processing techniques for identification purposes. Firstly, preprocessing techniques were applied on the images to for noise reduction using thresholding techniques like Otsu's binarization and closing morphological operations that address the problem of damaged leaves in the dataset. The shape, color, and texture features that are retrieved from the leaves for identification reasons are then explored. We used typical machine learning algorithms to achieve varying levels of accuracies. During the second phase of the experimentation, the leaf images were subjected to the process of data augmentation to synthetically expand the size and diversity of the dataset and reduce overfitting. Further, CNN models with optimised parameters were developed with fully connected layer of artificial neurons for plant species identification. This experiment demonstrated an accuracy of 84.12 in testing accuracy and 99.7% accuracy in Training accuracy.

Keywords: Image-Processing ,Computer-Vision, Data Augmentation,Pre Processing ,Otsu's binarization Machine-learning, Deep-learning, CNN, Western Ghats.

Introduction

There are approximately 500,000 species of plants growing on the land (angiosperms, gymnosperms, bryophytes, lycophytes, ferns), the diversity of these species mainly concentrating in the regions of the humid tropics of the world [1]. Some plant diversity is still unfamiliar to science, with one-third of them being at risk of extinction. Some species of plants are globally extinct. Plants play an essential role in maintaining the natural ecosystem, and they have varied uses for the general human population.

Perhaps a third of all terrestrial plants are in danger of extinction, including those that have yet to be documented or those that have been registered but lack sufficient data [2]. There have been a few known global species extinctions. Still, there's a chance that many more species have gone extinct that haven't been documented in recent years. Even though only a small percentage of plant species have a specialized human application, many more serve critical roles in nature. Rare species may possess unique characteristics that will be helpful in the near future. The mass destruction of various plant species has harmed the environment, and there is an urgent need to conserve all endangered plant species [3]. Identifying and classifying these species is a daunting task for botanists and plant ecologists as it requires expertise with years of experience in this field.

Taxonomists must place an individual plant to a specific taxon based on a variety of physiological and morphological characteristics before arriving at a species designation. The task is based on morphological elements of the plant, such as leaves, stems, fruit, flowers, and so on. The challenge faced by the taxonomists in the identification of plant species is numerous. The Botanists have coined a term called "Taxonomic Crisis" as there is a shortage of skilled expert taxonomists.

Taxonomic identification of plant species can rightly apply the advancement made in the field of computer vision in [4-5] and [6]. The application of computer vision techniques to enhance automated species identification plays a vital role in biodiversity identification and conservation across the globe. There is an urgent need for botanists and computer scientists to collaborate and work with the right identification applications.

The leaf is a crucial identifier, as it is vastly available in most species; it is perennial and has various morphological features that can characterize it unique to each species.

Some of the challenges in automated plant identification are listed below [24]

1 There are a large number of taxa to be identified and separated from.
2 Challenges of visual and morphological variations in plants belonging to the same species
3 Some species show minimal interspecies visual variations
4 The issues related to restricted datasets and the challenges in image capture techniques and low identification accuracies of the machine learning algorithms.

The method for constructing and training an artificial neural network to identify between a large number of plant species is demonstrated in this paper. The artificial neural network is designed to learn a hierarchy of self-learned features that are less abstract than the preceding layers' features. Unlike prior classification systems, these self learned characteristics are unaffected by variations in lighting, shadows, and obscured leaves in the photos recorded.

RELATED WORK

Lin et al. [7] computed basic descriptors including area, perimeter, length, width, and convex hull, as well as other dimensionless form parameters like compactness, roundness, elongation, and roughness according to the literature review for this research. Basvaraj S. Anami and colleagues [8-9] sought to classify medicinal plants using neural networks. They examine the color, texture, and borders of the entire plant in the image. Kadir et al. [10] used to form and vein, color, and texture parameters to categorize leaves in their study. The classifier is a neural network called Probabilistic Neural Network (PNN). ANN is used by Janani et al. [11] to identify medicinal plants based on leaf characteristics. In this proposed work, the experimental study was carried out to identify 12 Philippine herbal plant species utilizing Python and MATLAB for neural network implementation. C. H. Arun et al. [12] use textural traits to classify therapeutic plants. Wu et al. [13] concentrated on obtaining the leaf's five essential geometric features: diameter, length, width, area, and perimeter. They also come up with 12 morphological traits that can be employed for leaf recognition based on these geometric aspects. To describe the leaf venation, Amlekar et al. [14] proposed seven morphological parameters. The area, perimeter, main length, minor length, convex area, and solidity are the features used. They then used a k-nearest neighbour classifier (KNN) and a back-propagation artificial neural network to classify them (ANN). In training mode, he utilized 173 photos, and in testing mode, he used 46 images. The ANN classifier yielded a decent result of 80.43 percent, while the KNN classifier yielded a poor outcome of 54.35 percent. Shape-based traits can also be used to identify plants. Giselsson (2010) classified objects depending on their shape. Overall, there was a 94.8 percent categorization accuracy reached using 1,700 samples of plants belonging to eight species, where each species was represented only at one growth stage. By combining a shape-based classification of leaves and complete plants, Dyrmann and Christiansen (2014) [15] presented a framework that differentiated seven weed and crop species at distinct early growth stages. They achieved a 95.8% total accuracy rate. Kumar et al. [16] used their Leafsnap technology to identify plants by extracting curvature-based form properties of the leaf. Then, for identification, the method of nearest neighbours is used. Despite their outstanding performance, these solutions are heavily reliant on a certain set of tasks or dataset-dependent features.

METHODOLOGY

The paper is split into two parts. The methods and outcomes of using classic machine learning methods are discussed in the first part. The deep learning algorithms used and the results obtained are discussed in the second part. The process for creating data sets is discussed, as well as image processing techniques for pre-processing, feature extraction, and the usage of various machine learning algorithms and their accuracy in identification.

We also go through how a deep learning method was implemented for identification and discuss the results that were obtained.

3.1 Dataset creation

The dataset is created using the plant species of the Western Ghats region. The samples are collected from the Dr. Shivarama Karantha Nisargadhama Pilikula, botanical garden, home for the rare and endangered species of Western Ghats plants. A total of 95 varieties of species were collected to form the dataset. The dataset creation involved the collection of healthy leaves with various stages of growth. The leaf's frontal portion images were obtained using a digital camera on a plain white background. The images, once obtained, were then transformed into a uniform resolution of 1200*1200 dpi.

The following table displays the botanical and vernacular names of the plant species.

Table 1. The botanical and vernacular names of the plant species

Sl. no	Botanical name	Vernacular name in Kannada
1	Ailanthus Triphysa	Gugguldhupa
2	Amoora Rohituka	Mullumuttaga
3	Artocarpus Lakoocha	Esuluhuli
4	Butea Monosperma	Palasha, Mutthugada Mara
5	Calotropis Gigantea	Ekkada Gida
6	Centella Asiatica	Urage Soppu, Saraswati Soppu, Brahmi Soppu
7	Cyclea Peltata	Paadavaliballi
8	Ficus Religiosa	Ashwathamara, Arali Mara
9	Gymnema Sylvestre	Kodapatre, Kadasige
10	Humboldtia Brunonis	Hasige Mara

Figure. 1 Sample of the plant species in the dataset

3.2 Pre-processing

We initially discuss the pre-processing stages involved in using image processing techniques for implementing various machine learning algorithms. For considerable improvement in the image quality, the pre-processing methods include noise reduction, contrast, and brightness enhancement, enhancing the image's sharpness.

The stages involved in pre-processing are as follows:

1 Original images are resized to 1200*1200 dpi

2 Thereafter, the color image information is transformed into a greyscale image.
3 Gaussian filters are applied for noise reduction.
4 Simple thresholding and Otsu's binarization techniques are applied for segmentation purposes.
5 In the final stages, the closing morphological transformations are used to allow any damages or holes present in the leaves to be closed for better feature extraction.

3.3 Feature extraction

By using feature extraction techniques, additional information can be recovered from an image. Our experimental setup extracts several features from the leaf images, like shape, texture, and color features.

1 Shape feature: Perimeter, Area, Circularity, Rectangularity, and aspect ratio are obtained by calculating image moments and contour feature extraction [17-18].
2 Colour features: We retrieved the mean and standard deviation of these hues from the corresponding leaves by separating the image into three channels: red, green, and blue.
3 Texture features: The grey level co-occurrence matrix is used to construct Haralick's characteristics (GLCM).

Correlation contrast, entropy, and inverse difference moments are among the features calculated.
The following are the details of the shape, color, and texture features represented in the table.

Table 2. Sample of the Extracted Shape Features

Plant species	Area	Perimeter	Phy_length	Phy_width	Aspect ratio	Rectangularity	Circularity
Alangium Salvifolium	1250474	4827.685	1034	1883	0.549124	1.557028	18.63817
Alangium Salvifolium	1385164	5073.81	1078	1971	0.54693	1.533925	18.5852
Alangium Salvifolium	1409535	5220.378	1133	2000	0.5665	1.607622	19.33428
Alangium Salvifolium	68.5	36.38478	13	11	1.181818	2.087591	19.32631
Alangium Salvifolium	4	9.656854	5	3	1.666667	3.75	23.31371
Alangium Salvifolium	1568708	5085.026	1098	1907	0.575773	1.334784	16.4833
Alangium Salvifolium	1482340	5048.454	1102	1915	0.575457	1.423648	17.19369
Alangium Salvifolium	1671859	5257.629	1122	1971	0.569254	1.322756	16.53409
Alstonia Scholaris	1570779	5059.771	1092	1900	0.574737	1.320873	16.29846
Alstonia Scholaris	1563453	5038.884	1087	1900	0.572105	1.320986	16.23992
Alstonia Scholaris	1593802	5129.979	1112	1943	0.572311	1.355637	16.5119
Alstonia Scholaris	1517768	5005.695	1090	1899	0.573986	1.363786	16.5091
Alstonia Scholaris	1543090	5136.658	1088	1880	0.578723	1.325548	17.09898
Alstonia Scholaris	1652459	5168.783	1135	1919	0.591454	1.318075	16.16762
Alstonia Scholaris	1482296	4897.803	1101	1861	0.591617	1.382289	16.18333

Alstonia Scholaris	1550577	5112.264	1092	1961	0.556859	1.381042	16.85518

Table 3. Sample of the Extracted Colour Features

Plant species	**Mean_r**	**Mean_g**	**Mean_b**	**Stddev_r**	**Stddev_g**	**Stddev_b**
Alangium Salvifolium	116.2635	121.9871	105.7067	85.59472	79.56838	87.06443
Alangium Salvifolium	105.5742	112.4828	95.55072	81.11632	75.07574	82.3083
Alangium Salvifolium	110.066	117.3923	99.18427	83.49347	77.05111	85.87645
Alangium Salvifolium	94.27254	102.3276	82.54222	80.9162	75.25972	83.40014
Alangium Salvifolium	108.1156	115.6583	98.81895	84.781	78.69042	87.05752
Alangium Salvifolium	96.04948	104.9308	85.4667	83.33598	77.64244	87.17021
Alangium Salvifolium	103.9905	113.2062	91.07762	77.25331	70.58726	81.86157
Alangium Salvifolium	88.26905	96.851	71.76458	79.87397	73.6549	83.92939
Alstonia Scholaris	96.80325	104.4434	90.76445	83.22917	78.21457	82.68665
Alstonia Scholaris	95.91718	103.9327	91.06492	84.05532	79.01616	84.38071
Alstonia Scholaris	93.96487	101.9864	89.72054	82.8678	77.81842	83.1646
Alstonia Scholaris	104.4733	112.9725	99.68263	82.04192	76.04925	82.60182
Alstonia Scholaris	103.2791	111.1938	96.75404	80.22774	74.66413	80.59756
Alstonia Scholaris	92.51631	100.2183	84.45433	79.86403	74.5595	79.44173
Alstonia Scholaris	108.5116	115.8568	101.8382	81.02513	75.41946	81.33235
Alstonia Scholaris	103.799	112.9016	97.72571	84.35044	78.09371	85.00019

Table 4. Sample of the Extracted Texture Features

Plant species	**Contrast**	**Correlation**	**Inv_diff_moments**	**Entropy**
Alangium Salvifolium	19.92602	0.998524	0.357088	10.27754
Alangium Salvifolium	18.99687	0.998426	0.357189	10.46038
Alangium Salvifolium	24.17108	0.998111	0.375439	10.30643

Alangium Salvifolium	20.03757	0.998345	0.36213	10.17782
Alangium Salvifolium	17.84832	0.998655	0.405952	10.13948
Alangium Salvifolium	14.9781	0.99884	0.398058	9.752304
Alangium Salvifolium	34.7537	0.99681	0.336439	10.91857
Alangium Salvifolium	17.15145	0.998538	0.377007	9.999426
Alstonia Scholaris	22.19081	0.998274	0.380474	10.09801
Alstonia Scholaris	27.8026	0.997885	0.349907	10.32049
Alstonia Scholaris	26.73314	0.997905	0.363688	10.22196
Alstonia Scholaris	22.28903	0.998195	0.377315	10.22122
Alstonia Scholaris	29.11597	0.997541	0.343192	10.51387
Alstonia Scholaris	25.35229	0.997841	0.338729	10.59043
Alstonia Scholaris	26.89296	0.997774	0.340337	10.46763
Alstonia Scholaris	27.07465	0.997922	0.341947	10.49979

After learning to use feature points, machine learning algorithms are employed to classify data. The performance of machine learning models like SVM and KNN is typically determined by the input feature points. One of the most significant drawbacks of machine learning models is that they are unable to extract the optimal feature points because the learning and classification procedures are carried out separately [19]. The classification models of SVM, LDA, Decision Tree, Naïve Bayes, KNN were applied. The accuracies of the models are as shown in the table.

Table 5. The accuracies of machine learning models

Machine Learning algorithm	**Accuracies**
SVN	74.7%
KNN	72.3%
Decision Tree	67.9%
Native bayes	58.8%
LDA	61.3%

5. Deep learning using CNN

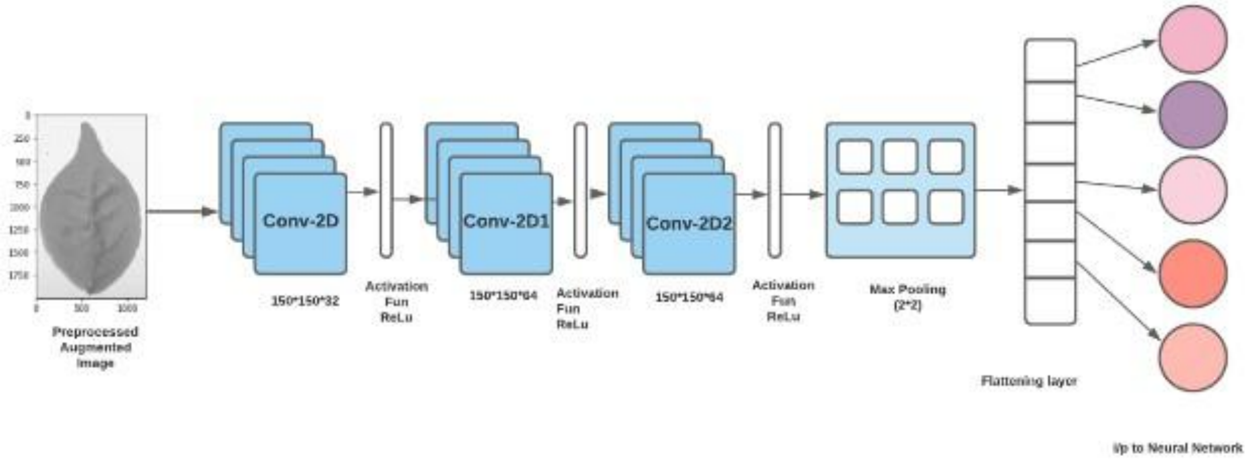
Deep learning techniques, notably Convolutional Neural Network CNN [20][21], have improved computer vision applications such as picture classification and object recognition. Since this system must detect the leaf image and determine which species it belongs to, plant species recognition is a mixture of object identification and image classification. To distinguish leaves of plant species, an intelligent system must be trained with an extensive, reliable collection of photos so that the algorithm can detect a leaf and predict its species. This method is referred to as supervised learning. To successfully guess the names of the unseen images, this method requires an external dataset containing labels. We trained a CNN to extract features from photos while also classifying them. More than one convolution layer is followed by a completely connected layer in this network [22]. CNNs are simpler to control and train. We employed the CNN to efficiently recognize plant species in this study project. The neural network is implemented using the Python programming language and the OpenCV libraries. The core principle behind a CNN is to create a hierarchy of self-learned features, with the abstraction between the features decreasing as you proceed from one layer to the next [23].

Various challenges encountered during leaf picture collection, such as fluctuations in lighting, occurrences of shadows, occlusion, skewed leaves, have no major impact on CNN.

5.1 Model architecture

The CNN model is a feed-forward neural network made up of layers that accepts an input image, applies an activation function like ReLu, and then predicts the input image's class or label.

Instead of employing handmade feature extraction methods, the CNN automatically learns the features present in the image utilizing several layers with learnable filters and combines the filters' findings to predict the input image class. For example, in CNN, the early-level layers may identify lower-level features such as outlines, and as the layers proceed, the layers at the network's far end detect even more finer features. The convolution layer, the pooling layer, and the fully connected layer are the three layers that makeup CNN.



5.1.1 Convolution layer

A convolution combines two functions that show how one function modifies the other. Below mentioned is a standard convolution formula of the convolution layer. A feature detector filter, ideally a 3*3 matrix, which has been slid over the subject image. The feature map, convolved feature, or activation map is generated for each position of the filter, and the dot product of the image region is covered by the filter. The purpose of the feature detector is to detect certain features that are integral to the image. The stride of the filter we have used is two, which is relatively conventional, for our experimentation purposes. With convolution, we have reduced the image's size, which can be input to further processing. Multiple feature maps are created in a similar way for multiple feature detection.

5.1.2 ReLu

ReLu is an activation function applied to each value in the feature map in our experimentation. ReLu is an additive step to the convolution operation. With the application of ReLu, the nonlinearities in the images are reduced. Once the images are rectified, the progression from one color to the other is more abrupt than gradual, indicating that the linearity is disposed of.

5.1.3 Pooling

Max pooling was introduced in our experimentation to down-sample the detection of features in the feature map .it is a summarised version of the features detected in the input image. The goal of pooling is to gradually reduce the spatial size of the picture representation while also lowering the network's parameters and computations. In max pooling, we calculate the maximum value for each section of the feature map by providing an abstracted form of representation. Thus, Max pooling reduces the issues with overfitting. The size of our pooling map is2*2 with a stride of 2. The non-overlapping sub-regions of the initial sub-regions is subjected to max-pooling using a max filter.

5.1.4 Flattening

This is the next stage in the process. During this stage, the data received after pooling is turned into a onedimensional array, which is then sent on to the next layer. The output of convolutional layers is then flattened, resulting in a lengthy feature vector. It is then connected to the final classification model once it has been flattened.

5.1.5 Full connection

We are adding a whole artificial network layer at this stage. This layer is known as a fully connected layer. That entire column or vector of outputs that we have after the flattening is passed into the fully connected layer. The artificial neural network's primary purpose is to combine the features into more attributes and develop new traits that predict the class at a higher accuracy rate.

Experimentation results

The CNN builds a hierarchy of self-learned features based on less abstraction from the model's previous layers. As a result, CNN is less affected by variations in illumination, shadow, occlusions. Furthermore, handcrafted segmentation is not a necessary step as the image can reduce the noise aspect and detect the image features of new plant species on its own; hence the need for new feature descriptors is eliminated.

In this CNN model

- Initially, the images are resized from 1200 * 1200 dpi to 150*150.
- The images are subjected to the data augmentation process of shearing, zooming, and horizontal flip.
- The resultant images after data Augmentation are then fed into three layers convolution layer and subject to activation function ReLu, so feature maps are derived.
- The first convolution layer is of size 3*3 of 32 filters with a stride of 2 is applied with the activation Function ReLu.
- The resultant feature maps are then convolved with two layers of convolution of size 3*3 of 64 filters with a stride of 2 combined with the activation function ReLu. This is followed by a 2*2 max-pooling layer.
- The resultant pooled feature map is then passed through the flattening layer to obtain single dimension feature data.
- The resultant features are then trained using one layer of the artificial neural network, finally leading to the output layer with plant species classification.

The testing accuracy stands at 84.21%, and the training accuracy is 99.74%.

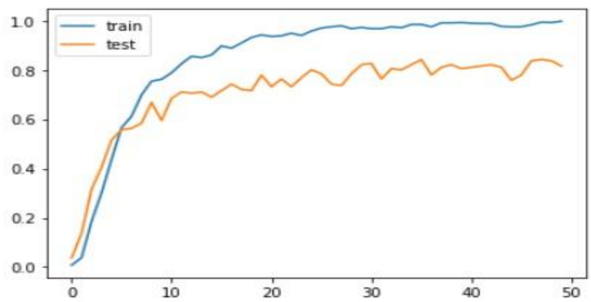


Figure. 3 Graphical representation of accuracy using the CNN model

In this paper, we have discussed creating a dataset for the plant species of Western Ghats followed by preprocessing and feature extraction stages. Then, the machine learning algorithms were applied to these images for identification purposes with varying accuracies. In the second stage, we used the CNN model architecture on the augmented images and obtained impressive accuracy. Hence, we have observed that the accuracy is higher with deep learning models than traditional machine learning models from the experimentation.

Conflicts of Interest

"The authors declare thats there is no conflict of interest."

Author Contributions

This research has equal contributions from both the authors. There is no external funding sources involved in this project

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