Indian Plant Recognition in the Wild

Vamsidhar Muthireddy, C. V. Jawahar

IIIT Hyderabad
vamsidhar.muthireddy@research.iiit.ac.in, jawahar@iiit.ac.in

Abstract. Conservation efforts to protect biodiversity rely on an accurate identification process. In the case of plant identification, traditional methods used are manual, time-consuming and require a degree of expertise to operate. As a result, there is an increasing interest today for an automated plant identification system. Such a system can help in aiding plant-related education, promoting ecotourism, creating a digital heritage for plant species among many others. We propose a solution using modern convolutional neural network architectures which achieves state-of-the-art performance for plant classification in the wild. An exhaustive set of experiments are performed to classify 112 species of plants from the challenging Indic-Leaf dataset. The best performing model gives Top-1 precision of 90.08 and Top-5 precision of 96.90.

1 Introduction

Diversity is an important trait of biological life that helps in sustaining itself. This biodiversity is decreasing across the world due to indirect or direct human interventions [16]. Conservation efforts employed to sustain biodiversity involve geographical mapping of species for better monitoring. These efforts rely on an accurate identification process which is almost always time-consuming. Take, for example, the case of plant species that form a significant portion of biodiversity. The traditional process for identifying them involves an expert who is required to identify qualitative morphological characteristics of a plant and compare them with discriminatory features of known plants to arrive at a species. This process is very long and tedious requiring the involvement of domain experts. Traditional plant species identification is challenging even for people like gardeners, farmers or conservationists whose daily jobs involve dealing with plants. Moreover, it cannot be used by nature enthusiasts since many of them are not equipped with domain knowledge. Thus, the process of plant species identification along with being accurate also needs to be robust and simple enough for the general public to use.

There are more than 3,00,000 [7] estimated plant species that inherit this world. It might not be possible for an experienced expert to identify all these plant species. They can be supplemented with a simple computational system that can identify these species. For this purpose, a recognition system based on images is considered a promising approach [5]. The image data captured for the said system should contain necessary features needed to recognise the plant

Fig. 1: This figure shows images from level-0 and Level-1 of Indic-Leaf dataset. The top row shows images from Level-0 and the bottom row from Level-1. Each column shows images of different species.

species such as its leaves. Leaves are the most abundant part of a plant that can be used for visual identification. They contain important visible features such as shape, texture, veins, colour, edge, and leaf type. Images of these leaves can be used in developing methods for plant species classification. It is crucial to create such image datasets tagged by different geographical locations. Keeping this in view, we created Indic-Leaf dataset composed of some of the plant species found in India.

1.1 Motivation

Plants play a crucial role in Indian culture. Among their many uses, some are described here. Our indigenous medicine uses beneficial plant parts. This practice is extensively used as primary modality, especially in rural areas. In a primarily agrarian society like ours, the farmers have to be provided with best-recommended practices for any specific crop to ensure that national crop yield remains high. As such, the necessary information must be provided to them about the various diseases and pests that can affect the crop. Further, knowing what a healthy plant looks like can help in early detection of disease. Culturally, plants and their parts play a significant role in many rituals and festivals. A systemic digital catalogue of the native species can have far-reaching consequences. Firstly, this catalogue is a part of digital heritage that can boost conservation efforts by helping identify various local species. Such a catalogue can help differentiate between similar species and allow for selective cultivation of more beneficial plants. It can be used to create Biodiversity parks to promote ecotourism. Having a digital platform can make plant-related education more accessible, allowing for generations of students to get interested in our bio-heritage.

1.2 Related works

Early work on plant species classification used handcrafted features to describe plant parts. Gu *et al.* [7] extract leaf skeleton from scan-like images and use it to classify leaf images. There are studies which used the venation pattern of

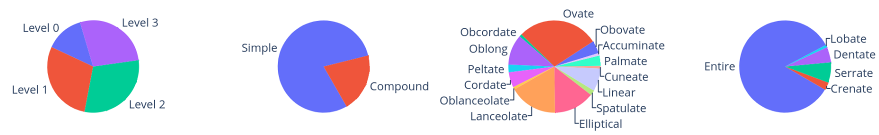
Fig. 2: This figure shows images from level-2 and Level-3 of Indic-Leaf dataset. The top row shows images from Level-2 and the bottom row from Level-3. Each column shows images of different species.

the leaves for the same [14]. Some use the texture of the leaf as a key feature [11]. The shape information is also used by the leaf-based methods [13]. Several studies used the combination of texture and shape [10] while other studies used the features from shape and veins [15]. Some used colour and polygon models to segment a leaf followed by extracting handcrafted shape features for leaf recognition [4]. Handcrafted features designed for leaf classification based on its morphological characteristics often assume an image with a simple background of uniform colour. They fail in the context of the natural environment as it is often hard to capture an image containing only a single leaf in a cluttered natural environment.

Neural networks automate the process of obtaining the features by learning a representation of training data. Sun *et al.* [19] and Barr *et al.* [3] propose custom architectures for plant identification. Existing VGG model is modified [8] and used in classifying PlantCLEF dataset [6]. Pl@ntnet, a plant identification system has also shifted from using classic handcrafted features[12] to a CNN based architecture for plant identification. We also take an approach of starting with pre-trained state-of-the-art convolutional neural networks and fine-tune them on a challenging leaf classification dataset.

1.3 Existing datasets: Problems and a Solution

An image-based dataset should capture features that help human experts identify the object of interest. For plant recognition, experts analyze foliage from various distances to take note of the plant shape, arrangement of leaves, and characteristics of the leaf. They study a plant from different levels of distance to identify it. Publicly available datasets such as Herbarium [1], Flavia [20], Swedish Leaf [18], Leafsnap [13], PlantCLEF [6] have assisted in furthering the work in plant species classification. Other than PlantCLEF, all the others are composed of scan-like images in a lab constrained environment. PlantCLEF that captures plants in their natural environment doesn't organise the images of the species according to different distance levels mentioned above. Moreover, none of these datasets contain images specific to Indian sub-continent. Keeping this in view, we created the Indic-Leaf dataset.



(a) Level (b) Leaf division (c) Leaf shape (d) Leaf margin

Fig. 3: Figure shows the distribution of different dataset attributes. Contribution of each (a) level, (b) leaf divison type, (c) leaf shape, and (d) margins.

Our proposed Indic-Leaf dataset is composed of 27,000 images belonging to 112 Indian plant species. It is divided into groups based on distance levels between the camera and the plant. This will allow for a broader set of tasks to be done using our dataset. As per our knowledge, this is the first dataset where the images are grouped according to different levels. More details about the dataset are provided in section 2. Further sections describe the methods and our experimental setup. They detail the qualitative and quantitative analysis that has been done on the dataset to achieve a Precision@1 of 90.08.

2 Indic-Leaf Dataset

The Indic-Leaf dataset contains 27K images belonging to 112 plant species found in IIIT-H campus. For every image, there is an associated XML file containing annotations that include attributes of the leaf present in the image. Further, images from each species are divided into groups: Level-0, Level-1, Level-2, and Level-3. Level-0 contains scan-like images. The rest of the groups contain "in the wild" images of the leaves. These groups are designed to act as distinct datasets to assist with relevant research problems. The above-mentioned groups are explained in detail below.

Level 0: Scan-like images in our dataset are grouped into this *level*. Leaves collected from a plant are pressed for a short time to make them relatively flatter. Each leaf is placed on a sheet of white paper; its picture is taken from a camera at a fixed height with no flash.

Level 1: Leaves can be simple(a single leaf blade or lamina) or compound(with several leaflets). Level-1 contains images that capture a single leaf in its entirety so that the visibility of the blade area is maximized as shown in the bottom row of Fig 1. The process of capturing is simpler in the case of simple leaved plants that have one leaflet. For plants with compound leaves, where a leaf is divided into many small leaflets, this process is rather challenging. In this case, the image is captured to contain the majority of these leaflets belonging to the leaf. Level-1 images capture the finer details of the leaf such as its shape, colour, texture, and veins.

Level 2: Images in this *level* capture details of a leaf cluster; the arrangement of the leaves along a stem/branch. The top row of Fig 2 shows different types of leaf groups in different species. For example, the second image in this row shows leaves arranged in a rosette pattern.

Level 3: Images capturing partial/full view of the plants are grouped into this *level*. Images in this *level* give an overview of the shape of the plant/tree.

2.1 Annotation schema

Each image in our dataset has an associated XML file that provides the annotations. These annotations describe the morphological characteristics of the leaf along with other information related to plant species captured in the image. These annotations are as follows:

- *Scientific Name:* This tag specifies the scientific name of the species captured in the image. It is a two-part name based in Latin.
- *Common Name:* Common name varies with the geography of the species. A species can have multiple common names.
- *Family:* Every plant species belongs to a family. The name of the family usually ends with "aceae" for plants. This tag gives the family of the species captured in the image.
- *Picture Type:* As mentioned in section 2, each image is grouped into one of the levels. This tag records it.
- *Leaf Shape:* This tag describes the shape of the leaf in the image. Fig 3c shows different shapes of leaves available in Indic-Leaf dataset.
- *Leaf Margin:* Leaf margin refers to the outside perimeter of a leaf. Fig 3d shows different types of leaf margins found in Indic-Leaf dataset.
- *Leaf Divison:* Two basic forms of leaves can be described considering the way the blade (lamina) is divided. This tag describes whether the division of the plant species is simple or compound.
- *Picture season:* This tag captures the season in which the image was taken.
- *Disease:* This tag informs us of any common diseases that affect the leaves of the species captured in the image.
- *Description:* Detailed information about the plant species is provided in this tag. It contains a visual description of the species; detailing height of the plant/tree, colour and size of flowers and fruits, etc.
- *Utility:* Utility tag describes how the resources from a plant species are utilized.

3 Methods

Plant recognition "in the wild" is a challenging classification task. During classification, all the images of a particular species are considered into one class. Some species can be recognized from afar, while some need a closer inspection. This is emulated by using levels mentioned in section 2 during classification task. A significant portion of plants have a variation of green hue as the leaf colour. The dataset was used in different colour spaces to identify any significant differences in class predictions. We wanted to understand whether the problem of plant classification is inherently a difficult one or it depends on the complexity of the model. We used VGG-16 and various architectures of ResNet to experiment on different dataset configurations.

Layer	Output size	ResNet18	ResNet34	ResNet50	ResNet101	ResNet152
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 1024\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1 × 1	average-pool, fc, softmax				

Table 1: This table shows different ResNet architectures with stacked building blocks. The first column displays the name of the parent blocks and the second column shows the size of the output of the block. Columns 3-8 specify the size, depth, number of the filters and blocks.

3.1 VGG-16

VGG-16 [17] is a feed-forward convolutional neural network with 16 weight layers. This network is characterized by its simplicity for using convolutional filters with a receptive field of 3×3 in every layer. Convolutional layers in the network are followed by two fully connected layers and a softmax classifier. Due to its known efficacy in classification tasks, we use VGG-16 as our baseline model.

3.2 ResNet

Residual networks (ResNet) [9] are feed-forward neural networks that use skip connections in their architecture. ResNet based architectures out-rank their predecessors [2] in classification ability since they do not suffer from the vanishing gradient problem. We use ResNets of 18, 34, 50, 101, and 152 layers in our work. All of them have similar architectures with a single conv. layer that takes $224 \times 224 \times 3$ image as an input. This conv. layer is followed by 4 parent blocks. A block or a basic block represents stacked convolutional layers. Each parent block contains multiple basic blocks and their number varies with the position of the block and the depth of the ResNet. Each basic block in ResNet-18, 34 has two conv. layers while each block in ResNet-50, 101, 152 have three conv. layers. Table 1 explains the detailed architecture of different ResNets.

4 Experiments, Results, and Discussion

In this section, we present the experimental results of the networks used for classifying the test dataset. We then proceed to discuss the obtained results.

4.1 Experiments

Data Augmentation: This is a crucial strategy employed to improve the diversity of the data available for training the networks. It improves the performance

Model	Cfg	P@1			P@3			P@5		
		YCbCr	RGB	HSV	YCbCr	RGB	HSV	YCbCr	RGB	HSV
VGG-16	*cfg1*	88.49	89.30	88.99	94.43	94.82	94.93	96.34	96.54	96.29
	cfg2	85.47	85.21	86.08	93.07	93.39	93.48	95.08	95.24	95.28
Res-18	*cfg1*	86.97	85.90	86.50	93.64	92.85	93.57	95.24	94.67	95.38
	cfg2	82.63	82.95	82.46	91.62	91.70	91.26	93.83	93.66	93.63
Res-34	*cfg1*	86.99	86.92	87.24	93.48	93.20	93.70	94.93	94.99	95.37
	cfg2	83.98	84.35	84.11	92.31	92.53	92.71	94.79	94.90	94.93
Res-50	*cfg1*	89.85	88.84	89.43	95.35	94.40	95.15	96.62	95.90	96.80
	cfg2	86.05	86.50	86.50	93.43	93.45	94.10	95.22	95.46	95.95
Res-101	*cfg1*	89.45	**90.08**	89.94	95.11	95.35	**95.51**	96.71	**96.90**	96.74
	cfg2	86.75	87.39	86.92	94.30	94.28	94.28	96.25	95.96	96.49
Res-152	*cfg1*	89.25	89.65	89.11	94.79	94.79	95.00	96.24	96.49	96.49
	cfg2	87.21	87.20	86.72	94.41	94.40	94.17	96.22	96.00	95.80

Table 2: This table presents P@K values obtained by all the models on the test sets for K=1, 3, 5. The first column shows the name of the model and the second column shows the configuration. Each of the rest of the columns have three sub-columns showing P@K value for different colour spaces. Each row displays the P@K values for the model used for different colour spaces. Each of these rows have two sub-rows, one for each dataset configuration. The first sub-row displays the results from *cfg1* and the second, *cfg2*.

of the networks by making them robust to variance in new data. During training, we used random vertical-horizontal flipping, and rotation. The smaller side of the image is then resized to 672 pixels followed by cropping the central 560×560 patch. A 448×448 region from this patch is then randomly cropped. This region is resized to 224×224 pixels to be used as an input to the networks.

Experimental setup: All the deep networks used in our work are pre-trained on ImageNet dataset. Fine-tuning of each network parameters was done on Indic-Leaf dataset. The dataset is split into train, validation, and test sets in the order of 60:20:20. The batch size is set to 100 and cross-entropy is used as the loss function. Stochastic gradient descent(SGD) with the momentum of 0.9 is used for optimization. All the networks have been trained for 100 epochs with an initial learning rate of 0.01. It is decayed by a factor of 0.5 when there is no reduction in validation loss for 3 consecutive epochs.

We evaluate ResNet-18, 34, 50, 101, 152, and VGG16 models on our dataset. Each one of these models is trained and tested on two configurations of the dataset and three colour spaces. Each species in Indic-Leaf dataset is categorized into levels as mentioned in section 2. The images in one *level* look visibly different from images in another. We use this information to create two different data configurations for experimentation. In the first configuration (*cfg1*), all the images belonging to a species are considered into one training class (*label=specie*). In the second configuration (*cfg2*), each *level* of a species is considered a training class(*label=specie_level*). If there are s species and each has maximum of l levels, then *cfg1* will have s classes where as *cfg2* will have maximum of $s \times l$ classes in the softmax layer.

4.2 Results

Table 2 shows the exhaustive set of experiments performed on Indic-leaf dataset. As seen in Table 2, Res101 *cfg1* in RBG colour space outperforms other models with P@1 of 90.08. Our baseline, VGG-16 achieves P@1 of 89.30 outperforming ResNet-18, 34, and 50 architectures. It can be observed that models using images in RBG colour space outperform models using images in other colour spaces.

Model \ Levels	**0, 3**	**1, 3**	**1, 2**	**2, 3**	**0, 1, 2**	**0, 1, 3**	**0, 2, 3**	**1, 2, 3**
VGG-16	44.73	61.89	54.65	56.39	61.06	68.80	68.10	68.60
Res-18	45.25	60.36	54.20	57.31	60.21	67.12	66.64	66.99
Res-101	48.07	64.09	56.75	60.41	63.24	69.54	69.70	69.90

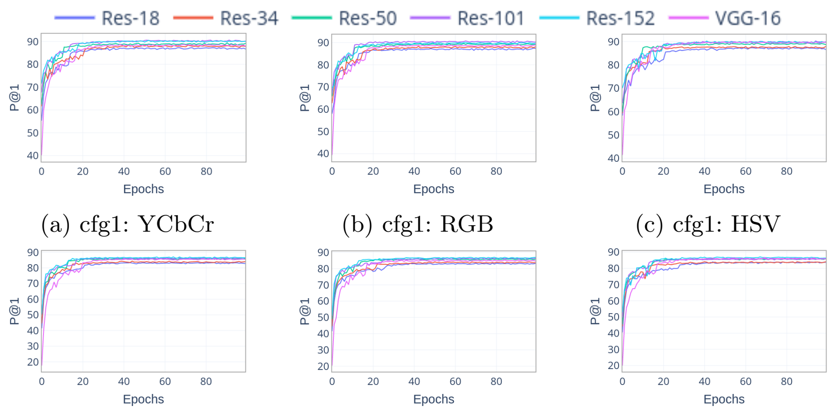
Table 3: Table shows the P@1 values of different models when training set is constrained to specific *levels*. The header of each column specifies the *levels* used for training the specified model in each row.

Table 2 shows that in each colour space, models trained in *cfg1* outperform the models trained in *cfg2*. This is expected due to models in *cfg2* having more than thrice the number of classes compared to *cfg1* in their softmax layer and low inter-class difference due to the split of each species into multiple levels. To test this hypothesis, the best performing model in *cfg2* is made to predict species(*label=specie*) from the test data. We noticed an increase in P@1 value from 87.39 to 89.47. This significant improvement in P@1 supports our hypothesis.

To ascertain the significance of different *levels* in the dataset, a series of experiments were conducted by constraining the training set to contain only specific levels. The best performing model from Table 2 along with the baseline VGG-16 are used to analyse the impact of different levels on the test set from Table 2. ResNet-18 architecture is used to understand the impact of depth in obtained predictions. Obtained results are presented in Table 3.

4.3 Discussion

In both the experimental configurations, the best performing models use data in RGB colour space. We find ResNet-101 achieving P@1 of 90.08 to be the best tradeoff between model capacity and optimization difficulty. The increase in P@1 for *cfg2* model (*label=specie_level*) when made to predict species(*label=specie*) implies an accurate prediction of species when compared with the species prediction along with their level by the model. Moreover, the models in *cfg2* have low P@K values than their *cfg1* counterparts suggesting a complex nature of *cfg2* variant of dataset. From Table 3, it is evident that the higher the number of *levels* in the training process, better the performance of the model. But, from second column we can deduce that the higher inter-level variance also provides for better performance of the models.



(a) cfg1: YCbCr (b) cfg1: RGB (c) cfg1: HSV

(d) cfg2: YCbCr (e) cfg2: RGB (f) cfg2: HSV

Fig. 4: This figure depicts P@1 of validation data plotted against epochs for different models in multiple colour spaces. Top row(a,b,c) shows P@1 from *cfg1* models and Bottom row(b,d,f) shows P@1 from *cfg2*. First column(a,c) shows P@1 for models trained on YCbCr colour space, second column(b,d) shows the same for RGB colour space and the third column(c,f) for HSV colour space.

5 Conclusion

We introduced and described a new dataset for recognizing Indian plant species in the natural environment. Images of the plant species are collected from various distances and emphasis was placed on categorizing them into different levels. We conducted quantitative analysis by using different convolutional neural network models on our dataset in different colour spaces. Our experiments into different dataset configurations show that the models perform better when all the images of a species are considered under a single class. We also observed that the complexity of the classification task increases when models are made to predict the *level* of the species (*label=specie_level*). The results obtained from experiments constraining the dataset to specific levels during training phase ascertain the importance of different levels of data for identifying "in the wild" test data. Apart from the name of the species, additional information like leaf shape, family of the species can be used in future work to improve the models.

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