Indian Flora Project: Social Image Data Based Plant Species Identification and Disease Detection using Deep Learning

Benedict Florance A

National Institute of Technology, Tiruchirappalli, Tamil Nadu - 620015

Prof. Jawahar C. V.

International Institute of Information Technology, Hyderabad, Telangana- 500032

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Abstract

Plant species data collection and identification is a crucial step in the conservation of biodiversity and sustainable productivity of agriculture. Speeding up this process can hasten the efforts taken towards the protection of plant species and help in educating the public. One of the significant contributors to an economy, agricultural productivity, is hugely affected by plant leaf diseases. Automatic detection of leaf diseases at an early stage is the need of the hour to eliminate the traditional and highly unprecise naked-eye predictions by experts. This paper proposes a collaborative workflow for image-based plant identification as a way to engage new contributors and provide botanical data to the public. At the time of writing, an image database of 100 Indian species has been manually collected. This initial database has been synchronized with growing data from a collaborative web-portal and mobile application where users can add new observations and query for species identification. We employ a convolutional neural network model (ResNet) to automatically identify 68 of the collected plant species. Experimental observations using the proposed approach shows efficient computation time and high top-5 precision of 99.85% compared to the state-of-the-art approaches that focus on hand-engineered features for detection.

Keywords: Plant Classification, Leaf Recognition, Collaborative Network, Leaf Disease, Crop Diseases, Disease Detection, Deep Learning, Convolutional Neural Network, Fine-Grained Image Classification

1 Introduction

1.1 Rationale

Plant cultivation plays a fundamental role in people's lives and also acts as the lifeline of the national economy. Understanding this diversity and distribution of plants is essential for the conservation of biodiversity and sustainable productivity of agriculture. Speeding this process and making it accessible to the general public is necessary to alleviate the increasing threats to the ecosystem such as the extinction of species and imbalance of the ecosystem. However, this process of quantifying the biodiversity by plant species identification is highly challenging even for botanical experts, farmers and nearly impossible for the general public. Manual identification of plants is highly time-consuming and laborious.

Crop diseases are a major threat to food security and also increases the cost of control towards the damage incurred. Traditionally, diseases were detected by experts using naked-eye. But, this method of disease detection is time-consuming and highly inaccurate. Further, it requires continuous monitoring by experts which is expensive and impractical for large fields. Automatic detection of diseases at an early stage is much cheaper, less time consuming and more accurate. The rise in the smartphone usage and advances in computer vision and deep learning technologies has facilitated the automatic detection of plant diseases.

1.2 Objective

The main goal of this paper is to speed up this collection of plant species data with a collaborative pipeline, to provide an efficient way for the general public to view the catalogue of species and to automatically identify plant species and detect plant diseases. This collaborative pipeline focuses both on plant species identification and encourages new contributors to add their observations to the repository and enrich the existing data. We have set up this social network with multiple levels of users - curators and moderators to approve and ensure the quality of the content being added to the network. The observations and collections on the network are validated by a set of amateurs and experts specialized in botany. This setup has been publicly deployed as a web-application so that interested users can submit new observations as well as view the catalogue of species. With the explosion of smartphones among the general public, a mobile application has been developed to identify plant species and detect diseases just by capturing images through the smartphone.

The use of convolutional neural networks (CNN) has achieved tremendous results in the field of image classification. The paper concerns the identification of plant species by use of a deep convolutional network ResNet18 [1]. We discuss the experimental results and accuracy of the proposed approach and demonstrate the feasibility of the approach over state-of-the-art methods that use handcrafted features.

2 Literature Review

Primarily, plant classification work has been conceived through four different approaches: manual classification, using image processing and computer vision, using DNA barcoding and using machine learning and deep learning approaches. Manual classification by answering a series of questions about the plant's characters is time-consuming as well as highly prone to human errors. Plant detection using image processing and computer vision is primarily done through leaf characteristics - as leaves are easily observable and accessible than other organs of the plant.

[2-5] employ image processing and computer vision methods to automatically identify plant leaf species. For instance, [2] uses shape, vein, colour and texture features to classify the leaves on Flavia dataset with an accuracy of 93.75%. [3] reviewed a variety of morphometric features like leaf outlines, flower shape, vein structures, leaf textures used for identification and concludes that no single method provides a panacea for the detection of all plant species. [4] analysed the features used in the contemporary techniques, extracts a set of fifteen best features for further classification and reports an aggregate accuracy of 87.4% on 32 species. [5] employs a classical image processing sequence: image binarization to separate the leaf and its background, detection of contours and contour corners, geometrical derivations of leaf tooth features. It was evaluated on eight species and resulted in species-specific identification up to 79.3%.

Similarly, plant disease detection work primarily revolved around three approaches: using spectral reflectance and sensing, using image processing and computer vision methods with the latest trend shifting towards machine learning and deep learning approaches. [6] examines the potential of multi-spectral remote sensing for multi-temporal analysis of wheat plant diseases and aims at real-time sensing before the disease could occur. Classification accuracy ranged from 56.8% to 88.6%. However, the results showed that high-resolution multi-spectral data are generally suitable to detect in-field heterogeneities of crop vigour but are only moderately suitable for early detection of crop infection.

[7] converts the image into H, I3A, I3B colour transformations, segments by analysing the distribution of intensities in the histogram and compares the automatically segmented images of the diseased leaves with those that were manually done. [8] implements feature extraction, segmentation, boundary and spot detections, applies zooming algorithm and classifies into various diseases using SOM neural network. [9-12] follows a classic pipeline: acquisition of images, converting the input image from RGB space to a different color space, masking and removing the green pixels, segmenting the components by methods like Otsu, k-means clustering, obtaining useful segments, computing important texture features using color co-occurrence methodologies and recognizing through classifiers like k-nearest-neighbors, SVM, SOM, probabilistic and backpropagation neural networks. [13] uses a genetic algorithm for

segmentation of the diseased leaves and reports an accuracy of 95.71% using SVM classifier. [14] proposes a mobile client-server architecture for leaf disease detection and diagnosis using a combination of Gabor wavelet transform and gray level co-occurrence matrix where a mobile client captures and pre-processes the leaf image, segments diseased patches in it and transmits to the pathology server.

However, computer vision based approaches use handcrafted and chosen features of the leaves apriori to the experimentation. Given the extreme diversity of botanical data, these approaches do not scale and generalize well as it produces absurd results when the given species has no significant appearance of the chosen features.

In recent times, DNA barcoding has started gaining traction. However, barcoding initiatives and database construction are still in progress. Further, it is an invasive method and is not applicable to herbarium specimens where DNA quality has degraded. As a result, model-free approaches and machine learning methods have been proposed to eliminate these shortcomings. One such notable approach is active learning that implements user-in-the-loop concept to engage users in the system by means of social image data contributions and mobile species recognition. [15] implements a mobile application called LeafSnap for automatically detecting tree species by computer vision components and identifies the trees with a top-5 recognition rate of 96.8% for 185 species. [16] proposed a collaborative approach called Pl@ntNet to speed up the collection and integration of raw botanical data. The web platform of Pl@ntNet hosts images of different plant organs (full plant, flower, leaf, fruit, bark, leaf scan) to identify the species. The approach was tested on a robust dataset of 2200 species, resulting in top-1 and top-5 identification rates up to 45% and 69% respectively.

A key difference between collaborative, active learning approaches such as LeafSnap and Pl@ntNet and the approach that we propose is that these methods are highly dependent on a chosen set of hand-engineered features that are selected apriori to identify a given plant species with the help of stored images in the dataset.

The ImageCLEF 2013 plant identification task [17] covered 250 species of herbs and trees present in France. Contrary to the previous versions of the tasks, the coverage of 2013 task was extended to different organs of the plants. The task identification was split into two categories of images: *SheetAsBackground* and *NaturalBackground*. The *Sabanci Okans* team reached the highest score of 0.607 in the *SheetAsBackground* category with an approach mainly centred on leaf shape boundary features [18]. *NLabUTokyo* team achieved the highest score in *NaturalBackground* category, albeit significantly lower than *SheetAsBackground* category due to the noisy background, focused on local visual features like Scale Invariant Feature Transform (SIFT) variations [19].

With the rise in computing power through graphics processing units (GPU) and the availability of large-scale image data, deep learning CNNs have made a tremendous breakthrough in the field of visual recognition, especially fine-grained image classification. Essentially, deep CNNs automatically learn task-specific features and representations of the input image data and replaces traditional computer vision methods that require hand-crafted features. [20] presented a deep CNN that uses AlexNet architecture pre-trained on the

ImageNet 2012 dataset to learn unsupervised feature representation of 44 different species and reported a performance of 99.5% outperforming conventional methods. [21] used a six-layered CNN model to classify data augmented images of 32 different species on the Flavia dataset and achieved an accuracy of 94.69%. [22] used a custom CNN architecture on the LeafSnap dataset achieving an average top-1 accuracy of 86.3% and an average top-5 accuracy of 97.8%. However, this accuracy has been obtained after a tremendous computation time involving 200,000 iterations. [23] designed a 26-layer deep learning model consisting of 8 residual building blocks and achieves a recognition rate of 91.78% on the BJFU100 dataset and 99.65% on the Flavia dataset.

The LifeCLEF 2017 plant identification challenge [24] covered a more robust dataset of 1.1 million images of 10,000 plant species. It aimed at evaluating the extent to which a large noisy training dataset collected through the web and containing a lot of labelling errors can compete with a smaller but trusted training dataset checked by experts. All the submitted runs for the challenge were based on CNNs confirming the absolute supremacy of this kind of approach over previous methods. *MarioTSABerlin* team proposed the best system among all the participating teams by using ensembles of fine-tuned CNNs pre-trained on ImageNet based on three architectures (GoogLeNet, ResNet-152 and ResNeXT) each trained with bagging techniques and thereby achieving a mean reciprocal rank of 92% and a top-5 accuracy of 96% [25]. [26] compares local feature descriptors and bags of visual words with different classifiers to from-the-scratch and fine-tuned versions of deep CNNs like AlexNet and GoogleNet on three plant datasets; AgrilPlant, LeafSnap, and Folio and concludes that deep CNN methods outperform the hand-crafted features. [27] provides an extensive review of the technical progress on computer vision and deep learning approaches for plant species identification, highlights the research challenges to overcome in designing real-world tools and explains the trends and future directions for this research area.

Following the trend, plant disease detection approaches have moved in the direction of deep learning. [28] uses CaffeNet CNN architecture to recognize 13 different types of plant diseases with an average precision of 96.3%. [29] uses a deep CNN model on a public dataset of 54,306 images to identify 14 crop species and 26 diseases with an accuracy of 99.35%. However, the dataset has images of the plant leaves on a plain background which would not scale well to real-world conditions. [30] developed CNN models for the detection of 9 different tomato diseases and pests, with satisfactory performance. [31] analyses the performance of five different models for the disease detection of 25 plant species using a public dataset of 87,848 images and achieves a success rate of 99.53% using a CNN that implements VGG architecture.

There are several limitations to the existing work:

1. A set of handcrafted features are chosen apriori to the experimentation for recognition of the diseased leaves. This approach does not scale well.
2. The implementation still lacks in accuracy of the result in a few cases and requires further optimization.
3. The existing database shows bias towards the Asian plant species. Thus, database extension is needed to incorporate diversity in recognition of plant leaves and diseases.

4. Plant leaf disease detection covers a very few diseases and work must be extended to include a larger number of diseases.
5. Few of the deep-learning approaches that have been taken requires huge computation time and a larger number of iterations. We need a simpler network with higher performance and less computational costs.

3 Indian Flora Project: plant identification based on collaborative workflow

In contrast to the other datasets where images are collected by automatic crawling of image search engines and crowdsourced applications like Amazon Mechanical Turk, the expansion of our dataset relies on a social and collaborative network of users. The Indian Flora Project platform aims to connect experts like botanists and foresters, amateur enthusiasts and general public for the integration and expansion of the dataset. This work has been deployed in two platforms - as a web interface where users can view a catalogue of plant images in the dataset, add new observations and validate the existing data and a mobile application that can be used by the general public to identify the images of plants that they capture.

3.1 Interactive web application

The web-interface of the Indian Flora Project is dedicated to the speeding up of the collection and integration of the Indian plant species and the identification of plant species using the collected data. It is composed of three main parts: a catalogue module where users can see a list of species already present on the web portal with a few sample images and details about the species, a tagging module where users can tag the images by providing the details of the plant present on the image and an annotation module where users can annotate the images of the plant species by drawing bounding boxes around the important regions present on the plant images. Fig. 1 shows these three modules of the web portal.

The web portal contains multiple levels of users ranging from normal users, curators, moderators to administrators. Every new user can sign-up by submitting a request on the portal, and the administrator approves the requests. The catalogue of images present on the portal can be viewed by any user who visits the site - irrespective of whether he has an account or not. Users can submit new observations to the dataset of the portal. If the user knows the relevant plant present on the image, the user can submit details of the plant like the scientific name, common name, family, level of the image, leaf shape, leaf margin, leaf division, health status, season and location where the image was taken, description and utility. If the user is not aware of the plant present on the image, the user can submit the image as an unknown plant. Also, while an image is being uploaded, top ten recommendations are given based on the existing species on the portal so that the user can autofill the data if it's already present. Metadata of the images are recorded when the user submits the image to the portal.

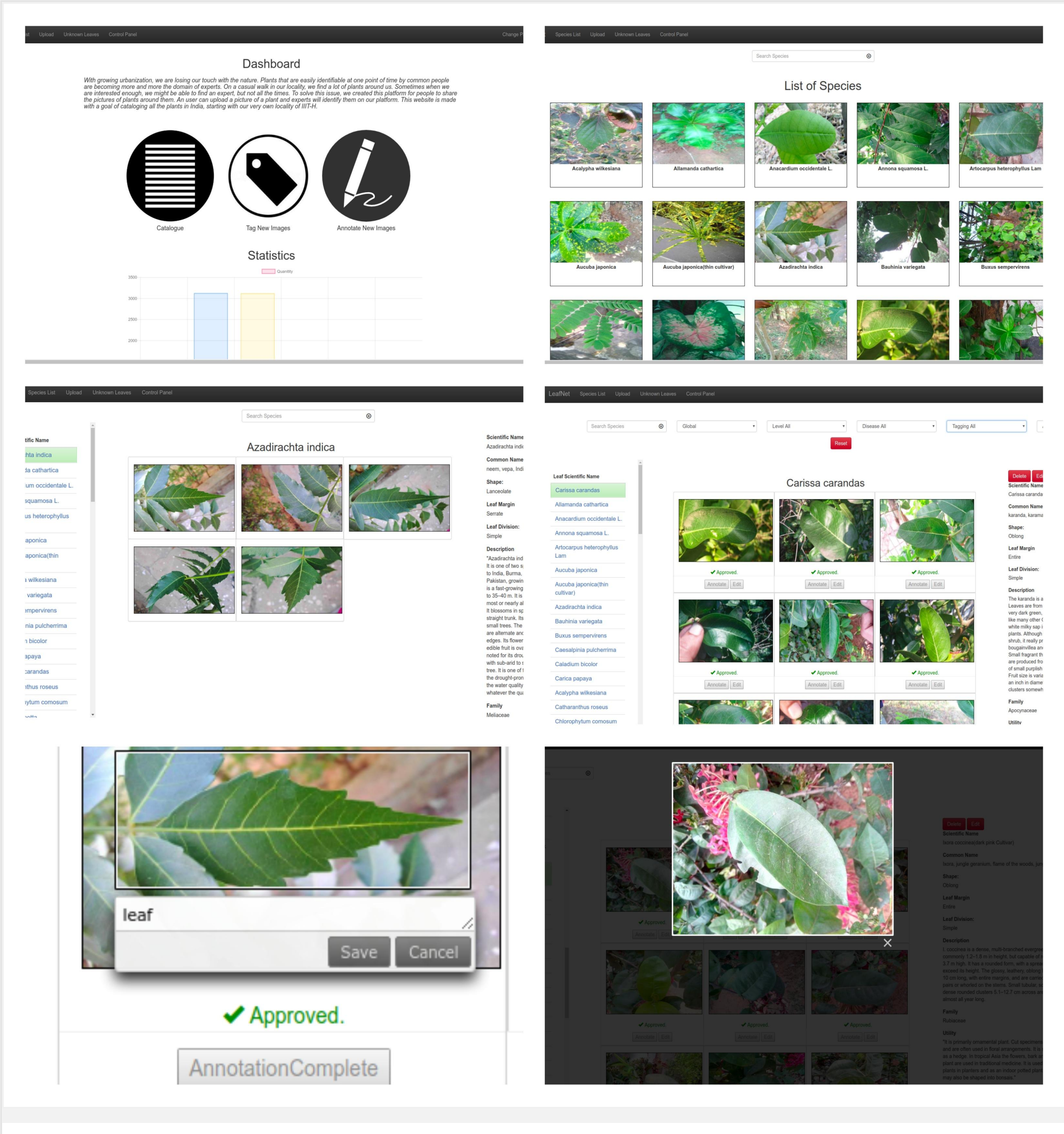
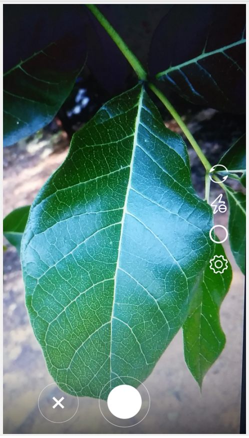


Fig 1 a) Dashboard of the portal with historical statistics of the number of species, no. of tagged, annotated images, images submitted by the respective user. b) List of species present on the portal with a responsive search bar that supports multi-language querying. c) Catalogue of species. Shows sample images and details for every plant species present on the portal. d) Tagging module. Contains all the leaf images present on the portal with an option to tag the details of the images. Also, contains an exhaustive search tool that can search the images based on multiple leaf features. e) Annotation Module - Contains all the unannotated leaves so that users can annotate the important parts of the image. f) A sample leaf image present on the portal. (Ixora coccinea - Dark Pink Cultivar)

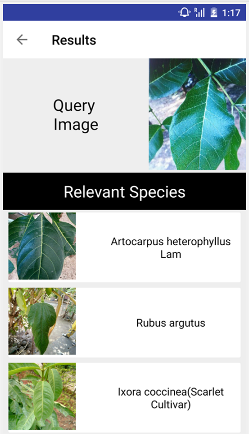
Every upload of a plant image submitted by a user is validated and approved by a set of moderators and curators who are specialized in botany to ensure the sanity of the dataset.

Untagged, unannotated and unidentified images are tagged, annotated and associated with relevant data by consensus among a pool of enthusiasts and experts. The web portal also supports robust search by multiple options such as scientific name, common name, family, shape etc. with an advantage of multi-language support. Many of the leaf images have been associated with their common names and their vernacular names in Tamil and Telugu languages.

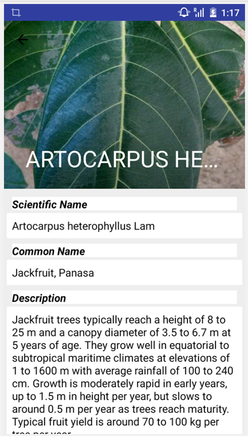
3.2 **Leaf recognition - Android mobile application**



a) Capturing a leaf image on the app.



b) The app recognizes the plant with a list of relevant species ranked on the confidence level.



c) The details of th recognized species can be viewed on the application.

Fig 2 Screenshots of the mobile application.

To allow the general public to use the results of the research work, we have developed a mobile application for plant recognition. The mobile application is now compatible with Android devices and will later be extended to iOS devices. To recognize a plant, the user has to capture a leaf or a bunch of leaves or the entire plant, crop the image and upload it through the app. The mobile application sends the processed image to the server where the image is given as input to our trained model and we display a list of candidate species ranked in the order of relevance with the uploaded plant image. The user can also view the details about the predicted species through the app. Plant species that are well illustrated in the existing botanical reference database can be easily recognized just with a click on the smartphone. Fig. 2 illustrates the user-interface of the mobile application developed for plant identification.

4 Materials and Methods

4.1 Dataset and Data Augmentation

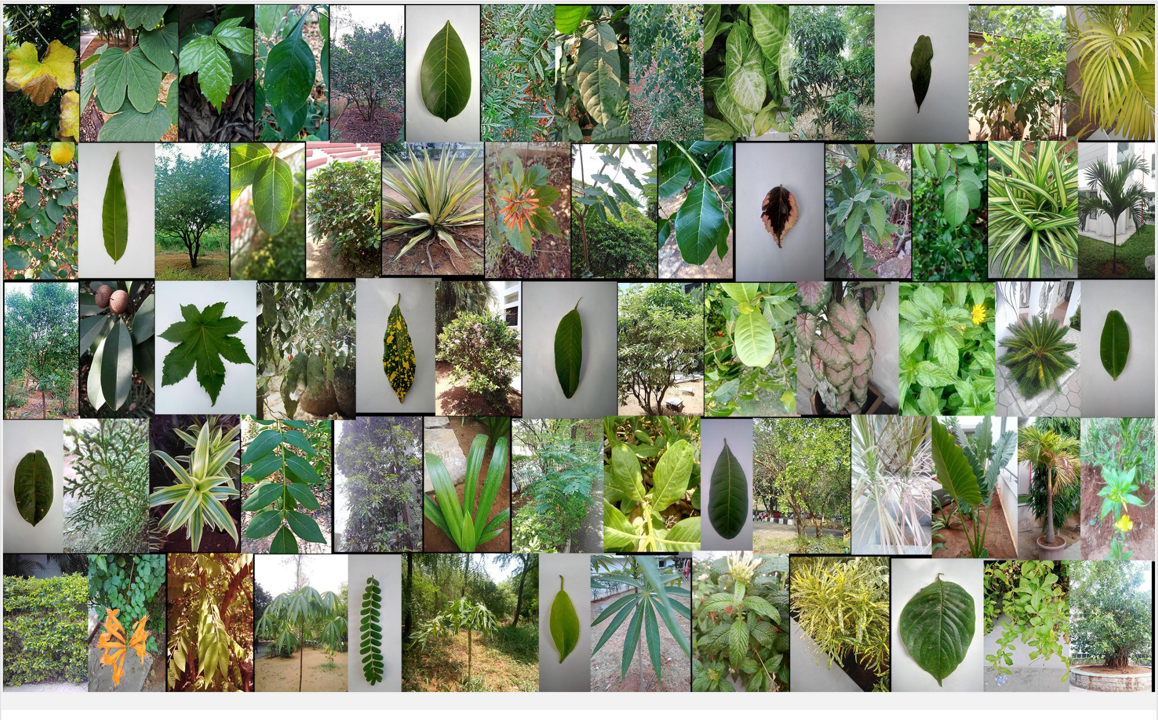


Fig 3 Example of plant images randomly chosen from the 68 species used for training and evaluation.

From the phase of training till evaluating the performance of a recognition model, suitable datasets are required at all stages of an image recognition task. A steadily expanding, new dataset of plant leaves was created with 100 Indian plant species (at the time of writing) with a target to increase the diversity of the plant species by covering the entire Indian flora. All the images in the dataset were collected manually through smartphone cameras in and around the campus of International Institute of Information Technology, Hyderabad. The plant recognition work was carried over 9500 images of 68 species in the dataset. Thus, the images of the dataset were grouped into 68 classes for the training and the evaluation phase. Samples of the dataset are illustrated in Fig. 3 and we could observe that the dataset is very challenging as leaves of different species look similar, and the images contain varying amounts of blur, background noises, illumination patterns, shadows etc.

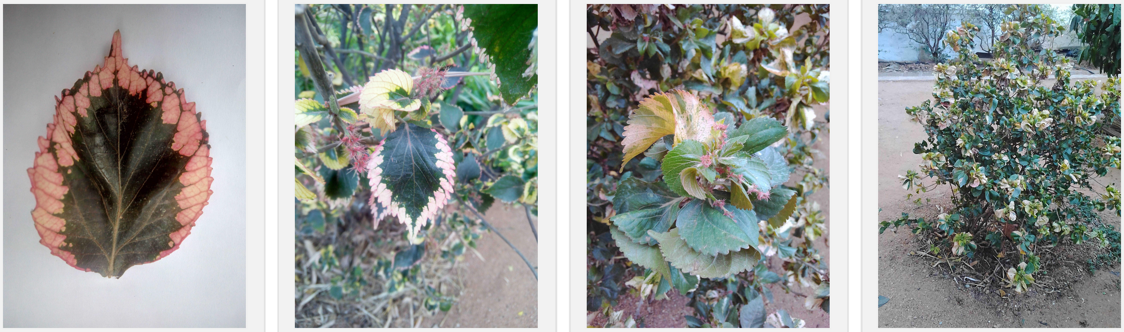
The existing datasets suffer from a few critical problems. Firstly, most of the robust plant datasets like LeafSnap, Pl@ntNet, ICL and iNaturalist cover the regions United States, Canada, European countries like France and the United Kingdom. The datasets do not take into account the diversity of Asian plant species in plant recognition. Our manually collected dataset primarily focuses on Asian species, emphasizing Indian flora. A vast number of the existing dataset contains very few number of per-species images, thus trading intra-species diversity for a high number of species. Further, the distribution of the number of images per species is abysmal - with very few species well populated, and a vast majority of species with one or few images. Much of the existing datasets contains images of leaves in a plain colour background completely neglecting the natural setting of leaves and other extraneous noises (like highly cluttered images, other plants in the background, or other objects such as fingers) [16].

In addition, the existing datasets mostly contain scanned images of a single leaf of the plant neglecting different views, focus, zoom, resolution and orientations of the plant images (scanned leaf specimens, single leaf in its natural setting, bunch of leaves, full plant view, portrait and landscape views) and different distances between the camera and the considered plant. To eliminate all these biases, each class of our dataset contains roughly 110 to 150 images ensuring equal distribution. Further, every species has four sub-classes or levels of images to incorporate the diversity of image views and orientations.

1. **Level 0:** A leaf placed on a sheet of paper or with a plain colour background.
2. **Level 1:** A leaf in its natural environment.
3. **Level 2:** A bunch or a cluster of leaves or a branch of the tree.
4. **Level 3:** A distant view of the full plant or the tree.

Having multiple levels of images for each species in the dataset generalizes well when scaled to larger usage. This is a unique addition to our dataset in comparison to the existing datasets for plant identification as these datasets mostly have images of a single leaf in a plain background (level 0 images only).

The different levels of the images of a species (Acalypha wilkesiana) are illustrated in Fig. 4. A list of species that are a part of the dataset can be found in Appendix A. Thus, for training the CNN and evaluating, we use 68 classes from this new dataset. We have used data augmentation to introduce slight distortions to the image data and eliminate the issue of overfitting by performing transformations to the image. The augmentation procedure included multiple transformations including translation, random horizontal and vertical flips, rotation and scaling of the images.



a) Level 0 Image | b) Level 1 Image | c) Level 2 Image | d) Level 3 Image

Fig 4 The four levels of images of a shrub Acalypha wilkesiana in the dataset.

4.2 Deep Learning Framework and Equipment

For all the training and evaluation, we use a deep learning framework called PyTorch [32]. PyTorch is a python package that provides several high-level features including tensor computation with strong GPU acceleration and deep neural networks built on a tape-based autodiff system. For all experiments, we employed two NVIDIA GTX GeForce 1080 GPUs in parallel using the CUDA parallel programming platform. The compute nodes ran on Ubuntu 16.04 LTS. Faster convergence due to the use of high-end GPUs facilitated in the quick iteration of different models and hyperparameter values.

4.3 Neural Network Training

We are using the ResNet18 network architecture [1] for the identification of plant species using Stochastic Gradient Descent (SGD) and cross-entropy loss. Deep CNNs can represent complex functions and can automatically learn features at various levels of abstraction. This helps in distinguishing between species that are almost similar in appearance which would go unnoticed if we use handcrafted features. However, deep networks are very hard to train because of the vanishing gradients problem. Since the gradient is backpropagated to the earlier layers, repeated matrix multiplication decreases the gradient exponentially and makes it infinitely small. Hence, the performance of the network gets saturated and starts degrading rapidly as the depth increases. The ResNet architecture introduces "identity skip connections" making it easy for the blocks to learn identity function. Thus, stacking such layers would not degrade the performance of the network as we could simply stack identity mappings and the resulting architecture would perform the same and would not result in a training error higher than shallow architectures. Thus, we use the ResNet18 model to address the problem of vanishing gradients.

Further, the image data is augmented and resized to 224x224 before feeding into the ResNet18 network. Also, the RGB colour channels are normalized by computing the mean and standard deviation of the training set.

We use four different configurations for training and evaluating out dataset.

1. **M1:** Training on our dataset from scratch.
2. **M2:** Finetuning our dataset from the weights pre-trained on ImageNet dataset [33].
3. **M3**: Training the PlantCLEF Encyclopaedia of Life (EoL) dataset from scratch. Further, finetuning our dataset from the weights that we obtained on pre-training the PlantCLEF EoL dataset,
4. **M4:** Finetuning the PlantCLEF Encyclopaedia of Life (EoL) dataset from the weights pre-trained on ImageNet dataset. Further, finetuning our dataset from the weights that we obtained on pre-training the PlantCLEF EoL dataset.

PlantCLEF dataset is a trusted training set based on the online collaborative Encyclopedia Of Life (EoL). The dataset contains 256,287 images belonging to 10,000 species. The dataset has a strong imbalance of images with a minimum of 1 picture to a maximum of 1245 pictures per class. This dataset was used as a part of the LifeCLEF plant identification challenge 2017 [24]. It is considered as an important milestone in automatic plant identification due to the larger number of species it has, albeit the species predominantly belonging to Europe and North America.

We try configurations pre-trained on datasets like ImageNet and PlantCLEF EoL as

- By pre-training our dataset from the weights and features extracted from training a CNN for visual recognition on very large datasets like ImageNet and PlantCLEF, it is likely that they have learned a diverse enough set of visual patterns to avoid underfitting.
- Our training set is not as large as PlantCLEF EoL or ImageNet.

4.4 Results and Metrics

We experimented with the above four different architectures and tuned the hyperparameters to optimize our performance metric. Our goal was to use a sufficiently deep network to be able to learn and represent complex features, but no deeper than necessary to minimize computation time. We used top-1 and top-5 precisions as our optimizing metric for the evaluation. Given m evaluation samples and y_i as the correct species class for input sample x_i, i

= 1,⋯,m, and *j = 1,⋯n*, the highest ranked species predictions according to their probability values and *I* is the indicator function that returns 1 when there is a match and 0 otherwise.

$$top - n \quad precision = \frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{n} I(\hat{y}_i = y_i) \tag{1}$$

For models M2 and M4, pre-trained weights on the ImageNet dataset are publicly available and can be downloaded from the PyTorch website. However, we trained the ResNet18 architecture manually on the PlantCLEF EoL dataset and obtained the weights with a top-1 precision of 48.32% and top-5 precision of 66.97%. CMP Czech Republic achieved the highest top-1 and top-5 precision of 74.1% and 88.7% by training on the PlantCLEF EoL dataset in the PlantCLEF 2017 challenge [24]. The participant used a combination of 8 Inception-ResNet-v2 architecture networks that were trained on the trusted EOL data solely. Since we use a much simpler ResNet18 architecture with less depth and computation time, we were able to achieve a top-1 precision of 48.32% on the PlantCLEF EoL dataset. Ultimately, these pre-trained weights are used on models M3 and M4 for further training. Table 1 illustrates the best hyperparameters and performance metrics obtained during the architecture search for the four models.

Table 1 Best hyperparameters and performance metrics obtained during architecture search.

Model	**Dataset**	**Pre-trained?**	**Optimizer**	**Batch Size**	**Learning Rate Decay**	**Number of epochs**	**top-1 precision**	**top-5 precision**
P1	PlantCLEF EoL	No	SGD with momentum = 0.9	10	Decay of 0.1 when there is no improvement after 5 epochs.	50	40.35	59.08
P2	PlantCLEF EoL	Yes. Pre-trained on ImageNet	SGD with momentum = 0.9	10	Decay of 0.1 when there is no improvement after 5 epochs.	50	48.32	66.97
M1	Our dataset (IIIT-H)	No	SGD with momentum = 0.95	5	Decay of 0.15 every 7 epochs.	30	78.22	95.87
M2	Our dataset (IIIT-H)	Yes. Pre-trained on ImageNet	SGD with momentum = 0.9	5	Decay of 0.1 every 7 epochs.	30	94.38	99.57

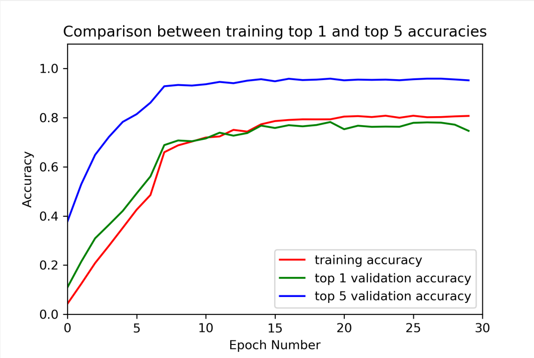
M3	Our dataset (IIIT-H)	Yes. Pre-trained on weights from model P1.	SGD with momentum = 0.9	5	Decay of 0.1 when there is no improvement after 5 epochs.	30	94.92	99.64
M4	Our dataset (IIIT-H)	Yes. Pre-trained on weights from model P2.	SGD with momentum = 0.9	5	Decay of 0.1 when there is no improvement after 5 epochs.	30	**96.76**	**99.85**

It is to be noted that the PlantClef EoL dataset contains 256,287 images belonging to 10,000 species and our dataset (IIIT-H) contains 9386 images belonging to 68 species. All the training work was done with an initial learning rate of 0.001. We used a training-validation split of 80-20 for models P1, P2 and 70-30 for models M1, M2, M3 and M4 to obtain the best performance metric for the respective models.

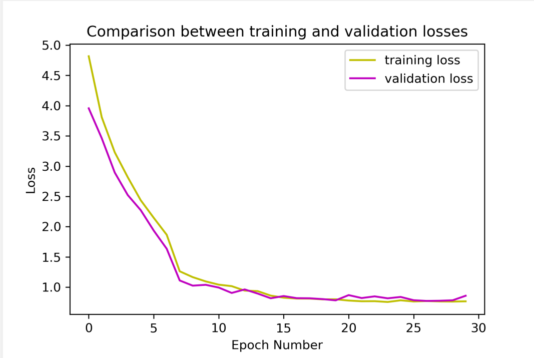
On iterating through different hyperparameters and models, we found that the learning rate decay and the batch size had the largest effect on speeding up the convergence and getting the desired performance metric. Precision benefitted from data augmentation as it introduced slight variations to the image data and allowed the model to learn on rotation invariant properties of the leaf such as colour, shape, texture rather than orientation. Fig 5 and 6 illustrates the precision and loss curves obtained from training the models M1, M2, M3 and M4 with the best set of hyperparameters.

For our highest performing model we obtained an average top-1 and top-5 precision of 96.76 and 99.85 respectively. We used the pre-trained weights of ImageNet that were publicly available on the internet for training models P2 and M2. On the contrary, we used the weights obtained from model P1 and P2 to train model M3 and M4 respectively. In spite of the fact that these pre-trained weights achieve a maximum top-1 precision of 48.32% on the PlantCLEF EoL dataset, these weights performed well on our dataset than the ImageNet weights by reporting a top-1 and top-5 precision of 96.76 and 99.85.

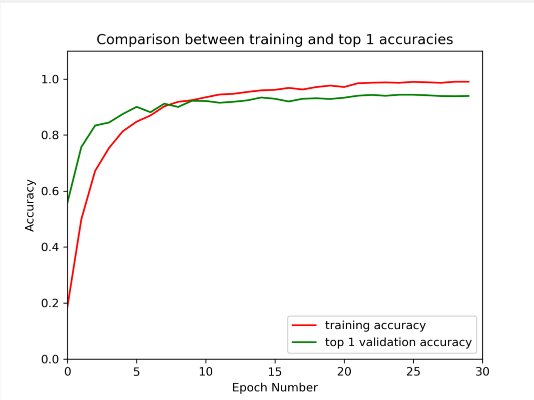
ImageNet is the largest visual database consisting of tens of millions of images belonging to several thousand categories of English nouns. On the other hand, the PlantCLEF EoL dataset contains lakhs of images of plant species belonging to ten thousand categories. One key observation from our result is that using pre-trained weights from a plant-exclusive dataset like PlantCLEF EoL (96.76%) outperforms the training done using a more large, robust and generalized dataset like the ImageNet (94.38%).



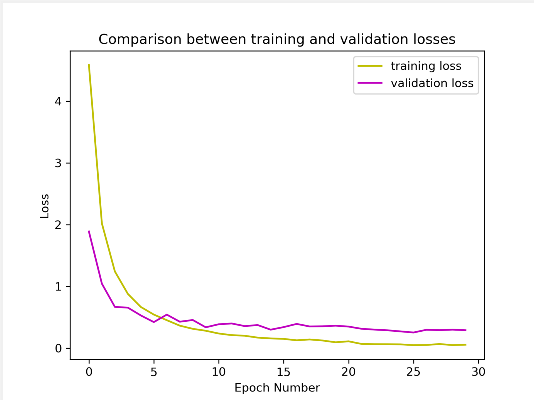
a) Precision Curve (M1)



b) Loss Curve (M1)

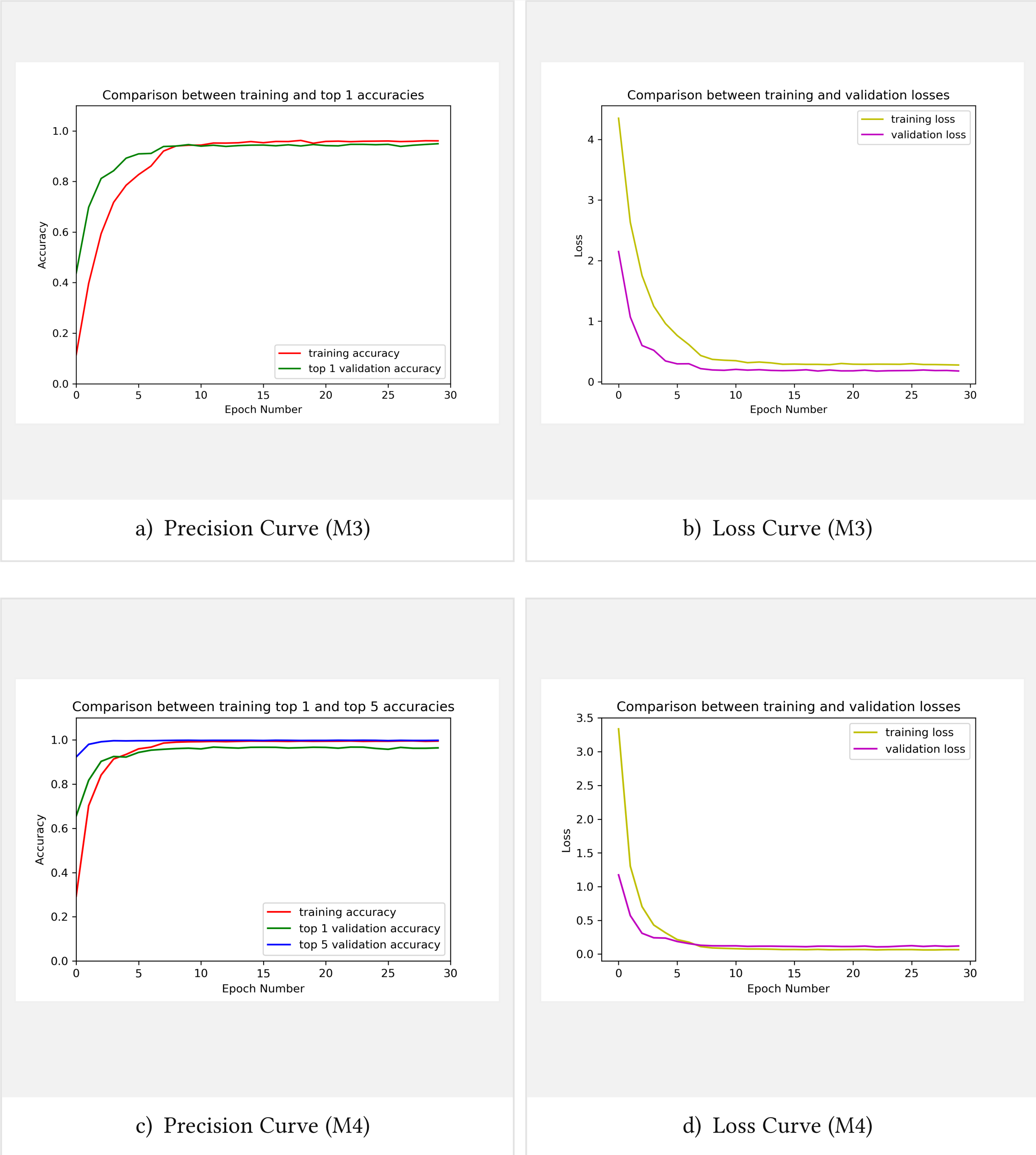


c) Precision Curve (M2)



d) Loss Curve (M2)

Fig 5 Precision and Loss Curves for models M1 and M2



a) Precision Curve (M3)

b) Loss Curve (M3)

c) Precision Curve (M4)

d) Loss Curve (M4)

Fig 6 Precision and Loss Curves for models M3 and M4

The analysis of the few outliers shows that the misclassification happens in the following cases:

- Species that show very strong visual similarities, shape and textures.

- Species that were represented in our dataset with a fewer number of images making the training process difficult.

5 Future Work and Conclusion

Extending the ResNet18 CNN architecture for disease detection and diagnosis of plant species remain inconclusive and will be a part of our future work. Another line of our future work includes expanding the dataset with a larger number of plant species by use of the proposed collaborative platform. Further, the extracted metadata and geolocation from the images will be used as features in the training process to make it more robust to strong visual similarities. Also, a number of collaborative features and feedback loop will be added to the existing platform. Though the proposed CNN architecture achieves a very high success rate, it is still quite far from being a generic tool that can be used in real-world conditions. However, as the proposed deep learning approach showed a very high precision, real-world identification can be greatly improved and made more robust by increasing the quantity, quality and diversity of the available data through the proposed platform.

This paper proposed an online collaborative pipeline for speeding up the collection and integration of botanical data through a web platform and provide a user-friendly plant-identification tool through a mobile application. The efforts taken towards initiating this workflow has resulted in a dataset of 100 Indian Species with images of various levels, views and orientations. We demonstrated plant identification through a deep convolutional neural network architecture ResNet18 to classify 68 species from our dataset as an efficient method than detection through image processing methods that employ a set of hand-crafted features. We discussed the results of four different models used for experimentation by training from scratch, from pre-trained weights on the ImageNet and PlantClef EoL datasets. From the experimental results, we observe a high top-1 precision of 96.76% and a top-5 precision of 99.85%. We also noted that transfer learning from a more specific plant dataset like PlantCLEF EoL outperforms transfer learning from a more large and generalized dataset like ImageNet. In conclusion, we deployed an effective collaborative system for enriching the dataset, and the results of our experimentation show that transfer learning from a large relevant dataset offers high precision, high throughput and a non-invasive solution for plant identification. More specifically, ResNet18 model pre-trained on the PlantCLEF EoL dataset with SGD and learning rate decay outperforms all other methods in terms of top-1 precision while using a relatively smaller number of layers and less number of epochs to converge than other models.

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References

[1] He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. 2016.

[2] Kadir, Abdul, Lukito Edi Nugroho, Adhi Susanto, and Paulus Insap Santosa. "Leaf classification using shape, color, and texture features." arXiv preprint arXiv:1401.4447 (2013).

[3] Cope, James S., David Corney, Jonathan Y. Clark, Paolo Remagnino, and Paul Wilkin. "Plant species identification using digital morphometrics: A review." Expert Systems with Applications 39, no. 8 (2012): 7562-7573.

[4] Ahmed, Nisar, Usman Ghani Khan, and Shahzad Asif. "An automatic leaf based plant identification system." Science International 28, no. 1 (2016).

[5] Jin, Taisong, Xueliang Hou, Pifan Li, and Feifei Zhou. "A novel method of automatic plant species identification using sparse representation of leaf tooth features." PloS one 10, no. 10 (2015): e0139482.

[6] Franke, Jonas, and Gunter Menz. "Multi-temporal wheat disease detection by multi-spectral remote sensing." Precision Agriculture 8, no. 3 (2007): 161-172.

[7] Camargo, A., and J. S. Smith. "An image-processing based algorithm to automatically identify plant disease visual symptoms." Biosystems engineering 102, no. 1 (2009): 9-21.

[8] Phadikar, Santanu, and Jaya Sil. "Rice disease identification using pattern recognition techniques." In Computer and Information Technology, 2008. ICCIT 2008. 11th International Conference on, pp. 420-423. IEEE, 2008. Harvard

[9] Al-Hiary, H., S. Bani-Ahmad, M. Reyalat, M. Braik, and Z. ALRahamneh. "Fast and accurate detection and classification of plant diseases." Machine learning 14, no. 5 (2011).

[10] Al Bashish, Dheeb, Malik Braik, and Sulieman Bani-Ahmad. "Detection and classification of leaf diseases using K-means-based segmentation and." Information Technology Journal 10, no. 2 (2011): 267-275.

[11] Kulkarni, Anand H., and Ashwin Patil. "Applying image processing technique to detect plant diseases."*International Journal of Modern Engineering Research*2, no. 5 (2012): 3661-3664.

[12] Arivazhagan, Sai, R. Newlin Shebiah, S. Ananthi, and S. Vishnu Varthini. "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features."*Agricultural Engineering International: CIGR Journal*15, no. 1 (2013): 211-217.

[13] Singh, Vijai, and A. K. Misra. "Detection of plant leaf diseases using image segmentation and soft computing techniques." Information Processing in Agriculture 4, no. 1 (2017): 41-49.

[14] Prasad, Shitala, Sateesh K. Peddoju, and Debashis Ghosh. "Multi-resolution mobile vision system for plant leaf disease diagnosis."*Signal, Image and Video Processing*10, no. 2 (2016): 379-388.

[15] Kumar, Neeraj, Peter N. Belhumeur, Arijit Biswas, David W. Jacobs, W. John Kress, Ida C. Lopez, and João VB Soares. "Leafsnap: A computer vision system for automatic plant species identification." In Computer vision–ECCV 2012, pp. 502-516. Springer, Berlin, Heidelberg, 2012.

[16] Joly, Alexis, Hervé Goëau, Pierre Bonnet, Vera Bakić, Julien Barbe, Souheil Selmi, Itheri Yahiaoui et al. "Interactive plant identification based on social image data." Ecological Informatics 23 (2014): 22-34.

[17] Goëau, Hervé, Alexis Joly, Pierre Bonnet, Vera Bakic, Daniel Barthélémy, Nozha Boujemaa, and Jean-François Molino. "The imageCLEF plant identification task 2013." In Proceedings of the 2nd ACM international workshop on Multimedia analysis for ecological data, pp. 23-28. ACM, 2013.

[18] Yanikoglu, Berrin A., Erchan Aptoula, and S. Tolga Yildiran. "Sabanci-Okan System at ImageClef 2013 Plant Identification Competition." In CLEF (Working Notes). 2013.

[19] Nakayama, Hideki. "NLab-UTokyo at ImageCLEF 2013 Plant Identification Task." In CLEF (Working Notes). 2013.

[20] Lee, S.H., Chan, C.S., Wilkin, P., Remagnino, P., 2015. Deep-Plant: Plant Identification with convolutional neural networks. Image process. ICIP 2015. IEEE Int. Conf. IEEE 452–456.

[21] Zhang, Chaoyun, Pan Zhou, Chenghua Li, and Lijun Liu. "A convolutional neural network for leaves recognition using data augmentation." In Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing (CIT/IUCC/DASC/PICOM), 2015 IEEE International Conference on, pp. 2143-2150. IEEE, 2015.

[22] Barré, Pierre, Ben C. Stöver, Kai F. Müller, and Volker Steinhage. "LeafNet: A computer vision system for automatic plant species identification." Ecological Informatics 40 (2017): 50-56.

[23] Sun, Yu, Yuan Liu, Guan Wang, and Haiyan Zhang. "Deep Learning for Plant Identification in Natural Environment." Computational intelligence and neuroscience 2017 (2017).

[24] Goeau, Herve, Pierre Bonnet, and Alexis Joly. "Plant identification based on noisy web data: the amazing performance of deep learning (LifeCLEF 2017)." CEUR Workshop Proceedings, 2017.

[25] Lasseck, Mario. "Image-based plant species identification with deep convolutional neural networks." *Working Notes of CLEF*2017 (2017).

[26] Pawara, Pornntiwa, Emmanuel Okafor, Olarik Surinta, Lambert Schomaker, and Marco Wiering. "Comparing Local Descriptors and Bags of Visual Words to Deep Convolutional Neural Networks for Plant Recognition." In ICPRAM, pp. 479-486. 2017.

[27] Wäldchen, Jana, Michael Rzanny, Marco Seeland, and Patrick Mäder. "Automated plant species identification—Trends and future directions." PLoS computational biology 14, no. 4 (2018): e1005993.

[28] Sladojevic, Srdjan, Marko Arsenovic, Andras Anderla, Dubravko Culibrk, and Darko Stefanovic. "Deep neural networks based recognition of plant diseases by leaf image classification." Computational intelligence and neuroscience 2016 (2016).

[29] Mohanty, Sharada P., David P. Hughes, and Marcel Salathé. "Using deep learning for image-based plant disease detection." Frontiers in plant science 7 (2016): 1419.

[30] Fuentes, Alvaro, Sook Yoon, Sang Cheol Kim, and Dong Sun Park. "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition." Sensors 17, no. 9 (2017): 2022.

[31] Ferentinos, Konstantinos P. "Deep learning models for plant disease detection and diagnosis." Computers and Electronics in Agriculture 145 (2018): 311-318.

[32] Paszke, Adam, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. "Automatic differentiation in pytorch." (2017).

[33] Deng, Jia, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. "Imagenet: A large-scale hierarchical image database." In Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, pp. 248-255. Ieee, 2009.

Appendices

Appendix A - List of plants in the dataset

List of plants in the dataset. Common names and the Scientific names of the plant species has been provided.

1	Jackfruit	Artocarpus heterophyllus Lam
2	Kadamba	Neolamarckia cadamba
3	Kanchanara	Bauhinia variegata
4	Bakul	Mimusops elengi
5	Plumeria	Plumeria obtusa
6	Euphorbia	Euphorbia milii
7	Periwinkle	Catharanthus roseus
8	Indian Rhubarb	Darmera peltata
9	Mandaram	Hibiscus rosa-sinensis L.
10	Rose	Rosa kordesii
11	Custard Apple	Annona squamosa L.
12	Sausage Tree	Kigelia africana
13	Karanda	Carissa carandas
14	Jasmine Crape	Tabernaemontana divaricata
15	Ashoka	Polyalthia longifolia
16	Sapota	Manilkara zapota
17	Lemon	Citrus limon (L.) Osbeck
18	Mosambe	Citrus limetta
19	Gauva	Psidium guajava L.
20	Kanakambharam	Crossandra infundibuliformis (L.) Nees

21	Marigold	Tagetes erecta L.
22	Tamarind	Tamarindus Indica
23	Pomegranate	Punica granatum L.
24	Repala Chettu	Wrightia tinctoria R.BR

Note The first 68 plants were used for training and evaluation.

(*Continued*)

25	Gliricidia	Gliricidia sepium
26	Drumsticks	Moringa oleifera
27	Gandham	Santalum album
28	Cashew	Anacardium occidentale L.
29	Plumbago	Plumbago zeylanica
30	Boxwood	Buxus
31	Ixora Orange	Ixora coccinea(Orange Cultivar)
32	Ixora Bright Pink	Ixora coccinea(Bright pink Cultivar)
33	Ixora Dark Pink	Ixora coccinea(Dark pink Cultivar)
34	Ixora Scarlet	Ixora coccinea(Scarlet Cultivar)
35	Arrow Head	Synogonium podophyllum
36	Cape Honey Suckle	Tecoma capensis
37	Jasmine Pinwheel	Tabernaemontana divaricata(pinwheel)
38	Gold Dust	Aucuba japonica
39	Peacock Tail	Cupressus sempervirens
40	Neem	Azadirachta indica
41	Mango	Mangifera indica
42	Acalypa	Acalypha wilkesiana
43	Song Of India	Dracaena reflexa

44	Amla	Phyllanthus emblica
45	Black Berry	Rubus argutus
46	Spider Plant	Chlorophytum comosum
47	Gold Dust(Thin)	Aucuba japonica(thin)
48	Tangedu	Senna auriculata
49	Spider Lily	Hymenocallis littoralis

(*Continued*)

50	Caladium	Caladium bicolor
51	Snoutbean	Rhynchosia courtallensis
52	Peacock Flower	Caesalpinia pulcherrima
53	Indian Tree Spurge	Euphorbia tirucalli
54	Singapore Diasy	Sphagneticola trilobata
55	Schefflera	Schefflera taiwaniana
56	Sago Palm	Cycas revoluta
57	Castor	Ricinus communis L.
58	Papaya	Carica papaya
59	Butterfly Palm	Dypsis lutescens
60	Java Plum	Syzygium cumini
61	Mauritius Hemp	Furcraea foetida ‘Medio-picta’
62	Weeping Fig	Ficus benjamina
63	Banyan	Ficus benghalensis
64	Star Cluster	Pentas lanceolata
65	Dragon Tree	Dracena marginata 'Colorama'
66	Colocasia	Colocasia esculenta
67	Golden Trumpet	Allamanda cathartica

68	Rela Chettu	Cassia fistula
69	Ganneru	Nerium oleander L.
70	Gulmohar	Delonix regia
71	Tulsi	Ocimum tenuiflorum L.
72	Four O'Clock	Mirabilis jalapa
73	Air Plant	Bryophyllum pinnatum
74	Perfume Flower Tree	Fagraea ceilanica

(*Continued*)

75	Badam	Terminalia catappa
76	Curry Leaves	Murraya koenigii
77	Insulin	Costus pictus
78	Kamala	Citrus sinensis.
79	Kanuga	Millettia pinnata
80	Candle Bush	Senna alata (L.) Roxb.
81	Nalleru	Cissus quadrangularis
82	Junglee Kikar	Prosopis juliflora
83	Touch Me Not	Mimosa pudica
84	Etha	Phoenix sylvestris Roxb.
85	Lipstic Tree	Bixa orellana
86	Jasmine Arabian	Jasminum sambac var. 'Belle of India'
87	Sarpagandha	Rauvolfia serpentina
88	Pulla Jemudu	Euphorbia Tirucalli
89	Pink Paper	Bougainvillea Glabra Choisy
90	Subabul	Leucaena leucocephala
91	Canna	Canna x generalis 'Yellow King Humbert'

92	Thorn Apple	Datura innoxia Mill.
93	Pumpkin	Cucurbita Maxima
94	Whistling Pine	Casuarina equisetifolia (Syn. C. muricata)
95	Chamanti	Chrysanthemum indicum
96	Teku	Tectona grandis
97	Subabul	Leucaena leucocephala
98	Jilledu	Calotropis gigantea
99	Gorintaku	Lawsonia inermis

(*Continued*)

100	Red Sandal	Pterocarpus santalinus