Identification Of Medicinal Plants from Leaf Images

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Abstract*—Recognition quest for medicinal herbs is a continuous field of exploitation and is crucial in ayurvedic industries. Incorrect identification leads to adverse effects. One of the most entrusted classification tools is Support Vector Machine(SVM), which deals with high dimensional feature space and is generally a crucial aspect of image data. This paper proposes a comparison of a novel multi-class prediction to segregate plant leaves based on an SVM classifier and a deep ensemble learning based on Resnet50 and InceptionV3 for leaf classification implemented, each model was individually trained before ensembling. The findings from the trained model can be integrated into a web application. The SVM model was built in four stages. Stage 1 involves data preprocessing using techniques like grayscaling, smoothing, thresholding, morphological transformation, and boundary extraction to make the data suitable for SVM-based classification. In Stage 2 shape based, colour-based, and texture-based features are extracted, and a comma-separated delimiter file is generated that would be fitted in an SVM classification model. Stage 4 is the model-building and testing stage wherein classification, feature scaling, and parameter tuning is done to obtain optimal hyperparameters for the SVM classifier. The transfer learning approach was used to initialize the parameters and pretrain Neural networks namely InceptionV3, and ResNet50. When training the models on the relevant dataset, the softmax layer coupled to the dense layer served as the classifier and was used to extract features from the input photos. The last stage involves integrating the solution into a web application. The real-time leaf images can be captured by the user utilizing a camera to obtain plant names from images and upload them to a web interface. The whole framework is compared with the existing frameworks for plant leaf classification.

Index Terms—SVM, preprocessing, hyperparameters, ensemble, Resnet50, feature extraction ,Inception, Transfer Learning.

***Index Terms*—SVM,preprocessing, hyperparameters**

I. Introduction

For millennia, plants have played a crucial role in traditional medicine. They offer a wide diversity of chemicals that can be utilised to treat a wide range of illnesses and are the source of many contemporary medications. As a result, there is a rising level of interest in identifying and describing plants with therapeutic characteristics. Predicting a plant's therapeutic qualities from its physical features, such as its leaves, is one method of doing this.

Plants' leaves are an essential component and can reveal vital information about their therapeutic potential. They may be used to identify different plant species and contain a variety of substances that can be utilised to treat various ailments. It is now possible to infer a plant's therapeutic qualities from photographs of its leaves because of the growing accessibility of digital imaging technologies and machine learning algorithms. Fig.1. shows a general framework of the Leaf detection model. In this study, we investigate how machine learning algorithms might be used to infer a plant's therapeutic qualities from photographs of its leaves. In order to forecast the medicinal characteristics of a plant, we examine a dataset.

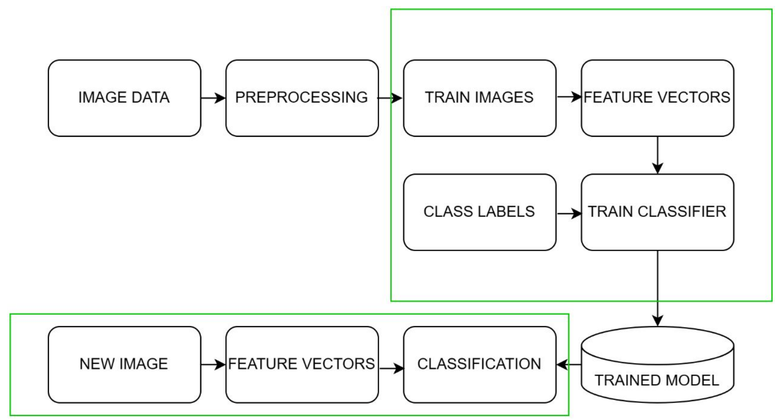

Fig. 1. General framework of the leaf recognition system

II. Literature Review

In recent years, there has been an increased interest in using machine learning techniques to predict the medicinal properties of plants based on their physical characteristics, including leaf morphology. This approach holds promise for identifying novel sources of natural remedies and improving the efficacy and safety of existing medicines.

Multi-feature sets have been investigated by the authors of [1] for the identification of medicinal plant leaves. Leaf shape, colour, texture, vein, and other characteristics make up the feature set for the training process in standard plant identification. Even while they might not be identical, there are situations when the leaf exactly matches the image from the training phase. Therefore, it is crucial to determine the system's correctness. Accuracy is a very important consideration in the identification of medicinal plants. Typically, the shapes of the images—such as oval, rectangular, oblong, etc.—are used to categorise them. Unfortunately, this shape trait has not been characterised in any of the research.

A transfer learning technique was put out by Y. R. Azee and C. Rajapakse[2] to identify the 5-7 different herbal plant varieties that were collected in Sri Lanka. The inception model's feature extraction component extracted and cached about 2048 features for each leaf. The target job of classifying plants required the application of taught concepts. The Resnet achieved the greatest accuracy of 95.5(%) when the model was retrained and compared with various deep learning models, including Inception-v3, Resnet, MobileNet, and Inception Resnet v2.

Using a neural network model, Nadia Jmour, Sehla Zayen, and Afef Abdelkrim [3] demonstrated the automatic detection of medicinal plants. The RGB leaf image was turned into a grayscale image during the preprocessing stage. A median filter was used to eliminate noise from this image. In addition to removing noise, the median filter preserves important characteristics like the leaf tip and border. Dynamic thresholding was used for the partitioning. The binary image contained eight features that were extracted. The neural network model, which categorises the plants based on the leaf, was given the extracted features.

Vickneswari Durairajah [4] proposed a comparison of SVM and Deep Convolutional Neural Networks, two categorization models. The Malaysian Agriculture Department's botanical garden provided about 50 leaves of 20 distinct sorts. We used FindContours to get the leaf's border. Hu and Zenkire moments were used to derive shape descriptors. Based on GLCM characteristics, the texture features were obtained. On both the test images and the live shots that were taken, two categorization models were used. On test images, SVM and DNN both scored 86.63 (%) recognition accuracy, but SVM only managed to achieve 74.63 (%) recognition accuracy and DNN only managed to achieve 93(%) accuracy on live collected images.

Archita Shastry[5] proposed a paper whose main objective is to classify seven classes of medicinal plants based on their leaves using three different techniques-Support Vector Machines, Transfer Learning - VGG16 Model, and a real-time object detection algorithm You Only Look Once. This paper has been use as **Base Paper**.

Kayiram Kavitha; Prashant Sharma; Shubham Gupta; R.V.S. Lalitha [6]compares the Convolutional Neural Networks (CNN) variants viz., MobileNet, ResNet50, Inception v3, Xception, and DenseNet121 for Indian origin medicinal plant species detection.

III. Proposed Solution

A. Data Description

Our dataset consists of 1891 images belonging to 30 classes. It has been splitted in ratio 0.2 into training and testing images.

Fig. 2. Glimpse of dataset

A glimpse of the dataset is shown in fig 3

A. Scientific Name	B. Common Name
Alpinia Galanga	Rasna
Amaranthus Viridis	Arive-Dantu
Artocarpus Heterophyllus	(Jackfruit)
Azadirachta Indica	Neem
Basella Alba	Basale
Brassica Juncea	Indian Mustard
Carissa Carandas	Karanda
Citrus Limon	Lemon
Ficus Auriculata	Roxburgh fig
Ficus Religiosa	Peepal Tree
Hibiscus Rosa-sinensis	China Rose
Jasminum	Jasmine
Mangifera Indica	Mango
Mentha	Mint
Moringa Oleifera	Drumstick
Muntingia Calabura	Jamaica Cherry-Gasagase
Murraya Koenigii	Curry
Nerium Oleander	Oleander
Nyctanthes Arbor-tristis	Parijata
Ocimum Tenuiflorum	Tulsi
Piper Betle	Betel
Plectranthus Amboinicus	Mexican Mint
Pongamia Pinnata	Indian Beech
Psidium Guajava	Guava
Punica Granatum	Pomegranate
Santalum Album	Sandalwood
Syzygium Cumini	Jamun
Syzygium Jambos	Rose Apple
Tabernaemontana Divaricata	Crape Jasmine
Trigonella Foenum-graecum	Fenugreek

fig.3 : Scientific and common names of plant species

B. Data Visualisation

We can see the data is quite balanced except for a couple of outliers for a couple of classes.

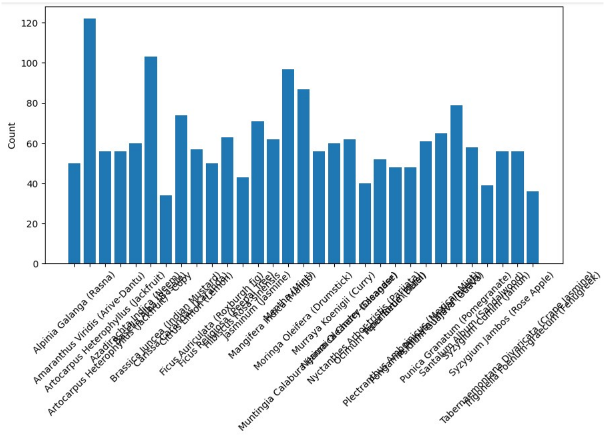

fig.5 : Class distribution for 30 species

C. Feature Extraction

SVM model- The most important features of an image-based classification problem are rooted in the shape, colour, and texture of data. Hence extraction of such features was done using the implementation of various methods. For shape-based features area and perimeter are calculated. Best fit rectangle and ellipse fit, however, rectangle bounding is been preferred so as to inculcate the slightest extreme ends. Now the shape-based features -aspect ratio, rectangularity, eudiometer, and circularity are calculated. Extraction of Color based features revolves calculation of the mean and standard deviation of the RGB channels. Next Hara licks moments were formulated to extract texture-based features- contrast, correlation, and entropy.

Ensemble Classifier- The ensemble classifier initially pre-processed, scaled and split the images into training and test sets. An ensemble classifier of InceptionV3 and ResNet50 typically uses transfer learning to perform feature extraction on a dataset. Transfer learning is a popular technique in deep learning, where a pre-trained model on a large dataset is used as a starting point for a new task. The following steps were performed to extract feature vectors from pre-trained Resnet50 and InceptionV3-

1. Pre-trained Inception V3 and ResNet50 models were loaded the top classification layers were removed.

2. The weights of the pre-trained models were frozen to prevent them from being updated during training.

3. The pre-trained models were used as feature extractors to extract features from the input data. This was typically done by passing the input data through the pre-trained models and collecting the activations from one of the intermediate layers.

4. The extracted features from both models were combined into a single feature vector. This can be done by concatenating the feature vectors or using a more complex method, such as a neural network.

```
Total params: 24,652,190
Trainable params: 1,064,478
Non-trainable params: 23,587,712
```

fig.6 : Network Parameters

D. Building the classification model and training

A classification model was built upon one of the most entrusted multi-class classification tool support vector machines (SVM). Furthermore, features were standardized using the required scaler. The SVM classifier achieved an accuracy of around 89(%).

InceptionV3 was made by modifying the previous Inception architecture. It consumes less computational power and proved to be more efficient in terms of the number of parameters generated by the network and expenses incurred in terms of memory or other resources. The main points in the architecture are factorized convolutions to check network efficiency, smaller convolutions for faster training, asymmetric convolutions, an auxiliary classifier that acts as a regularizer, and a reduction in grid size using pooling operations.

Resnet 50 stands for Residual Networks and comprises 50 layers. It increases the recognition accuracy and overcomes the vanishing gradient or degradation problems of CNN. It introduces an identity mapping concept that provides a shortcut for the gradient to flow if the presentation layer is not necessary. This also helps to reduce the overfitting problem of the training set. The residual networks help to optimize the deep neural network models.

Two Convolutional Neural Network models—InceptionV3, and ResNet50—were individually trained for the training set photos and transfer learning. In order to add our pooling and dense layers and output the leaf species from the dataset, these models were imported without their final layers. These models underwent 10 epochs of training.

Transfer learning- Transfer Learning as a machine learning approach has been widely used in the field of image recognition. The purpose of transfer learning is to use existing knowledge to solve a completely new or different problem. The extent to which the features are common between the target and source fields, the easier the knowledge transfer becomes. The main problem it tries to solve is the problem of a limited number of training samples in the target domain which makes it hard for the deep learning algorithm to learn features. It can be further divided into inductive and unsupervised based on whether the samples are marked in source and target fields and whether the tasks are the same. Based on the contents of the transfer learning methods can be divided into feature representation, transfer, instance transfer, parameter transfer, and association relationship transfer. Based on the feature space of source and target domains, it can be divided into homogenous and heterogeneous transfer learning.

Ensemble learning- Ensemble learning enhances the performance of the classifiers. The methods mainly include bagging, boosting, and stacking. An ensemble takes into consideration homogenous or heterogeneous classes. In the former, there is a single base classifier that is trained on different datasets while in the latter, different classifiers are trained on the same dataset. The ensemble then predicts the output based on the average, weighted average, and voting on the outputs obtained by the base classifiers. For the automatic detection of medicinal leaves, we have used the heterogenous ensemble approach using weighted averages to obtain the final result. The ensemble framework is shown in fig 7.

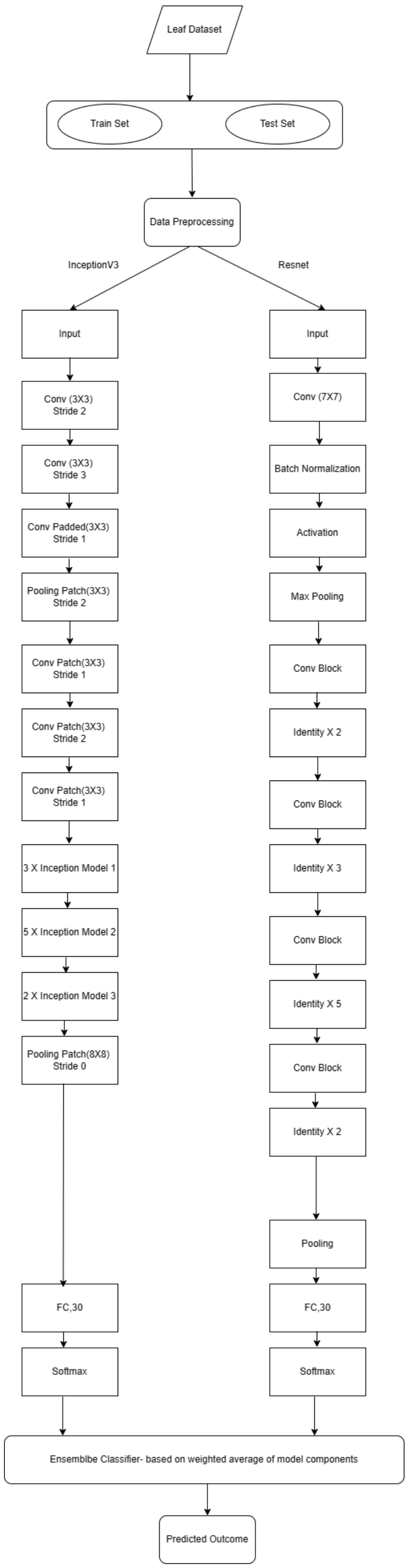

fig.7 : Ensemble Framework

E. Evaluating SVM model

Measuring accuracy, precision, recall, and F-1 score metrics to ensure that the model is performing as expected. The classification metrics values are shown in Fig. 5.

	precision	recall	f1-score	support
0	0.92	0.73	0.81	15
1	0.79	0.92	0.85	36
2	0.91	0.83	0.87	24
3	0.85	0.89	0.87	19
4	0.89	0.97	0.93	34
5	1.00	1.00	1.00	10
6	0.94	0.94	0.94	17
7	0.72	1.00	0.84	13
8	0.87	0.81	0.84	16
9	0.91	1.00	0.95	20
10	1.00	0.90	0.95	10
11	0.83	0.92	0.87	26
12	0.87	0.95	0.91	21
13	1.00	0.93	0.96	28
14	0.90	0.90	0.90	20
15	0.92	1.00	0.96	11
16	0.89	0.80	0.84	20
17	0.74	0.95	0.83	21
18	1.00	0.86	0.92	14
19	0.92	0.75	0.83	16
20	1.00	0.56	0.71	18
21	1.00	1.00	1.00	7
22	0.95	0.90	0.93	21
23	1.00	0.89	0.94	18
24	0.91	0.95	0.93	22
25	1.00	0.86	0.92	14
26	0.71	0.91	0.80	11
27	1.00	0.90	0.95	29
28	0.91	0.83	0.87	12
29	1.00	1.00	1.00	8
accuracy			0.89	551
macro avg	0.91	0.90	0.90	551
weighted avg	0.90	0.89	0.89	551

fig.8 : SVM classification report

Thereby, terminating the model-building process and providing a framework for categorization in the field of research. A detailed plan of action involves the following steps.

F. Optimizing SVM classifier using GridsearchCV

Since the hyper-parameters regulate the training process, parameter tuning using GridSearchCV was performed in order to obtain appropriate hyper-parameters. The SVM model is improved using the GridSearchCV, which chooses the parameter that best fits the model out of the provided list of estimator parameters. The SVM model improved its accuracy to roughly 90.1(%) after optimization. The classification metrics values after optimizing are shown in Fig. 9.

	precision	recall	f1-score	support
0	0.87	0.87	0.87	15
1	0.76	0.81	0.78	36
2	1.00	0.83	0.91	24
3	0.94	0.89	0.92	19
4	0.89	0.94	0.91	34
5	1.00	1.00	1.00	10
6	0.94	0.94	0.94	17
7	0.68	1.00	0.81	13
8	0.82	0.88	0.85	16
9	1.00	1.00	1.00	20
10	0.82	0.90	0.86	10
11	0.93	0.96	0.94	26
12	0.95	0.95	0.95	21
13	1.00	0.96	0.98	28
14	0.90	0.90	0.90	20
15	1.00	1.00	1.00	11
16	0.84	0.80	0.82	20
17	0.77	0.95	0.85	21
18	1.00	1.00	1.00	14
19	0.87	0.81	0.84	16
20	0.90	0.50	0.64	18
21	1.00	0.86	0.92	7
22	0.95	0.90	0.93	21
23	1.00	0.94	0.97	18
24	0.92	1.00	0.96	22
25	1.00	0.86	0.92	14
26	0.73	1.00	0.85	11
27	1.00	0.90	0.95	29
28	0.83	0.83	0.83	12
29	1.00	1.00	1.00	8
accuracy			0.90	551
macro avg	0.91	0.91	0.90	551
weighted avg	0.91	0.90	0.90	551

fig.9 : SVM classification report after GridsearchCV

G. *Evaluating ensemble classifier and component models*

The component models gave a training accuracy of 99.93 and validation of 98.09 for Resnet50 and 99.79 and 98.17 for InceptionV3. The ensemble classifier gave an accuracy of 73.89 and 79.51

IV. Result

The above-proposed solution was hence implemented and the results obtained with SVM were - 89(%) accuracy before GridSearchCV was applied and 90(%) accuracy after. The performance was evaluated using a variety of evaluation metrics like confusion matrix, f-1 score, precision, and recall. The test case and predicted output are shown in Fig.10. and Fig.11. for SVM is respectively.

The result for the individual Resnet50 model were much improvised as compared to the ensemble, InceptionV3 and SVM classifier, hence Resnet50 was integrated with a web interface.

<matplotlib.image.AxesImage at 0x1935d275f70>

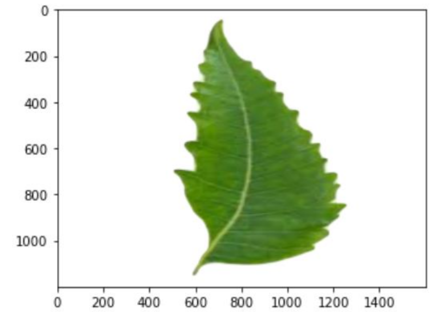

fig.10 : Test Image of Neem Leaf

```
In [64]:  common_names[y_pred_mobile[0]]
Out[64]: 'Azadirachta Indica (Neem)'
```

fig.11 : Outcome of the SVM model

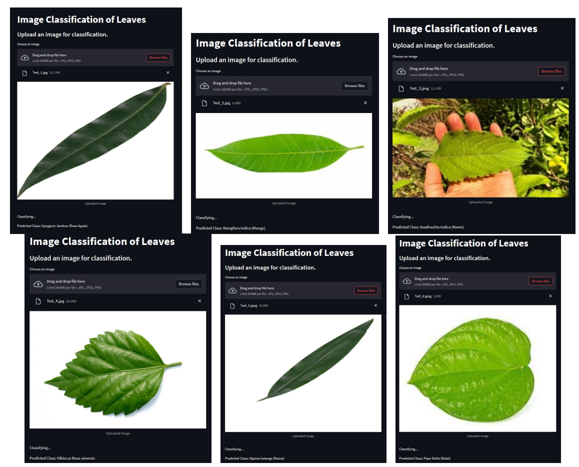

fig.12 : Predicted Outcome

V. Conclusion and Future Scope

The majority of plants, particularly those with significant medicinal benefits, are in danger of going extinct. Such plants are difficult to identify because many of their leaves resemble one another and some of their characteristics are invisible to the human eye. Using machine learning and deep learning algorithms is the most effective way to handle such data and extract non-notifiable features. SVM algorithms were used in the experiment. SVM provides an accuracy of approximately 89(%) in the experiment; after applying GridSearchCV, 90(%) accuracy was attained. The train accuracy and validation score for ensemble, Resnet50 and InceptionV3 are shown below-

Ensemble Classifier - Train accuracy-73.89(%)
Validation accuracy-79.51(%)

Resnet50 - Ttraining accuracy-99. 93(%)
Validation accuracy-98.09(%)

InceptionV3 - Training accuracy-99. 79(%)
Validation accuracy-98.17(%)

The prediction were most accurate for Resnet50 for the given dataset hence, it was integrated with a web interface created using streamlit.

A. The following is a summary of the proposed techniques that can be derived from implementation.

More images with different variations must be included in the dataset for the model to learn better, avoiding overfitting. SVM underperforms with noisy data. CNN requires the noise removal or addition of more data in the dataset.

B. However, there are a few suggestions for the future development of the implemented algorithms.

The dataset with the different multiple overlapping objects in the background can be taken and trained using YOLO. To implement the methods in the mobile-based environment.

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