

Ayurvedic medicinal plant identification system using embedded image processing techniques

Arnab Das
Electronics & Communication
Engineering
Amrita Vishwa Vidyapeetham
dasarnab1122@gmail.com

B Siva Sai Kumar
Electronics & Communication
Engineering
Amrita Vishwa Vidyapeetham
balesivasaikumar0405@gmail.com

S Shiva Shankar Reddy
Electronics & Communication
Engineering
Amrita Vishwa Vidyapeetham
shivasangati8500@gmail.com

S Naveen Reddy
Electronics & Communication
Engineering
Amrita Vishwa Vidyapeetham
naveenreddy810607@gmail.com

Peeyush K.P
Electronics & Communication
Engineering
Amrita Vishwa Vidyapeetham
kp_peeyush@cb.amrita.edu

Abstract—Plant taxonomy has a variety of classification methods, such as plant cell classification, plant genetic classification, plant serum classification and phytochemical classification. For the vast majority of non-research professionals, it is difficult to master some classification methods, difficult to operate, and poor practicality. The traditional methods of plant classification and recognition require the recognizer to have a wealth of taxonomic knowledge and long-term practical experience, and even to take the corresponding key to complete the classification effectively. Identifying a medicinal plant with required medicinal values is one of the major challenging tasks. The shortage of qualified taxonomists and anticipated requirements in medicinal plant identification and classification can be bridged using computer vision and image processing approaches. The main objective is to develop a Deep Learning/ML based model, to identify medicinal plants using leaf features such as shape, color, texture and Morphological features and to develop a standalone device that clicks a picture and identifies the medical plant

Keywords—feature extraction, segmentation, classification, CNN, image processing

I. INTRODUCTION

Plants play an essential role in the preservation of life and biodiversity on Earth by allowing the flow of air and water for all living things. One of the most significant classes of plants is medicinal herbs, that were used to treat various diseases. The knowledge of medicinal plants that has been passed down through the years must be conserved and protected. For the identification and categorization of medicinal plants, computer vision, pattern recognition, and image processing technologies offer promising results. One of the most difficult jobs is identifying a medical plant with the needed therapeutic properties. Even if herbal therapy has no negative effects, a patient's life might be lost if a therapeutic plant is misidentified. As a result, at this point in time, a completely automated method to accurately recognize medicinal plants is inevitable.

For production of ayurvedic medications, the identification and categorization of medicinal plants is critical. Agronomists, botanists, ayurveda medicinal practitioners, forest department officials, and those involved in the manufacturing of ayurvedic medications all benefit from appropriate categorization of medicinal plants. However, a critical shortage of skilled taxonomists exists in this field. There is a growing segment of the population who prefers ayurvedic medicine over other medications. Taxonomists employ leaf, flower, trunk, and branch characteristics to classify based on their respective features. The leaves are the greatest choice for plant categorization.

II. LITERATURE SURVEY

The insights of the paper [1] is that Deep learning belongs to the neural network structure. It can automatically learn features from big data and use an artificial neural network based on a backpropagation algorithm to train and classify plant leaf samples. The basis of plant classification mainly includes leaf shape, color, and texture. Compared with color and shape, the texture veins of leaves have more stable characteristics.

In this paper [2], an efficient plant leaf recognition system using morphological features and adaptive boosting methodology has been presented. They have used different classification techniques, namely, k-NN, decision tree, and multilayer perceptron. The adaboost technique has boosted the precision rate.

Ayurleaf [3] is a CNN based model proposed to classify medicinal plants. For feature extraction, a deep neural network inspired by Alexnet is used. Softmax and SVM classifiers are used to perform classification.

Author made a comparative study between well known models VGG16, VGG19 and proposed a detailed analysis about deep learning based Convolution Neural Network. They made [4] their own dataset which consists of 64 species of medicinal plants with 1000 samples from each medicinal plant species were collected.

The working processes described in this paper [8] are applied for detecting contour edges of overlapping leaves from a complex background. Proposed model segments those selected contour areas as leaf regions from the main image. From the experimental results, we can see that the model achieved an overall segmentation rate 90.46% while segmentation rates for single and overlapping leaves are 95.34% and 86.73% respectively.

III. METHODOLOGY

The major part of the classification/identification deals with feature extraction. The recognition process is mainly divided into three steps: image processing, image feature extraction and image classification.

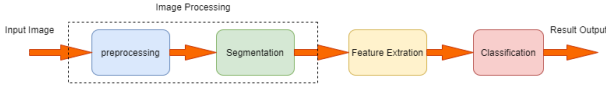


Fig. 1. classification process

Image recognition process, mainly divided into two steps: image preprocessing and image segmentation. Image preprocessing mainly includes image restoration and image transformation. Its main purpose is to remove the interference and noise in the image, enhance the useful information in the image, and improve the detectability of the object. Image segmentation is to segment the recognized image into several sub-regions.

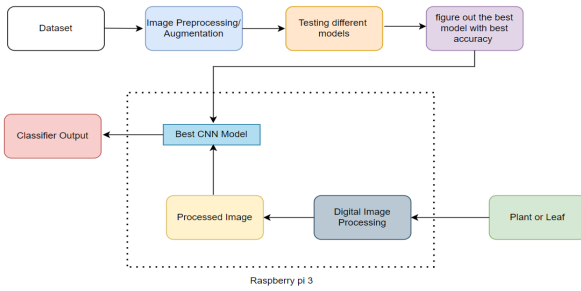


Fig. 2. methodology

A. Deep Learning Model(CNN)

A sequential model with CNN is implemented by considering VGG16 and Alexnet as reference. The first layer is the input layer which specifies the dimension of the input images. The second layer, the convolution layer, used 32 (3 x 3) filters with a stride size of 1. This layer is followed by a ReLU layer which thresholds output, and then a max pooling layer with filter size 2x2. This layer reduces the size of its output exactly by half. This max pooling layer is followed by a second convolution layer which operates on 32 kernels with the dimension 3x3. Next layer is a ReLU layer followed by a max pooling layer with filter size 2x2 and stride 1. The next two layers are two back to back convolution layers with the following configurations. Both use 3x3 kernels with a stride of 1 and the number of kernels in first and second is 64 and 250 respectively. These layers are again followed by a ReLU layer. The next layer is convolution layer with 128 (3x3) kernels and followed by relu activation function and average pooling layer of size (2,2) and next layers are also of similar pattern with filters of 64 (3x3) and relu activation function and followed by average pooling layer of size (2,2).

Last Convolution layer is of size 256 (2x2) and followed by ReLU activation function and max pooling layer of size (2x2). The output from the last max pooling layer is given to the first fully connected layer which consists of 6400 neurons. And which is again processed through another fully connected layer of size 30 as our dataset consists of 30 classes. Final classification of the model is done with the help of softmax which is used for multi classification purposes.

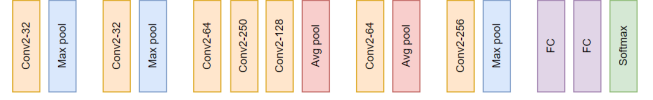


Fig. 3. Implemented CNN model

B. ML Model

Gabor Filters:

Gabor is a convolutional filter representing a combination of gaussian and a sinusoidal term. The gaussian component provides the weights and the sine component provides the directionality.

Gabor can be used to generate features that represent texture and edges. Gabor kernel actually mimics the visual cortex meaning, the way we recognize textures with our eyes can be simulated using gabor kernel.

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \exp\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right)$$

where
 $x' = x \cos \theta + y \sin \theta$
and
 $y' = -x \sin \theta + y \cos \theta$

Parameters labeled in the diagram:
- Std. dev. of the gaussian envelope: σ
- Spatial aspect ratio: γ
- Wavelength of the sine component: λ
- Orientation of the filter: θ
- Phase offset: ψ

Fig. 4. Gabor filter expression & parameters

For example, if we change the parameters like lambda, theta, phase offset of the standard deviation of the gaussian, we can generate an ideally infinite number of filters.

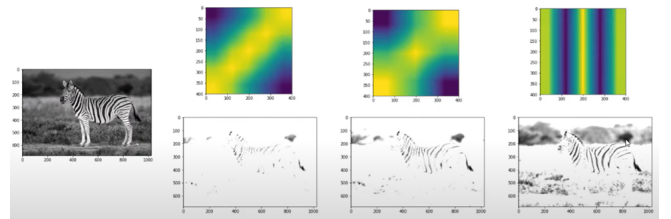


Fig. 5. Different orientations of Gabor filter

In the above figure we can observe that by changing the parameters of the filter it generates filters with various orientations through which we can extract features from the original image. Usually one filter is not enough, so we generate nearly 30 Gabor filters, convoluted with the image and then feed to our ML model.

Random Forest Classifier (RFC):

Random Forest Classifiers and SVMs are the mostly used traditional ML models. As the name says, Random Forest means it has a number of decision trees. Random Forest Classifier randomly picks the attributes or features that are generated previously, the Gabor filter banks among a selection or subselection of all the attributes or features. RFC uses Gini impurity to pick a node to split that yields maximum information gain. This is used to take the decision of the tree.

Random Forest consists of a large number of individual trees that operate as an ensemble. Each tree makes a prediction and the class with the most votes will be the model's prediction.

We have chosen this classifier since it helps to minimize overfitting (works great on training data but not on new data). Bootstrap / bagging in Random Forest allows each tree to randomly sample from the dataset. Feature randomness is introduced by only allowing a subset of available features at each node.

In our model we have used 200 `n_estimators` (decision trees) and the image size which is given to our model is 256x256 which is resized from our original image which is of size 1600x1200. We have used all the features i.e Gabor filter banks, original pixel values and Sobel filter to train our model. We have also used bootstrapping of samples technique to minimize overfitting.

C. Dataset

Dataset plays a major role in classification of objects. We have collected a segmented leaves dataset from kaggle which consists of leaves of 30 classes of which each class has an average of 60 images of size 1600x1200.

Data augmentation is a strategy for extending the quantity of data available by generating new data from current data. It allows us to improve the dataset's size and variety without having to acquire fresh information.

The following data enhancements were performed: Rotation of the images, Horizontal flip. For data augmentation, Gaussian noise is injected into the picture. The process of blurring a picture entails averaging nearby pixels. This blurs the image and lowers the amount of information. The dataset size grows larger, and the model's training improves. We used data augmentation method to improve the accuracy of the deep learning based model. The dataset is divided into the train and test sets at random. The train set comprises 80% of the dataset, 20% for testing.

D. Segmentation

Because leaves are most typically observed in groups with natural backgrounds, leaf identification and segmentation is a challenging task. Because of their similar colors, the edges of leaves are difficult to see from the photograph. It's also more difficult to separate each individual leaf, especially overlapping ones, because leaves are almost identical in color, texture, and shape.

Leaf segmentation includes two major procedures: (1) segmenting foreground leaf region from natural background and (2) segmenting each single leaf and each

occluded or overlapping (i.e., object on object) leaf individually from image. Segmentation is done based on a contour selection based leaf segmentation approach.

- Input Image

The input image is read in BGR color format instead of RGB as we use OpenCV library for model implementation.

- Preserve Edges

Since our objective is to identify the contours or outlines of each leaf and segment the related regions within them, we must first find the contours or outlines of each leaf. Edge Preserving Filter is used at this stage to smooth internal texture and preserve boundary edges.

- Stylize Leaf Boundary

We use a Stylization Filter to make every item edge, outline, or contour smooth and sharp at the same time. It employs the Normalized Convolution (NC) filter to improve accuracy and speed over conventional outline sharpening filters. It thickens all outline edges over time and is unaffected by internal texture.

- Multi-Channel to Single Channel

The next step is to convert the BGR format (3 channel) image to a grayscale image (1 channel). In comparison to BGR images, we only need to process one-third of the image data in grayscale images, which greatly minimizes the amount of computation and memory usage.

- Expand Boundary Edges

This process enlarges the outline borders of leaves by expanding the areas of bright regions. This processing phase also aids in the separation of overlapping edges. This is done using a sobel filter.

- Smooth Edges

When the dilation process enlarges the brighter edges, it may also enlarge parts of the leaf's interior texture edges that are still present. After dilatation, we execute a smoothing operation to deal with the problem.

- Separate Background and Foreground

Here we separate the foreground region's pixels with a single intensity from the pixels in the background.

- Contour Detection

By recognising the contours of the connected regions, we are able to identify them. The OpenCV Libraries `findContours()` method is used to detect contours.

IV. RESULTS

For the implemented CNN based model which is constructed taking VGG16 and Alexnet as reference consists of 15 layers with various functions. Validation and training accuracy of the model are around 77% and 78% respectively.

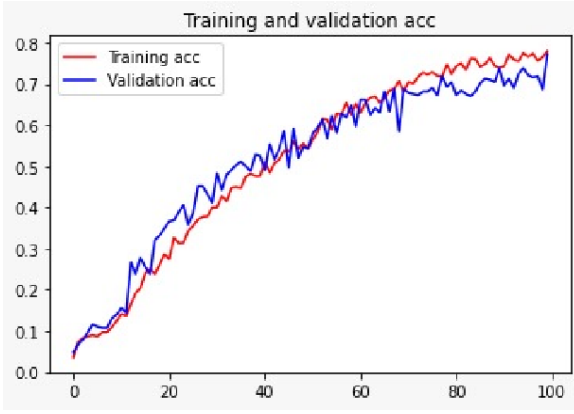


Fig. 6. Training & validation accuracy

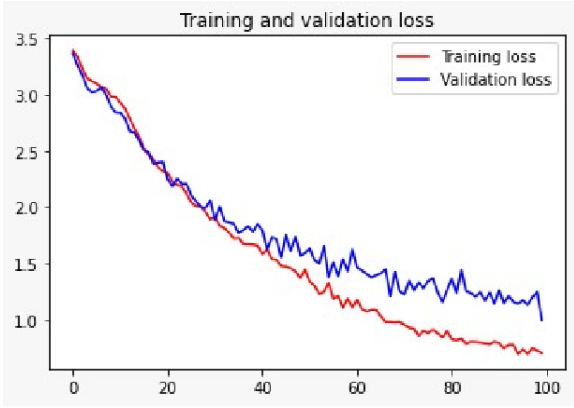


Fig.7 Training & Validation loss

Above we can see the graphs of training and validation accuracy, loss of the implemented sequential model. When an image is given as input to a model to predict we have achieved an accuracy of 75%.

A. ML Model

For the RFC based ML model due to memory constraints we have tested our model with only 8 classes which consist of data from following classes.

S.no	Class
1	Basella Alba (Basale)
2	Carissa Carandas (Karanda)
3	Ficus Religiosa (Peepal Tree)
4	Jasminum (Jasmine)
5	Mangifera Indica (Mango)
6	Mentha (Mint)
7	Moringa Oleifera (Drumstick)
8	Psidium Guajava (Guava)

TABLE I. opted classes for model implementation

We have used Gabor filter banks to extract the features of leaves which is the most widely used filter and which depends on various parameters like theta, sigma, lambda and gamma etc. It generates filters of various orientations which makes it easier for models to train.

```
Gabor1 : theta= 0.0 ; sigma= 1 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor2 : theta= 0.0 ; sigma= 3 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor3 : theta= 0.0 ; sigma= 5 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor4 : theta= 0.7853981633974483 ; sigma= 1 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor5 : theta= 0.7853981633974483 ; sigma= 3 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor6 : theta= 0.7853981633974483 ; sigma= 5 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor7 : theta= 1.5707963267948966 ; sigma= 1 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor8 : theta= 1.5707963267948966 ; sigma= 3 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor9 : theta= 1.5707963267948966 ; sigma= 5 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor10 : theta= 2.356194490192345 ; sigma= 1 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor11 : theta= 2.356194490192345 ; sigma= 3 ; lambda= 0.7853981633974483 ; gamma= 0.5
Gabor12 : theta= 2.356194490192345 ; sigma= 5 ; lambda= 0.7853981633974483 ; gamma= 0.5
```

Fig. 9. Gabor filter parameters

The accuracy of each class we trained is shown below respectively and overall accuracy is around 96.5%.

Class	Class Name	Accuracy
1	Basella Alba (Basale)	0.96
2	Carissa Carandas (Karanda)	0.92
3	Ficus Religiosa (Peepal Tree)	0.96
4	Jasminum (Jasmine)	0.96
5	Mangifera Indica (Mango)	1.0
6	Mentha (Mint)	0.96
7	Moringa Oleifera (Drumstick)	0.96
8	Psidium Guajava (Guava)	1.0
overall accuracy		0.965

Table II. implemented classes and model accuracy

Confusion matrix is plotted below which describes the validation accuracy of each class from Table I.

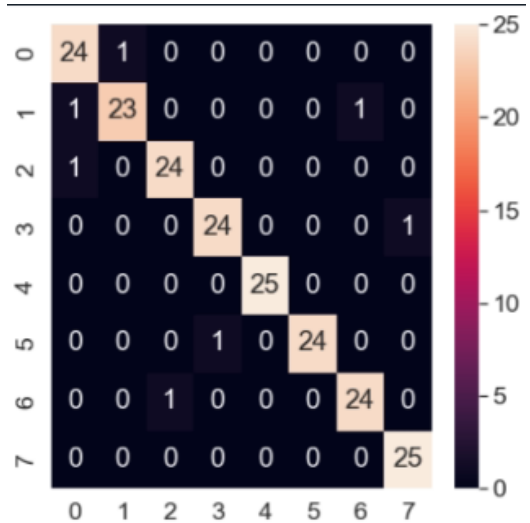



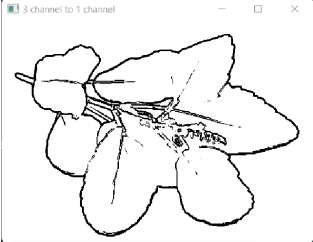



Fig. 10. Confusion matrix of implemented model

B. Segmentation Results

When an image consisting of multiple leaf images of the same class is given as input our task is to segregate or find contours from the image and give it as an input to implemented models to classify it.

stage	output
input image	
edge preserving filter	
Stylization Filter	
Multi-Channel to Single Channel conversion	
Sobel filter	


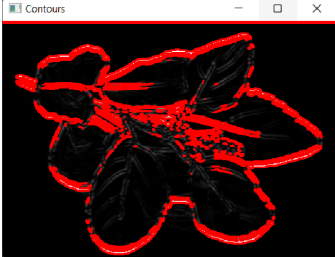
Smoothing edges	
Contour Detection	

TABLE III.. SEGMENTATION RESULTS

REFERENCES

- [1] Jiang Huixian, "The Analysis of Plants Image Recognition Based on Deep Learning and Artificial Neural Network", IEEE(Data Mining for Internet of Things),DOI:10.1109/ACCESS.2020.2986946,13 April 2020 <https://ieeexplore.ieee.org/document/9062591>
- [2] Munish Kumar, Surbhi Gupta, Xiao-Zhi Gao, AmitojSingh, "Plant Species Recognition Using Morphological Features and Adaptive Boosting Methodology", IEEE Access (Volume: 7), DOI: 10.1109/ACCESS.2019.2952176,07 November 2019 <https://ieeexplore.ieee.org/document/8894140>
- [3] M.R. Dileep, P.N. Pournami, "AyurLeaf: A Deep Learning Approach for Classification of Medicinal Plants", TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON), Kochi, India, DOI: 10.1109/TENCON.2019.8929394, 17-20 Oct. 2019 <https://ieeexplore.ieee.org/document/8929394>
- [4] Anu Paulson, S Ravishankar, "AI Based Indigenous Medicinal Plant Identification", 2020 Advanced Computing and Communication Technologies for High Performance Applications (ACCTHPA), Cochin, India, DOI:10.1109/ACCTHPA49271.2020.9213224, 2-4 July 2020 <https://ieeexplore.ieee.org/document/9213224>
- [5] LiwenGao,XiaohuaLin, "Fully automatic segmentation method for medicinal plant leaf images in complex background", ELSEVIER, Computers and Electronics in Agriculture Volume 164, September 2019, 104924 <https://www.sciencedirect.com/science/article/pii/S0168169919305629>

- [6] MadsDyrmann, HenrikKarstoft, Henrik SkovMidtiby, **“Plant species classification using deep convolutional neural network”**, ELSEVIER, Biosystems Engineering Volume 151, November 2016, Pages 72-80 <https://www.sciencedirect.com/science/article/pii/S1537511016301465>
- [7] C. Amuthalingeswaran, M. Sivakumar, P. Renuga, S. Alexpandi, J. Elamathi, S. Santhana Hari, **“Identification of Medicinal Plant's and Their Usage by Using Deep Learning”**, 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, DOI:10.1109/ICOEI.2019.8862765, 23-25 April 2019 <https://ieeexplore.ieee.org/document/8862765>
- [8] Rafflesia Khan, Rameswar Debnath, **“ Segmentation of Single and Overlapping Leaves by extracting appropriate Contours”**, DOI: 10.5121/csit.2019.91323, <https://csitcp.net/paper/9/913csit23.pdf>
- [9] <https://www.youtube.com/playlist?list=PLHae9ggVvqPgyROOOtENr6hK0m1UquGaG>
- [10] https://www.ijarce.com/upload/2015/may-15/IJARCC_E%2045.pdf
- [11] <https://www.youtube.com/playlist?list=PLZoTAELRMXVPGU70ZGsckrMdr0FteeRUi>