



# A Methodology for Identification of Ayurvedic Plant Based on Machine Learning Algorithms

Marada Srinivasa Rao<sup>1</sup>, S.Praveen Kumar<sup>2</sup> and K.Srinivasa Rao<sup>3</sup>

<sup>1,2,3</sup>Department of Computer Science and Engineering, GITAM (Deemed to be University), Visakhapatnam, Andhra Pradesh, India.

Received 8 Dec. 2022, Revised 17 Sep. 2023, Accepted 21 Sep. 2023, Published 1 Oct. 2023

**Abstract:** Modern advances in automated plant species recognition systems have made it easier for laypeople to identify a wide range of plant species. Comparatively difficult is the automatic computer analysis of plant species compared to human interpretation. Many studies have been undertaken to improve plant identification in this region. Plant species cannot be properly classified using these approaches. The problem stems from the inefficient classification algorithm. Particularly in regards to the identification of the numerous species of medicinal plants, accuracy will be the most crucial consideration. The research has led to the conclusion that deep learning is the best approach to improving the precision of computer vision-based classification and recognition systems. To achieve its objectives, this system employs convolutional neural networks. With this effort, we were able to create a neural network with a 96.6% success rate

**Keywords:** Support vector machine (SVM), Logistic Regression (LR), K-Nearest Neighbor (K-NN), Convolutional neural network (CNN)

## 1. INTRODUCTION

Plants are important to people's lives because they give us air, food, fiber, fuel, gum, and medicines. There are a lot of plants that can be used as medicine because they have good traits and active ingredients that can be used in medicine. There are a lot of useful plant species that have gone extinct or are in the process of being killed. Some of the things that are making this problem worse are climate change, a growing population, professional secrecy, a lack of government funding for study, and a lack of treatment plants. Identifying medical plants by hand takes a lot of time, so it's important to get help from people who know what they're doing. Automatic recognition and classification of medicinal plants will have to be used to solve this problem. All people will be better off because of this. Several areas of study in image processing are now being pursued by scientists. One of these is the automatic classification and identification of medicinal plants. Identifying medical plants and putting them into groups involves two main steps: extracting features and putting them into groups. These processes, which have an effect on the general accuracy of the classification system, also determine how medicinal plants are classified. The lighting in the surroundings changes all the time, making it hard to tell a leaf from its background. Here, we show you how to use a sample of a plant's leaves to figure out what kind of plant it is. In many situations, like recognizing a plant or a face, for example, a picture is more useful than a natural description. It is a lot harder for computers and

systems than it is for people to pull out features. To get good accuracy, the machine or system must be taught correctly using training data sets. The number of feature vectors used in the extraction process depends on how big the training data set is. It also makes the process of recognition pretty accurate. The most important thing when trying to tell the difference between similar and different items is how well you can recognize them.

The world is home to thousands of plant species, many of which have medicinal properties, are at risk of extinction, or can be used to prepare delicious foods that are harmful to human beings. Plants are essential not only as sustenance for people but as the building blocks of all food webs. The manufacture of herbal, ayurvedic, and folk medicines makes the most use of medicinal plants. Natural alternatives to conventional medicine can be found in herbal plants. Around 80% of people worldwide still rely on conventional medical care. Herbalists define plants as those whose plant parts, such as leaves, stems, or roots, provide therapeutic benefits. They can be used as starting materials to create both traditional and modern treatments. Plants have been used in Ayurvedic medicine ever since its Vedic origins. The identification of the right plant is the most important manual step involved in the manufacturing of Ayurvedic medication. The need for large production makes automatic identification of these components essential. Numerous groups and individuals can benefit greatly from accurate plant identification, including forestry services, botanists,



taxonomists, doctors, pharmaceutical laboratories, groups working to save endangered species, the government, and the general public. Therefore, there is a growing need for automated systems that can distinguish between numerous plant species.

Herbal medicine is thought to be efficient, secure, and reasonably priced. Although there are many herbal plants around, people are unable to fully utilize them since it is difficult to distinguish between the many species' names. There are 13,500 plant species in the Philippines, 1,500 of which are used medicinally, and more than 3,500 are regarded as indigenous[1]. Twelve percent, or 120, of the medicinal plant species on record have been shown to have positive effects in clinical trials[1]. Currently, an expert performs manual herbal plant identification, but the process is labor-intensive, slow, and prone to human error[2]. Several studies have examined characteristics like leaf size, shape, texture, and bloom color to determine the most effective ways to use and apply herbal plants. Exploring plant species' medicinal uses and appropriate exploitation remains difficult[2][3].

An intelligent system for the recognition of medicinal plants might be created using machine-vision technology. This will improve upon and replace the labor-intensive manual process. The goal of this research is to create an effective machine-vision-based system for identifying medicinal plants and assigning them appropriate names. The pictures are taken with the help of a capture box, and the processing and feature extraction are done in MATLAB. Sci-kit Support Vector Machine (SVM), Logistic Regression (LR), and K-Nearest Neighbor (K-NN) models employing ML techniques for classification were designed and trained using learn packages in the Python IDE (KNN). The aforementioned three models are the most popular choices for categorization jobs utilizing machine learning.

## 2. REVIEW OF LITERATURE

Diverse methodologies are used in research on the identification of medicinal plants. Some supporters of artificial intelligence and machine learning employ form characteristics [4], color features, and texture features[5]. While leaf analysis is often used to determine a plant's species, it's important to have a tried-and-true method that yields precise results every time.

C. H. Arun et al.[6] developed a model to determine which plants can be used for medical purposes. The model was trained using a total of 8,000 images from four different categories. In the end, 85% accuracy was achieved during testing with images taken in open field areas. Contrarily, A. Rahmad et al. [7] employed convolutional neural networks and deep learning to identify medicinal plants using flower species using color, texture, and shape (CNN). The textural properties of herbal plants were extracted and developed using a unique fuzzy local binary pattern (LBP) model for efficient herbal identification[7][8].

Image processing[9] is a technique where several operations are carried out on the images to improve their quality and extract specific information for subsequent analysis to produce the desired outcome. For simpler identification, various image processing techniques were used to improve plant leaf photos. Aspect ratio, area, and rectangularity are examples of shape-based characteristics of leaves. The standard deviation and mean are examples of color-based characteristics of leaves. A. Salima et al.[8] used the solidity, main and minor axes, perimeter, size, aspect ratio, and eccentricity to characterize leaves. Utilizing microscopic pictures and distinguishing characteristics, A. Rahmad et al.[7] classified plants. The ratio, main and minor axis length, and area are the features that were used in the study. A 15-megapixel digital camera was utilized to take pictures of various leaves[10]. Important characteristics of leaf characteristics, such as form, leaf edges, and vein structure [8], as well as color and texture[11]. Feature selection was carried out to eliminate unnecessary data and enhance the training duration and learning rate. N. Krisnawijaya et al. [12] have developed a framework and made effective use of images. Leaf of a medicinal plant: pattern recognition, feature extraction, processing, and categorization.

L. Gao et al. [13] used the Histogram of Oriented Gradients (HoG) and the Speed Up Robust Feature (SURF) to get scale-invariant features from images of plant leaves. After the features were taken out, a K-NN algorithm was used, which gave almost perfect accuracy[14]. Principal component analysis (PCA)[6] and near-infrared spectroscopy (NIR) spectra were used to correctly classify several types of medicinal plants based on their leaves[15].

The idea to apply the CNN method for deep learning to recognize plants was put forth by T. Sathwik et al.[16]. The CNN algorithm is employed in this method for learning unsupervised situations. The 44 plant species in the Royal Botanic Garden's collection span a wide variety of species and are used in these experiments. The findings of the trial demonstrate consistency and superiority over previous manual feature extraction techniques. The use of a genetic algorithm (GA) is another method for feature extraction, as demonstrated in the study by A. Sabu and K. Sreekumar[17]. Despite the little information available, this research employed Direct Classification of Differential Classification Learning (DECIML) to categorize medicinal plants according to their leaf structures. The study used the multi-layer back propagation perceptron (BP-MLP) and the gray-level regression matrix (GLCM) to extract features and classify the plants, although feature selection and optimization were not performed to further improve the classification rate.

To identify plants, I. Gogul and V. S. Kumar [18] propose employing the deep learning CNN method. In this approach, the CNN algorithm is used to learn feature representations without supervision. The Royal Botanic Garden is home to 44 different plant species, all of which



are used in these investigations. The findings of the trial are consistent and demonstrate an improvement over previous manual feature extraction techniques.

A novel structure-based feature descriptor, the Multi-channel Modified Local Gradient Model (MCMLGP), was proposed by Y. G. Naresh and H. S. Nagendra swamy[19]. It employs several color channels in color images to extract numerous important features that help with classification performance. This paper will directly classify medicinal plants. Different kernels, including linear, multiple, and HL, were used by the author to train the suggested SVM classification algorithm. In addition, we performed a thorough experiment using various MCMLGP experimental analysis instructions on our database of medicinal plants[20]. The proposed method is a significant improvement over current methods for discovering and categorizing medicinal plants, with an accuracy of 96.11%.

In order to categorize medicinal plants according to leaf properties, N. Jamil, et al.[21] propose employing a convolutional neural network (CNN) model named AyurLeaf trained with Deep Learning. This study lends credence to the establishment of a centralized database for Kerala's (a state on India's southwestern coast) wealth of medicinal plants. The suggested data set contains forty types of medicinal plant leaves. In order to efficiently extract features from the dataset, a deep Alexnet-based neural network is used. The final step of classification is performed with the help of softmax and SVM classifiers. After five rounds of cross-validation, our model achieved a classification accuracy of 96.76% on the AyurLeaf dataset.

Despite some misclassification in the training model due to inadequate common features, a support vector machine (SVM) classifier was utilized in[22]. An artificial neural network (ANN) recognized tree leaves with 98.8% accuracy using the model. Other research, such as the A. Gopal et al. study [23], used SVM classification with 90% classification accuracy. The study used leaves to diagnose plant diseases using SVM, Random Decision Forest, and ANN [24]. Random Decision Forest had the highest F1 score[25].

U. Habiba et al.[26] state that they have developed a mechanism to aid in the identification of the plant and the disclosure of its medicinal characteristics, which may then be used in the treatment of various illnesses in a more holistic, natural way. Collecting data, extracting features with texture and HOG, and classifying with the Support Vector Machine method are all discussed here.

N. G. Gavhale et al.[27] offer a method to classify leaves automatically using images by collecting shape, color, and texture information. To achieve both high productivity and low computing complexity, the best photo input characteristic must be chosen. The accuracy of the network was evaluated using a variety of input characteristics. In a dataset consisting of 63 photos of leaves, this approach obtains an accuracy of 94.4% with only 8 input features. Because

it requires less time and effort from the human operator, this technique is favored by automated leaf identification systems.

T. Vijayashree et al. [28] identified plant leaves using DT, Naive Bayes, Knearest Neighbor (KNN), and ANN, with ANN performing best. Other studies have used pre-trained plant leaf recognition models like VGG16 [29]. S. Prasad and P. Singh [30] have established a database of 127 different types of herbal leaves. When compiling the database, eleven separate textural criteria are considered. The inverse difference moment, the aspect ratio, the correlation, the mean, and the sum average are all instances of parameters. Analysis of entropy, homogeneity, contrast, and energy can be obtained through the use of gray-level co-occurrence matrices (GLCMs). One can determine how different an example image is from the images stored in the database by using the parameters that were retrieved.

B. Fataniya et al.[31] suggested a brand-new approach to classifying plant leaves. The feature extraction and classification steps in this method make use of the CNN algorithm. This CNN architecture introduces 10 layers. In this strategy, a leaf augment was used to increase the database size in order to enhance categorization performance. The examination of the variables impacting accuracy was done using the visualization technique[32]. On the Flavia dataset, this CNN approach was tested, and it produced an accuracy of 87.92%.

According to the research of T. Vijayashree et al. [33], in their study, a new and efficient strategy for collecting leaves is introduced. Putting the image into a device-independent color space allows the VGG-16 feature map to be calculated. The performance of species identification is improved by re-projecting this feature map to the PCA subspace. In the study, two different plant leaf datasets are employed to prove the study's robustness. Feature extraction, image processing, and AI have been used to identify herbal plants [34]. Although faster learning and processing times could have been achieved with the use of an optimized model-based machine vision system, this was not done [35]. The authors used machine vision to swiftly and reliably categorize herbal leaf photos. The dataset was created using machine learning to extract leaf features such as aspect ratio[36], circularity[37], overlap[38], solidity [39], and rectangularity[40]. The optimal machine learning model can be found by comparing learning performances with common and unique features and parameters.

### 3. EXISTED SYSTEM

#### A. Motivation

In the past, ayurvedic doctors chose and made their patients' medicines. This strategy is used by a few practitioners. The Rs. 4000 crore ayurvedic pharmaceutical industry is expanding. Ayurvedic medication manufacturers in India number around 8500. As the Ayurveda sector has commercialized, worries regarding the quality of its raw materials have arisen. Women and children who haven't

been trained to identify therapeutic plants select them from forests today. Medicinal plants are often misdelivered to manufacturing plants. Most of these factories lack quality control procedures. Regional name differences sometimes cause confusion. Manual plant identification is more difficult for dried plants.

The incorrect application of Ayurvedic principles to the use of medicinal plants is the root reason for the practice's lack of efficacy. In addition to that, unanticipated negative consequences are a possibility. Strong quality control requirements need to be established for the Ayurvedic remedies and raw materials used by the sector in order to preserve the industry's current growth as well as the efficacy and reputation of the medicines. An experienced botanist will inspect a plant for all of its unique traits in order to correctly identify it. These qualities include the plant's stem, leaves, flowers, seeds, and roots.

All of the other objects, excluding the leaf, are in three dimensions, which makes computer analysis more difficult. Plant leaves, on the other hand, are 2D objects and contain enough data to identify the plant. It is simple to gather leaves, and image acquisition can be done using low-cost digital cameras, cell phones, or document scanners. Unlike flowers and seeds, it can be found at any time of the year. The color, texture, and shape of leaves gradually alter as they grow, but these transformations are only subtle. In order to recognize plants based on their leaves, precise descriptors must be found and feature vectors must be extracted from them. Then, a suitable classifier is used to compare the feature vectors of the training and test samples in order to determine how similar they are.

#### B. Problem definition

Machine learning, an area of study that focuses on the development of algorithms, is inspired by the human mind. Deep learning is gaining traction across a variety of data science applications, from robotics and AI to speech and picture identification. The backbone of any deep learning strategy, ANNs are essential. Tensor-Flow, Caffe, MX Net, and many others are only some of the many libraries that make deep learning possible. Keras is based on popular deep learning frameworks like TensorFlow and others, making it one of the most trustworthy and approachable Python libraries for developing deep learning models. By identifying the most effective medical plants, pharmaceutical companies, botanists, and taxonomists can provide safe, effective treatments and reduce the harm caused by incorrect drug dosing.

Convolutional neural networks (CNNs) are used to identify individual plant leaves and their respective species. In this study, the Densenet121 convolutional neural network architecture was utilized because of its strong model and potential for high accuracies when used with challenging datasets.

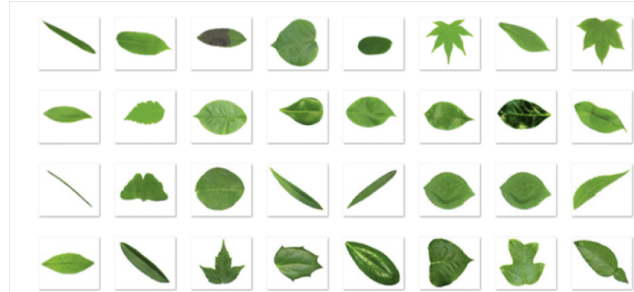


Figure 1. Images from Flavia Dataset

## 4. METHODOLOGY AND RESULTS

### A. Dataset Description

The Department of Health's list of medicinal plants includes oregano, bayabas, yerba buena, ulasimang-bato, ampalaya, malunggay, sambong, lagundi, tsaang-gubat, and niyog-niyogan (DOH). This investigation focuses on the list of medical applications that have been granted. Images of the sample herbal plant used in the investigation are shown in Figure 1. A total of 600 images were gathered. To create physical properties of the leaf that will be utilized to create machine learning models, collected photos are subjected to numerous image processing procedures.

Several image processing methods were used on the 600 photos. Softening an image's background brings attention to the subject. In the first stage of thresholding, the RGB component is transformed into a grayscale value, yielding a monochrome picture. In order to learn about the geometric properties of the subject, the binary image is converted into a convex hull image by locating its edges. Geometrical features were extracted after preconditioning the photos. The primary features were area, width, length, and perimeter. These estimations were made using a method published in [22] and applied to secondary qualities such as sphericity, symmetry, aspect ratio, rectangularity, convexity, and solidity. The comma-separated value (csv) file that was made had 600 samples (rows) and 6 traits (columns), with one column labeled "Herbal" for data classification.

After image processing and feature extraction, intelligent models using SVM, NBC Classification and Regression Trees (CART), and KNN algorithms are created. Models were generated with default parameters, and then optimized for learning performance. The process model is shown in Figure.2.

### B. Materials and Methods

i. Image gathering and preparation: The necessary information for determining plant species should be collected. One of the most important steps is collecting high-quality images of the selected plants for use in creating the database, from which the necessary features can be extracted to instruct the computer.

ii. Acquiring a plant leaf: A scanner (HP ScanJet G4010)

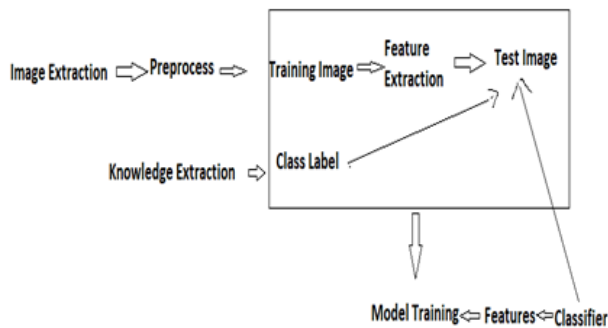


Figure 2. Process Model

was used to take 600-dpi color digital images of single plants of St. John's wort (*Hypericum perforatum* L.), Melissa, Echinacea, Thyme, and Mint. These 752 photos were extracted from the MAP database [23]. Random leaf samples were gathered from the experimental field's MAP populations in 2013–2014. We collected 152 thyme, 88 echinacea, 112 mint, 200 St. John's Wort, and 200 Melissa leaves to analyze leaf shape development.

iii. Image preparation: First, binary images of leaves were transformed. Figure. 3 a) displays a threshold binary picture (b), normalised (c) Threshold based image

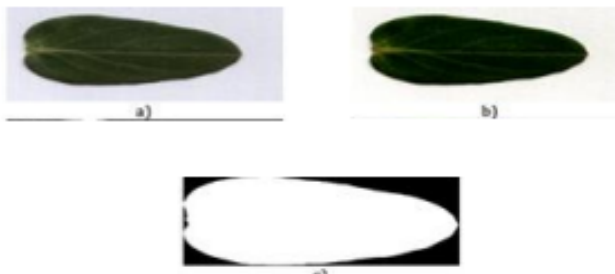


Figure 3. Image Pre-processing

### C. Machine Learning Methods

The goal of machine learning is to let massive volumes of data determine the methods and solutions to challenging issues. In addition, machine learning should be compared against the conventional strategy of relying on subject-matter experts to produce answers. Machine learning techniques such as SVM and CNN were applied in this study.

Classification by SVM: The SVM implementation includes the phases listed below.

Support Vector Machine (SVM) algorithms have trouble processing noisy input during the training phase. Directly extracting features from noisy input can compromise the recognizability of the data, as evidenced by previous studies [10, 11]. To address this issue, images are downsized and their backgrounds are blurred to reduce noise.

Additionally, a Gaussian filter is employed to denoise the images [12]. The initial phase of the image processing, referred to as picture segmentation, utilizes Otsu's thresholding method to determine the center point of the maximum values of bimodal images [13]. Subsequently, the image's shape is modified to fill in any gaps, and anti-aliasing procedures are applied to enable feature extraction. At last, feature extraction is performed on the image. Digital image processing techniques are used to classify leaves according to their shape, color, and texture (DMF, or Digital Morphological Features). The 17 floating data points were used to derive seven form parameters, including leaf area, length, height, breadth, circumference, and rectangle. TABLE I displays the accuracy of the model and its validation.

TABLE I. MODEL AND VALIDATION ACCURACY

Model Accuracy	Validation Accuracy
0.15	0.54
0.54	0.66
0.56	0.62
0.62	0.64
0.66	0.69
0.78	0.80
0.80	0.87
0.867	0.88

### D. Convolution Neural Networks

Convolutional neural networks have demonstrated significant efficacy and accomplishment in the realm of image recognition. A type of neural network known as a convolutional neural network (CNN) is composed of various layers including convolutional layers, batch normalization, a rectified linear unit (ReLU) activation function, and a max-pooling layer. Our study on leaf recognition involves the development of a CNN model that comprises three convolutional layers as its fundamental architecture. Subsequent to the first two convolutional layers, a layer of max-pooling, a rectified linear unit (ReLU) activation, and two fully connected layers are employed. Subsequently, a softmax layer is employed to compute the probability. Convolutional neural networks (CNNs) employ various techniques such as max-pooling activation function, batch normalization, and ReLU to effectively learn features from data. Max-pooling is a technique employed to downsample convolutional features and minimizes computational expenses. The product retains the frequently utilized characteristics while prolonging the lifespan of less frequently used ones. Furthermore, the utilization of batch normalization within the convolutional neural network layers serves to stabilize the means and variances of the input layer and mitigate the occurrence of covariate shift. The utilization of this technique facilitates accelerated acquisition of knowledge, thereby resulting in a decrease in the duration of the initialization phase. The ReLU activation function is utilized for the purpose of acquiring knowledge about the pre-activation feature maps this entire architecture shown in Figure.4 and process of pooling shown in Figure.5.

The dataset has undergone preprocessing procedures to eliminate extraneous data, such as the leaf's background or non-essential components. The process involves partitioning the dataset into distinct subsets, namely the training, validation, and testing sets. During the training process, the CNN learns to extract and recognize unique features from the leaf images, such as shape, texture, and color. In order to improve the model's accuracy in identifying the proper leaf species, we use a loss function as a metric to minimize.

Subsequently, the model is assessed by means of the validation set in order to detect any potential overfitting. Upon completion of fine-tuning the model and optimizing its accuracy, it is subsequently employed to make predictions regarding the species of the leaf within the testing dataset. The accuracy of the model is evaluated using several different measures, such as accuracy, precision, recall, and F-score.

E. Learning transfers: VGG16 model

The Convolutional Neural Network (CNN) model, upon which VGG16's architecture is built, has received a lot of support from the ImageNet competition. Using the transfer learning method, VGG16 is a convolutional neural network (CNN) architecture that can learn from data and store that information as weights. Rather than commencing the neural network creation process from the beginning, the weights in question are appended to an existing network [14].

Convolutional layers with a stride of 2x2 and a kernel size of 3x3 are both present in the VGG16 design. According to reference [14], the SoftMax layer, responsible for producing visual symbols, follows the initial two layers that are fully incorporated into the architecture. The initialization of the model employs a serial approach. Following the smoothing of the data, additional layers, such as hidden layers and output layers, are incorporated.

Features are extracted from various setups using convolutional layers in the VGG-16 model. When a picture is shrunk in size, the Max Pooling layer of the neural network decides which pixel value to use as the filter based on its maximum. Layers that are entirely connected to the black box functionality aid in the transmission of data from it. To pick the best signal for the selected category, the SoftMax layer function is used. The original collection of 1000 categories in the SoftMax layer has been narrowed down to a subset of 7. Figure.6 displays the results of the neural network implementation, while Figures.7 and 8 display the results for the leaves of *Alpinia galanga* and *Mentha*, respectively, both of which attained an overall accuracy of 96.6% when partitioning the data into training and test sets in an 8.5:1.5 ratio.

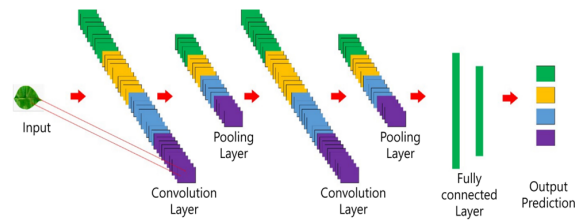


Figure 4. Architecture of CNN

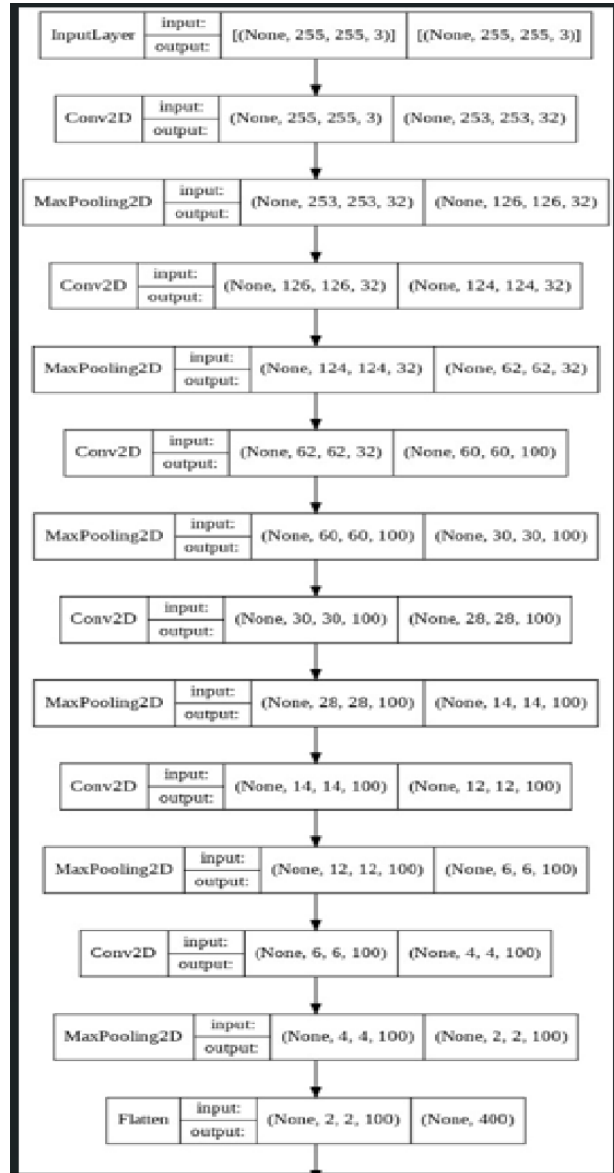


Figure 5. Process of Pooling

```

Epoch 18/30
61/61 [=====] - 238s 4s/step - loss: 0.2398 - accuracy: 0.9169
Epoch 19/30
61/61 [=====] - 239s 4s/step - loss: 0.2223 - accuracy: 0.9302
Epoch 20/30
61/61 [=====] - 238s 4s/step - loss: 0.2157 - accuracy: 0.9263
Epoch 21/30
61/61 [=====] - 238s 4s/step - loss: 0.1733 - accuracy: 0.9457
Epoch 22/30
61/61 [=====] - 239s 4s/step - loss: 0.2024 - accuracy: 0.9407
Epoch 23/30
61/61 [=====] - 237s 4s/step - loss: 0.1599 - accuracy: 0.9424
Epoch 24/30
61/61 [=====] - 238s 4s/step - loss: 0.1255 - accuracy: 0.9346
Epoch 25/30
61/61 [=====] - 241s 4s/step - loss: 0.1821 - accuracy: 0.9346
Epoch 26/30
61/61 [=====] - 238s 4s/step - loss: 0.1255 - accuracy: 0.9584
Epoch 27/30
61/61 [=====] - 233s 4s/step - loss: 0.1709 - accuracy: 0.9440
Epoch 28/30
61/61 [=====] - 233s 4s/step - loss: 0.1413 - accuracy: 0.9524
Epoch 29/30
61/61 [=====] - 242s 4s/step - loss: 0.1721 - accuracy: 0.9463
Epoch 30/30
61/61 [=====] - 236s 4s/step - loss: 0.1454 - accuracy: 0.9518
Epoch 30/30
61/61 [=====] - 238s 4s/step - loss: 0.1184 - accuracy: 0.9662
    
```

Figure 6. Accuracy and Loss values

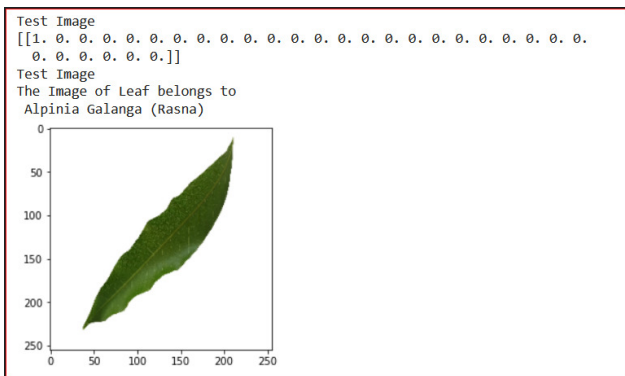


Figure 7. Output of Alpinia Galanga

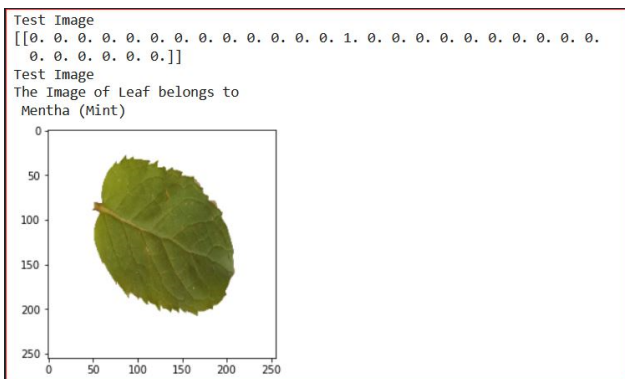


Figure 8. Output of Mentha

TABLE II. COMPARISON OF CURRENT AND SUGGESTED METHODS FOR EVALUATING PERFORMANCE

Method	Accuracy	Precision	Recall	F-Score
SVM	93.3	89	92	88.4
Random forest	90.1	87.3	88	86.5
Multiclass SVM	93.26	92.17	90.5	90.26
CNN	96.6	92.5	93.2	90.2

Traditional methods and the suggested model are compared in TABLE.II. As compared to other methods, the

proposed model is superior in its ability to recognize therapeutic plants.

### 5. CONCLUSION

The presence of plants is crucial for the sustenance of human life. Indigenous communities have a long-standing history of utilizing traditional herbal medicine. Medical professionals frequently rely on their olfactory perception or accumulated clinical expertise to accurately recognize various botanical specimens. Advancements in analytical technologies have facilitated the accurate identification of herbs through scientific data. This is beneficial for a broad readership, particularly individuals who are new to the field of herbology. Familiarity with sample healing and data explanation is imperative in the laboratory due to the time-intensive nature of certain techniques. As a result, there is a need for a prompt and dependable method of herb detection. The integration of computers and statistical analysis presents a promising avenue for the identification of herbs. The non-destructive technique is preferred for prompt herb identification among individuals who face limitations in utilizing conventional methods. The proposed CNN model achieves an accuracy of 96.6% in this study, and in our future work, we want to conduct experiments on the use of hybrids of various machine learning approaches

### REFERENCES

- [1] H. F. Eid, A. E. Hassanien, and T. hoon Kim, "Leaf plant identification system based on hidden naïve bays classifier," *2015 4th International Conference on Advanced Information Technology and Sensor Application (AITS)*, pp. 76–79, 2015.
- [2] S. Singh, D. Srivastava, and S. Agarwal, "Glm and its application in pattern recognition," *2017 5th International Symposium on Computational and Business Intelligence (ISCBI)*, pp. 20–25, 2017.
- [3] Y. Zhang, "Support vector machine classification algorithm and its application," in *Information Computing and Applications*, C. Liu, L. Wang, and A. Yang, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 179–186.
- [4] M. Hossin and M. Sulaiman, "A Review on Evaluation Metrics for Data Classification Evaluations," *International Journal of Data Mining & Knowledge Management Process (IJDKP)*, vol. 5, no. 2, pp. 1–11, Nov. 2019. [Online]. Available: <https://doi.org/10.5281/zenodo.3557376>
- [5] E. S. Kumar and V. Talasila, "Leaf features based approach for automated identification of medicinal plants," *2014 International Conference on Communication and Signal Processing*, pp. 210–214, 2014.
- [6] C. H. Arun, W. R. S. Emmanuel, and D. D. C. Durairaj, "Texture feature extraction for identification of medicinal plants and comparison of different classifiers," *International Journal of Computer Applications*, vol. 62, pp. 1–9, 2013.
- [7] A. Rahmad, Y. Herdiyeni, A. Buono, and S. Douady, "Multiscale fractal dimension modelling on leaf venation topology pattern of indonesian medicinal plants." 10 2014.
- [8] A. Salima, Y. Herdiyeni, and S. Douady, "Leaf vein segmentation of medicinal plant using hessian matrix," 10 2015, pp. 275–279.



- [9] G. Mukherjee, A. Chatterjee, and B. Tudu, "Morphological feature based maturity level identification of kalmegh and tulsi leaves," *2017 Third International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*, pp. 1–5, 2017.
- [10] I. Pavaloiu, R. Ancuceanu, C.-M. Enache, and A. Vasiliateanu, "Important shape features for romanian medicinal herb identification based on leaf image," *2017 E-Health and Bioengineering Conference (EHB)*, pp. 599–602, 2017.
- [11] Y. Putri, C. Djamal, and R. Ilyas, "Identification of medicinal plant leaves using convolutional neural network," *Journal of Physics: Conference Series*, vol. 1845, p. 012026, 03 2021.
- [12] N. Krisnawijaya, Y. Herdiyeni, and B. P. Silalahi, "Parallel technique for medicinal plant identification system using fuzzy local binary pattern," *Journal of ICT Research and Applications*, vol. 11, pp. 78–91, 04 2017.
- [13] L. Gao and X. Lin, "A study on the automatic recognition system of medicinal plants," *2012 2nd International Conference on Consumer Electronics, Communications and Networks (CECNet)*, pp. 101–103, 2012.
- [14] H. Borase, B. Salunke, R. Salunkhe, C. Patil, J. Hallsworth, B. S. Kim, and S. Patil, "Plant extract: A promising biomatrix for ecofriendly, controlled synthesis of silver nanoparticles," *Applied biochemistry and biotechnology*, vol. 173, 03 2014.
- [15] A. Sabu, K. Sreekumar, and R. R. Nair, "Recognition of ayurvedic medicinal plants from leaves: A computer vision approach," *2017 Fourth International Conference on Image Information Processing (ICIIP)*, pp. 1–5, 2017.
- [16] T. Sathwik, R. S. Yaraswini, R. Venkatesh, and A. Gopal, "Classification of selected medicinal plant leaves using texture analysis," *2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT)*, pp. 1–6, 2013.
- [17] A. Sabu and K. Sreekumar, "Literature review of image features and classifiers used in leaf based plant recognition through image analysis approach," *2017 International Conference on Inventive Communication and Computational Technologies (ICICCT)*, pp. 145–149, 2017.
- [18] I. Gogul and V. S. Kumar, "Flower species recognition system using convolution neural networks and transfer learning," *2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN)*, pp. 1–6, 2017.
- [19] Y. G. Naresh and H. S. Nagendraswamy, "A novel fuzzy lbp based symbolic representation technique for classification of medicinal plants," *2015 3rd IAPR Asian Conference on Pattern Recognition (ACPR)*, pp. 524–528, 2015.
- [20] M. Sainin and R. Alfred, "Feature selection for malaysian medicinal plant leaf shape identification and classification," 08 2014.
- [21] N. Jamil, N. A. C. Hussin, S. Nordin, and K. Awang, "Automatic plant identification: Is shape the key feature?" *Procedia Computer Science*, vol. 76, pp. 436–442, 2015, 2015 IEEE International Symposium on Robotics and Intelligent Sensors (IEEE IRIS2015). [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1877050915037886>
- [22] M. A. F. Azlah, L. S. Chua, F. R. Rahmad, F. I. Abdullah, and S. R. Wan Alwi, "Review on techniques for plant leaf classification and recognition," *Computers*, vol. 8, no. 4, 2019. [Online]. Available: <https://www.mdpi.com/2073-431X/8/4/77>
- [23] A. Gopal, S. Prudhveeswar Reddy, and V. Gayatri, "Classification of selected medicinal plants leaf using image processing," in *2012 International Conference on Machine Vision and Image Processing (MVIP)*, 2012, pp. 5–8.
- [24] D. Venkataraman and N. Mangayarkarasi, "Computer vision based feature extraction of leaves for identification of medicinal values of plants," *2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIIC)*, pp. 1–5, 2016.
- [25] J. Abdollahi, "Identification of medicinal plants in ardabil using deep learning : Identification of medicinal plants using deep learning," in *2022 27th International Computer Conference, Computer Society of Iran (CSICC)*, 2022, pp. 1–6.
- [26] U. Habiba, M. R. Howlader, M. A. Islam, R. H. Faisal, and M. M. Rahman, "Automatic medicinal plants classification using multi-channel modified local gradient pattern with svm classifier," in *2019 Joint 8th International Conference on Informatics, Electronics Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision Pattern Recognition (icIVPR)*, 2019, pp. 6–11.
- [27] N. G. Gavhale and D. A. P. Thakare, "Identification of medicinal plant using machine learning approach," 2020.
- [28] T. Vijayashree and A. Gopal, "Leaf identification for the extraction of medicinal qualities using image processing algorithm," 06 2017, pp. 1–4.
- [29] S. Prasad and P. Singh, "Medicinal plant leaf information extraction using deep features," 11 2017, pp. 2722–2726.
- [30] D. Venkataraman, S. Narasimhan, N. Shankar, S. Sidharth, and D. Prasath, "Leaf recognition algorithm for retrieving medicinal information," *Advances in intelligent systems and computing*, vol. 530, pp. 177–191, 2016.
- [31] B. Fataniya, P. M. Patel, T. H. Zaveri, and S. Acharya, "Microscopic image analysis method for identification of indian herbal plants," *2014 International Conference on Devices, Circuits and Communications (ICDCCom)*, pp. 1–5, 2014.
- [32] M. Dileep and P. Pournami, "Ayurleaf: A deep learning approach for classification of medicinal plants," in *TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON)*, 2019, pp. 321–325.
- [33] T. Vijayashree and A. Gopal, "Database formation for authentication of basil (ocimum tenuiflorum) leaf using image processing technique," *Gate to Computer Vision and Pattern Recognition*, vol. 1, pp. 9–17, 04 2015.
- [34] A. Deshmukh, P. Mudhaliar, and D. Thorat, "Ayurvedic plant identification using image processing and artificial intelligence," *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, pp. 212–218, 12 2021.
- [35] P. M. Kumar, C. M. Surya, and V. P. Gopi, "Identification of ayurvedic medicinal plants by image processing of leaf samples," in *2017 Third International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*, 2017, pp. 231–238.
- [36] A. Sujith and S. Aji, "An optimal feature set with lbp for leaf



image classification,” in *2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC)*, 2020, pp. 220–225.

- [37] T. Dhara, A. Adhikary, K. Majumder, S. Chatterjee, R. Shaw, and A. Ghosh, *Prediction of Glaucoma Using Deep Learning Based Approaches*, 02 2023, pp. 134–145.
- [38] Apoorva, Sathya, S. Rs, and N. Mathappan, “Human activity recognition using machine learning techniques,” 10 2018.
- [39] A. Adhikary, K. Majumder, S. Chatterjee, R. Shaw, and A. Ghosh, *Machine Learning Based Approaches in the Detection of Parkinson’s Disease – A Comparative Study*, 04 2022, pp. 774–793.
- [40] S. De, I. Bhakta, S. Phadikar, and K. Majumder, “Agricultural image augmentation with generative adversarial networks gans,” in *Computational Intelligence in Pattern Recognition*, A. K. Das, J. Nayak, B. Naik, S. Vimal, and D. Pelusi, Eds. Singapore: Springer Nature Singapore, 2022, pp. 335–344.



**Marada Srinivasa Rao** is currently pursuing Ph.D in Department of Computer Science and Engineering from GITAM School of Technology, GITAM deemed to be University and working as Assistant Professor in the department of Information Technology, MVGR College of Engineering, Vizianagaram, India. He has 8 years of experience in teaching and research. He has authored or co-authored 15 research papers in international journals and conferences.



**Dr. S. Praveen Kumar** is currently working as Assistant Professor in the Department of Computer Science Engineering, GITAM School of Technology (GST), GITAM deemed to be University, Visakhapatnam, India. He received his PhD in Computer Science with Specialization in Information Security from Centurion University, Orissa, India. He has 15 years of experience in teaching and research. He is currently guiding four scholars for Ph.D. His research interests include Big Data Analytics, Deep Learning, knowledge discovery and image analysis. He has authored or co-authored more than twenty five papers in various reputed international journals and conference.



**Dr. K. Srinivasa Rao** is currently working as Associate Professor in the Department of Computer Science Engineering, GITAM School of Technology (GST), GITAM deemed to be University, Visakhapatnam, India. He received his PhD in CSE with specialization in Image Processing from Acharya Nagarjuna University, Guntur, Andhra Pradesh, India. He has more than 25 years of experience in teaching. He is currently guiding six scholars for Ph.D. His research areas include Artificial Intelligence, Machine Learning, Soft Computing and Image Processing