DOI: https://doi.org/10.52756/ijerr.2023.v32.009 *Int. J. Exp. Res. Rev.*, Vol. 32: 115-123 (2023)

Original Article | Peer Reviewed | Open Access

International Journal of Experimental Research and Review (IJERR)

ISSN: 2455-4855 (Online)
www.iaph.in

Effective medical leaf identification using hybridization of GMM-CNN

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Article History:
Received: 01st Jun., 2023
Accepted: 10th Jul., 2023
Published: 30th Aug., 2023

Keywords:
Plant leaf recognition, Flavia dataset, GMM, CNN

Abstract: Medical plants play a vital role in curing many diseases. These plants, along with their leaves, have medicinal values. If these leaves are identified appropriately, they can be chosen directly to have more significant relief from the disease. Therefore, the identification of these medical species is a challenging task. The ecologically motivated Convolutional Neural Networks (CNNs) have substantially contributed to computer visual research. This article introduces a unique approach to medical leaf identification based on the hybridization of the Gaussian mixture model and a Convolutional Neural Network (GMM-CNN). The experimentation is performed on the Flavia dataset and is carried out using benchmark evaluation metrics. The parameters like index volume, probability of random index, and global consistency error are evaluated. The Python simulation model is utilized for the evaluation of the proposed methodology. The hybrid technique combining GMM and CNN has considerable potential in medical leaf identification. The experimental findings indicate that the hybrid strategy exhibits superior performances. The methodology suggested in this study demonstrates exceptional levels of accuracy, precision, and recall when applied to a wide range of medical leaf categories. Moreover, integrating Gaussian Mixture Model (GMM) and Convolutional Neural Network (CNN) addresses concerns associated with a scarcity of training data by offering a more resilient structure for extracting features and performing classification. By combining the advantages of statistical modelling with deep learning, we develop a resilient and precise system that has the potential to enhance botanical research, medical diagnostics, and environmental monitoring applications.

Introduction

The phrase "computer vision" refers to a broad concept that depicts a computer acting as an eye by applying various algorithms with mathematical model to a digital picture. In this field, photographs from the actual world are processed automatically while features are extracted and information is immediately interpreted by user needs (Sarraf et al., 2021). Image recognition is the core function of computer vision (Yang et al., 2021). The ability of human eyesight to quickly recognize and distinguish between the items around it makes it outstanding and unique. Perfect 3-D structure perception and effective categorization are system capabilities (Welchman et al., 2016). Despite being modelled after the human vision framework, computer vision (CV) is still more effective at detecting, identifying, and differentiating things. The CV can be seen as an approximate representation of human vision since it is such a sophisticated system (Rainey et al., 2021).

The science of plant taxonomy focuses on acquiring, recognizing, explaining, characterizing, and naming plants. Techniques used in this field include morphological, anatomical, and chemotaxonomic classifications (Sing et al., 2018). Morphological and

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anatomical categories are seen to be more conventional than chemotaxonomy (Simpson, 2019). The two main components that play essential roles in plant taxonomy are the categorization of plant and the authorization of plant, which deal with identifying a recently noticed plant concerning a formerly collected specimen and placing a known plant in a group depending on its similarities with other plants.

Random noises will be injected into the obtained pictures as a result of the impacts of variable lighting and throughout picture capture, transmission, and digitalization, there are changes in sensor temperature, and these noises usually have Gaussian characteristics (Li et al., 2018; Feng et al., 2020). The presence of noise will not only impact the aesthetic appeal of the picture. However, it will also impact future image processing, including feature extraction, classification, and identification, among other things. Denoising must thus be applied to the captured picture before image processing to enhance the image's quality and make post-processing easier.

Traditional medical practises have long made use of medicinal plants. In order to detect medicinal plants, many real-time vision systems have recently been created employing computational approaches and machine vision applications (Azadnia et al., 2021). Since deep learning (DL) approaches can manage feature extraction and picture selection concurrently, they have primarily been used. Because of this, DL has recently become quite popular in various farm automation applications where object recognition and picture categorization are necessary (Azadnia et al., 2022). One of the most effective DL techniques is the convolutional neural network (CNN), which has shown to be highly effective in pattern recognition and picture segmentation (Yamashita et al., 2018). The CNN employs properly trained layers for the identification of plants and categorization (Ghazi et al., 2017) and the detection of plant diseases (Arsenovic et al., 2019). Low-level features like colours, corners, and edges are learnt from the first layer of CNN's hierarchy of self-learning characteristics. In contrast, the deep layer teaches high-level properties like textures and objects of the image. The sensitivity of CNNs to environmental factors like variations in light has been decreased through automated feature learning.

Medical leaf identification is of greater importance as these leaves help in the preparation of drugs, and some of these leaves can be taken in raw form to help cure diseases. However, there are issues concerning the identification of these medical leaves. Some of the most significant issues include;

- Identifying a leaf and ascertaining whether it belongs to the group of medical leaves.
- Identification of the medical leaf despite certain constraints such as degradation, speckle noise, color changes, orientation changes, changes in shape, etc.

To meet the above challenges in this proposed work, we present a methodology wherein the input leaf is pre-processed, then denoising using GMM model, and finally a neural network system is utilized to extract the features of the leaf. Various parameters are been evaluated to support and analyze the performance of proposed methodology.

Related works

The classification process is presented as a unique CNN architecture in Habibollah (2016). The author arbitrarily selected 20 leaves from 40 different species to represent the front and back of Ayurveda. Weka is a program used to recognize medicinal plants using machine learning methods. Based on these metrics, SVM and MLP classifiers are employed to identify the leaves. Using neural networks (Li et al., 2018), authors devised a method for identifying medicinal plants. As expected, MLP outperformed SVM (94.5%). Consideration is given to the leaves of five distinct plant species. To determine the location of the leaf's edges, the Prewitt Edge Detection method is utilized. An overview of the techniques for classification used for recognizing medicinal plants using ANN, SVM, and PCA (Chau et al., 2017). In order to distinguish neem leaves by their shape, colour, and vein properties, the authors have assessed the angle percentage, centroid, region, edge, and roundness in their proposed study. Sabu et al. (2017) proposed a new classification scheme for Ayurvedic herbs based on the characteristics of their leaves' morphology is proposed. The Laplacian filtering approach is used for edge detection.

A deep CNN is suggested as a solution by (Grinblat et al., 2016) to correctly classify plants based on the vein patterns in their leaves. The precision of the suggested pipeline is significantly improved by utilizing this deep-learning method. In addition to this, they provide evidence that the accuracy that has been claimed is attainable by increasing the model depth. A deep learning algorithm for classifying leaves was suggested, replacing the red channel of colors with leaf pre-processing to obtain vein form information (Huynh et al., 2020). Both the Flavia leaf data set and the Swedish leaf data set, which are collections of actual leaves, were used to verify the accuracy of this model.

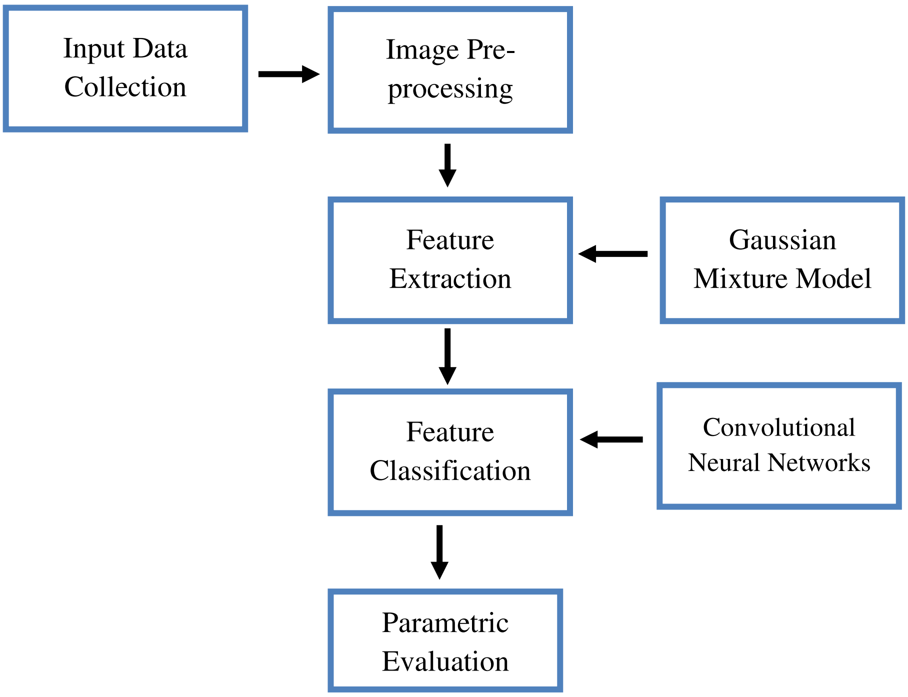

Figure 1. Process flow of the proposed model

The author (Wang et al., 2021) created AMSCNN, a novel multi-scale CNN, to enhance the detection of species of plants. To improve feature extraction and network training efficiency, this network is built to learn lower and higher-frequency features from the given images as input to the system via multi-scale convolution, and it incorporates an attention mechanism to capture complicated contextual interactions. To classify photos of medicinal plant leaves (Azadnia et al., 2022), describe a Deep Learning (DL) model that utilizes CNN block to extract features. The classifier block is comprised of layers of Global Average Pooling, thick layers, dropout layers, and softmax layers. Images of medicinal plant leaves recorded at varying resolutions were used to test the algorithm (64x64, 128x128, and 256x256 pixels).

A disease detection model by (Shelar et al., 2022) uses image processing with a CNN to aid in detecting plant illnesses. The study is driven by the fact that pests can majorly affect agricultural output and that diagnosing plant illnesses is a laborious and inaccurate process. To overcome this difficulty, the researchers recommend utilizing a convolutional neural network (CNN) to handle pixel inputs like photos. A hybrid model is evaluated to detect plant disease (Bedi et al., 2021), which was trained and validated with the publicly accessible Plant village dataset. The suggested hybrid model's combination of deep learning and machine learning approaches; represents an original contribution to the field of plant disease identification.

The author has developed an autonomous system for diagnosing diseases in potato plants utilizing CNN architectures. The different types of networks that can be modelled for the extraction of features are VGG-19, VGG-16, and InceptionV3 and different classifiers are utilized for classification. Some of them are Logistic Regression (LR), k-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Neural Network (Mohameth et al., 2020). The researchers determined that the combination of VGG-19 and Logistic Regression produced the highest accuracy of 97.8% based on their findings. The author proposed an automated system for identifying medicinal plants in the Borneo region. It uses a computer vision system with a deep learning model trained on a dataset of plant images, a knowledge base, and a mobile application for user interaction (Tiwari et al., 2020). The author discussed how to use deep convolutional neural networks (CNN) to identify the leaves of medicinal plants (Malik et al., 2022). However, a deep CNN model can be developed and improved to speed up the identification process. Multi-layer models and data augmentation (including image cropping and rotation) dramatically increased precision in this research.

Proposed methodology

The approach contributed to this work mainly utilizes three core steps after collecting the data that need to be considered for evaluating the work. The first step is pre-processing, second is image denoising and finally features extraction and classification. The process flow of the work is shown in Figure 1.

Data collection

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. 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 2; a total collection of 600 images was gathered. The leaf dataset utilized is flavia.

Figure 2. Flavia Dataset

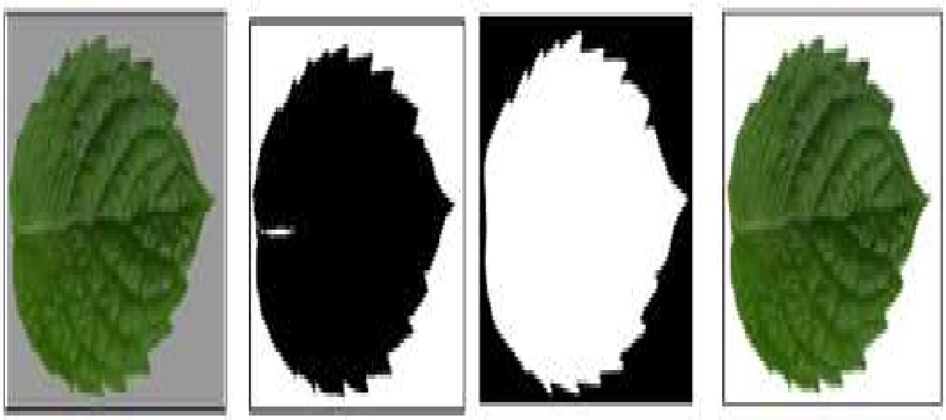

Figure 3. Pre-Processing output sample

Image preprocessing

In this step, all the images in the dataset are considered and resized for performing further operations. The leaf images are pre-processed to remove unwanted information, such as the image's background, and extract the image's foreground. For this purpose, a particular threshold value is selected and applied on the leaves to separate the background. To identify the optimal threshold value OSTU model is utilized (Vala et al., 2013). Several pixels are identified in the image in which some of the empty pixels in the leaf are suppressed using morphological dilation operation. The background noise present in the leaf will be removed using a smoothing filter. After this stage, the data is sent for feature extraction.

Image feature extraction

Gaussian Mixture Models (diagonal, tied, spherical, and full covariance matrices supported) sample the leaf data, and estimate the features from the provided dataset. GMM resources may be used to determine how many components should be present in each leaf.

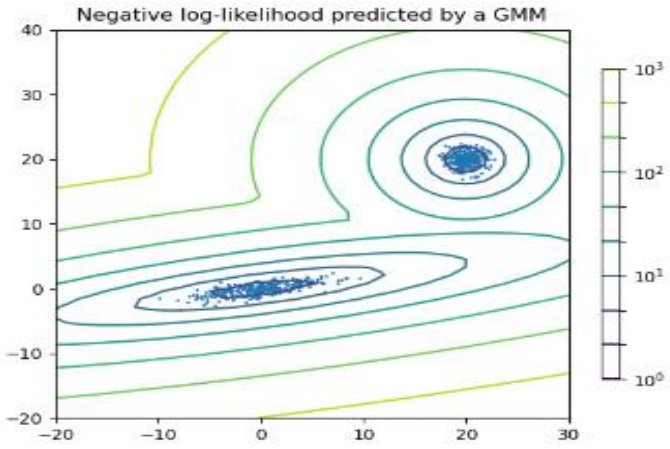

Figure 4. GMM model for extracting features

A "Gaussian mixture model (GMM)" is a probabilistic framework that assumes each data point was generated by blending a small number of Gaussian distributions with unknown features. As an extension of k-means clustering, mixture models are a way to account for the structure of covariance in data and the locations of latent Gaussian centers.

The GMM is examined in this article as a means of accurately identifying the characteristics of medicinal plants. These features are essential to classify the plant labels. Every plant leaf attributes a symmetric pattern; hence, to model these sorts of plant leaves, a bell-shaped or symmetric distribution is well suited. Therefore, in this article, we have considered the GMM model.

The probability distribution function of GMM is given by

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(\frac{x-\mu}{\sigma})^2} \quad \text{.................................(1)}$$

where μ and σ are the parameters inside the image regions. To have a better approximation of the features, the initial estimates obtained by the GMM are to be

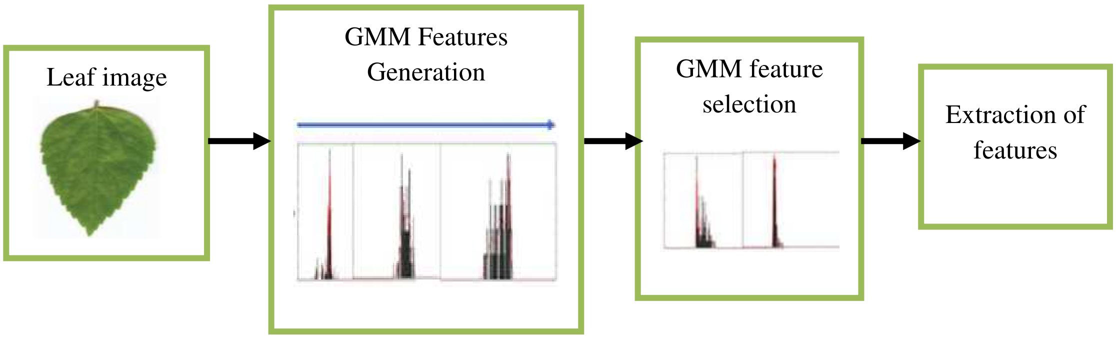

Figure 5. Selection of targeted features from the dataset

processed and updated. The GMM utilizes the EM technique for fitting a Gaussian mixture model. It can evaluate the availability of original data and produce confidence ellipses for multivariate models.

Machine Learning algorithms. The next step is to classify the data using CNN.

Features classification

The process of feature classification is performed using CNN. The final layer present in the CNN acts as classifier. The features need to be extracted for the given

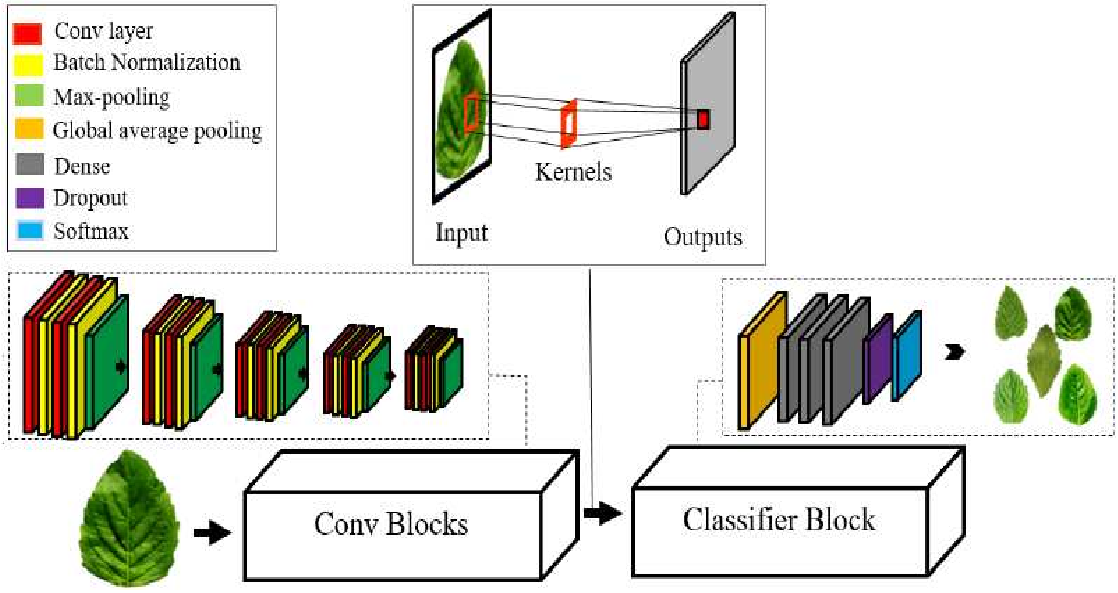

Figure 6. CNN model for suggested work (R. Azadnia et al., 2022)

Every plant leaf has different shape and colour features. To have more approximation of identification among the medical leaves from the dataset, the leaves have different orientations, degradation, damages, etc. The leaf should be identified more concurrently. For this purpose, effective modelling is necessary. Therefore, the Gaussian Mixture Models are considered to model the leaf images precisely in this article. Another advantage of the GMM is that it accurately estimates the leaves with symmetric properties. Therefore, with this approximation, the GMM is proposed.

However, to better understand the pixels' connectivity and the relationship between the pixels, the accuracy can be much more increased. The Convolutional Neural Networks algorithm has this advantage among the input image to identify the type of medicinal plant. The classification of features helps in finding the accurate measure of parameters evaluated. The model of CNN considered for evaluating the proposed work is shown in Figure 6.

CNNs are sophisticated deep-learning algorithms that excel at image analysis. They excel at object detection, image classification, and segmentation in computer vision. CNNs filter or kernel input data. Filters recognize edges, corners, and patterns. A feature map is created by convolving the filters with the input data. After each filter, an activation function like ReLU adds non-linearity to the network, letting it learn more complex patterns and features. The steps involved during the performance of the CNN process are stated below:

DOI: https://doi.org/10.52756/ijerr.2023.v32.009

Step 1. The first layer of a convolutional neural network (CNN), the input layer, takes in the original picture data. Most of the time, the input data is shown as a 3D array of pixel values.

Step 2. In the convolutional layer, filters are applied to the input image, each looking for a different feature type. A feature map is made by sliding the filter across the image and multiplying its values by the pixels' values.

Step 3. The pooling layer down-samples the feature map, decreasing its dimensionality in space. The fewer parameters a network has, the better it will perform computationally, and this helps.

Step 4. The output of the convolutional layer is applied to a non-linear activation function in the activation layer. This gives the network some non-linearity, which improves its ability to learn complicated characteristics.

Step 5. In order to make a fully connected layer, each neuron in the prior layer must have a connection to each neuron in the subsequent layer. Using the preceding layers' output as input, this layer learns more abstract characteristics.

Step 6. The final output layer of the network predicts the class or label of the image sent in.

A complete control across the entire dataset utilized for training is referred to as an epoch. The CNN iteratively adjusts its parameters during each epoch to minimize the loss function and improve its accuracy. By training the CNN with many epochs, it can learn to detect complex image features and make accurate predictions. To avoid underfitting or overfitting, it's crucial to find a balance between training for an appropriate number of epochs and not enough epochs.

Image classification using CNN has revolutionized computer-vision tasks by enabling automated and accurate recognition of objects within images. CNN-based image classification algorithms have gained immense popularity due to their ability to automatically learn and extract intricate features from raw image data. Image classification involves assigning labels or classes to input images. It is a supervised learning task where a model is trained on labelled image data to predict the class of unseen images. CNNs are commonly used to classify images as they can learn hierarchical features like edges, textures, and shapes, enabling accurate object recognition in images. CNNs excel in this task because they can automatically extract meaningful spatial features from images.

Metrics evaluated

Performance metrics like Average Distance (AD), Maximum Distance (MD), Image Fidelity (IF), and image segmentation metrics like volume of index (VOI), Probability Random Index (PRI), and Global Consistency Error (GCE) have been used to assess data precision. These equations define the evaluation of the metric.

Average Distance (AD):

$$AD = (1/N) * \sum d$$

Here, N represents the total number of pixels in the ground truth region, and d represents the closest point on the segmented border to the ground truth boundary.

Maximum Distance (MD):

$$MD = \max(d)$$

Where d is the same as in the AD formula, and max(d) is the maximum distance between the segmented boundary and the ground truth boundary over all pixels in the ground truth region.

Image Fidelity (IF):

$$IF = 10 * \log 10((MAX\hat{}2) / MSE)$$

MSE is the mean squared error between the segmented image and the ground truth image, and MAX is the maximum pixel value (255 for an 8-bit image).

Volume of Index (VOI):

$$VOI(A, B) = [VOI(A) + VOI(B)] / 2 - VOI(A \cap B)$$

Where A and B are the segmented regions, $A \cap B$ is their intersection, and $VOI(A)$ *and* $VOI(B)$ are given by:

$$VOI(A) = -\log(V(A))$$

$$VOI(B) = -\log(V(B))$$

Where $V(A)$ *and* $V(B)$ are the volumes of the segmented regions A and B, respectively.

Probability of Random Index (PRI):

$$PRI(A, B) = [PRI(A) + PRI(B)] / 2 - PRI(A \cap B)$$

Where A and B are the segmented regions, $A \cap B$ is their intersection, and $PRI(A)$ *and* $PRI(B)$ are given by:

$$PRI(A) = \sum [p(i, j) * p(i', j')] / \sum p(i, j) * \sum p(i', j')$$

$$PRI(B) = \sum [p(i, j) * p(i', j')] / \sum p(i, j) * \sum p(i', j')$$

Where $p(i,j)$ is the probability of a pixel in region A *and* $p(i',j')$ is the probability of a pixel in region B.

Global Consistency Error (GCE):

$$GCE = 1 - [\sum(\min(d(A,i), d(B,i))) / \sum(\max(d(A,i), d(B,i)))]$$

Where A and B are segmented regions and $d(A,i)$ *and* $d(B,i)$ are the distances of the ith pixel in the image to the boundary of regions A and B, respectively. The numerator adds the minimum distances between each pixel and its region's boundary, while the denominator adds the maximum distances.

Results and discussion

The findings show that the suggested GMM-CNN algorithm can detect medicinal plants with comparable leaves successfully. The experimentation is considered in a Python environment, and around 350 medical images are considered for training the data. For testing purposes, around 200 medical images are considered. The results derived are presented in Table 1.

Table 1. Evaluated parameters

Image of leaf	Name of Leaf	Quality Metric	Without GMM Model	Proposed Method
	Tulasi Leaf	AD	0.678	**0.802**
		MD	0.61	**0.882**
		IF	0.388	**0.786**
	Curry leaf	AD	0.61	**0.88**
		MD	0.25	**0.81**
		IF	0.35	**0.85**
	Hibiscus leaf	AD	0.58	**0.73**
		MD	0.62	**0.85**
		IF	0.56	**0.88**
	Thanduvalai leaf	AD	0.35	**0.68**
		MD	0.37	**0.85**
		IF	0.33	**0.86**
	Neem leaf	VOI	2.453	**5.4523**
		GCE	0.234	**0.4321**
		PRI	0.654	**0.674**
	Tulasi leaf	VOI	0.267	**0.768**
		GCE	0.056	**0.0834**
		PRI	0.598	**0.678**

A number of problems, such as a large cost of computation, difficulty, and a long duration of processing, have made it difficult to employ the primary CNN models. We employed two alternative strategies to address this problem: (1) increasing the amount of smaller-sized and more numerous pictures used during the operation of pre-processing of the image and (2) utilizing the FC layer for both extraction and classification of features, drastically paring down the model's complexity and number of variables. Finally, it has been demonstrated that these methods boost the model's precision and speed of computation while also reducing the risk of the over-fitting problem. The comparison of parameter values is shown in Figure 7.

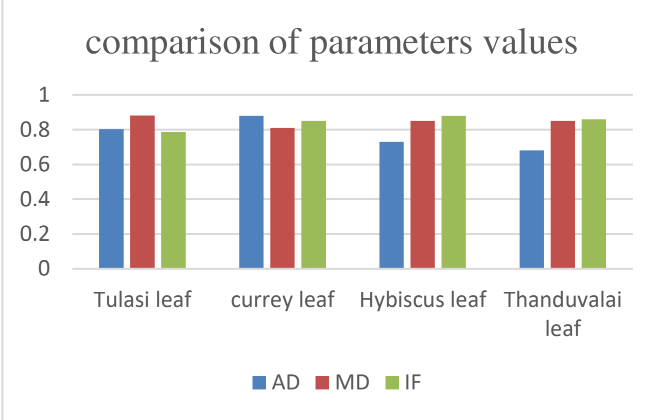

Figure 7. Comparison of values obtained for different leaves

Conclusion

In botany and agriculture, it is crucial to differentiate between medicinal plants and other types of plants that humans do not consume. Identifying medicinal plants using conventional methods is laborious, time consuming, and requires experts. An autonomous, real-time, vision-based approach that could identify frequently used plants for medicinal purposes with similar leaves had favorable outcomes. The suggested solution uses a convolutional network, an upgraded CNN version. The integration of Gaussian Mixture Models (GMM) with Convolutional Neural Networks (CNN) effectively mitigates certain constraints inherent to each method when employed in isolation. The Gaussian Mixture Model (GMM) provides a robust framework for representing complicated data distributions, enabling the system to effectively capture nuanced changes in leaf characteristics. In contrast, Convolutional Neural Networks (CNNs) have exceptional proficiency in autonomously extracting hierarchical features from unprocessed picture data, hence facilitating the system's ability to acquire discriminative patterns straight from images. The hybrid model combines the utilisation of feature extraction from Convolutional Neural Networks (CNNs) with the probabilistic modelling capabilities of Gaussian Mixture Models (GMMs) in order to generate a more complete representation of leaf attributes. The model could recognize the medical species even in rotation, orientation, and shape patterns. For evaluation, we have considered different evaluation metrics like Average Difference, Image Fidelity, VOI, GCE, and PRI, and the results showcase better improvement using the proposed model.

Nevertheless, it is crucial to recognise that there are still obstacles that need to be addressed. Ongoing research efforts are focused on the refinement of parameters for the hybrid model, optimisation of computing resources, and the establishment of scalability. Furthermore, it is necessary to do further research on the interpretability of the model's decision-making process and its potential applicability to different areas.

Conflict of Interest

The authors declare no conflict of interest.

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How to cite this Article:

Marada Srinivasa Rao, Sekharamantry Praveen Kumar and Konda Srinivasa Rao (2023). Effective medical leaf identification using hybridization of GMM-CNN. *International Journal of Experimental Research and Review*, *32*, 115-123.

DOI : https://doi.org/10.52756/ ijerr.2023.v32.009