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Deep - Morpho Algorithm (DMA) for medicinal leaves features extraction

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Abstract

Presently, for the identification and classification of images, various deep learning techniques are being used. In these techniques, the whole image is considered to produce similar feature sets for many images. As a result, this mechanism loses many of its features at the final stage. Therefore, to analyze and identify medicinal leaves through an artificial eye of botanists, it was emphasized that the leaf image features should remain preserved till the final stage of classification for better accuracy. The existing plant identification approaches are trained using the leaf images. So leaf features are lost in the different stages of the convolution process and the same feature values are generated for similar type leaf images. This raises ambiguity in the results and affects the accuracy of leaf image identification. But here, in this proposed deep learning-based plant leaves morphological feature recognition system, leaf morphological features are used to train the system. Morphological features are identified to recognize a plant leaf. Here, morphological features of medicinal plant leaves, venation, shapes, apices, and bases are extracted and analyzed to predict the image class. So, the leaf features remain persevered until the final stage. The proposed feature recognition analysis improves the accuracy of the leaf identification method. In this, more than 300 leaves from 18 different plant families are collected and trained to build the deep learning classifier and achieve 96% accuracy. The performance evaluation was also conducted over "Flavia", "Swedish" and

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"Leaf" data set and obtained 91%, 87% and 91% accuracy. The performance of image classification and feature preservation algorithms with less computational power are indicating the potential applicability of the proposed Deep - Morpho Algorithm (DMA) in medicinal plants and leaves identification.

Keywords Deep learning · Leaf morphology · Medicinal plant · Plant recognition · Feature recognition

1 Introduction

In ancient times, physicians themselves selected plant leaves for preparing medicines for their patients. In recent years, the popularity of mobile phones and digital cameras are becoming user friendly, and automatic plant leaf detection through image processing also explored adequate alternative technology. Image identification researchers and developers also assisted botanists to recognize plant species more rapidly through deep learning algorithms [20].

Image processing-based leaf identification process depends upon:

(1) Data set selected for training,
(2) Leaf features selected for recognition and.
(3) Accuracy of the algorithm.

In the normal deep learning network, the arrangements of image pixels are processed for leaf identification. However, in the medicinal plant identification, where accuracy of the result is more important, morphological features of leaf images playing a big role.

Researchers, earlier extracted colour features for conducting similarity calculations of the leave images for plant identification. They identified leaves by counting the colour difference in concentric circles of binary images and fuzzy colour histogram (FCH) based background subtraction in the Leaf data set [3, 14]. For the colour feature-based leaf identification, colour frequency histograms are compared to classify the plants [12].

Shape features are used to study the arrangements of leaves and the border of leaves. Boundary based shape analysis is commonly employed in shape-based plant recognition. Natural and artificial shape changes that happened on input leaves are the questionable problem facing if shape used as a common feature. In [44], leaf shape is recognized based on the support vector machine and the curvature bag of words (CBoW) shape feature descriptors. A chord bunch walks (CBW) descriptor for leaf shapes is described in [41]. Shape features and their inner properties of the leaf shape are acquired by travel and measuring along with a set of a straight line that passes through the shape. In [22], a region proposal Convolutional neural network is used to detect shape showed high detection speed and accuracy and proposed that the patterns on the surface of leaf image according to the colour and greyscale variations form the leaf texture.

In [29], a different shape measure like area, perimeter, and the ratio of major and minor axis used leaf recognition is detailed. In [6] geometric features of leaf shape are used for multi-layer neural network-based leaf recognition. In [5], k-means clusters-based shape analysis logic on the Swedish and the Leaf data sets is explained with deformation-based representation space for curved shapes. Segmentation and classification of scanned legume leave based on veins, shape, size, texture and colour is reported in [19] by Larese et al. is economically and effectively more effective than manual leaves recognition.

Researchers have also attempted texture feature in KNN based plant identification [13]. The texture of leaves sometimes degrade due to climate change will reflect the inaccuracy of the result. The detailed research review on plant leaf identification system leaves colour, shape and texture has pointed out that the patterns may vary according to the climate and other physical reasons [39]. In [2], authors reported a supervised locality projection analysis (SLPA) algorithm for the label propagation to present a new weight standard for leaf image categorization. In [44], 10 k image categories are trained and organised using the Visual-Semantic Tree with the help of visual similarities and semantic correlations [45]. Colour feature [38] is easily retrievable from the leaves, but the colour of leaves many times changes due to prevailing weather and climatic conditions, which could lead to errors in results.

In existing deep learning methods, image pixel values are processed using convolution, Relu and Meanpool functions to generate features. This feature completely depends on the pixel colour value and size of the image. In-Plant leaf identification, most of the leaf colours and sizes are similar. To identify accurate plant species, it is important to verify the morphological leaf features. The deep learning process is not able to identify the exact morphological features from a leaf image, so, it is required to train the morphological features in the training and testing phases to get a Morphological Feature-based Deep Learning Approach. This morphological leaf features based deep learning approach is identical to human judgment in identifying a leaf image.

In this paper, we are considering venation, margins, shape, bases, and apices of leaves particularly for medicinal plant identification and in general for any plant identification using deep learning pattern recognition in image processing.

1.1 Leaf morphological features

A leaf morphological feature includes leaf apex shape, margin structure, venation, midrib structure, blade structure and base structure. The leaf apex or leaf tip is the top portion of a leaf. The leaf margin is the edge structure of a leaf. Leaf venation is the collection of veins in a leaf. The midrib is the main vein of the leaf.

The flat and plane exterior portion is called lamina or blade of a leaf. The bottom portion, which links to the petiole of the leaf, is called the leaf base. The features of a single leaf are shown in Fig. 1.

Plants classification is a process of identifying their morphological characteristics. For plants identification, taxonomist and botanist follow morphological and molecular approaches. [4] Describes various techniques for extracting physiological characteristics from a leaf component to classifyplants based on morphological features. The closed path at the edge of the leaf picture is leaf Shape. Shape feature limiting other parts of leaves provides details of the image into the overall boundary. Edge detection techniques provide information about the details of boundary pixels of leaf shape, as in the Canny edge leaf shape detection method, local maxima-based segmentation technique is performed over the Gaussian filter [1]. The canny operator operates two entries to discover the strong and weak edges from the image, The weak edges which all are connected to strong edges are selected. To complete the border pixels and extract the shape feature, the double threshold is applied over this result [39].

The leaf vein pattern is a biometric feature, taxonomy tool and key determinant of plant adaptation, however, its extraction is a challenging task since some leaves do not show a clear

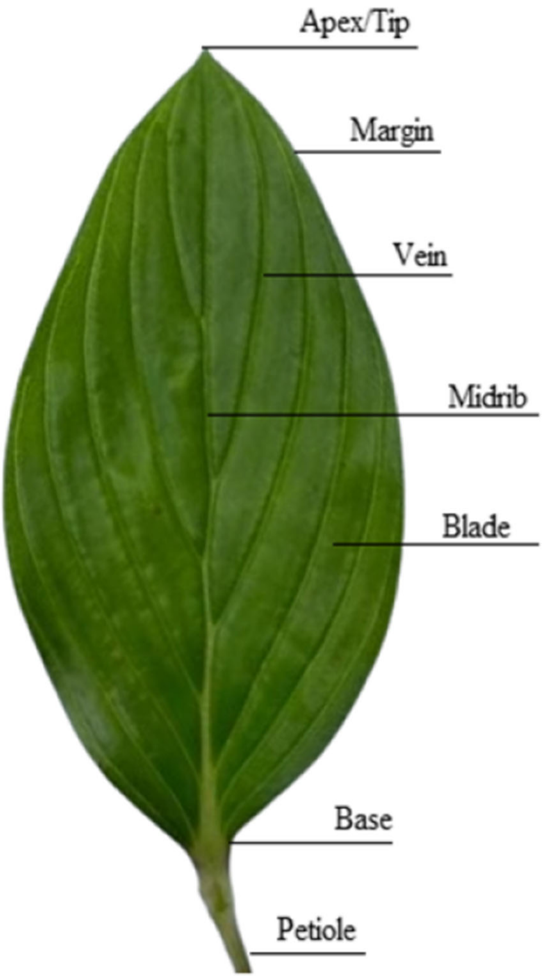

Fig. 1 Morphological features of a single leaf

vein pattern [30]. To improve the accuracy of vein extraction, pre-processing and segmentation techniques are applied. In [39], the leaf vein extraction method using the Canny edge detection method is described. Grayscale converter and contrast stretching process applied over input image to reduce error in vein extraction using canny edge detection. The various cut, irregularities, free form or incisions shape formed on leaf shape boundary is defined as leaf margin.

This shape of margin is genetically fixed and at least a dozen unique characteristics on a species. Like leaf shape extraction, a double threshold applied canny edge detection method is used here to extract leaf margin [39]. Atoum et al. [2] proposed a computer vision system, CLS Rater, to automatically and accurately rate plant images in the real field to the "USDA scale". Numerous studies have focused on procedures or algorithms that maximize the use of leaf databases for plant predictive modelling, but these results in leaf features that are liable to change with different leaf data and feature extraction techniques [20]. Pawara et al. [26] proposed a One-vs-One (OvO) classification scheme for deep neural networks that trains each output unit to distinguish between a specific pair of classes and reported that the method increases the number of output units compared to the One-vs-All classification scheme but makes learning correct decision boundaries much easier.

1.2 Leaf features and attributes

The large teeth part of a leaf margin is called leaf Lobes and sinus. The roundish and projected part of margin teeth is called lobes. The sinus part is the gap generated between two lobes. The projected part of the leaf is identified by detecting curvature maxima and curvature minima using the method specified in [24].

The presence of petiole in a leaf may be long or short, or completely absent. Researchers are describing different petiole detection methods for leaf image. Leaf petiole has narrowed width than shape. This assumption used as a key to finding out petiole by image analysis [24]. The lowest part of a leaf shape is called a leaf base [15], and a leaf base is also considered as a classification tool because it is different in each plant species. However, this has not been appropriately employed in image processing analysis.

1.3 Leaf identification and classification

In the computer vision world, various plant identification and classification methods are available. The artificial brain of a computer processor takes decisions based on neural networks, and calculations are fuzzy theory or probability theory-based comparisons. The resulting accuracy of these comparison methods depends upon the number of feature set selected from the input image [10, 38].

In general leaf identification and classification approaches, leaf pre-processing and leaf contour extraction is a major step. But, using the histogram-based pattern representation and without the help of preprocessing methods, [48] accurately recognized simple leaves from their shape patterns. This self-determining outline, leaf texture and leaf veins are extracted using elliptical half Gabor and the directions of outlines are take out from the local contour shape. A counting based shape descriptor is used in this research article that improved the computation speed and accuracy of leaf identification.

A Supervised binary partition tree-based object separation algorithm that can retrieve several objects from a single image is discussed in [28], Image sections are representing on each node of the binary partition tree. An algorithm defined in this method can estimate the value of binary partition tree which holding image region details help for the separation of several objects from an image. Both intrinsic and extrinsic analysis of image structure concerning the nodes of binary partition tree help to extract the specific object and desired properties of that image segment.

Colour thresholding-based image segmentation for leaf images, using the help of K-means clustering is discussed in [21]. Leaf classifier in [9], generated the leaf features with the help of Local Binary Pattern and Histogram Oriented Gradient. Eliminating the background of an image to extract the details of objects using Principal Mode Component Analysis is discussed in [18]. In [26], a code matrix-based encoding scheme is implemented for the deep neural networks-based classification, which supports to ease of handling the labels of different classes. Sensing devices using the Human activity recognition technology to studies the received data.

In [43], a shape description approach called Triangle-distance representation is used to extract the image characteristics of the leaf. In [47], researchers discussed leaf detection based on Fast Region-based Convolutional Neural Networks with K means clustering algorithm.

In image processing, the importance of shape numbers is discussed in [40]. This algorithm is an explanation for the pixel selection problem of Freeman chain code and shape number generation method for single. First, with the help of a multi-scale curvature integral descriptor used in the discrete contour evolution algorithm, object contour is defined then the shape outline is divided into outline sets sing based on the polygonal shape vertices. Finally, the contour sets are represented by the help of the curvature bag of word-based model. In a Convolutional Neural Networks based Plant identification systems authors of [20] reported that venation of leaf image is the best characteristic features than the leaf shape.

In recent years, deep learning has been used in leaf classification. Convolutional neural networks are commonly used model in deep learning for leaf detection and classification. In [37], leaf veins segmentation using the Sobel edge detection method and CNN-based plant identification system using D-Leaf is explained. In [49], the result of learning process comparing the test image's each feature separately with the leaf morphological database. These separate classes will mimic the Support Vector Machine (SVM) classification model.

The feed forwarding network explained in [11] extracted geometric and morphological features of leaf images and processed them using Principal Component Analysis (PCA) method. The authors used 95 types of leaves and 20 leaves for testing purposes and achieved more than 90% of accuracy. In [25], leaf shape-based plant identification is conducted using Elliptic Fourier (EF) and discriminate analyses and achieved above 93% of accuracy. Area, colour histogram and edge histogram-based medicinal plant identification is conducted in [16] and achieved 94% accuracy. Support Vector Machine based leaf classification using 12 leaf features for plant recognition is explained in [27], which achieved above 94% accuracy. AdaBoost methodology [17] along with k-NN, Decision Tree and Multilayer perception-based machine learning classifier for automatic identification of plants explained in [46] achieved 95.42% precision rate.

In the deep learning-based image detection method, the whole input image is not processed in the neural network, but the input image is partitioned into overlying tiles. In the object localization time, a fixed-sized sliding window (Kernel, or square matrix) scan over and crop fixed-sized the image. Then deep learning is applied to all cropped images for generating the outputs. This output describes which portion of the image is most remarkable for the image's feature generation. The selection of this region will result in overlapping boxes, so maximum scored boxes are selected in the result time. In the classification time, these labelled morphological features used to identify the leaf category.

In many cases, this continuous partition and complicated merging process of a deep learning-based image process is leading to the loss of many important details from the features generated for the images. The incomprehensible features used for leaf identification will lead to the wrong classification of similar types of leaves. Intermediate results of normal deep learning of a Peepal leaf (Botanical name: *Ficus religiosa*) are shown in Fig. 2. In different steps of the convolution process, the main morphological features of the Peepal leaf are lost. Similarly, the quality of the image object is degrading with each step. In a detailed analysis of the Convolution result, ReLu function and final mean pool result, the shape properties of the leaf are changing slowly and very narrow and important features like leaf vein and leaf margin features are lost.

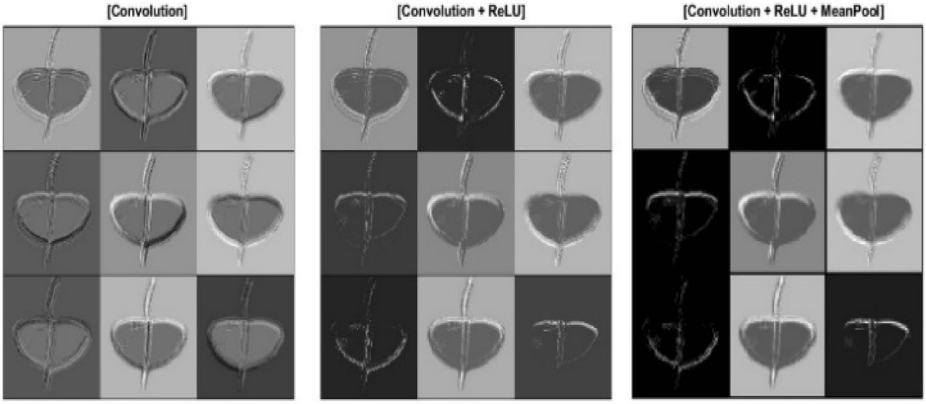

Fig. 2 The result of an existing deep learning method. Here, the whole image is considered to produce feature sets. However, in the final stage of the convolution process, most of the morphological features are lost

2 Proposed Deep - Morpho Algorithm (DMA)

The intention of this work is to build a deep learning algorithm for leaf identification by preserving the internal leaf morphological features. Therefore, we extracted morphological features from the leaf images, and then applied deep learning over these leaf features.

2.1 Database

The first step of this algorithm is leaf morphological feature database generation. The leaf morphological feature dataset contains the shape, apex, base and venation details of leaf images. Sample images from the leaf morphological feature dataset are shown in Fig. 3. Here, standard images are used to train the database, for more complex classification this morphological feature dataset must be increased accordingly. This morphological database is used in both training and testing time.

First process is the extraction of morphological features. Then, these leaf morphological features are analyzed using convolution neural networks. The final process is the comparison of feature map with the morphological database to understand the category extracted features. Our dataset which contains 300 leaves from 18 different plant families. Details of the plant leaves including the information of common name of the plant, Malayalam vernacular name of the plant, scientific name of the plant, sample leaf Image from the plant and image size are given in Table 1. Most of the existing leaf databases are plucked leaf images from the plants and are later scanned to generate a leaf database. Most of the vein and texture information is lost due to the leaf plucking and drying effects. Here these image files are captured from live plants using the mobile camera. Here these leaves are not plucked, so all the image features are available for feature extraction.

2.2 Morphological leaf features extraction (MLFE)

The next process is the leaf morphological features generation. All the leaf images are preprocessed based on petiole direction and converted into Grayscale format. In Morphological Leaf Features Extraction (MLFE), image is converted into grayscale using

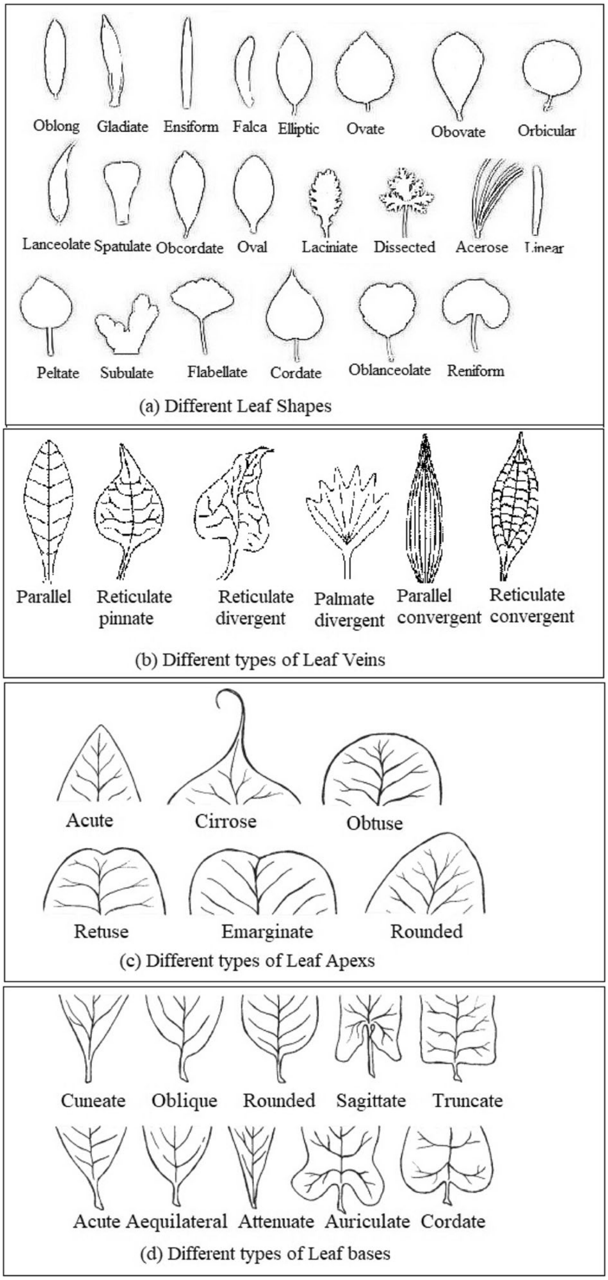

Fig. 3 Sample images from the leaf morphological feature dataset

grayscale converter. Normal Canny edge detection is perfect for the shape extraction, but vein details are more complicated and leaf texture features have also been received in the result of normal Canny edge detection method, so the Advance Canny edge detection is applied over the grayscale image to extract the vein feature from the leaf image [39].

Table 1 Details of leaves used for training

Sr. No.	Common name	Malayalam vernacular name	Scientific name	Sample Image	Image Size in pixels
1	Neem	Aaryaveppu	*Azadirachtaindica*		690 x 362
2	Peepal tree	Arayal	*Ficus religiosa*		450 x 554
3	Curry leaves	Curry veppu	*Murrayakoenigii*		517 x 341
4	Cinnamon	Karuvapatta	*Cinnamomumverum*		630 x 396
5	Phyllanthus	Kizharnelli	*Phyllanthus amarus*		403 x 251
6	Holy basil	Krishna tulasi	*Ocimumtenuiiflorum*		438 x 570
7	Frankincense	Kunthirikkam	*Boswellia serrata*		351 x 712
8	Black pepper	Kurumulak	*Piper nigrum*		493 x 580
9	Indian Pennywort	Muthil	*Centellaasiatica*		522 x 478
10	Arjun	Neermaruth	*Terminalia cuneata*		340 x 544
11	Indian borage	Panikoorkka	*Plectranthusamboinicu s*		419 x 595
12	Guava	Pera	*Psidium guajava*		716 x 348
13	Mint	Puthina	*Mentha arvensis*		551 x 453
14	Red sandalwood	Rakthachanthanam	*Pterocarpus santalinus*		417 x 598
15	Rudraksha	Rudhraksham	*Elaeocarpus sphaericus*		385 x 803
16	Hopea	Thambakam	*Hopea parviflora*		187 x 644
17	Hogweed	Thazhuthama	*Boerhaviadiffusa*		427 x 584
18	Shoe flower	Chembarathi	*Hibiscus rosa-sinensis*		62 x 107

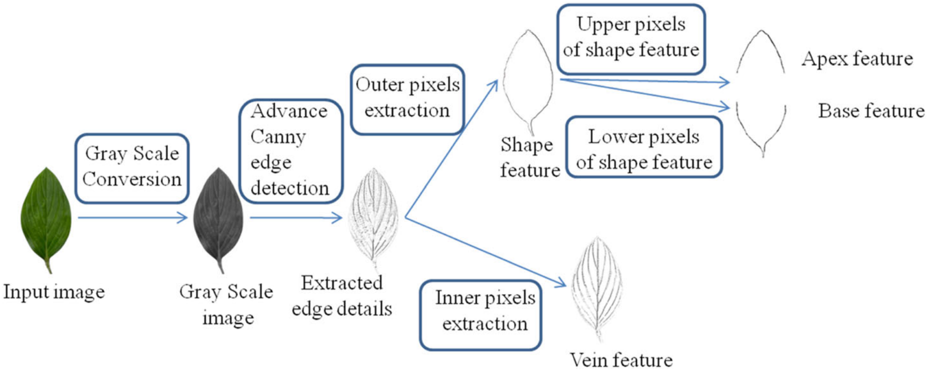

Fig. 4 Morphological Leaf Features Extraction (MLFE)

Outer pixels of the result of Advance Canny edge detection algorithm providing the shape feature. So, 128 × 128 sized binary image is generated using the shape feature result. Inner pixels of the result of Advance Canny edge detection algorithm providing the vein feature. So, 128 × 128 sized binary image is generated using the vein feature result. In the next step, shape image pixels are horizontally dividing to generate apex and base features. Upper portion of shape feature pixels are collected for apex feature and lower portion pixels of shape feature saving as base feature. Apex and base feature pixels are saving into 128 × 128 sized binary images. The Morphological Leaf Features Extraction (MLFE) is explained in Fig. 4. From the Table 1, images are in different sizes, so the extracted features are converted into 128 × 128 pixel format for the accurate learning process.

2.3 Morphological feature-based deep learning approach (MP-DLA)

Morphological Leaf Features extracted using Morphological Leaf Features Extraction (MLFE) algorithm is the input to the deep learning process. Each Morphological Leaf Features are separately processed and more detailed feature set is generated. The morphological feature-based deep learning approach (MP-DLA) process is shown in Fig. 5.

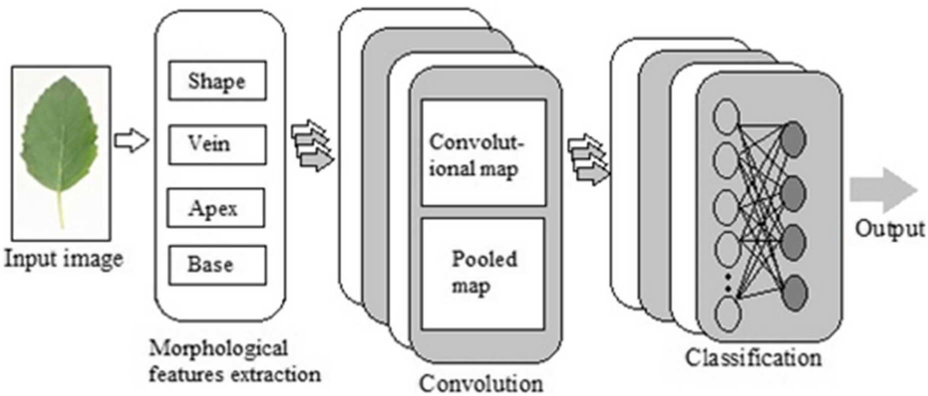

Fig. 5 Morphological Feature-based Deep Learning Approach (MP-DLA)

In the training phase of morphological feature-based deep learning approach (MP-DLA), input image is received one by one to extract the morphological features using Morphological Leaf Features Extraction (MLFE) process. The convolutional neural network receiving the morphological features and generates feature map for all the morphological features.

In the testing phase of morphological feature-based deep learning approach (MP-DLA), first phase is the leaf features extraction. Morphological leaf features are passing into convolutional part for extracting deep learning features from the images. Convolutional map processing each pixel of the image and kernel calculates the class to which individual morphological feature is belongs to. Result of convolutional layer is shown in eq. (1).

$$X_j^l = \sum_{\mathrm{i \in mj}} X_i^{l-1} k_{ij}^l + b_j^l \tag{1}$$

In eq. (1), X_j^l, X_i^{l-1} is earlier result, k_{ij}^l is the current layer, b_j^l is bias and mj is input map. Down sampling method carried over the data created from convolutional map to filter the essential information. Down sampling is also called sub-sampling layer or pooling layer. This Down sampling method reduces the size of each dimension of the output map but there will be exactly N output map for N input map. Down sampling is same as the max pooling mechanism shown in Fig. 3. Result of down sampling layer is shown in eq. (2). Output of the down sampling layer is represented as D_j^l, D_j^{l-1} is the previous layer output.

$$D_j^l = \mathrm{down}\left(D_j^{l-1}\right) \tag{2}$$

In the classification part, fully connected input layer and fully connected output layer process the output of convolutional part. Fully connected input layer flattening the result of Convolutional part into single vector and fully connected output layer gives the final leaf family label. Equation for classification function of CNN is given in eq. 3. Here, D is the input matrix to classification part, W is the weight matrix and b is a constant.

$$Z = W^T * D + b \tag{3}$$

Feature maps are then compared with the trained database to predict the shape, vein, apex and base features from the database. In the final stage, suitable leave is identified by comparing the result of morphological features. The flowchart of classification of leaf images using morphological features and deep neural network is shown in Fig. 6.

In this flowchart (Fig. 6), different steps involved in training and testing of leaf images are shown. Firstly, all the collected images are passed through training phase to generate image features. These image features and labels are saved in database. Later, in the testing phase, input image feature is generated and compared with the database to detect the leaf category. Detailed architecture for MP-DLA is shown in Fig. 7.

The result of the Morphological feature-based deep learning approach (MP-DLA) with extracted leaf vein, shape, apex and base morphological features using our proposed deep

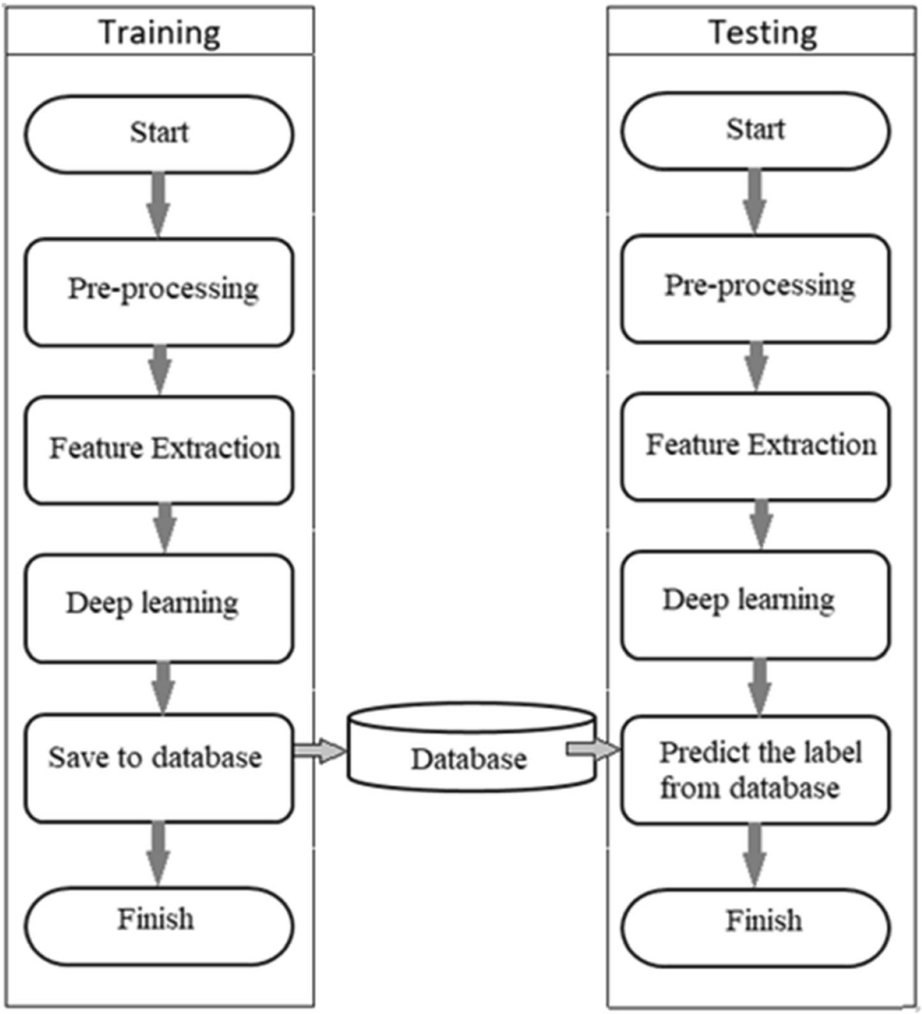

Fig. 6 Flowchart of classification of leaf images using morphological features

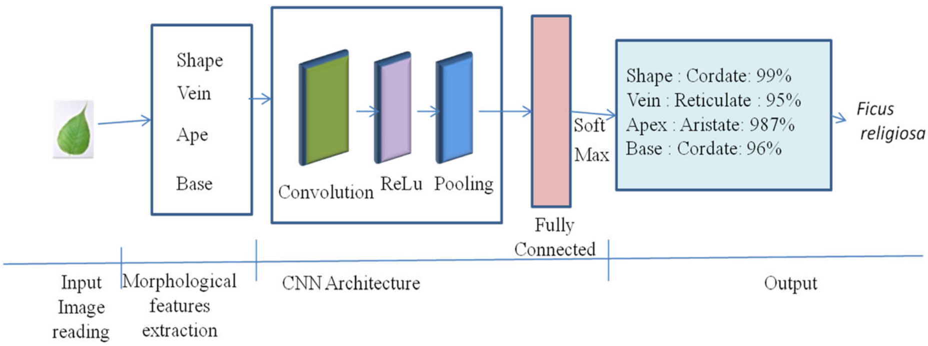

Fig. 7 Detailed Architecture of MP-DLA

learning method is shown in Fig. 8. By comparing Fig. 2 and Fig. 8 our proposed method provides a more accurate result in the medicinal plant identification. The proposed method preserves complete information of the leaf at each stage. The comparison for normal deep learning result and proposed method is given in Fig. 9.

3 Performance Evaluation

Various performance measures are existing in image processing, and they are handled in a predefined standard. The selection of any measure for performance evaluations of image processing algorithms depends on the requirements application and the nature of the algorithm itself. Performance evaluation using principal component analysis and morphological features is explained in [11]. Performance evaluation of Probabilistic Neural network together with five categories of geometrical features is explained in [25]. Performance evaluation of Multilayer Perceptron (MLP) classifier and leaf features are employed in [16]. In [27], evaluation of morphological and geometric features is considered. The commonly used four performance

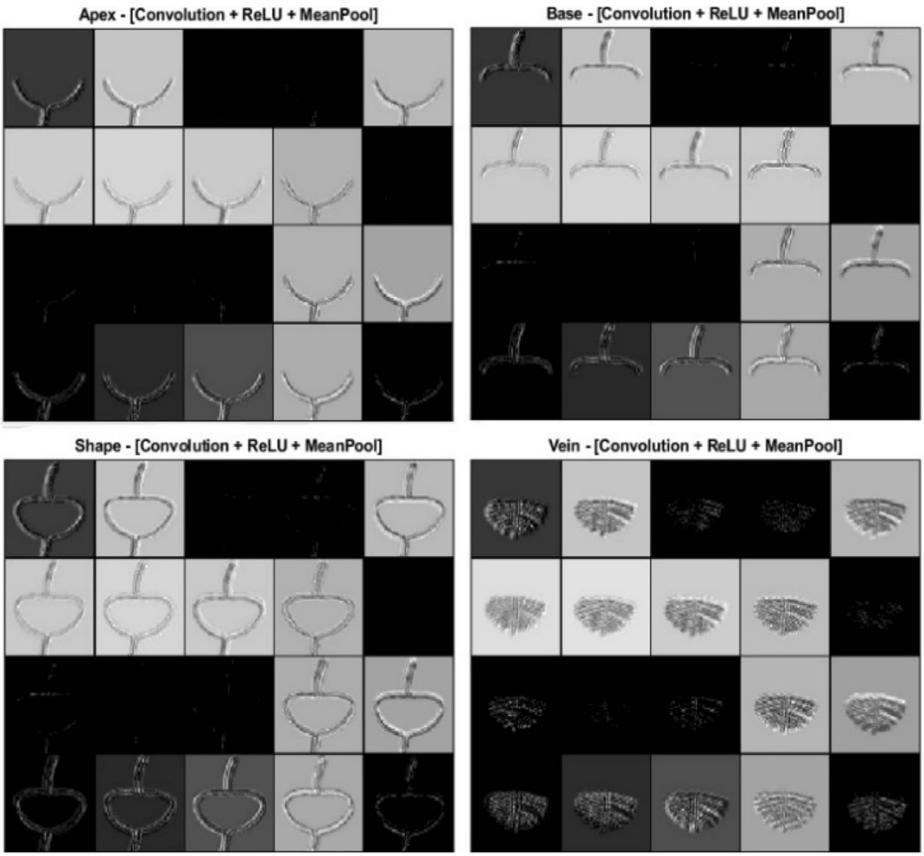

Fig. 8 The output of MP-DLA. Here, all the details are preserved and generated feature set for leaf identification

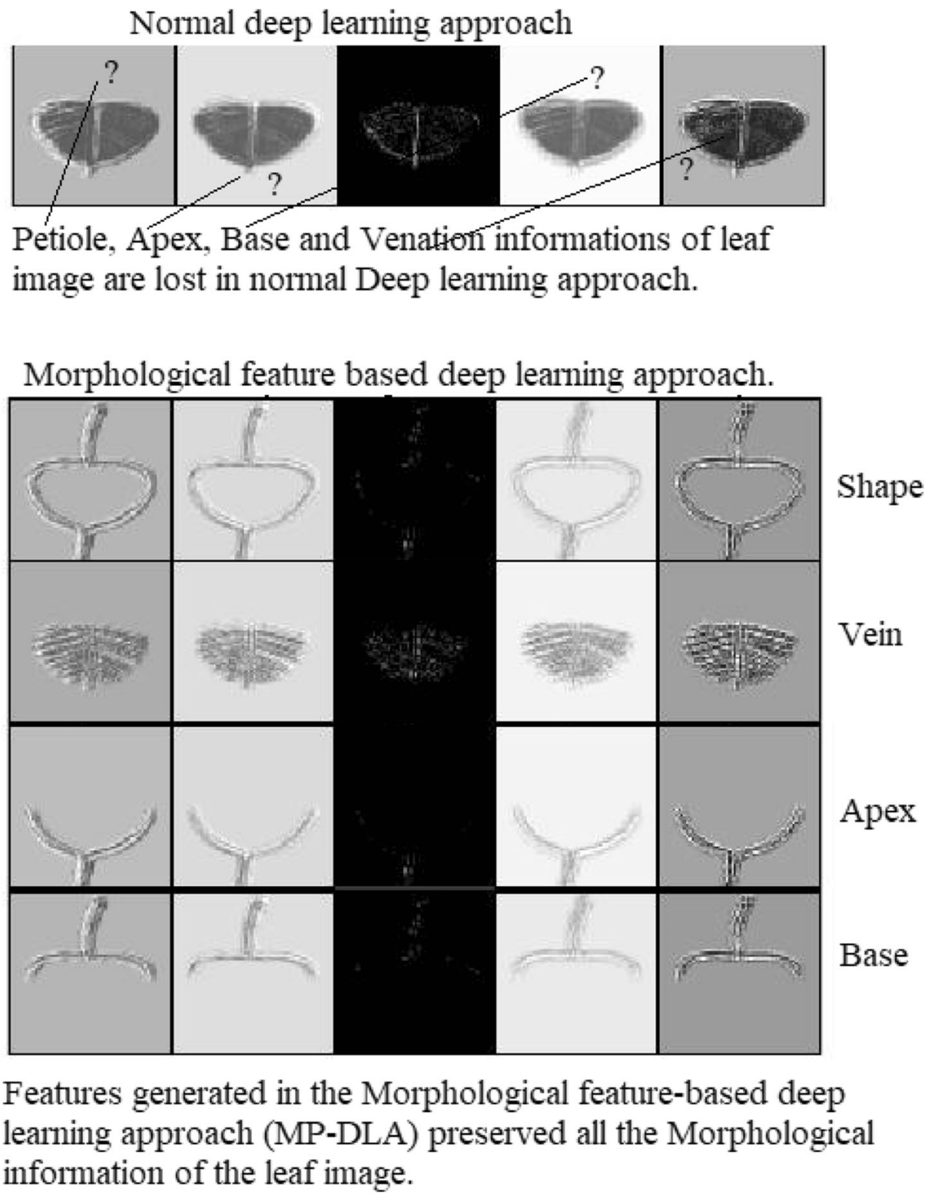

Fig. 9 Comparison between existing approach and MP-DLA

evaluation criteria [35] based on the confusion matrix are explained below. Here, true positive (TP) is the accurately identified positive leaf set and true negative (TN) is the accurately identified negative leaf set. False-positive (FP) is the wrongly identified positive leaf set and False negative (FN) is the incorrectly identified negative leaf set. The equations for accuracy [Eqs. (4) and (5)], precision [Eqs. (6) and (7)], recall [Eqs. (8) and (9)] and F1-measure [Eq. (10)] are as follows:

3.1 Accuracy

The term accuracy shows the percentage of correctly classified images as given in (4) and (5):

$$Accuracy = (Correctly\ Retrieved\ Images/Total\ Images) \times 100\% \tag{4}$$

OR

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{5}$$

3.2 Precision - positive predictive value

$$Precision = Relevant\ Images/Retrieved\ Images \tag{6}$$

OR

$$Precision = TP/TP + FP \tag{7}$$

3.3 Recall or sensitivity

$$Recall = Relevant\ Images/Retrieved\ Images \tag{8}$$

OR

$$Recall = TP/TP + FN \tag{9}$$

3.4 F1-measure

$$F{-}Measure = 2\ ((Precision{*}Recall)/(Precision + Recall)) \tag{10}$$

Performance evaluation of our database and algorithm is shown in Table 2.

4 Results and Discussions

The proposed system elaborated on each of the medicinal leaf features in multiple layers and studied and classified them into related classes. The leaf identification process takes place in the different layers between input and output with the help of a leaf morphological dataset. Multiple layers of deep learning representation applied in this proposed system led to an increase the computing power and act as human brains seem to. This very flexible framework from deep learning helped to achieve high accuracy results.

This algorithm is like how botanists identify a plant species. The enhanced leaf characteristics analyzed here to identify medicinal plant leaves. This method is extendable to test and train other image processing technologies. The advantages of our system are the fastest feature extraction by avoiding the limitation of leaf images and improves the accuracy of the proposed system. The training set of the proposed algorithm can easily explain the importance of

Table 2 Accuracy of proposed algorithm

Scientific name	Sensitivity	Precision	Accuracy	F1 Score
Azadirachtaindica	0.99	0.99	0.99	0.99
Ficus religiosa	0.99	0.99	0.99	0.99
Murrayakoenigii	0.99	0.97	0.96	0.98
Cinnamomumverum	0.95	0.98	0.94	0.97
Phyllanthus amarus	0.99	0.98	0.97	0.98
Ocimumtenuiiflorum	0.98	0.97	0.96	0.98
Boswellia serrata	0.98	0.95	0.94	0.97
Piper nigrum	0.99	0.97	0.96	0.98
Centellaasiatica	0.98	0.99	0.97	0.98
Terminalia cuneata	0.99	0.99	0.99	0.99
Plectranthusamboinicus	0.98	0.94	0.93	0.96
Psidium guajava	0.99	0.92	0.91	0.95
Mentha arvensis	0.99	0.97	0.96	0.98
Pterocarpus santalinus	0.99	0.95	0.94	0.97
Elaeocarpus sphaericus	0.99	0.99	0.98	0.99
Hopea parviflora	0.99	0.98	0.97	0.98
Boerhaviadiffusa	0.99	0.99	0.99	0.99
Hibiscus rosa-sinensis	0.99	0.96	0.95	0.97

morphological leaf features for each network. This deep learning algorithm can uncover the existing relations between each morphological feature like shape, vein, margin, base and apex separately.

For the overall performance assessment of our system, comparison to benchmarked deep learning models [23] is conducted. A depth-wise separable convolution network called Mobile Net [8] is lighter neural network for real-time identification. VGG19 is the 19 layered deep learning networks for classification [33]. In 2019, Mingxing Tan and Quoc designed a deep learning neural network architecture using a compound coefficient called Efficient Nets [36]. ResNet-18 [7] is known as an easy training benchmarked network. Comparison of accuracy between benchmarked deep learning models are shown in Table 3. From the Table 3, morphological features along with deep learning-based classification of leaf images showing high accuracy compared to existing algorithms [9]. These methods also explaining the importance of leaves identification based on morphological features.

Table 3 Performance comparison with state-of-the-art methods

References	Classifier	Accuracy
Janahiraman et al. [9]	LBP and HOG	90.22%
Kadir et al. [11]	Probabilistic Neural Network	90.00%
Neto et al. [25]	Probabilistic Neural Network	93.75%
Kumar [16]	Neural Network	94.00%
Priya et al. [27]	SVM	94.20%
Kumar et al. [17]	Multilayer Perception	95.40%
Howard et al. [8]	Mobile Net	91.71%
Simonyan and Zisserman [33]	VGG19	90.89%
Tan and Le [36]	Efficient NetB0	91.71%
He et al. [7]	ResNet18	91.28%
Proposed Method	Morphological Feature based Deep Learning Approach (MF-DLA)	96.00%

Medicinal plant recognition result achieved from enhanced features is also evaluated using the "Flavia" [42], "Swedish" [34] and "Leaf" [32] data sets. The performance of our algorithm has calculated using the medicinal plant leaf identification test results and statistical measures. Evaluation and comparison of our database with "Flavia", "Swedish" and "Leaf" databases are shown in Fig. 10.

4.1 Memory analysis

In the training time of a normal deep learning process, 6199 MB of memory is used. But, 42,607 MB of memory is used in this proposed system to train feature-based deep learning. According to normal convolution training, this is a little larger value because in normal deep learning direct images are used to train. Here image features are extracted and trained separately to increase the accuracy of identification.

4.2 Sensitivity analysis

Sensitivity analysis is the process of understanding the influence of input parameters on the image processing problem [31]. Here in this medicinal leaf image identification process, the relationship and influence of the training dataset and testing outputs are investigated. So, the influence of the shape, vein, apex and base image features in the image identification process is investigated by using and without using the morphological features based on a deep learning system. Result of sensitivity analysis for morphological features are shown in Fig. 11.

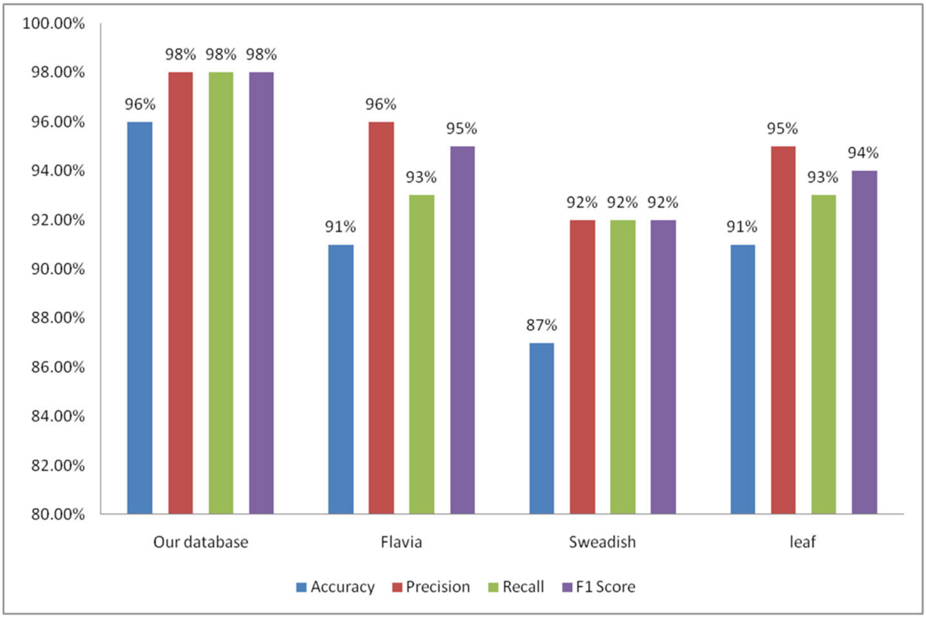

Fig. 10 Performance comparison of proposed DMA over different data bases

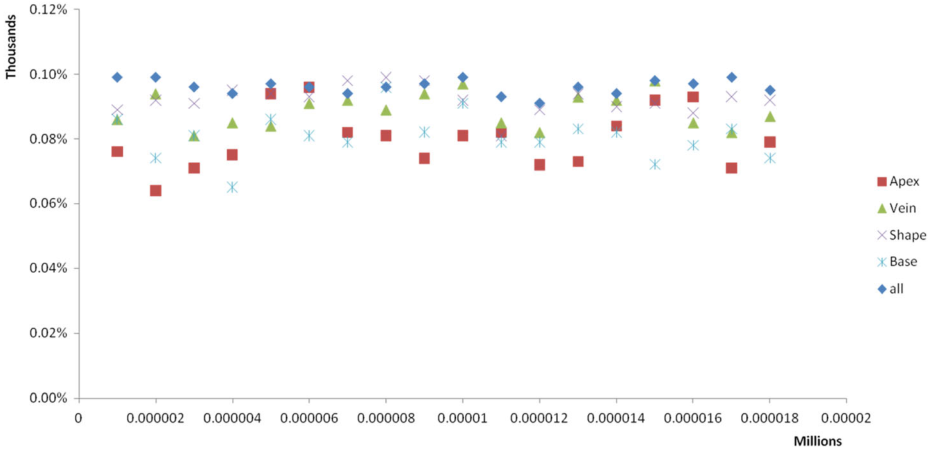

Fig. 11 Result of sensitivity analysis for morphological features

4.3 Advantages

This is the first morphological features based deep learning system. This algorithm helps to generate leaf morphological features from a single leaf. Here in this algorithm, we are training the morphological features and identifying each shape, vein, apex and base feature to recognize a leaf image. This training method works like how human brains and enhances artificial intelligence. This algorithm is not only applicable in the plant identification but also extendable to other object detection applications.

4.4 Limitation

The limitation of our system is, in some cases, the separate analysis of each morphological feature makes the algorithm more time-consuming. This deep learning system identifies the shape, vein, apex and base category. So, additional leaf detection method is required to identify the leaf category using the shape, vein, apex and base features.

5 Conclusion

In this paper, we carried out a detailed analysis of the existing deep learning-based leaf image's features extraction process and the proposed novel Deep - Morpho Algorithm (DMA) for medicinal plant leaf identification. In the normal deep learning-based leaf image feature extraction process, we lost the important features of leaf image details but, in the proposed novel Deep - Morpho Algorithm (DMA) for medicinal plant leaf identification method, we succeed to preserve all the leaf image features till the end of result. The DMA for medicinal plant leaf identification is computationally more efficient than the existing feature extraction algorithms. In this paper, the morphological leaf features extraction (MLFE) algorithm for leaf vein, shape, margin, petiole, apex, and base features are also discussed for better understanding.

In the proposed DMA based medicinal plant leaves morphological feature and digital description generation are very similar to human intelligence (specially Botanist) to recognize the species. In existing methods, researchers have used the entire image for feature extraction process that reduces the accuracy of classification, enhances the memory space and computational power requirements.

The Deep-Morpho Algorithm (DMA) showed remarkably better performance than the existing algorithms in terms of identification accuracy which is 96%. Using DMA, the memory space requirements shall be reduced. The proposed DMA is tested over "Flavia", "Swedish" and "Leaf" data sets and achieved 91%, 87% and 91% accuracy respectively. Extending the proposed method with larger medicinal plant leaf datasets and the fastest image classification problems will pave a new way in the medicinal plant recognition and image processing area.

The proposed DMA can understand and process the data for other image processing and pattern recognition-based applications. The proposed DMA can be used to train and build models such as face recognition, anomaly detection, and scene matching etc. with improved accuracy.

Code availability Custom code.

Funding Not Applicable.

Data availability "Flavia" [42] available at: http://flavia.sourceforge.net/
"Swedish" [34] available at: https://www.cvl.isy.liu.se/en/research/datasets/swedish-leaf/
"Leaf Data Set" [32] available at: https://archive.ics.uci.edu/ml/datasets/leaf

Declarations

Ethics approval Not Applicable.

Consent to participate I consent to participate.

Consent for publication I consent for publication.

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