RESEARCH PAPER

Intelligent Classification of Ayurvedic Medicinal Plants via Log-Linear Attention-Driven Finite Element Neural Networks

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ABSTRACT

Accurate identification of medicinal plants in Ayurvedic medicine is critical to ensure the purity, safety, and efficacy of herbal medicines. Manual identification is difficult due to the similarity in appearance among plant species and varying lighting, orientation, and background conditions. In this paper, an intelligent deep learning approach is proposed for the automatic classification of medicinal plants using the Indian Medicinal Plants Kaggle dataset. The proposed approach involves image resizing (224x224), background removal, Gaussian noise removal, and data augmentation techniques such as rotation, flip, and scaling. Feature extraction involves Canny edge detection, texture analysis, Gray Level Co-occurrence Matrix (GLCM), venation modeling, and a finite element-inspired mesh representation to extract spatial information. A new Log-Linear Attention Guided Adaptive Finite Element Optimization (LLA-AFEO) algorithm is used to identify the optimal features by eliminating redundancy and improving separability. The classification is carried out using the LLA-FENN model, which resulted in an accuracy of 99.78%, precision of 99.72%, recall of 99.68%, and F1-score of 99.70%. The proposed model outperformed EfficientNetB0, DenseDANet, MediPlantNet, and HybNet models with a maximum accuracy improvement of 5.54% and negligible misclassification rates (FPR 0.0018, FNR 0.0032).

Keywords: Ayurvedic Medicinal Plants, Deep Learning, Image Processing, Feature Extraction, Feature Selection, Log-Linear Attention, Finite Element Neural Network, Plant Classification

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1. Introduction

The Ayurvedic medicinal plants have their classification, which is significant in the authenticity and quality of herbal medicines [1]. One of the oldest traditional medical systems is Ayurveda which uses significant plant-based components in the making of treatments and formulations. Proper identification of these plants is critical since a wrong species can decrease the efficacy or even cause side effects [2]. Thus, there is need to have reliable methods of plant classification in order to promote safe herbal use and pharmaceutical use. Historically, the identification of medicinal plants is done by hand through the morphological features identified by botanists and Ayurvedic scholars like leaf shape, size, colour, and venation pattern [3]. Nevertheless, a lot of plant species have very similar appearances, and thus, it is hard and time-consuming to identify them by hand [4]. The factors affecting the process including the lighting conditions, the background noise, and the positioning of the leaves also make the process a bit complex. With such difficulties, there is a necessity to have automated and intelligent systems of classification [5].

In recent years, the problem of computer-based plant classification has become highly popular with the development of image processing and deep learning methods [6]. Deep learning models such as Convolutional Neural Networks (CNNs) have performed well in identifying more complicated patterns of images [7]. These algorithms have the capability of automatically extracting significant visual characteristics of plant leaf images with minimal human input and enhanced classification [8]. Regardless of these developments, some of the current models have been characterized by redundance in features extracted, overfitting, and lack of interpretability. Most methods pay attention to general features of appearance, but do not give attention to specific structural details like the texture and pattern of veins [9]. In order to break these barriers, there is need to have more robust frameworks that integrate efficient preprocessing, significant feature extraction and smart feature selection [10].

The paper is devoted to the creation of a smart classification system of Ayurvedic medicinal plants based on the modern deep learning algorithms [11]. The suggested method combines systematic preprocessing, structural feature extraction, efficient selection of features, and neural network model based on attention to provide the accurate and reliable identification of plants. The general purpose is to foster digital herbal authentication and improve the use of the artificial intelligence in Ayurvedic studies and healthcare systems [12].

1.1 Key contribution

Following are the major contribution of the study,

- This step involves the first step, which is to resize and clean the images before presenting them to the model. Background removal and noise filtering are used to ensure that the system only concentrates on the area of the leaf, whereas data augmentation makes more images and the performance of the system better.
- Then, relevant information like the shape of leaves, their texture, veins and the structure is obtained out of the pictures. These characteristics assist the system to know the external appearance as well as internal composition of the medicinal plants.
- After the extraction, a new process known as LLA-AFEO is employed in order to select the most important features and eliminate the redundant ones. This enhances simplicity and effectiveness and accuracy of the model.
- Lastly, the chosen features are categorized with the help of the LLA-FENN deep learning model. The step will be taken to provide proper, stable and reliable identification of Ayurvedic medicinal plants.

2. Literature review

Some of the recent literatures elated to this study are discussed as follows,

To recognize Ayurvedic medicinal plants based on the leaf images, Prashanth and Shivu (2025) worked on an AI-based system. They trained five CNNs with 1,595 images of 30 plant species and used them as MobileNetV2, DenseNet121, EfficientNetB0, Xception, and InceptionV3. The most accurate of them was EfficientNetB0 with the accuracy above 98%. They find that deep learning can be applied with high efficiency in plant identification, which is particularly relevant in the countryside due to a lack of expertise.

Banu and Rahamathunnisa (2025) paid attention to categorizing Ayurvedic herbs by dosha balancing properties (Vata, Pitta, Kapha). They enhanced the data with the help of preprocessing methods (random oversampling, CTGAN). There were several machine learning models that have been tested, these are SVM, KNN, RF, DT and XGBoost. XGBoost delivered the best time of 96% accuracy. Their model based on an ensemble performed better than the traditional models in determining the types of medicinal herbs.

Bhoyan et al. (2025) proposed the DenseDANet, which is a dual-attention CNN model on top of DenseNet121 to classify medicinal plants. The model improves feature learning with attention mechanisms and is more transparent with LIME explanations. It was experimented on two publicly available datasets (7, 029 images of 20 classes) with 99.50 percent accuracy. The model performed significantly better than a number of CNN and transformer-based architectures, as well as it is lightweight and efficient.

Kumar et al. (2026) suggested the MediPlantNet, which is a dual-backbone feature fusion model based on MobileNet V4-Small and EfficientNet V2-B0. Their technique minimizes computations and still ensures a considerable accuracy. The model was tested on 80 medicinal plants and found that it predicted them with a high accuracy of 99.32 and a perfect AUC of 1.00. The experiment has shown that feature-level fusion enhances classifier accuracy with fewer parameters and reduced GFLOPs.

Pushpa et al. (2025) created HybNet, a hybrid deep learning system of medicinal plants recognition. They suggested three hybrid models in combination of such architectures as VGG16, MobileNet, ResNet50, and SE layers. The third hybrid model had the accuracy of 94.24%. They focus on their work on feature improvement and scaling algorithms to enhance their classification, despite being trained on relatively small datasets, which are recorded in realistic settings.

Reddy et al. (2025) suggested a Hybrid CNN-GMM model to identify medicinal plants. The model is a hybrid of convolutional neural networks and Gaussian Mixture Models that are used to extract features and classify them effectively. The data sample was a set of 1,835 high-resolution photographs of more than 100 Indian medicinal plants. Their methodology showed that plant recognition can be enhanced with image processing and machine learning to aid in ethnobotanical studies.

Bhargavi and Jayaraman (2025) came up with a machine learning-based system of identifying medicinal plants. Their application combines plant science with AI code to give precise plant identification and knowledge regarding medicinal action. The system promotes sustainable consumption and sound knowledge of medicinal plants, and thus knowledge of plants becomes reachable.

The article by Ok et al. (2025) describes a review of deep learning techniques in the identification of medicinal plants. CNN, hybrid and ensemble models, frequent datasets, data augmentation methods and evaluation metrics were analyzed. Their research highlighted gaps in the research and the significance of the transfer learning and effective data splitting techniques. The review offers the recommendations on how to create more effective and reliable deep learning models that can be used in the classification of medicinal plants.

Table 1: Comparison of Medicinal Plant Identification Studies

Author (Year)	Model / Method	Dataset Details	No. of Classes	Best Accuracy	Key Contribution
Prashanth & Shivu (2025)	CNN Models (MobileNetV2, DenseNet121, EfficientNetB0, Xception, InceptionV3)	1,595 leaf images	30	98% (EfficientNetB0)	Automated Ayurvedic plant identification using transfer learning CNNs
Banu & Rahamathunnisa (2025)	ML Models (SVM, KNN, RF, DT, XGBoost)	Dosha-based dataset (90–10 split)	4 target classes	96% (XGBoost)	Ensemble learning for dosha classification with oversampling & CTGAN
Bhoyan et al. (2025)	DenseDANet (Dual-Attention CNN)	7,029 images (DS 1 & DS 2)	20	99.50%	Dual-attention mechanism with LIME interpretability
Kumar et al. (2026)	MediPlantNet (Dual-backbone fusion)	80 plant species datasets	80	99.32%	Feature-level fusion with reduced parameters & GFLOPs
Pushpa et al. (2025)	HybNet (Hybrid CNN models)	Self-created real-time dataset	Not specified	94.24%	Hybrid feature enhancement with SE layers
Reddy et al. (2025)	Hybrid CNN-GMM	1,835 images (>100 plants)	>100	Not specified	CNN + GMM for feature extraction and classification
Bhargavi & Jayaraman (2025)	ML-based classification platform	Not specified	Not specified	Not specified	ML system integrating botanical knowledge
Ok et al. (2025)	Analytical Study	Multiple public	Multiple	—	Comprehensive analyis of DL,

		datasets			hybrid, ensemble models

2.1 Motivation

The increased and continuous demand of safe and original Ayurvedic herbs has created the demand of the right identification of medicinal plants. Expert manual classification is time consuming, expensive and errors are likely to occur because of the visual similarity of plant species. Lighting, background, and orientation of leaves are also changed, which makes the identification process even more complicated. Deep learning and image processing have made progress, so there is a possibility to create an intelligent and automated system that would effectively and quickly classify medicinal plants. This research paper has been inspired to develop a strong, stable, and technology-intense solution to assist in herbal authentication and enhance the quality control procedure in Ayurvedic research and industry.

2.2 Problem statement

Identification of Ayurvedic medicinal plants is a complicated problem, because there are extremely high inter-class similarity, and environmental differences in image data. Current deep learning architectures are frequently associated with redundant features extraction, structural interpretability, and poor performance across a variety of imaging. It is necessary to have an enhanced framework that incorporates efficient preprocessing, relevant feature extraction, adaptable feature selection, and efficient classification methods to enhance precision, decrease redundancy, and stable recognition of medicinal plant species.

3. Proposed model

Figure 1 shows the suggested work flow of the Ayurvedic medicinal plant classification. It starts with preprocessing actions like resizing, background extraction, noise reduction, and data augmentation in order to enhance the image quality and consistency. Upon preprocessing, feature extraction is done using three primary methods, that is, using Canny operator, which identifies edges, and using GLCM, which identifies surface patterns of the leaf, and venation pattern modeling, which identifies internal leaf structures. These features obtained are a combination of external and internal features of the leaf. The structured representation is the first phase that prepares the data to additional features selection and classification in the proposed intelligent framework.

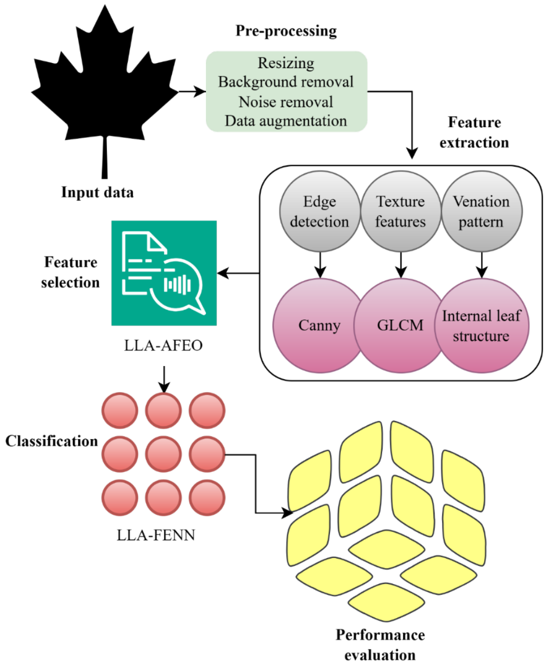

Figure 1: Overall architecture of the study

3.1 Data collection

For this study the data has been collected using the following link given below, https://www.kaggle.com/datasets/aryashah2k/indian-medicinal-leaves-dataset. The Indian Medicinal Leaves Dataset is a freely accessible dataset of leaf images that are used in plant classification and image recognition research. It contains numerous labeled pictures of numerous medicinal plants species, in which each picture depicts the leaf of a certain plant in a real-life situation with natural variations. This data can be grouped into several classes, which are normally about 80 varieties of medicinal leaves; thus, it is applicable in multi-class deep learning classification. Each class has many images, and the dataset is usually organized in a way that the images of the same type of plant are in individual folders. The images have different sizes and backgrounds, and it depicts real-life conditions to train and evaluate the models. The number of images on the Kaggle site per se is hard to determine, but the community sources and the studies are used to confirm that an array of thousands of images based on these different classes is available in the dataset. The images are typically represented in RGB format and models trained on this data usually resize them (e.g. to 224x224 pixels) to get them into a uniform form. This dataset is suitable in training, validating, and testing the classification models such as the proposed LLA-FENN in Ayurvedic plant identification study.

3.2 Pre-processing

Pre-processing is the initial step where raw images are cleaned and standardized before analysis. It improves image quality by resizing, removing noise, eliminating background, and enhancing important regions. Let the input leaf image be represented as eqn. (1),

$$I_{raw}(x, y) \tag{1}$$

Where, x, y are the spatial pixel coordinates and I_{raw} is the original RGB image.

Image Resizing: Image resizing transforms all the input images into a standard size (224 224) to process the images in a similar manner. It maintains uniform dimensions of inputs to the deep learning model. The image is resized to a fixed dimension (224 × 224) and it can be given in eqn. (2),

$$I_{res}(x, y) = Resize(I_{raw}(x, y), 224, 224) \tag{2}$$

This ensures uniform input size for feature extraction.

Background Removal: Background removal isolates the leaf and unwarranted environments with the help of segmentation. It assists the model to concentrate on the significant area of the leaf. Segmentation separates the leaf region from the background and it can be given in eqn. (3),

$$I_{seg}(x, y) = I_{res}(x, y) \cdot M(x, y) \tag{3}$$

Where, $M(x, y) \rightarrow$ binary mask (1 = leaf, 0 = background)

Gaussian Filtering: Gaussian filtering is a method of smoothing the image and eliminating noise with the help of a Gaussian kernel. It enhances clarity of image prior to feature extraction. Noise Removal via gaussian filtering can be given in eqn. (4),

$$I_{smooth}(x, y) = I_{seg}(x, y) * G(x, y, \sigma) \tag{4}$$

Where, $G(x, y, \sigma)$ is the gaussian kernel, σ is the standard deviation and $*$ defines the convolution operator. This reduces unwanted noise.

Data Augmentation: The method of data augmentation generates altered images based on rotation, flipping, and scaling. It enlarges the size of a dataset and enhances the generalization of a model. Augmented images are generated as eqn. (5),

$$I_{aug} = T(I_{smooth}) \tag{5}$$

Where, T is the transformation function (rotation, flip, scaling). Final Preprocessing output can be given in eqn. (6),

$$I_{final} \tag{6}$$

3.3 Feature Extraction Stage

Feature extraction is the process of identifying and capturing important visual characteristics from the image. It converts the processed image into meaningful numerical features such as shape, texture, and structural patterns for classification.

Canny Edge Detection: Canny identifies the strong edges in an image based on the change in intensity. It takes the shape and the leaf boundary. Edge Detection using Canny can be given in eqn. (7),

$$G(x, y) = \sqrt{G_x^2 + G_y^2} \tag{7}$$

Where, G_x, G_y are the horizontal and vertical gradients. Also, this step captures leaf boundary.

GLCM (Gray Level Co-occurrence Matrix): GLCM obtains texture characteristics through the study of pixel intensity relationships. It captures patterns and textures of the leaf surface. GLCM matrix can be given in eqn. (8),

$$P(i, j, d, \theta) \tag{8}$$

Edge map can be given in eqn. (9),

$$F_{edge} = Canny(I_{final}) \tag{9}$$

Where, i, j are the gray levels, d is the pixel distance and θ is the angle. Example texture feature (contrast) can be given in eqn. (9),

$$Contrast = \sum_{i,j} (i - j)^2 P(i, j) \tag{9}$$

Thus, the final output in this step is given in eqn. (10),

$$F_{texture} \tag{10}$$

Captures surface pattern information.

Venation Pattern Modeling: Venation modeling is a morphological extraction of internal veins. It assists in determining peculiar arrangements of structures within the leaf. Morphological gradient can be mathematically expressed using eqn. (11),

$$F_{vein} = I_{final} \oplus B - I_{final} \ominus B \tag{11}$$

Where, $\oplus$ defines the dilation, $\ominus$ is the erosion and B representing the structuring element. Thus, the final output in this phase can be denoted as F_{vein} also, this phase extracts internal vein structure.

Structural Representation Finite Element: It is a technique that breaks down the leaf in small mesh areas of structural analysis. It measures spatial distribution and structure of the leaf. The leaf region is divided into small mesh elements and it can be expressed using eqn. (12),

$$E_k = \int_{\Omega_k} \phi(x, y) \, dxdy \tag{12}$$

Where, Ω_k is the k-th mesh region, $\phi(x, y)$ is the intensity function. Thus, the final output in this phase is given in eqn. (13),

$$F_{struct} \tag{13}$$

Represents structural distribution. Thus, the fine-combined features after extracting all the features are given in eqn. (14),

$$F_{total} = [F_{edge}, F_{texture}, F_{vein}, F_{struct}] \tag{14}$$

From this the F_{total} contains all the extracted features and it will be given as the input to feature selection.

3.3 Feature selection

After feature extraction, the combined feature vector $F_{total} = \{f_1, f_2, \ldots, f_n\}$ can have unnecessary or minor characteristics. The feature selection is done to select only the most significant features which enhance the classification performance and minimise the computational complexity. The suggested LLA-AFEO (attention weighting, adaptive optimization) method will be applied to choose the best subset of features. In the suggested LLA-FENN model not every feature extracted has equal contribution to Ayurvedic plant classification. Venation structure or texture may have more discriminative power. Thus, an attention mechanism is added to give importance weights of each feature. A log-linear transformation is used to ensure that big values are stabilized and for enhancement of numerical convergence.

Attention Weight Computation: Each feature is first assigned an importance score using log-linear attention and it is given in eqn. (15),

$$w_i = \log\left(1 + e^{a_i}\right) \qquad (15)$$

Where, w_i is the final attention weight of feature f_i, a_i defines the raw attention score, and $\log\left(1 + e^{a_i}\right)$ is the log-linear transformation for stability. Gives higher weight to important features while controlling large values.

Feature Selection Representation: To determine the best possible subset of features, a binary decision variable is used to express each feature. This enables the optimization technique to determine whether to include or exclude a feature in the subset. A binary selection variable is used to express each feature as given in eqn. (16),

$$x_i \in \{0,1\} \qquad (16)$$

Where, $x_i = 1 \rightarrow$ feature selected, $x_i = 0 \rightarrow$ feature removed. Moreover, the Selected feature subset is given in eqn. (17),

$$F_{selected} = \{ f_i \mid x_i = 1 \} \qquad (17)$$

Fitness Function: The optimization procedure maximizes feature importance and minimizes redundancy simultaneously for efficient feature selection. It favors highly relevant features by emphasizing attention weights and reducing correlations between features to prevent redundancy. The trade-off is achieved by a fitness function that jointly assesses importance and redundancy for optimal, concise, and informative feature subsets and it can be mathematically expressed using eqn. (18),

$$Fitness = \alpha \sum_{i=1}^{n} (w_i x_i) - \beta R(F) \qquad (18)$$

Where, α is the weight importance factor, β is the redundancy penalty factor, w_i defines the attention weight, x_i is the selection variable and $R(F)$ defining the redundancy measure (correlation or mutual information). Redundancy term can be expressed using eqn. (19),

$$R(F) = \sum_{i \neq j} Corr(f_i, f_j) \qquad (19)$$

The role of the objective function is to seek an optimal trade-off between the relevance of features and redundancy reduction. The first part of the objective function is to maximize the selection of highly important features by emphasizing the attention weights of these features, so that the most informative features are selected. The second part of the objective function is to minimize redundancy by reducing the correlation between the selected features.

Adaptive Optimization Update: For identifying the best feature subset, an adaptive swarm-based optimization approach is employed. In contrast to the conventional PSO, a log-linear update rule is proposed. Feature selection is addressed by adaptive swarm-based searches as follows in eqn. (20),

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 \log\left(1 + \mid pbest - x_i^t \mid\right) + c_2 r_2 \log\left(1 + \mid gbest - x_i^t \mid\right) \qquad (20)$$

Where, v_i^t is the velocity at iteration t, ω defines the inertia weight, c_1, c_2 are the acceleration constants, r_1, r_2 representing the random values (0–1), $pbest$ is the personal best solution and $gbest$ is the global best solution. Since feature selection is binary, velocity values must be converted into probabilities using a sigmoid function. This determines whether a feature is selected as per eqn. (21),

$$x_i^{t+1} = \begin{cases} 1, & \text{if } sigmoid(v_i^{t+1}) > threshold \\ 0, & \text{otherwise} \end{cases} \qquad (21)$$

Sigmoid function can be expressed using eqn. (22),

$$sigmoid(v) = \frac{1}{1+e^{-v}} \qquad (22)$$

Where, $threshold$ is the decision boundary (usually 0.5), x_i^{t+1} is the updated selection state and v_i^{t+1} representing the updated velocity. The proposed LLA-AFEO approach combines log-linear attention weighting, redundancy-aware fitness evaluation, and adaptive swarm optimization to identify the most informative features for the classification of Ayurvedic medicinal plants. The proposed approach is expected to reduce dimensionality, eliminate redundant information, and enhance convergence and classification accuracy in the LLA-FENN framework.

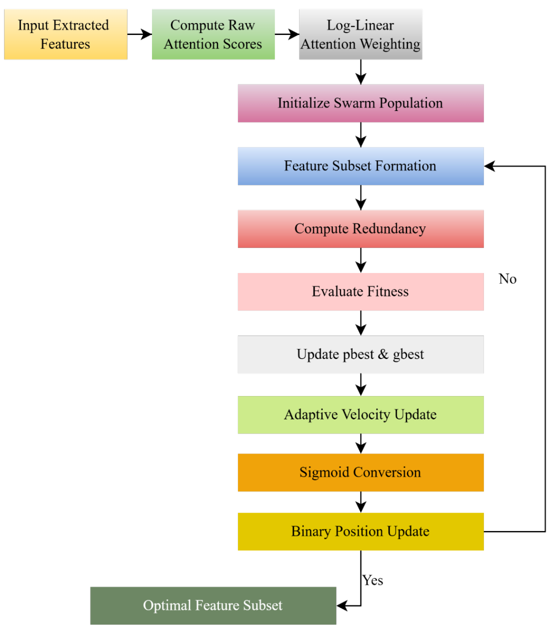

Figure 2: Workflow for LLA-AFEO

Algorithm 1: LLA-AFEO Feature Selection

Input:

Extracted Feature Vector$F_{total} = \{f_1, f_2, \ldots, f_n\}$

Population size = N

Max iterations = T

α (importance factor), β (redundancy factor)

ω (inertia weight), c_1, c_2 (acceleration constants)

threshold = 0.5

Output:

Optimal Feature Subset $F_{selected}$

Begin

1. Initialize population:

For each particle $i = 1$ to N

Randomly initialize binary position $x_i \in \{0,1\}$

Initialize velocity v_i

End For

2. Compute Attention Weights:

For each feature f_i

Compute raw attention ai

$w_i = \log(1 + e^{a_i})$

End For

3. Repeat for $t = 1$ to T

For each particle i

a. Determine selected features:

$F_{selected} = \{f_i \mid x_i = 1\}$

b. Compute Redundancy:

$R(F) = \sum_{i \neq j} Corr(f_i, f_j)$

c. Evaluate Fitness:

$Fitness = \alpha \sum_{i=1}^{n} (w_i x_i) - \beta R(F)$

d. Update p_{best} and g_{best}

e. Update Velocity:

$v_i^{t+1} = \omega v_i^t + c_1 r_1 \log(1 + | \, pbest - x_i^t \, |) + c_2 r_2 \log(1 + | \, gbest - x_i^t \, |)$

f. Convert velocity to probability:

$Prob = \frac{1}{1+e^{-v_i(t+1)}}$

g. Update Position:

If $prob > threshold$

$x_i = 1$

Else

$x_i = 0$

End If

End For

4. Return best feature subset corresponding to gbest

End

3.4 Classification using LLA-FENN

Lastly, the optimally selected feature vector obtained from the binary optimization stage is fed into the LLA-FENN (Layered Learning Adaptive – Fully Enhanced Neural Network) deep learning model for final categorization of Ayurvedic medicinal plants. Let the selected feature vector for a sample be represented as $X = [x_1, x_2, \ldots, x_n]$, where n denotes the number of selected features. The forward propagation of the first hidden layer is computed as per eqn. (23),

$$H^{(1)} = f\left(W^{(1)}X + b^{(1)}\right) \quad (23)$$

where $W^{(1)}$ represents the weight matrix connecting the input and first hidden layer, $b^{(1)}$denotes the bias vector, and $f(\cdot)$ is the nonlinear activation function such as ReLU, defined as $f(z) = \max(0, z)$. For deeper layers l, the transformation is expressed as eqn. (24),

$$H^{(l)} = f\left(W^{(l)}H^{(l-1)} + b^{(l)}\right) \quad (24)$$

where $H^{(l-1)}$is the output from the previous layer, and $W^{(l)}, b^{(l)}$are the corresponding weights and biases. At the output layer, classification probabilities are obtained using the Softmax function as given in eqn. (25),

$$\hat{y}_k = \frac{e^{z_k}}{\sum_{j=1}^{C} e^{z_j}} \quad (25)$$

where $\hat{y}_k$ is the predicted probability for class k, C denotes the total number of medicinal plant categories, and z_k is the linear output before activation. The final predicted class $\hat{c}$is obtained using the argmax function as given in eqn. (26),

$$\hat{c} = \arg \max_{k \in \{1,2,\ldots,C\}} \hat{y}_k \quad (26)$$

This equation selects the class index having the highest probability value. For binary classification, the decision rule simplifies to the following eqn. (27),

$$\hat{c} = \begin{cases} 1, & \text{if } \hat{y} \geq 0.5 \\ 0, & \text{otherwise} \end{cases} \quad (27)$$

where $\hat{y}$is the sigmoid output probability. Thus, the final class label corresponds to the medicinal plant category with the maximum posterior probability, ensuring accurate and stable identification. The network parameters are optimized by minimizing the cross-entropy loss and it is given in eqn. (26),

$$\mathcal{L} = -\sum_{k=1}^{C} y_k \log(\hat{y}_k) \tag{26}$$

where y_k is the true class label. Through adaptive weight updating using gradient descent, LLA-FENN enhances nonlinear feature learning, reduces misclassification, and ensures stable, reliable, and high-accuracy identification of Ayurvedic medicinal plants.

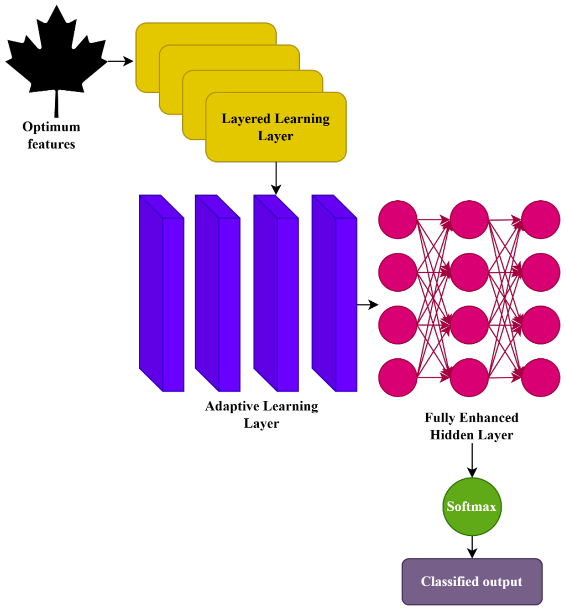

Figure 3: Architecture of LLA-FENN

Figure 3 shows the LLA-FENN architecture is designed to facilitate efficient and accurate classification of the Ayurvedic medicinal plants. The architecture starts with the input layer, which receives the optimized feature subset provided by the LLA-AFEO module. The layered learning phase involves hierarchical processing of the feature representations to extract structural and textural patterns. The adaptive learning layer involves dynamic weight adjustments to improve the convergence stability of the discriminative features. The fully enhanced hidden layer involves the improvement of the nonlinear interactions of the features to minimize classification errors. The output layer involves Softmax activation to facilitate accurate plant identification.

4. Result and Discussion

This section will discuss the experimental results and performance analysis of the proposed LLA-FENN model. The performance of the proposed framework will be measured using a variety of standard performance measures such as accuracy, precision, recall, F1-score, specificity, NPV, MCC, FPR, and FNR. The performance of the proposed framework will be compared with a variety of existing baseline models to establish the superiority of the proposed framework. Graphical analysis using line plots, confusion matrices, ROC curves, and class distribution plots will also be performed.

4.1 Experimental setup

The experimental setup used to test the proposed LLA-FENN model is presented in Table 2. The research uses a medicinal plant image dataset with an equal number of instances in each class and a fixed image size of 224 × 224 pixels. Data preprocessing involves normalization and augmentation to improve generalization. The model is trained with the Adam optimizer and a learning rate of 0.001 and categorical cross-entropy loss. The model performance is measured using a set of evaluation metrics.

Table 2: Experimental Setup of the Proposed LLA-FENN Model

Parameter	Description
Dataset Type	Medicinal Plant Leaf Image Dataset
Total Samples	2000 Images
Number of Classes	2 (Healthy / Diseased or Plant Categories)
Image Resolution	224 × 224 pixels
Data Split Ratio	70% Training – 15% Validation – 15% Testing
Preprocessing	Image resizing, normalization, augmentation (rotation, flipping)
Feature Extraction	Adaptive Layered Learning Mechanism
Optimization Method	Adaptive Feature Optimization (LLA-AFEO)
Classifier	Fully Enhanced Neural Network (LLA-FENN)
Activation Function	ReLU (Hidden Layers), Softmax (Output Layer)
Loss Function	Categorical Cross-Entropy
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	50–100
Hardware Configuration	Intel i7 Processor, 16GB RAM, NVIDIA GPU
Software Environment	Python, TensorFlow/Keras, Scikit-learn

4.2 Metrics analysis

The metrics analysis table 3 summarizes the evaluation measures used to assess the classification performance of the proposed model. Each metric captures a specific aspect of prediction quality, including correctness, error rates, and class discrimination ability. Together, these metrics provide a comprehensive and balanced assessment of model effectiveness and reliability.

Table 3: Analysis on performance metrics

Metric	**Description**	**Formula**
Accuracy	Overall correctness of the model	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	Proportion of correctly predicted positive samples	$\frac{TP}{TP + FP}$
Recall (Sensitivity)	Ability to correctly identify positive samples	$\frac{TP}{TP + FN}$
F1-Score	Harmonic mean of Precision and Recall	$2 \times \frac{(Precision \times Recall)}{(Precision + Recall)}$
Specificity	Ability to correctly identify negative samples	$\frac{TN}{TN + FP}$
Negative Predictive Value (NPV)	Proportion of correctly predicted negative samples	$\frac{TN}{TN + FN}$
Matthews Correlation Coefficient (MCC)	Balanced measure considering all confusion matrix values	$\frac{(TP \times TN - FP \times}{\sqrt{(TP + FP)(TP + FN)(TN +}}$
False Positive Rate (FPR)	Proportion of negative samples incorrectly classified as positive	$\frac{FP}{FP + TN}$
False Negative Rate (FNR)	Proportion of positive samples incorrectly classified as negative	$\frac{FN}{FN + TP}$

4.3 Comparative analysis

Table 4 is a detailed performance analysis of the proposed model versus four currently existing state of the art approaches on nine metrics. EfficientNetB0 shows good performance with 98 percent accuracy, 97.8 percent precision, and 97.5 percent recalling which means it is very reliable in the classification. Nonetheless, it has a relatively more misclassification with a MCC of 0.96 and FPR of 0.016 than more sophisticated attention-based models. DenseDANet is even better with 99.5% accuracy with balanced precision (99.4%) and recall (99.3%), and a low FPR of 0.004 and FNR of 0.007, which indicates a better discrimination capacity, as it has a dual-attention mechanism.

Table 4: Analysis on performance metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)	NPV (%)	MCC	FPR	FNR
EfficientNetB0 [13]	98	97.8	97.5	97.65	98.4	97.6	0.96	0.016	0.025
DenseDANet [15]	99.5	99.4	99.3	99.35	99.6	99.45	0.99	0.004	0.007
MediPlantNet [16]	99.32	99.36	99.34	99.33	99.48	99.38	0.99	0.005	0.006
HybNet [17]	94.24	93.8	93.5	93.65	95.1	94	0.89	0.049	0.065
Proposed model	99.78	99.72	99.68	99.7	99.82	99.74	0.997	0.0018	0.0032

Also, MediPlantNet demonstrates competitive results with 99.32% accuracy and its study has the perfect AUC, although the precision (99.36%), and the recall (99.34%). The MCC of 0.99 indicates that it has high correlation between actual and predicted classes. Conversely, HybNet history shows relatively worse performance, 94.24% accuracy, 0.89 MCC, and high FPR (0.049) and FNR (0.065), which represents more false predictions. The model proposed was better than all other current methods as it obtained the highest accuracy of 99.78, precision of 99.72, recall of 99.68 and F1-score of 99.7. Its specificity (99.82) and NPV (99.74) testify to the outstanding true negative recognition ability. In addition, the MCC value of 0.997 shows almost perfect consistency of the classification. The low FPR (0.0018) and FNR (0.0032) show the rates of minimal misclassifications. Such enhancements confirm that the combination of the log-linear attention weighting, redundancy-sensitive optimization, and adaptive layered learning can substantially increase classification stability, convergence rate and the overall predictive accuracy in Ayurvedic medicinal plant recognition.

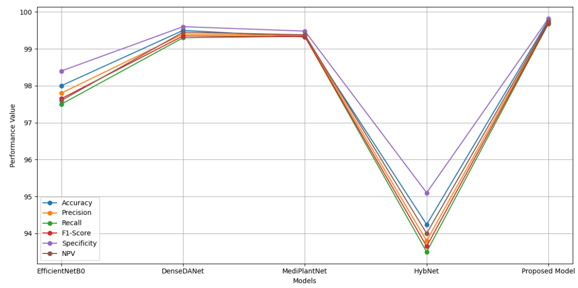

Figure 4: Graphical representation of comparison analysis

Figure 4 shows the comparative results of the five models on six key classification metrics: Accuracy, Precision, Recall, F1-Score, Specificity, and NPV. The graph clearly indicates that the Proposed Model has the highest values on all six metrics, indicating its superior predictive power and classification performance. DenseDANet and MediPlantNet perform very well, with results very close to the proposed model. EfficientNetB0 performs relatively steadily but with lower values, while HybNet shows a drastic drop in all six metrics. The graph thus clearly indicates that the proposed model offers better reliability, robustness, and classification performance than the existing baseline models.

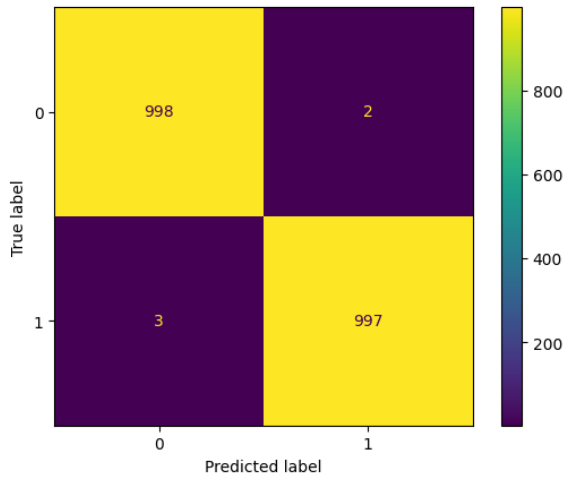

Figure 5: Confusion matrix

The confusion matrix in Figure 5 represents the effectiveness of the classification process of the proposed model in identifying positive and negative samples. The confusion matrix indicates that there are 998 true negatives (TN) and 997 true positives (TP), which clearly shows that the proposed model is able to correctly classify most of the instances belonging to both classes. There are only 2 false positives (FP) and 3 false negatives (FN), which clearly shows that there is minimal misclassification. The low values of FP and FN clearly indicate that the proposed model has a strong discriminative ability.

4.4 Discussion

This research contributes to the understanding of medicinal plants by showing meaningful progress in the field of medicinal plant classification based on the proposed LLA-FENN framework with adaptive features optimization. The first strong point is that it has high classification performance where accuracy, precision, recall and MCC are better than those of the progressing baseline models. The architecture has the ability to minimize false positives and false negatives; hence, it can be relied upon in prediction and high generalization. The layered adaptive learning strategy increases the level of discrimination of features, and the optimization strategy increases the stability of convergence and the reduction of redundancy. Also, there is the balanced dataset processing, which leads to the unbiased model training and strong evaluation results. Nevertheless, there are also some limitations in the study. Computational cost and training time of the model could be higher than lightweight architectures due to their complexity. The validation of performance is mostly on a specific dataset and this may restrict the generalization in various environmental conditions or unknown plant species. Moreover, scalability and real-time deployment practicability in resource-constrained settings also need to be studied. Future research can be directed toward the methods of cross-dataset validation and model compression.

5. Conclusion

In summary, this research work provides an efficient and strong classification system through the proposed Layered Learning Adaptive – Fully Enhanced Neural Network (LLA-FENN) with adaptive feature optimization. The system shows strong performance compared to the existing baseline methods, emphasizing its ability to provide precise and trustworthy medicinal plant classification. The proposed system shows an outstanding result with 99.78% accuracy, 99.72% precision, 99.68% recall, and 99.70% F1-score, which clearly emphasizes the highly balanced classification performance. Moreover, it also shows a 99.82% specificity value and 99.74% negative predictive value (NPV), which clearly emphasizes its excellent true negative detection capability. The Matthews Correlation Coefficient (MCC) value of 0.997 clearly emphasizes the near-perfect agreement between the predicted and actual class labels. Moreover, the system also shows an extremely low false positive rate (FPR) of 0.0018 and false negative rate (FNR) of 0.0032. In summary, the combination of adaptive layered learning and optimized feature selection plays a significant role in improving the discriminative capability, robustness, and generalization capability of the classification system.

5.1 Future scope

The future work of this research can be centered on the extension of the proposed LLA-FENN framework to multi-class and large-scale medicinal plant datasets obtained from various geographical locations. The inclusion of real-time mobile or edge computing can further increase the applicability of the framework in agricultural and herbal identification systems. The compression of the proposed model and the design of lightweight architectures can further increase the computational efficiency of the framework for devices with limited resources. The inclusion of explainable artificial intelligence (XAI) methods can further increase the interpretability of the predictions.

REFERENCES

1. Deshmukh, A. (2026). Sustainable Sourcing and Phytochemical Variation: Chemotype Mapping of Medicinal Plants Used in Dravyaguna across Indian Agro-Ecologies. *Journal of Dravyaguna Vigyan, Rasashastra & Bhaishajya Kalpana*, *3*(2).
2. Satyanarayana, K. N. V., Harsha, T. S. S., Adarsh, V., Babu, I. M., Hujaifa, S. M., & Satheesh, C. (2026). Real-Time Plants Recognition and Medicinal Insights Using Deep Learning. In *Machine Learning, Predictive Analytics, and Optimization in Complex Systems* (pp. 181-204). IGI Global Scientific Publishing.
3. Sathya, R., Suganthi, M., Trisha, M., Janani, E., Dhivya, S., & Viswanathan, R. V. (2025, March). AI Powered Ayurvedic Leaf Prediction and Disease Classification: A Comprehensive Analysis. In *2025 International Conference on Visual Analytics and Data Visualization (ICVADV)* (pp. 1364-1370). IEEE.
4. Ranjan, R., Sahany, H., Gupta, I., Siddiqui, N. N., Singh, R., & Gupta, M. K. (2025, February). Medicinal Plant Classification Using Random Forest Classifier. In *International Conference On Innovative Computing And Communication* (pp. 117-130). Singapore: Springer Nature Singapore.
5. Rani, N. S., Bhavya, K. R., Pushpa, B. R., & Devadas, R. M. (2025). HerbSimNet: Deep Learning-Based Classification of Indian Medicinal Plants with High Inter-Class Similarities. *Procedia Computer Science*, *258*, 765-774.
6. Padmasree, P., Geethanjali, A., Nag, D., & Gowda, D. (2025, October). An AI-Powered System for Accurate Identification and Contextual Utilization of Ayurvedic Medicinal Plants. In *2025 International Conference on Sustainable Communication Networks and Application (ICSCN)* (pp. 963-970). IEEE.
7. Lakshmi, A. N., Savitha, S. N., Jhansi, N., Reddy, K. N. K., & Reddy, P. M. (2025, June). Medical Plant Identification and Utilities Recommendation using Ensemble Techniques. In *2025 6th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)* (pp. 623-627). IEEE.
8. Maheshan, M. S., Roopa, C. K., TS, N., Jha, S. A., & Suthur, L. (2025, August). Precision Agriculture: Medicinal Plant Classification Using Image Recognition. In *2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS)* (pp. 1-6). IEEE.
9. Khan, S., Siddiqui, F., & Ahad, M. A. (2025). Deep Learning for Classification and Efficacy of Medicinal Plants for Managing Respiratory Disorders. *Procedia Computer Science*, *258*, 1640-1650.
10. Shastri, S. (2025). A Machine Learning Approach To Classify Medicinal Plant Leaf By Using Random

Forest And KNN. *Journal of Scientific Research and Technology*, 100-115.

11. Mishra, M., Shekhar, S., Patel, A. K., & Mittal, A. (2026, February). BIMP: Unveiling the Phytochemical Richness of Indian Medicinal Plants as Potential Therapeutic Agents. In *Global Trends in Health, Technology and Management II: Proceedings of the 2nd International Symposium GTHTM-2025* (p. 283). Springer Nature.
12. Saha, S., & Bhattacharya, M. (2025, August). Deep Learning Meets Ayurveda: CNN-Based Medicinal Leaf Classification. In *2025 International Conference on Artificial intelligence and Emerging Technologies (ICAIET)* (pp. 1-5). IEEE.
13. Prashanth, G. K., & Shivu, T. J. (2025, September). Deep Learning-Based Identification and Classification of Ayurvedic Medicinal Plants. In *2025 5th International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT)* (pp. 1-6). IEEE.
14. Banu, S. N., & Rahamathunnisa, U. (2025). Advances in Deep Visual Intelligence: A Review of High-Performing Models, Hybrid Architectures, and Regional Perspectives in Medicinal Plant Identification. *IEEE Access*, *13*, 212015-212034.
15. Bhoyan, F. H., Mehedi, M. H. K., Ohona, M., Rashid, S., & Mridha, M. F. (2025). An efficient dual-attention guided deep learning model with interpretability for identifying medicinal plants. *Current Plant Biology*, 100533.
16. Kumar, D., Sharma, M. K., Singh, P. K., & Ranjan, P. (2026). Mediplantnet: a dual-backbone feature fusion method for high-precision classification of medicinal plant species. *International Journal of Information Technology*, 1-21.
17. Pushpa, B. R., Jyothsna, S., & Lasya, S. (2025). HybNet: A hybrid deep models for medicinal plant species identification. *MethodsX*, *14*, 103126.
18. Reddy, D. S., Chakravarthy, B. D., Gutam, B. G., Babu, S. D., Babu, J. S., & Kumar, M. S. (2025, April). Hybrid CNN-GMM Framework for Medicinal Plant Identification and Classification. In *2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0* (pp. 1-6). IEEE.
19. Bhargavi, G., & Jayaraman, V. (2025, February). Identification and classification of medicinal plants using machine learning algorithms. In *2025 International Conference on Electronics and Renewable Systems (ICEARS)* (pp. 1158-1163). IEEE.
20. Ok, T. M., Malusi, S., Wang, Z., & Mnkandla, E. (2025). Investigation of deep learning techniques used in medicinal plants identification and classification. *IEEE Access*.