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Tri-Category Medicinal Plant Classification Using Fine-Grained Lightweight Transfer Learning Model

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ABSTRACT
The identification of medicinal plants plays a vital role in healthcare, agriculture, and traditional medicine systems such as Ayurveda. Traditionally, plant identification has relied on manual observation by experts, which is time-consuming and requires extensive domain knowledge. With advancements in Artificial Intelligence (AI) and Computer Vision (CV), automated approaches have emerged to improve accuracy and efficiency. However, conventional systems often depend on basic image processing and limited feature extraction techniques, leading to lower accuracy and poor generalization across diverse plant datasets. These challenges necessitate a robust and intelligent classification system. This study proposes an advanced image-based framework for medicinal plant identification. The system employs InceptionResNetV2 for deep feature extraction, capturing essential visual characteristics such as leaf shape, texture, and structural patterns. Extracted features are used to train multiple Machine Learning (ML) models, including Gaussian Naive Bayes (GNB), K-Nearest Neighbors (KNN), Restricted Boltzmann Machine (RBM) with Logistic Regression (LR), and a proposed hybrid model, Support Vector Extra Trees Network (SVETNet). SVETNet integrates Support Vector Classification (SVC) with Extra Trees (ET) to enhance classification performance. Experimental results demonstrate that SVETNet achieves superior accuracy, with 0.9947 for main class classification and 0.9594 for sub-class classification, outperforming baseline models. The system also includes a Graphical User Interface (GUI) and a Flask-based client–server architecture for remote predictions. Additionally, an explainable analysis module verifies whether the input image contains a medicinal plant before classification, ensuring reliability and scalability for real-world applications.

Keywords: Medicinal plant identification, Image-based classification, Deep feature extraction, Computer vision, Artificial intelligence, Leaf morphology analysis, Texture analysis, Structural pattern recognition.

1. INTRODUCTION

Medicinal plants are gaining popularity in the pharmaceutical industry as they are less likely to have adverse effects and are less expensive than modern pharmaceuticals. According to the World Health Organization, there are over 21,000 plant species that can potentially be utilized for medicinal purposes. It is also reported that 80% of people around the world use medicinal plants for the treatment of their primary health ailments. Systematic identification and naming of plants are often carried out by professional botanists (taxonomists), who have deep knowledge of plant taxonomy [1]. Manually identifying plant species is a challenging and time-consuming process. Furthermore, the process is prone to errors, as every aspect of the identification is entirely based on human perception [4]. There is also a dearth of these plant identification subject matter experts, which gives rise to a situation of "taxonomic impediment" [2]. It is, therefore, important to develop an effective and reliable method for the accurate identification of these valuable plants.

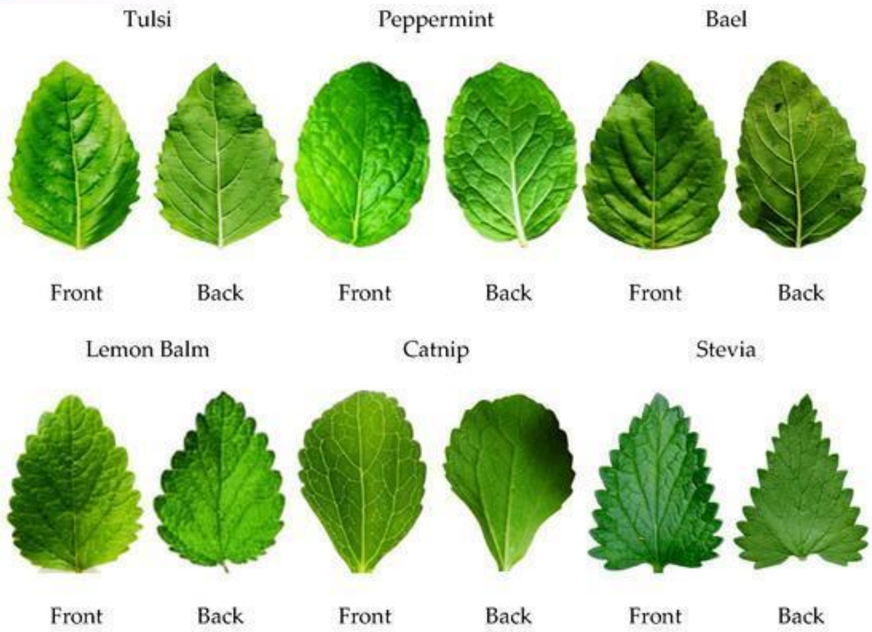


Fig. 1: Sample of the medicinal plants leaves.

Fig. 1 demonstrates the sample medicinal plants. ML is a sub-field of artificial intelligence that solves various intricate problems in different application domains with minimal human intervention. Deep learning (DL), inspired by the structure and functionality of biological neurons, is a sub-field of ML. DL involves the training of algorithms and demands a large amount of data to achieve better identification results. Due to the advancements in hardware technology and the extensive availability of the data, DL has gained popularity in various tasks like natural language processing, game playing, and image processing, and outstanding performance is being achieved, which could be otherwise impossible for humans to discern [3].

Various research studies have revealed that researchers are showing a great interest in the automatic identification and classification of plant species using plant image specimens and by employing ML and DL techniques. This automatic identification is carried out in different stages, viz. (a) image acquisition, (b) image preprocessing, (c) feature extraction, and (d) classification. Plant species identification can be performed using the different parts of plants like flowers, bark, fruits, and leaves or using the entire plant image. Researchers prefer to use leaf images for the identification process as leaves are easily identifiable parts of the plant. Leaf images are usually available for a long time during the year, while flowers and fruits are specific to a particular season only. There are more than one-hundred studies that have used plant leaf images for the automatic identification process [5].

2. LITERATURE SURVEY

Finger, A et al. [6] conducted to determine the effects on learning by means of a paper-based dichotomous identification key (Eikes Baumschule) and a digital identification app (ID-Logics). The results show that both tools have individual media-related differences that should be considered when designing learning strategies: With the previously reduced, paper-based tool, students can identify plants more quickly and often more correctly. However, the digital app has advantages in terms of enjoyment and learning about individual characteristics of plants. The study shows the challenges and opportunities associated with the (digital) medium. Furthermore, it sheds light on the process of species determination and reveals further fields of research in science education.

Subba, et al. [7] offered considerable information on plant wealth of therapeutic importance used traditionally by the residents of 11 villages under three subdivisions of Kurseong, Darjeeling Sadar, and Mirik in the Darjeeling District, West Bengal. For the acquisition of ethnomedicinal information, semi-structured interviews were conducted with 47 informants, of whom 11 persons were herbalists and 36

were knowledgeable persons. Free prior informed consent was obtained from each participant prior to the collection of field data. A total of 115 species were documented, which spread over 65 families and 104 genera. From the informants, a total of 101 mono herbal and 21 polyherbal formulations were recorded for treating 50 types of health conditions. The collected ethnobotanical data have been evaluated to measure the utilitarian significance of remedies using three quantitative tools, informant consensus factor (F_{ic}), use value (UV), and fidelity level (FL%). A statistical analysis revealed that among 11 disease categories, the highest F_{ic} value was estimated for the category of digestive diseases.
Sekharamantry, et al. [8] presented a neural network design based on PSR-LeafNet (PSR-LN). PSR-Leaf Net is a single network that combines the P-Net, S-Net, and R-Net, all intended for leaf feature extraction using the minimum redundancy maximum relevance (MRMR) approach. The PSR-LN helps obtain the shape features, color features, venation of the leaf, and textural features. A support vector machine (SVM) is applied to the output achieved from the PSR network, which helps classify the name of the plant. The model design is named PSR-LN-SVM. The advantage of the designed model is that it suits more considerable dataset processing and provides better results than traditional neural network models. The methodology utilized in the work achieves an accuracy of 97.12% for the Malaya Kew dataset, 98.10% for the IMP dataset, and 95.88% for the Flavia dataset. The proposed models surpass all the existing models, having an improvement in accuracy. These outcomes demonstrate that the suggested method is successful in accurately recognizing the leaves of medicinal plants, paving the way for more advanced uses in plant taxonomy and medicine.

Hajam, et al. [9] leveraged the power by three-component deep convolutional neural networks, namely VGG16, VGG19, and DenseNet201, to derive features from the input images of the medicinal plant dataset, containing leaf images of 30 classes. The models were compared and ensembled to make four hybrid models to enhance the predictive performance by utilizing the averaging and weighted averaging strategies. Quantitative experiments were carried out to evaluate the models on the Mendeley Medicinal Leaf Dataset. The resultant ensemble of VGG19+DensNet201 with fine-tuning showcased an enhanced capability in identifying medicinal plant images with an improvement of 7.43% and 5.8% compared with VGG19 and VGG16. Furthermore, VGG19+DensNet201 can outperform its standalone counterparts by achieving an accuracy of 99.12% on the test set. A thorough assessment with metrics such as accuracy, recall, precision, and the F1-score firmly established the effectiveness of the ensemble strategy.

Malik, et al. [10] proposed designing and developing an automated real-time plant species identification system of medicinal plants found across the Borneo region. The system is composed of a computer vision system that is used for training and testing a deep learning model, a knowledge base that acts as a dynamic database for storing plant images, together with auxiliary data, and a front-end mobile application as a user interface to the identification and feedback system. For the plant species identification task, an EfficientNet-B1-based deep learning model was adapted and trained/tested on a combined public and private plant species dataset. The proposed model achieved 87% and 84% Top-1 accuracies on a test set for the private and public datasets, respectively, which is more than a 10% accuracy improvement compared to the baseline model. During real-time system testing on the actual samples, using our mobile application, the accuracy slightly dropped to 78.5% (Top-1) and 82.6% (Top-5), which may be related to training data and testing conditions variability. A unique feature of the study is the provision of crowdsourcing feedback and geo-mapping of the species in the Borneo region, with the help of the mobile application. Nevertheless, the proposed system showed a promising direction toward real-time plant species identification system.

Azadnia, et al. [11] proposed an intelligent vision-based system to identify herb plants by developing an automatic Convolutional Neural Network (CNN). The proposed Deep Learning (DL) model consists of a CNN block for feature extraction and a classifier block for classifying the extracted features. The classifier block includes a Global Average Pooling (GAP) layer, a dense layer, a dropout layer, and a SoftMax layer. The solution has been tested on 3 levels of definitions (64 × 64, 128 × 128 and 256 × 256 pixel) of images for leaf recognition of five different medicinal plants. As a result, the vision-based system achieved more than 99.3% accuracy for all the image definitions. Hence, the proposed method effectively identifies medicinal plants in real-time and is capable of replacing traditional methods.

Radočaj, et al. [12] proposed a versatile module based on the Inception module, Mish activation function, and Batch normalization (IncMB) as a part of deep neural networks. A convolutional neural network (CNN) with transfer learning was used as the base for evaluated approaches for tomato disease detection: (1) CNNs, (2) CNNs with a support vector machine (SVM), and (3) CNNs with the proposed IncMB module. In the experiment, the public dataset Plant Village was used, containing images of six different tomato leaf diseases. The best results were achieved by the pre-trained InceptionV3 network, which contains an IncMB module with an accuracy of 97.78%. In three out of four cases, the highest accuracy was achieved by networks containing the proposed IncMB module in comparison to evaluated CNNs. The proposed IncMB module represented an improvement in the early detection of plant diseases, providing a basis for timely leaf disease detection.

Chandy, et al. [13] addressed these challenges by introducing a novel, well-curated leaf image dataset consisting of 39 classes of medicinal and aromatic plants collected from the Aromatic and Medicinal Plant Research Station in Odakkali, Kerala, India. To overcome performance bottlenecks observed with a baseline Convolutional Neural Network (CNN) that achieved only 44.94% accuracy, they progressively enhanced model performance through a series of architectural innovations. These included the use of a pre-trained VGG16 network, data augmentation techniques, and fine-tuning of deeper convolutional layers, followed by the integration of Squeeze-and-Excitation (SE) attention blocks. Ultimately, they propose a hybrid deep learning architecture that combines VGG16 with Batch Normalization, Gated Recurrent Units (GRUs), Transformer modules, and Dilated Convolutions. This final model achieved a peak validation accuracy of 95.24%, significantly outperforming several baseline models, such as custom CNN (44.94%), VGG-19 (59.49%), VGG-16 before augmentation (71.52%), Xception (85.44%), Inception v3 (87.97%), VGG-16 after data argumentation (89.24%), VGG-16 after fine-tuning (90.51%), MobileNetV2 (93.67), and VGG16 with SE block (94.94%).

Mahajan, et al. [14] proposed a plant species recognition model based on morphological features extracted from corresponding leaves' images using the support vector machine (SVM) with adaptive boosting technique. This proposed framework includes the pre-processing, extraction of features and classification into one of the species. Various morphological features like centroid, major axis length, minor axis length, solidity, perimeter, and orientation are extracted from the digital images of various categories of leaves. In addition to this, transfer learning, as suggested by some previous studies, has also been used in the feature extraction process. Various classifiers like the kNN, decision trees, and multilayer perceptron (with and without AdaBoost) are employed on the opensource dataset, FLAVIA, to certify our study in its robustness, in contrast to other classifier frameworks.

Feng, et al. [15] designed a model with an encoder–decoder architecture to efficiently classify plant diseases using a transfer learning approach, which effectively recognizes a large number of plant diseases in multiple crops. The model was tested on the "PlantVillage", "FGVC8", and "EMBRAPA" datasets, which contain leaf information from crops such as apples, soybeans, tomatoes, and potatoes. These datasets cover diseases caused by fungi, including rust, spot, and scab, as well as viral diseases such as leaf curl. The model's performance was rigorously evaluated on datasets, and the results demonstrated its high accuracy. The model achieved 99.9% accuracy on the "Plant Village" dataset, 97.4% on the "EMBRAPA" dataset, and 91.5% on the "FGVC8" dataset, showcasing its competitiveness with other state-of-the-art models. This study provides a robust and reliable solution for plant disease classification and contributes to the advancement of precision agriculture.

3. PROPOSED SYSTEM

The proposed methodology establishes a structured analytical framework for identifying medicinal plants from digital images using artificial intelligence techniques. The analytical pipeline begins with plant image acquisition and dataset organization, followed by image preprocessing and deep feature extraction. A pretrained convolutional neural network is utilized through transfer learning to extract meaningful visual representations such as leaf texture, colour distribution, and structural patterns. These extracted feature vectors are then analysed using multiple ML classifiers to perform plant category prediction. An explainable image analysis component is also incorporated to verify whether the captured image belongs to a medicinal plant before the classification process begins. A graphical interface enables user interaction for dataset handling, model training, performance visualization, and prediction tasks, as shown in fig. 2. A lightweight storage mechanism manages trained models and authentication data, while a server component allows remote image analysis and prediction. Continuous model evaluation and retraining further improve analytical accuracy and enable the system to adapt to newly available plant image data.

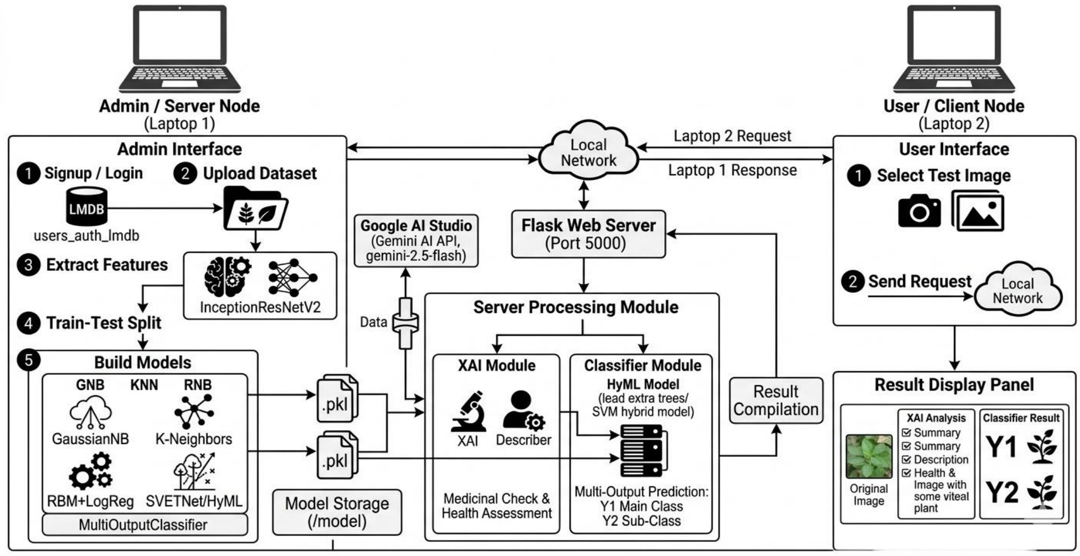


Fig. 2: System architecture

User Interface (Client Application)

- The user interacts with the system through a graphical interface developed using a desktop-based environment.
- The interface allows operations such as login, dataset upload, feature extraction, model training, performance comparison, and image prediction.
- Users can select plant images from local storage and submit them for analysis.
- All user interactions are processed within the interface and forwarded to the backend analytical modules.

Flask Application Server

- The Flask server acts as the central communication component of the system.
- It receives image requests from client systems and routes them through the prediction pipeline.
- The server manages image processing requests, prediction execution, and response generation.
- It enables remote client devices to send plant images and receive prediction results.

LMDB Database (Authentication Storage)

- The system uses LMDB as a lightweight key–value database for storing user authentication information.
- It maintains records of registered users including usernames, encrypted passwords, and user roles.

- The database interacts directly with the application layer to perform login verification and user management.
- Its memory-mapped architecture enables efficient read and write operations while maintaining persistent storage.

Image Dataset (Plant Image Collection)

- The plant image dataset serves as the primary input source for the analytical pipeline.
- It contains categorized images of medicinal plants organized into hierarchical folders representing plant classes and species.
- The images capture visual information such as leaf shape, surface texture, color distribution, and structural characteristics.
- This dataset is used for both training and evaluation of classification models.

Image Preprocessing and Feature Extraction

- The raw plant images undergo preprocessing operations including resizing, normalization, and pixel value transformation.
- A pretrained InceptionResNetV2 model is used to extract deep visual features from each plant image.
- This model captures complex visual patterns from the images and converts them into deep feature vectors.
- The generated feature vectors provide the numerical representations required as input for ML classifiers.

ML Classification Models

- The extracted feature vectors are analyzed using multiple ML classifiers to identify plant categories:
    - **GNB:** Evaluates probabilistic distributions of plant features.
    - **KNN:** Uses spatial proximity to classify based on similar plant samples.
    - **RBM:** Combines RBM for feature refining with LR.
    - **SVETNet:** A hybrid approach leveraging support vector machines and extra trees for high-accuracy classification.
- Each classifier independently predicts the plant category and species for comparison.

Explainable Image Analysis Module

- The system includes an image reasoning module that analyzes whether the uploaded image contains a medicinal plant.
- This component performs structured visual reasoning and generates descriptive information about the plant image.
- It verifies plant presence and image quality before the classification stage begins, improving the interpretability and reliability of the framework.

Prediction Results and Output Generation

- After processing, the system predicts both the main plant category and the specific plant species class.
- The results are displayed in the graphical interface along with visual output panels.
- Prediction outputs may also include confidence scores and model-wise performance information for user reference.

Remote Image Prediction Workflow

- The architecture supports remote prediction through a client–server communication mechanism.
- External client systems can send plant images to the Flask server for analysis.

- The server processes the images using trained classification models and returns the prediction results in a structured format.

Model Evaluation and Retraining

- The system evaluates classification performance using metrics such as accuracy, precision, recall, and F1-score.
- Visualization techniques such as confusion matrices and ROC curves are used to analyze model performance.
- When additional plant image data becomes available, models can be retrained to improve prediction accuracy, ensuring an adaptive learning cycle.

3.2 Feature Extraction (InceptionResNetV2)

The feature extraction stage is responsible for transforming raw plant images into meaningful numerical representations that can be processed by ML algorithms. In this study, a pretrained convolutional neural network model called InceptionResNetV2 is used to extract deep visual features from plant images. The model has been previously trained on a large-scale image dataset and can identify complex visual patterns such as leaf shape, texture, and structural characteristics. During the feature extraction process, plant images are first pre-processed and converted into numerical arrays before being passed through the convolutional neural network, as presented in Fig. 3. The network analyses the visual information present in the images and produces a deep feature vector that captures the most relevant characteristics of the plant image. These extracted feature vectors are then stored as structured numerical arrays that will later be used for ML classification.

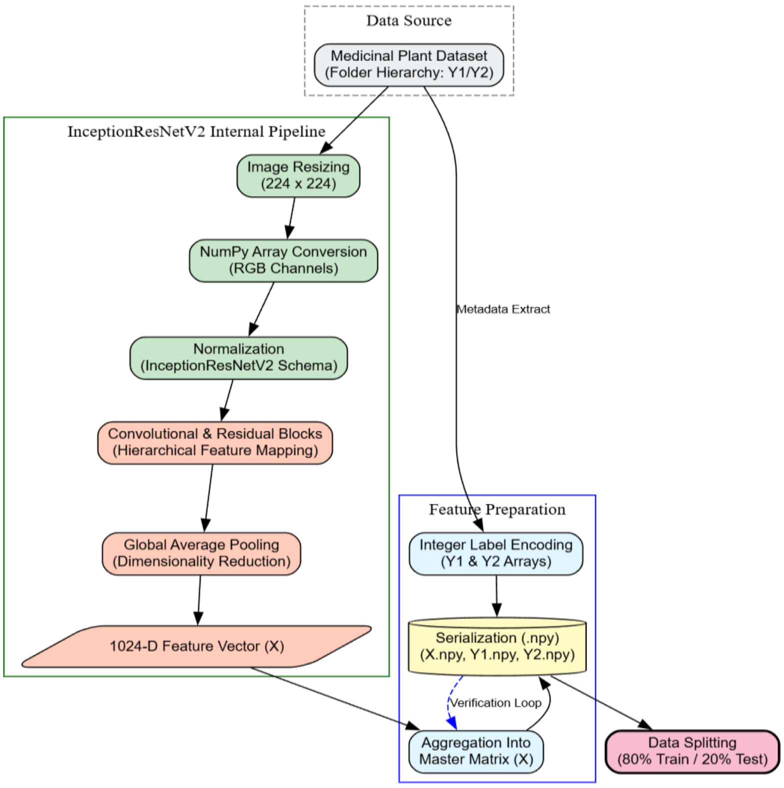


Fig. 3: Internal workflow of InceptionResNetV2

Image Loading and Dataset Traversal: The system begins by reading plant images from the dataset directory where images are organized according to plant categories and species. Each folder represents a class, and the images within those folders correspond to specific plant samples. The system iterates through each directory and loads individual images for processing using an image loading function.

Image Resizing and Standardization: Each loaded image is resized to a fixed dimension so that it matches the input size expected by the convolutional neural network model. The InceptionResNetV2 architecture requires images of size 224 × 224 pixels for proper processing. Resizing ensures that all images maintain consistent spatial dimensions before being forwarded to the feature extraction stage.

Image Conversion into Numerical Arrays: After resizing, the image is converted into a numerical format so that it can be processed by the neural network. The pixel values of the image are transformed into multidimensional arrays representing the red, green, and blue color channels. This conversion enables the computational model to analyze the image as structured numerical data.

Image Expansion and Batch Dimension Creation: Once the image is converted into an array, an additional dimension is added to represent the batch size expected by the neural network. This step converts the image array into a format suitable for model input during prediction. The expansion of dimensions ensures compatibility with the neural network processing pipeline.

Image Normalization and Preprocessing: The numerical pixel values are then normalized using a preprocessing function associated with the pretrained model. This step adjusts pixel intensities to match the distribution used during the original training of the neural network. Normalization improves the ability of the model to extract meaningful patterns from the image.

Deep Feature Extraction using InceptionResNetV2: The preprocessed image array is passed through the InceptionResNetV2 convolutional neural network model. The convolutional layers analyze different regions of the image to detect visual features such as edges, shapes, and textures. Instead of producing classification outputs, the model generates a deep feature vector representing the extracted visual information.

Feature Vector Generation: The output of the neural network is a high-dimensional feature vector that summarizes the important visual characteristics of the plant image. This feature vector contains deep representations learned by the convolutional network. These representations provide a compact numerical description of the plant image.

Storing Feature Vectors in Arrays: The generated feature vectors are appended to a feature list that stores extracted representations for all images in the dataset. Each image contributes one feature vector that corresponds to its visual characteristics. The associated class labels are also recorded for each feature vector.

Converting Feature Lists into NumPy Arrays: After processing all images in the dataset, the collected feature lists are converted into structured NumPy arrays. These arrays contain numerical feature representations for all plant images along with their corresponding labels.

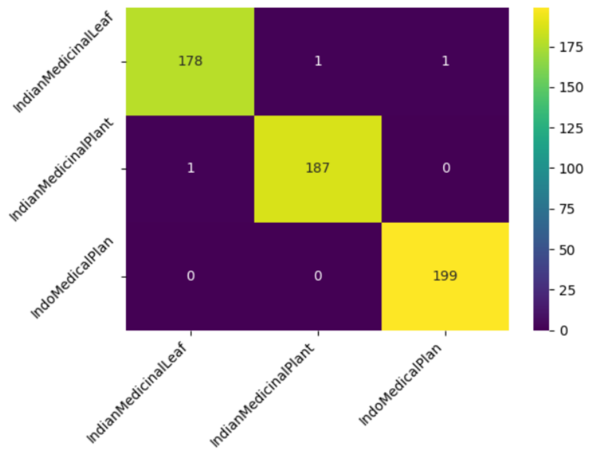
4. RESULTS ANALYSIS

The results obtained from the medicinal plant identification system demonstrate the effectiveness of combining deep learning–based feature extraction with multiple ML classifiers. The system was evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score to assess classification reliability. Experimental analysis shows that the extracted features from InceptionResNetV2 significantly enhance the discriminative capability of the models. Comparative evaluation of classifiers including GNB, KNN, RBM, and SVETNet highlights differences in performance across main and subcategory predictions. Visualization tools such as confusion matrices and ROC curves provide deeper insight into model behaviour and prediction accuracy. The results indicate that ensemble-based and hybrid approaches achieve better generalization on diverse plant datasets. Overall, the findings confirm that the system is capable of accurately identifying medicinal plants under varying image conditions.

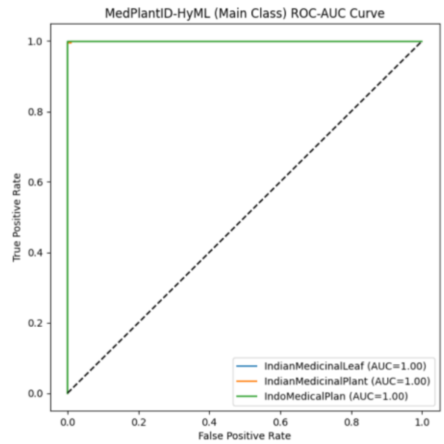
Fig. 4(a) illustrates the confusion matrix for main class (Y1) classification using the SVETNet model in the medicinal plant identification system. The figure shows strong diagonal dominance with almost all samples correctly classified into their respective categories. The presence of very few off-diagonal values indicate minimal misclassification among classes. This demonstrates the high accuracy and robustness of the hybrid model in distinguishing major plant categories. The clear separation between classes reflects the effectiveness of combined learning strategies.

Fig. 4(b) illustrates the ROC-AUC curves for the main class classification using the SVETNet model, highlighting the relationship between true positive rate and false positive rate. The curves are positioned along the top-left boundary of the graph, indicating optimal classification performance. The AUC values of 1.00 for all classes confirm perfect discrimination capability. This reflects the strength of the hybrid approach in capturing complex feature relationships. The visualization demonstrates that the model achieves maximum predictive accuracy across all categories. The results validate the superior performance of SVETNet compared to other models.

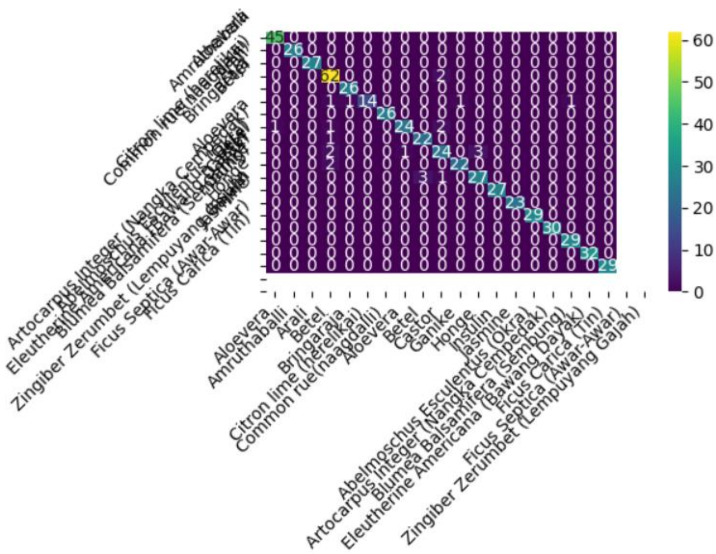
Fig. 4(c) illustrates the confusion matrix for sub-class (Y2) classification using the SVETNet model, providing a detailed view of classification across individual plant species. The matrix shows a strong concentration of values along the diagonal, indicating highly accurate subclass predictions. The absence of significant misclassification highlights the model's ability to distinguish even closely related plant species. This demonstrates excellent fine-grained classification capability. The visualization confirms consistent and reliable performance across all subclasses.



(a)



(b)



(c)

Fig. 4(a, b, c): SVETNet Model Performance showing Main Class Confusion Matrix, ROC-AUC Curve, and Detailed Classification Matrix

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Fig. 5 illustrates the prediction outcome generated by the medicinal plant identification system for a given test image. The figure presents both the original input image and the corresponding classification result produced by the trained model. It highlights the system's ability to accurately identify the plant category as IndianMedicinalPlant and the specific sub-class as Betel. This demonstrates the effectiveness of the feature extraction and classification pipeline in recognizing plant characteristics such as leaf shape and texture. The visualization reflects the successful mapping of image features to the correct labels. This stage confirms the system's capability to perform real-time and accurate medicinal plant identification.

Fig. 5: Medicinal Plant Classification Output (Betel Leaf)

4.1 Comparative Analysis

Comparative analysis is an essential step in evaluating the effectiveness of different ML models used for medicinal plant classification. It involves systematically comparing the performance of models such as GNB, KNN, RBM, and SVETNet using standard evaluation metrics. This analysis helps in identifying strengths and limitations of each model in handling feature representations and classification tasks. By examining confusion matrices, ROC-AUC curves, and accuracy scores, the study highlights variations in predictive performance. The comparison provides insights into model generalization and robustness across different plant categories.

Table 1: Main class performance comparison

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
KNN	0.9436	0.9466	0.9425	0.9432
GNB	0.8942	0.9039	0.8923	0.8939
RBM	0.4092	0.5429	0.3936	0.2928
SVETNet	0.9947	0.9947	0.9945	0.9946

The performance of different ML models for main class classification is presented in Table 1, highlighting their effectiveness in identifying medicinal plant categories. The comparison is based on key evaluation metrics including accuracy, precision, recall, and F1-score. Among the models, SVETNet achieves the highest accuracy of 0.9947, demonstrating superior classification capability and robustness. The KNN model also performs well with an accuracy of 0.9436, indicating strong predictive performance. GNB shows moderate performance with an accuracy of 0.8942, reflecting its probabilistic limitations in complex feature spaces. In contrast, the RBM model records a significantly lower accuracy of 0.4092, indicating poor classification effectiveness.

The performance comparison of different ML models for sub-class classification is presented in Table 2, highlighting their ability to distinguish between individual medicinal plant species. The evaluation is based on key metrics such as accuracy, precision, recall, and F1-score to assess fine-grained classification performance. Among the models, SVETNet achieves the highest accuracy of 0.9594, indicating excellent capability in identifying detailed plant subclasses. GNB demonstrates good performance with an accuracy of 0.8430, showing its effectiveness in probabilistic classification. The KNN model achieves an accuracy of 0.8078, reflecting moderate performance in handling complex subclass variations. In contrast, the RBM model records a very low accuracy of 0.1922, indicating poor performance in fine-grained classification tasks.

Table 2: Sub Class performance comparison

Model	Accuracy	Precision	Recall	F1-Score
KNN	0.8078	0.8382	0.8012	0.7907
GNB	0.8430	0.8547	0.8500	0.8437
RBM	0.1922	0.0780	0.1249	0.0850
SVETNet	0.9594	0.9648	0.9551	0.9588

5. CONCLUSION

The study demonstrates the successful development of an intelligent medicinal plant identification system by combining deep learning–based feature extraction with multiple ML classifiers. The use of InceptionResNetV2 enables effective extraction of discriminative image features such as texture, shape, and structural patterns. These features significantly improve the performance of classification models including GNB, KNN, RBM, and SVETNet. Comparative analysis shows that the SVETNet model achieves the highest accuracy and overall performance in both main and sub-class classification tasks. The system effectively handles diverse plant datasets with variations in lighting, background, and orientation. The implementation of multi-output classification further enhances the ability to predict both category and species simultaneously. The integration of a user-friendly interface and client–server communication ensures efficient and scalable operation. The inclusion of an explainable analysis component improves the reliability of predictions.

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