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SVETNet: A Deep Feature-Integrated Hybrid Framework for Hierarchical Multi-Output Medicinal Plant Classification

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ABSTRACT

The identification of medicinal plants has long been a crucial area 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 the advancement of artificial intelligence and computer vision, automated approaches have emerged to support faster and more accurate plant classification. However, conventional systems often depend on basic image processing techniques and limited feature extraction methods, resulting in lower accuracy and poor generalization when applied to diverse plant datasets. These challenges highlight the need for a more robust and intelligent system capable of analysing complex visual patterns in plant images. This study addresses the problem of accurately identifying medicinal plants from images by proposing an advanced image-based classification framework. The system utilizes InceptionResNetV2 for deep feature extraction, capturing essential visual characteristics such as leaf shape, texture, and structural patterns. These features are then 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 the proposed hybrid Support Vector Extra Trees Network (SVETNet). The SVETNet model combines the strengths of Support Vector Classification (SVC) and ensemble-based Extra Trees (ET) to achieve superior classification performance. Experimental results show that the proposed SVETNet model achieves the highest accuracy of 0.9947 for main class classification and 0.9594 for sub-class classification, outperforming all baseline models.

Keywords: Medicinal plant identification, Image classification, Deep learning. InceptionResNetV2, Machine learning (ML), Ensemble learning

1.INTRODUCTION

Medicinal plants are increasingly gaining importance in the pharmaceutical industry due to their lower risk of adverse effects and cost-effectiveness compared to modern synthetic drugs. According to the World Health Organization, more than 21,000 plant species have the potential to be used for medicinal purposes. It is also estimated that nearly 80% of the global population relies on medicinal plants for treating primary healthcare needs. The systematic identification and classification of plants are typically performed by expert botanists (taxonomists) who possess extensive knowledge of plant taxonomy [1]. However, manual identification of plant species is a complex and time-consuming task. Moreover, the process is highly susceptible to errors, as it largely depends on human observation and interpretation [2]. In addition, there is a shortage of skilled taxonomists, leading to a challenge known as “taxonomic impediment” [3]. Therefore, it is essential to develop an efficient and reliable approach for the accurate identification of these valuable medicinal plants. Fig. 1 illustrates sample medicinal plants. Machine Learning (ML) is a sub-field of artificial intelligence that addresses complex problems across various application domains with minimal human intervention. Deep Learning (DL), which is inspired by the structure and functioning of biological neurons, is a specialized sub-field of ML. DL involves training algorithms using large volumes of data to achieve improved identification performance. With

advancements in hardware technologies and the widespread availability of data, DL has gained significant popularity in tasks such as natural language processing, game playing, and image processing, delivering exceptional performance that often surpasses human capabilities [4].

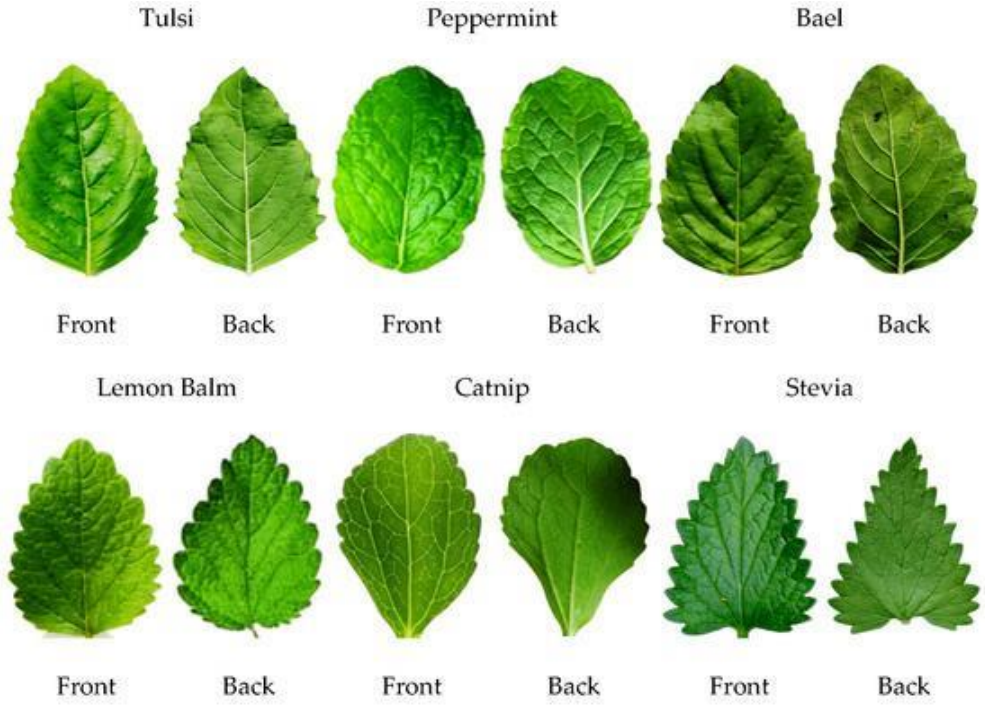


Fig. 1: Sample of the medicinal plants leaves.

Several research studies indicate a growing interest among researchers in the automatic identification and classification of plant species using plant image samples by applying ML and DL techniques. This automated identification process generally involves multiple stages, namely (a) image acquisition, (b) image preprocessing, (c) feature extraction, and (d) classification. Plant species identification can be performed using different parts of the plant, such as flowers, bark, fruits, and leaves, or by considering the entire plant image. However, researchers predominantly prefer leaf images for identification, as leaves are easily accessible and distinguishable parts of the plant. Additionally, leaf images are available throughout most of the year, whereas flowers and fruits are often seasonal. Consequently, numerous studies more than one hundred have utilized plant leaf images for automatic plant identification tasks.

2.LITERATURE SURVEY

Hajam, et al. [5] 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. [6] proposed designed and developed 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. [7] 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. Sekhara mantry, 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.

Radočaj, et al. [9] 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. [10] 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. [11] 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. Amin, et al. [12] proposed the integration of chemotaxonomy with genomics and proteomics allows a deeper understanding of plant biosynthesis and the mechanisms behind bioactive compound production. However, challenges due to variability in metabolite profiles and the lack of standardized methods remain, and future research should focus on developing global databases, improving standardization, and incorporating artificial intelligence and ML to enhance plant identification and bioactive compound discovery. The integration of chemotaxonomy with personalized medicine offers the potential to tailor plant-based therapies to individual genetic profiles, advancing targeted treatments. This review underscores chemotaxonomy's importance in bridging traditional knowledge and modern science, offering sustainable solutions for medicinal plant use and drug development.

Sun, et al. [13] proposed morphological observations and ISSR molecular markers were employed to discriminate between *A.* flavum and A. pendulum, with the objective of gaining insights into the interspecies classification of Aconitum. The pubescence on the inflorescence of *A. flavum* was found to be appressed, while that on the inflorescence of A. pendulum was spread. UPGMA (unweighted pair-group method with arithmetic average) cluster analysis, PCoA (principal coordinates analysis), and Bayesian structural analysis divided the 199 individuals (99 individuals from DWM population and 100 individuals from QHL population) into two main branches, which is consistent with the observations of the morphology of pubescence on the inflorescence. These analyses indicated that A. flavum and A. pendulum are distinct species. No diagnostic bands were found between the two species. Two primer combinations (UBC808 and UBC853) were ultimately selected for species identification of A. flavum and A. pendulum.

Wang, et al. [14] reviewed the highlights that while sequencing technologies offer substantial improvements, challenges such as high costs, technical expertise, and the lack of standardized protocols remain barriers to widespread adoption. Potential solutions, including AI-driven data analysis and portable sequencers, are discussed. Conclusions: This review provides a comprehensive overview of molecular techniques, their transformative impact, and future perspectives for more accurate and efficient medicinal plant identification. The literature search for this review was conducted across

databases such as Google Scholar, Web of Science, and PubMed, using keywords related to plant taxonomy, genomics, and biotechnology. Inclusion criteria focused on peer-reviewed studies closely related to plant identification methods and techniques that contribute significantly to the field.

Barrera-Vázquez et al. [15] focused on identifying medicinal plants with potential antioxidant, anti-inflammatory, anti-aging, and anti-senescence effects through network analysis and chemoinformatic screening of their phytochemicals. They used computational methods to analyze drug-like phytochemicals in Mexican medicinal plants, multi-target compounds, and signaling pathways related to antioxidant, anti-inflammatory, anti-aging, and anti-senescence mechanisms. A total of 1373 phytochemicals are found in 1025 Mexican medicinal plants, and 148 compounds showed no harmful functionalities. These compounds displayed comparable structures with reference molecules. Based on their capacity to interact with pharmacological targets, three clusters of Mexican medicinal plants have been established. Curatella americana, Ximenia americana, Malvastrum coromandelianum, and Manilkara zapota all have antioxidant, anti-inflammatory, anti-aging, and anti-senescence effects. Plumeria rubra, Lonchocarpus yucatanensis, and Salvia polystachya contained phytochemicals with anti-oxidant, anti-inflammatory, anti-aging, and anti-senescence reported activity. Lonchocarpus guatemalensis, Vallesia glabra, Erythrina oaxacana, and Erythrina sousae have drug-like phytochemicals with potential antioxidant, anti-inflammatory, anti-aging, and anti-senescence effects.

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, color distribution, and structural patterns. These extracted feature vectors are then analyzed 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.

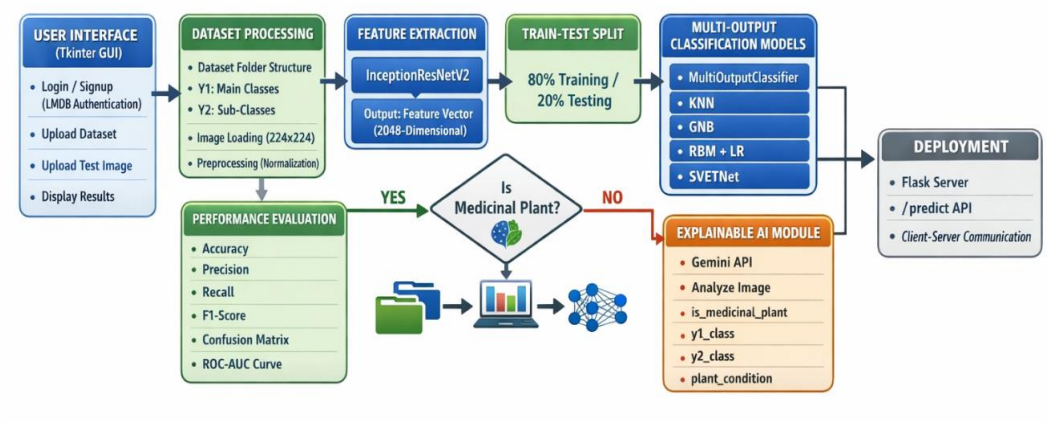


Fig. 2: Proposed system architecture.

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

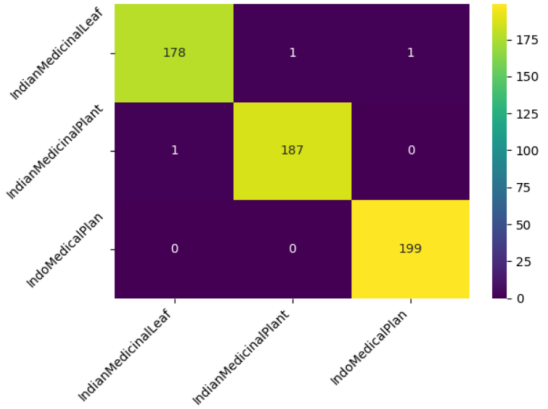
- The architecture supports remote prediction through a client–server communication mechanism.
- External client systems can send plant images to the Flask server for analysis.
- The server processes the images using trained classification models and returns the prediction results in a structured format.

Model Evaluation and Retraining

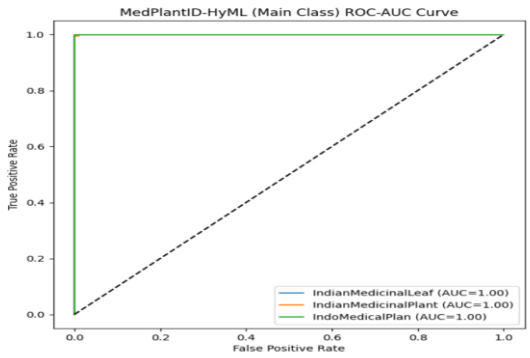
- The system evaluates classification performance using metrics such as accuracy, precision, recall, and F1-score.
- Visualization techniques such as confusion matrices and ROC curves are used to analyze model performance.
- When additional plant image data becomes available, models can be retrained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

4. RESULTS ANALYSIS

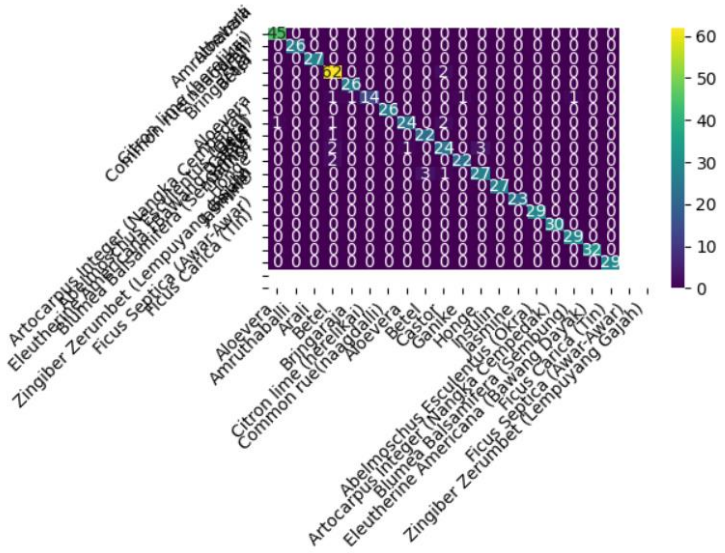
The results obtained from the medicinal plant identification system demonstrate the effectiveness of combining deep learning–based feature extraction with multiple ML classifiers. The system was evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score to assess classification 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.



(a)



(b)



(c)

Fig. 3 (a, b, c): SVETNet Model Performance showing Main Class Confusion Matrix, ROC-AUC Curve, and Detailed Classification Matrix

Fig. 3(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. 3(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. 3(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.



Fig. 4: Medicinal Plant Classification Output (Betel Leaf)

Fig. 4 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 Indian Medicinal Plant 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.

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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