SVETNet: A Novel Explainable Deep Learning Approach for Medicinal Plant Species Recognition

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Abstract
Medicinal plant identification is an important task in areas such as healthcare, agriculture, and traditional medicine systems like Ayurveda. Traditionally, this process has been carried out by experts through manual observation, which is not only time-consuming but also requires deep domain knowledge. With the rise of artificial intelligence and computer vision, automated methods have been introduced to make plant identification faster and more efficient. However, many existing approaches still rely on basic image processing and limited feature extraction, which often results in lower accuracy, especially when dealing with complex and diverse plant images. To overcome these challenges, this study proposes an intelligent image-based system for identifying medicinal plants. The system uses the InceptionResNetV2 model to extract important visual features such as leaf shape, texture, and structural patterns. These features are then used to train several machine learning models, including Gaussian Naïve Bayes (GNB), K-Nearest Neighbors (KNN), and a combination of Restricted Boltzmann Machine (RBM) with Logistic Regression (LR). In addition, a hybrid model called SVETNet is introduced, which combines Support Vector Classification (SVC) and Extra Trees (ET) to improve classification performance. The experimental results show that Support Vector Extra Trees Network (SVETNet) performs better than the other models, achieving an accuracy of 0.9947 for main class prediction and 0.9594 for sub-class prediction. The system also includes a user-friendly interface for easy interaction and a Flask-based client–server setup that allows remote predictions. An explainable analysis module is added to first check whether the input image contains a medicinal plant before performing classification. This work presents a reliable and scalable solution for medicinal plant identification, which can be useful in real-world applications such as healthcare, agriculture, and environmental monitoring.

Keywords: Medicinal Plant Identification, Deep Learning, InceptionResNetV2, SVETNet, Computer Vision.

1. Introduction

Medicinal plants have become increasingly important in the pharmaceutical field due to their cost-effectiveness and lower risk of side effects compared to synthetic drugs. According to the World Health Organization (WHO), more than 21,000 plant species have potential medicinal properties, and nearly 80% of the global population depends on plant-based remedies for primary healthcare. Traditionally, the identification and classification of plant species are carried out by expert botanists (taxonomists) who possess in-depth knowledge of plant taxonomy [1]. However, manual identification is both time-consuming and challenging, and it is highly dependent on human perception, making it susceptible to errors [4]. Moreover, the shortage of skilled taxonomists has led to a condition referred to as "taxonomic impediment" [2], further emphasizing the need for efficient and automated plant identification systems. Figure 1 presents examples of medicinal plant leaves used in the study. Machine Learning (ML), a branch of artificial intelligence, has been widely applied to solve complex problems across various domains with minimal human involvement. Deep Learning (DL), a subset of ML inspired by the functioning of biological neural networks, enables the development of advanced models that require large volumes of data for accurate predictions. With rapid advancements in computing power and increased data availability, DL has demonstrated exceptional performance in applications such as natural language processing, gaming, and image analysis, often achieving results beyond human capabilities [3].

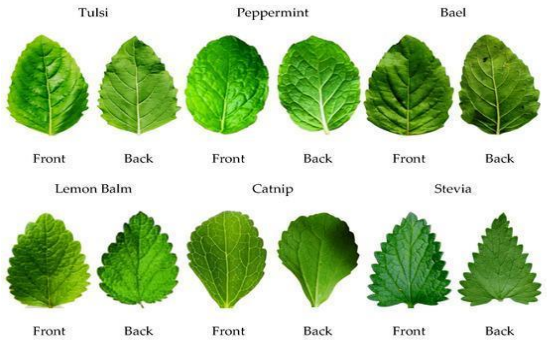

Figure. 1: Sample of the medicinal plant's leaves.

Recent studies highlight a growing interest in the automated identification and classification of plant species using image-based techniques combined with ML and DL approaches. This process generally involves multiple stages, including (a) image acquisition, (b) image preprocessing, (c) feature extraction, and (d) classification. Plant identification can be performed using different plant parts such as flowers, bark, fruits, and leaves, or by considering the entire plant image. Among these, leaf-based identification is most preferred, as leaves are readily available throughout most of the year, unlike flowers and fruits, which are seasonal. As a result, many studies have focused on using leaf images for automated plant identification [4].

2. Literature Survey

Bouakkaz, et al. [6] proposed this work highlighting medicinal flora, which was very essential for the conservation of biodiversity and the improvement of health throughout the world. More specifically, it underlined the need for accurate classification of medicinal plant species for their effective conservation and proper use. The complexity of plant features and a lack of annotated datasets made them difficult for traditional classification methods. This study provided evidence of the potential that DL models had in improving and automating identification and classification procedures for medicinal plants when integrated with botanical studies. S. Jyothsna, et al. [7] introduced real-time plant species detection which played an important role in fields ranging from medicine to biodiversity conservation. Images captured under unconstrained environments, scale variations, different lighting conditions, leaf orientation, complicated backdrops, and leaflet structure made plant species recognition rigorous and time-consuming. The study addressed this challenge by introducing three pioneering hybrid models, seamlessly integrating the strengths of convolution neural networks.

Yu-shi Huang, et al. [8] focused on Partial Least Squares Discriminant Analysis (PLS-DA) model which was utilized to screen for the optimal wavelength range of spectral data, revealing that the region of 1899–650 cm−1 held significant advantages in the identification of APMH. Furthermore, ten sophisticated machine learning (ML) models, including PLS-DA, Tree, Discriminant, and Naive Bayes (NB), were used. Gurusamy, et al. [9] discussed innumerable types of plants, many of which had therapeutic applications. Traditional medicine frequently made use of medicinal herbs. Accurate identification of medicinal plants was highly advantageous to the forest service, life scientists, physicians, pharmaceutical companies, governments, the public, and the people who took drugs. Manual methods were quick and accurate for identifying plants, but only subject-matter specialists used them. Shubham, et al. [10] stated that pharmaceutical companies increasingly used medicinal plants because they were cheaper and had fewer side effects than conventional drugs. Accurate identification and classification of medicinal plants was critical for guaranteeing scientific evidence-based usage of herbal treatments in traditional medicine, upholding pharmaceutical safety requirements, and contributing to biodiversity conservation efforts. However, conventional manual classification methods were time-consuming, error-prone, and required specialized knowledge. S. Elilmaniyamma, et al. [11] introduced an innovative method for the automated recognition of medicinal plants employing DenseNet, a highly layered neural network architecture commonly used for image categorization tasks. The method centered on gathering a wide array of portraits of various medicinal plants, together with their respective labels. It improved image quality and uniformity.

Naoaki Ono, et al. [12] implemented a multi-dimensional methodology to systematically identify potential natural antibiotics derived from the medicinal plants utilized in Ayurvedic practices. Two primary analytical techniques were employed to explore the antibiotic potential of the medicinal plants. The initial approach utilized a supervised network analysis, which involved the application of distance measurement algorithms to scrutinize the interconnectivity and relational patterns within the network derived from Ayurvedic formulae. Phuong Thuy Khuat, et al. [13] calculated the average response of a multidirectional gabor filter bank and optimized it with the structural similarity index measure (SSIM), which enhanced complex leaf features, such as veins, texture, and frequency variations, to improve the classification performance of DL models. The experimental results revealed that the OLSF-ViT model achieved excellent accuracy scores of 100 %, 99.05 %, and 89.65 % on the Folio, UCI Leaves, and JNUSafflower datasets, respectively. Dandan Zhai, et al. [14] stated that American ginseng was widely in demand as a famous medicinal herb, but the production conditions affected the content of ginsenosides in American ginseng, which in turn affected its medicinal value. It remained a challenge to simultaneously identify the origin and ginsenoside content of American ginseng in a non-destructive manner. In this study, a mixed multi-task DL network (MMTDL) was developed and combined with near-infrared (NIR) spectroscopy.

Jannatul Ferdous, et al. [15] attempted to assess the performance of seven advanced DL algorithms in the automated identification of plants from their leaf images and suggested the best model from a comparative study of the models. They meticulously trained VGG16, VGG19, DenseNet201, ResNet50V2, Xception, InceptionResNetV2, and InceptionV3 deep neural network models. Ljiljana Brankovic, et al. [16] stated that medicinal plants fulfilled critical global health needs, but reliable identification posed barriers. This systematic review analyzed 30 studies on DL for automated medicinal plant species classification to offer real-world insights. Convolutional neural networks (CNNs) demonstrated over 90% testing accuracy on plant organs such as leaves and flowers, enabling precise recognition models. Adibaru Kiflie, et al. [17] stated that medicinal plant species identification was necessary to preserve medicinal plants and safeguard biodiversity. The classification and identification of these plants by botanist experts were complex and time-consuming activities. This systematic review aimed to assess prior research efforts on the applications and usage of DL approaches in classifying and recognizing medicinal plant species. M. Chandrajith, et al. [18] proposed a novel hierarchical classification framework designed to categorize hundred Indian medicinal plant species. The innovation lay in introducing a comprehensive feature representation by integrating convolutional features with geometric, texture, shape, and multispectral features for classification tasks. In this study, a two-level hierarchical plant classification model was proposed to address the challenges of inter-class similarity and intra-class variations.

Azadnia, et al. [19] stated that poisonous plants were the third largest category of poisons known globally, posing a risk of poisoning and death to humans. The identification of medicinal and poisonous plants was done by humans using experimental methods, which were not accurate and were associated with many errors. The use of lab required experts,

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and this method was very costly and time-consuming. Therefore, distinguishing between medicinal and poisonous plants was very important using emerging, non-destructive, fast, and accurate methods such as computer vision and artificial intelligence. Roopashree, et al. [20] stated that utilizing herbs had been an integral part of the traditional system of medicine for centuries. However, its sustainability and conservation were critical due to climate change, over-harvesting, and habitat loss. The study revealed how machine learning algorithms, geographic information systems (GIS), and soil information contributed to a swift decision-making approach for proper planning and improving the productivity of vulnerable medicinal plants in specific regions.

3. Proposed System

The proposed methodology presents a well-defined analytical framework for the identification of medicinal plants from digital images using artificial intelligence techniques. The process begins with plant image acquisition and systematic dataset organization, followed by image preprocessing and deep feature extraction. A pretrained convolutional neural network is applied through transfer learning to extract significant visual features such as leaf texture, color distribution, and structural patterns. The extracted feature vectors are subsequently analyzed using multiple machine learning classifiers to perform plant category prediction. An explainable image analysis module is incorporated to verify whether the uploaded image contains a medicinal plant before proceeding to classification. A graphical user interface facilitates user interaction for dataset management, model training, performance visualization, and prediction tasks, as illustrated in Figure 2. A lightweight storage system is used to manage trained models and authentication data, while a server component enables remote image analysis and prediction. Continuous model evaluation and retraining enhance system accuracy and allow adaptation to newly available plant image data.

User Interface (Client Application)

- The user interacts with the system through a desktop-based graphical interface, designed to facilitate seamless plant analysis for researchers and botanists.
- It supports a robust suite of functionalities, including secure login, dataset uploading, feature extraction triggers, and real-time plant image prediction.
- Users can browse local storage to select high-resolution plant images and submit them to the analytical engine for classification.
- All user-initiated commands are processed through the GUI and forwarded to the backend modules for high-speed analysis.

Flask Application Server

- The Flask server functions as the central communication hub, managing the traffic between the client applications and the machine learning models.
- It receives image-based requests and intelligently routes them through the prediction pipeline, ensuring efficient resource allocation.
- The server coordinates the critical tasks of image processing, model execution, and the generation of structured prediction responses.
- This architecture enables remote clients to interact with the system, allowing for distributed plant identification across different geographic locations.

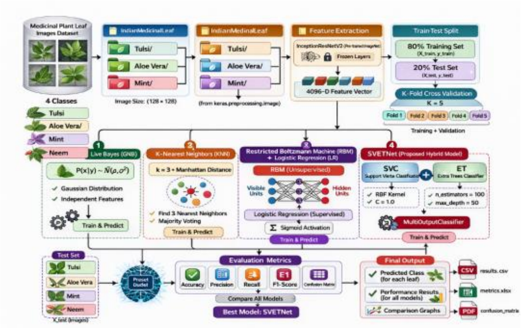

Figure. 2: System architecture.

LMDB Database (Authentication Storage)

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- The system utilizes LMDB (Lightning Memory-Mapped Database) as a high-performance, lightweight key-value store for authentication.
- It maintains persistent records of registered users, including usernames, encrypted credentials, and specific role-based access levels.
- The database interacts directly with the application layer to provide sub-second login verification and secure user management.
- Its memory-mapped architecture ensures that data access is both extremely fast and highly reliable, even during concurrent user sessions.

Image Dataset (Plant Image Collection)

- The dataset serves as the primary ground-truth source, containing a vast collection of medicinal plant images arranged in a hierarchical folder structure.
- Images are categorized by plant class and species, capturing vital visual markers such as leaf shape, texture, color, and venation patterns.
- This diverse collection is utilized to train the DL models and serves as the benchmark for rigorous performance evaluation.
- The dataset represents the foundational knowledge base that the system uses to differentiate between morphologically similar medicinal species.

Image Preprocessing and Feature Extraction

- Raw input images are subjected to a standardization process that includes resizing, normalization, and pixel value scaling to ensure data consistency.
- A pretrained InceptionResNetV2 model is employed as a sophisticated feature extractor, leveraging its deep architecture to identify complex visual patterns.
- The model converts the visual characteristics of the plant into a high-dimensional numerical feature vector, effectively "summarizing" the image content.
- These feature vectors serve as the optimized input for the subsequent machine learning classifiers, bypassing the need for manual feature engineering.

ML Classification Models

The system processes the extracted features through a committee of four distinct classification algorithms to achieve a consensus prediction:

- **GNB:** Analyzes the probabilistic distribution of plant features to establish a baseline classification.
- **KNN:** Categorizes samples based on their feature similarity to neighboring points in the training set.
- **RBM:** Enhances the feature representation through DL, combined with LR for final output.
- **SVETNet (Hybrid Model):** The primary innovation, combining SVM and ET to maximize classification precision and robustness.

Explainable Image Analysis Module

- To enhance system trust, the framework includes an Explainable AI (XAI) component that verifies the validity of the input image.
- It performs structured visual reasoning to confirm that the image contains a medicinal plant before proceeding to classification.
- This module generates descriptive insights, providing the user with an "explanation" of why the system considers the input valid or invalid.
- This step acts as a quality-control gate, significantly improving the reliability and interpretability of the identification results.

Prediction Results and Output Generation

- The system generates dual-track predictions, identifying both the broad plant category and the specific medicinal species.

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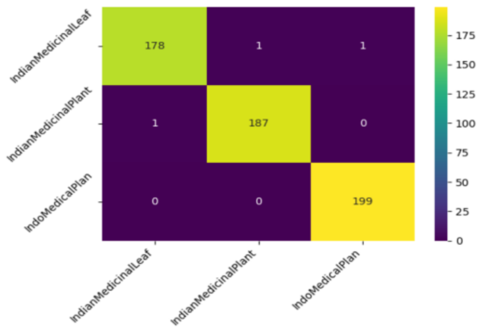
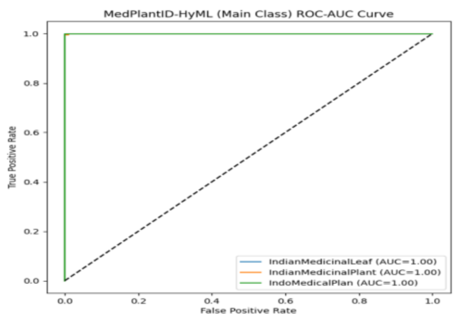
- Results are rendered in the graphical interface through intuitive visual panels, making the data accessible to non-technical users.
- Each output is accompanied by confidence scores and model-specific performance metrics to help the user gauge the reliability of the identification.
- This module turns raw image data into actionable botanical information in a matter of seconds.

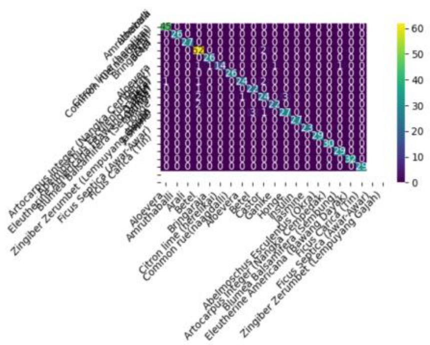
Model Evaluation and Retraining



(a)



(b)



(c)

Figure 3. SVETNet model performance. (a) Main class confusion matrix. (b) ROC-AUC curve. (c) Detailed classification matrix.Figure. 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.

- The framework subjects every model to a rigorous analytical audit using metrics such as Accuracy, Precision, Recall, and F1-score.
- Confusion Matrices and ROC Curves are generated to provide a visual summary of the system's strengths and potential misclassifications.
- The system features an "Adaptive Module" that supports retraining with newly captured images to improve the model's accuracy over time.

Figure. 3 (b) illustrates the ROC-AUC curves for the main 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.

Figure. 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

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model's ability to distinguish even closely related plant species. This demonstrates excellent fine-grained classification capability. Visualization confirms consistent and reliable performance across all subclasses.

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
SVET Net	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.

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
SVET Net	0.9594	0.9648	0.9551	0.9588

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.

Figure. 4: Medicinal plant classification output (Betel Leaf).

Figure 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.

4. Conclusion

This research proposed medicinal plants identification by integrating DL–based feature extraction with multiple machine learning classifiers. The use of the InceptionResNetV2 model allows for effective extraction of key visual features such as texture, shape, and structural patterns, which contribute significantly to improved classification accuracy. These extracted features are utilized by various classifiers, including GNB, KNN, RBM, and SVETNet, to perform plant classification. Comparative analysis reveals that the SVETNet model delivers superior performance, achieving the highest accuracy in both primary category and species-level classification. The system demonstrates robustness in handling diverse plant image datasets with variations in lighting conditions, backgrounds, and orientations. The adoption of multi-output classification enhances the system's capability to predict both plant category and species simultaneously. Moreover, the integration of a user-friendly interface and a client–server architecture ensures efficient, scalable, and accessible system operation. The inclusion of an explainable analysis module further strengthens the reliability and transparency of the prediction process.

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