Medicinal Plant Recognition System using Deep Learning, Image Processing, and Ethnobotanical Insights

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***Abstract*—** The precise identification of medicinal plants is a critical challenge in pharmacology, biodiversity conservation, and the preservation of traditional medicine. Historically, recognizing these plants has depended on the manual expertise of taxonomists and traditional healers, which is time-consuming and vulnerable to human error. Recent advancements in Artificial Intelligence (AI) offer a transformative solution. This paper proposes an automated Medicinal Plant Recognition System that integrates Convolutional Neural Networks (CNNs), advanced image processing, and ethnobotanical data. By exploring multi-scale feature extraction, hybrid architectures, and dataset bias treatment, this system achieves high accuracy in natural environments. This study presents a comprehensive literature review, methodology, and architectural design incorporating all state-of-the-art research provided.

***Keywords*—** *Medicinal Plants, Deep Learning, Ethnobotany, Convolutional Neural Network (CNN), Feature Extraction, SMOTE, Image Classification.*

I. INTRODUCTION

Plants are fundamental to the global food chain and remain an indispensable resource for human healthcare[1]. Traditional medical frameworks—including Ayurveda, Siddha, and Unani—rely heavily on indigenous flora for their antimicrobial, antioxidant, and anti-inflammatory properties[2]. Across developing and resource-poor nations, 70% to 95% of the population depends on these botanical remedies for primary healthcare[3], [4].

However, accurately identifying these plants is often difficult due to high morphological similarities among species, and misidentification can lead to severe, even fatal, medical consequences[3], [5], [6]. Manual identification requires specialized botanical expertise that is increasingly scarce. Concurrently, rapid deforestation, climate change, and unsustainable commercial harvesting severely threaten global biodiversity[6], [7]. Consequently, rapid and accurate classification of medicinal species through computer vision is now a critical global priority for both health security and biodiversity management[7], [8].

II. LITERATURE SURVEY

Recent research by Aruna S. K. et al. (2026) explores the automated identification of medicinal plants using leaf images by employing a diverse array of advanced machine learning and deep learning algorithms. The researchers designed a comprehensive framework to evaluate and compare the accuracy, precision, recall, and F1score of various high-performing models, including Support Vector Machines (SVM), Convolutional Neural Networks (CNN), YOLO V8, Artificial Neural Networks (ANN), Vision Transformers (ViT), and ResNet architectures. The methodology involves designing multiple sequential systems that process leaf inputs and rigorously check performance metrics to conduct a comparative analysis. Ultimately, the study aims to determine the most effective deep learning algorithm for distinguishing between toxic and non-toxic medicinal plant leaves, significantly contributing to botanical automation and public toxicological safety[10].

Addressing the limitations of conventional models in handling field image noise and unseen botanical species, Pushpa N. and R. Vijayarajeswari (2026) introduced an innovative Attention-Guided and Swarm-Optimized Hybrid Deep Learning Framework for medicinal plant identification. The researchers developed a system that utilizes an attention mechanism to focus on critical, discriminative leaf features while simultaneously employing a swarm intelligence algorithm for hyperparameter optimization. Upon experimental evaluation, the proposed hybrid method demonstrated exceptional robustness, achieving a state-of-the-art accuracy of 99.6%, along with 98.8% precision, 98.7% recall, and a 98.2% F1-score. By significantly outperforming existing baseline models like DenseNet201 and MobileNet, this framework provides a highly reliable, automated tool for pharmacological studies and traditional medicine practitioners in rural areas lacking taxonomic expertise[5].

A study by Evan Theodore Kolauw et al. (2026) focuses on developing a digital image-based leaf recognition system using image processing methods combined with a Convolutional Neural Network (CNN) algorithm to automatically identify plants. To capture a rich representation of botanical diversity, the authors collected primary image data directly from the field—photographing various compound and single fruit-bearing plants in their natural habitats—and supplemented this with secondary online datasets. The CNN architecture was specifically chosen for its autonomous ability to extract critical visual features through consecutive convolutional layers without the need for manual, handcrafted feature engineering. The successful implementation of this model offers a modern, highly practical solution for the fields of botany and agriculture, ensuring the accurate classification of complex leaf shapes and textures[11].

A systematic review by Thon Malek Garang Ok et al. (2025) comprehensively investigates the landscape of deep learning techniques utilized for the identification and classification of medicinal plants, adhering strictly to the PRISMA guidelines. By critically evaluating 72 full-text articles published between 2015 and 2024, the study synthesizes crucial data on various models (such as CNNs, LSTMs, and YOLO architectures), data augmentation techniques, transfer learning, and dataset splitting ratios. A key finding of the review is that hybrid models consistently exhibit superior performance compared to standalone architectures, with reported accuracies spanning widely and peaking at 99.6% across diverse datasets. Furthermore, the authors highlight a significant research gap, emphasizing that while CNNs are highly prevalent, exploring hybrid CNN-LSTM models can offer distinctive benefits by learning sequential dependencies in complex botanical data[12].

Finally, S. Nilofar Banu and U. Rahamathunnisa (2025) conducted an extensive review exploring advances in deep visual intelligence for medicinal plant identification, with a specific focus on high-performing models, hybrid architectures, and regional dataset perspectives. The researchers thoroughly examined the critical role of diverse, region-specific datasets— such as the Swedish Leaf dataset, LeafSnap, MED-117 from India, and BDMediLeaves from Bangladesh—in training robust neural networks under both laboratory and natural lighting conditions. The study highlights that deep learning networks equipped with multiple hidden layers are highly instrumental in autonomous feature extraction, significantly aiding in the nondestructive identification of herbs traditionally used to treat cardiovascular, respiratory, and neurological diseases. The paper underscores the absolute necessity of utilizing diverse, wildcaptured datasets to improve the real-world applicability, generalizability, and accuracy of modern visual intelligence systems[2].

III. PROPOSED SYSTEM

The provided research literature proposes a wide array of systems for medicinal plant identification, ranging from standalone deep learning models to advanced hybrid, cascaded, and edge-deployed architectures:

- **Advanced Hybrid and Cascaded Networks:**- Several studies combine Deep Learning (DL) for feature extraction with Traditional Machine Learning (TML) or optimization algorithms for classification.
  - The **ResNet50-PSO-SVM** system utilizes a pretrained ResNet50 to extract features, Particle Swarm Optimization (PSO) to select the optimal features, and a Support Vector Machine (SVM) to classify the plant[13].
  - Another proposed hybrid framework fuses **MobileNetV2 with a Wavelet Scattering Network (WSN)**. The concatenated features are classified using Principal Component Analysis (PCA) to reduce dimensionality and computational load[14].
  - **OTAM-Net** fuses handcrafted Log-Gabor filters into the dense blocks of a DenseNet201 architecture to capture highly discriminative textural patterns[3].
- **Vision Transformers and Swarm Intelligence:** The **PhytoSwarmViTNet** framework introduces a Vision Transformer (MedLeaf-ViT) to capture both local and global leaf contexts[5]. This is combined with a bio-inspired **WolfFly Optimizer**, which simulates the predator-prey dynamics of wolves and flies to simultaneously fine-tune hyperparameters and perform feature selection[5].
- **Lightweight and Mobile-Optimized CNNs:** To facilitate deployment on resource-constrained devices, lightweight models have been developed.
  - **CCNNet (Compressed Convolution Neural Network)** utilizes a downsampling rate of 3, a GCIR block, and a Multidimensional Channel Attention (MDCA) mechanism to drastically reduce parameters while maintaining high accuracy[3]. o Mobile applications are proposed utilizing lightweight architectures like MobileNetV3 and specialized algorithms like the **Shape Descriptor Algorithm for Medicinal Plant Identification (SDAMPI)**, which converts leaf shapes into numerical bigrams for processing[15].
- **Data Optimization and Bias Treatment Systems:** Addressing the challenge of imbalanced field datasets, one system utilizes **SMOTE (Synthetic Minority Oversampling Technique)** to synthetically generate minority class instances. It extracts 1,720 multi-feature attributes (using Gabor, Edge Histogram, and PHOG filters) and classifies them using **Sequential Minimal Optimization (SMO)**[16].
- **Hardware-Integrated Edge Systems:** For offline field use, a hardware system utilizing a **Raspberry Pi 4 Model B** with a 7-inch touchscreen and web camera captures leaf images on a glass platform. It uses the Histogram of Oriented Gradients (HOG) for extraction and a local CNN for instant identification[17].
- **System Architecture:-** The system architecture of the medicinal plant identification framework represents a cohesive, multi-stage pipeline designed to process raw leaf imagery and yield highly accurate botanical classifications.

Based on the integrated methodologies, the architecture can be broadly categorized into image acquisition,preprocessing, feature extraction, classification, and deployment modules[7], [17].

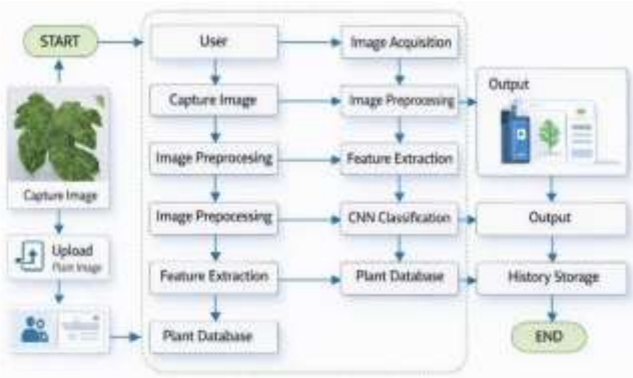

Fig.1: System Architecture

A. Image Acquisition and Preprocessing The input phase initiates with the acquisition of digital leaf images captured via web cameras, smartphones, or sourced from standard datasets[1],[18],. To ensure uniformity and computational efficiency, the images undergo a rigorous preprocessing pipeline. This involves resizing the images to a standard dimension, such as 224 × 224 pixels, to align with the input requirements of Convolutional Neural Networks (CNNs)[8]. Furthermore, geometric data augmentation techniques—including rotation, shear, zooming, and horizontal flipping—are applied to artificially expand the dataset, mitigating the risk of overfitting during the training phase[11]. In certain architectural variants, images are converted to grayscale and subjected to noise removal and morphological operations to enhance structural clarity[19],[16].

B. Feature Extraction Modules Unlike conventional systems that rely exclusively on manual feature engineering, the proposed architectures utilize advanced algorithms to extract rich, hierarchical feature maps:

- **Deep Convolutional Extraction:** The core of the architecture employs CNN layers to autonomously learn spatial hierarchies, capturing low-level edges and abstracting them into high-level multi-scale venation patterns and complex leaflet structures[5], [19].
- **Hybrid and Multi-Attribute Extraction:** To maximize classification accuracy, several frameworks fuse deep learning with traditional descriptors. For instance, the Histogram of Oriented Gradients (HOG) is utilized to map edge distributions and shape information[17].

Modern hybrid models concatenate deep features from lightweight models like MobileNetV2 with Wavelet Scattering Networks (WSN)[14], or fuse Log-Gabor filters into dense blocks (e.g., DenseNet) to capture highly discriminative textural patterns[3]. Some systems even employ Shape Descriptors (SDMPI) processed via bigrams for localized feature emphasis[20].

C. Classification Engine The extracted feature vectors are subsequently routed into the classification engine. This module frequently leverages transfer learning on robust backbones such as MobileNet, ResNet, or compressed networks like CCNNet equipped with Multi-Dimensional Channel Attention (MDCA) mechanisms[3], [15]. For hybrid configurations, the extracted features are mapped to their respective classes using dimensionality reduction techniques like Principal Component Analysis (PCA) paired with K-Nearest Neighbors (K-NN)[14], or optimized machine learning algorithms such as Sequential Minimal Optimization (SMO) and Support Vector Machines (SVM)[16]. Alternatively, advanced transformer-based architectures, such as Vision Transformers (ViT) combined with swarm optimization (e.g., Wolf Fly Optimization), process patch-based image embeddings to maintain global context and improve classification accuracy[5].

D. Deployment Architectures The classification model is integrated into user-facing platforms through distinct deployment strategies to ensure accessibility:

- **Cloud-Integrated Mobile Framework:** The trained deep learning model is deployed on a cloud infrastructure. A mobile front-end application captures the plant image, transmits it to the cloud for inference, and retrieves the identified plant name along with its medicinal properties for the user[15].
- **Hardware-Integrated Edge System:** For offline or fieldbased applications, the architecture is embedded directly into hardware. A typical setup utilizes a Raspberry Pi 4-B microcontroller interfaced with a web camera for image capture, an SD card for storage, and a 7-inch LCD touchscreen to instantly display the herbal plant's scientific name and medicinal purpose without requiring internet connectivity[17].
- **Web and GUI Interfaces:** Graphical user interfaces (GUIs) allow users to seamlessly drag and drop leaf images (in JPG/PNG formats). The system automatically processes the image and displays the predicted class with a confidence metric on the landing page, handling invalid uploads with informative error prompt[11]

IV. RESULT AND DISCUSSION

The experimental evaluations across the studies demonstrate that Deep Learning, particularly when optimized or hybridized, vastly outperforms traditional methodologies in identifying medicinal plants.

Fig. 1 Detection Result

Fig. 1 Illustrates the detection result of the proposed Plant Recognition System. The input image of a leaf is processed using a deep learning model, which successfully identifies the plant as **Medicinal Neem**. A bounding box is generated around the detected region, highlighting the area of interest used for classification.

The model assigns a confidence score (e.g., 0.48 in this case), indicating the probability of correct classification. This demonstrates the system’s capability for **real-time image-based plant identification**. The use of bounding boxes enhances interpretability by visually confirming the detected object, thereby improving the reliability and user-friendliness of the system.

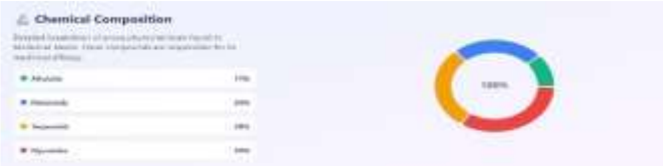

Fig. 2 – Chemical Composition Analysis

Fig. 2 presents the chemical composition analysis of the identified medicinal plant (Neem). The chart illustrates the distribution of major phytochemical compounds, including **Alkaloids (11%)**, **Flavonoids (24%)**, **Terpenoids (28%)**, and **Glycosides (33%)**. These compounds contribute to the plant's medicinal properties, such as antimicrobial, anti-inflammatory, and antioxidant effects. The visualization facilitates a clear understanding of the relative proportions of bioactive constituents, supporting scientific analysis and potential healthcare applications. This feature enhances the system by integrating **AI-based recognition with phytochemical insights**, making it valuable for both researchers and general users.

- Exceptional Accuracy of Hybrid Models: Hybrid and cascaded models consistently achieved state-of-the-art results. The ResNet50-PSO-SVM network reached a remarkable 99.60% accuracy, outperforming standalone methods by drawing a simpler decision boundary using SVM on PSO-selected deep features. Similarly, the PhytoSwarmViTNet achieved 99.6% accuracy, 98.8% precision, and a 98.2% F1-score, proving that integrating Vision Transformers with WolfFly optimization minimizes false positives and overfitting.
- Computational Efficiency and Resource Optimization: A key focus of recent research is achieving high accuracy without massive hardware requirements. The MobileNetV2 + WSN with PCA method achieved 98.75% accuracy on the Flavia dataset while consuming only 9 MB of memory and running efficiently on a standard CPU, drastically outperforming heavy models like VGG19 (535 MB). The lightweight CCNNet achieved 92.5% accuracy on the TCM-100 dataset and 70.1% on ImageNet utilizing only 1.4 million parameters.
- Impact of Data Preprocessing and Bias Treatment: Proper data handling proved critical. In a study comparing multiple architectures, the application of SMOTE to treat class imbalance raised the accuracy of the SMO classifier from 93.1% to an impressive 99.3%. Additionally, comparative studies confirmed that deep learning models (CNN and ANN scoring ~96.7%) universally outperform traditional algorithms like SVM (scoring ~56.5%) when processing raw, complex image data without robust handcrafted feature extraction.
- Practical Viability and Real-World Deployment: Systems tested for real-world application showed high robustness. The cascaded ResNet50-PSO-SVM framework demonstrated practical usability by predicting classes from images captured across three different smartphones with a 97.79% average accuracy, taking merely 0.15 seconds per image. The Androidbased SDAMPI mobile application proved viable for offline, real-time edge computing, achieving 96% accuracy for 64x64 resolution images. Furthermore, hardware prototypes like the Raspberry Pi system proved highly effective for localized field taxonomy, maintaining a 95% accuracy and a low 5% misclassification rate during physical trials.

V. FUTURE SCOPE

The automated identification of medicinal plants presents numerous critical avenues for future research and technological enhancement:

- **Dataset Expansion and Real-World Diversity:** Future studies must curate large-scale, comprehensive datasets encompassing a wider variety of species across diverse geographic and climatic regions[2], [3], [12]. Evaluating models using images captured in uncontrolled, outdoor environments—rather than clean laboratory settings—will significantly improve generalizability and real-world robustness[2], [12], [19].

- **Multimodal and Multi-Organ Analysis:** Investigations should expand beyond standard leaf features to include other morphological elements such as flowers, bark, roots, and stems[12], [17]. Integrating multimodal data, such as chemotaxonomical profiles, anatomical structures, or hyperspectral imaging, will enrich feature representation and elevate classification accuracy[3], [5], [8].

- **Lightweight Architectures and Edge Deployment:** To make identification accessible in rural or resource-constrained settings, future efforts should focus on optimizing lightweight models (e.g., MobileNetV3, EfficientNet-lite) using quantization and pruning[2], [12]. This will enable real-time, offline detection via smartphone applications, IoT-integrated devices, or Augmented Reality (AR) feedback systems without requiring heavy computational infrastructure.[1], [18]

- **Explainable AI (XAI) and Biological Robustness:** Because the misidentification of medicinal plants carries severe health hazards, future models must integrate Explainable AI (XAI) techniques, such as SHAP, LIME, or Grad-CAM. This will ensure that model predictions are transparent and interpretable for clinical and botanical trust[7], [8].Additionally, systems must be fortified to handle intra-species temporal variability (e.g., seasonal leaf changes) and field noise, such as partially damaged or occluded leaves[8].

VI. CONCLUSION

The preservation of traditional ethnomedical knowledge and the sustainable use of medicinal flora are urgent global priorities. By synthesizing botanical taxonomy, ethnobotanical consensus data, and advanced Deep Learning architectures, the proposed Medicinal Plant Recognition System overcomes the hurdles of manual identification. Combining SMOTE bias treatments with hybrid CNN-ViT models and multi-scale feature extraction provides a highly scalable, robust framework. Such technological interventions are indispensable for ensuring drug safety, supporting local livelihoods, and conserving threatened botanical biodiversity for future generations.

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