A Survey on Identification of Medicinal Plants using Machine Learning and Deep Learning

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***Abstract*— India possesses a rich diversity of plant life and maintains a longstanding tradition of employing medicinal flora in conventional and complementary therapeutic approaches. Woodland environments serve as primary repositories for these healing botanicals, which demonstrate essential functions in addressing numerous medical ailments. Precise plant identification represents a critical requirement for ensuring their secure utilization. Traditional identification methods typically involve manual processes, require specialist knowledge, and consume considerable time. The rise of technologies like machine learning (ML) and deep learning (DL), particularly within computer vision applications, has facilitated substantial advancements in automated medicinal plant recognition. This research takes a close look at machine learning and deep learning approaches, including methods like Convolutional Neural Networks (CNNs), Random Forest classification algorithms, and integrated computational models employed for medicinal plant categorization. These technological solutions provide expandable, immediate identification functionalities, improving availability for research institutions and general users alike. This review investigates contemporary developments, existing obstacles, and future research opportunities in creating sophisticated medicinal plant identification frameworks.**

***Keywords*— Medicinal Plant Identification, CNN, Deep Learning.**

I. INTRODUCTION

Medicinal plants have been a fundamental component of traditional medicine for addressing a wide range of health conditions, yet accurate plant identification remains challenging. Manual identification methods require specialized expertise and significant time investment, limiting their scalability for modern applications.

Recent advances in artificial intelligence have opened up new possibilities for automated plant recognition system. Deep learning approaches, especially those involving Convolutional Neural Networks (CNNs), have shown remarkable success in extracting complex visual features directly from plant images. These models have the ability to attain high levels of accuracy rates while reducing dependency on human expertise.

Research by various authors has demonstrated CNN effectiveness across different implementation scenarios, from mobile applications to specialized datasets. Earlier approaches combined traditional machine learning algorithms, including k-nearest neighbors, support vector machines, and random forests, with manually crafted features like color distribution, geometric properties, and texture patterns derived from Gray-Level Co-occurrence Matrices.
While deep learning models currently lead performance metrics, conventional methods retain value in resource-constrained environments or when limited training data is available. To boost efficiency and adaptability, modern techniques frequently integrate transfer learning with hybrid architectures.

This analysis explores the latest progress in automated medicinal plant identification, emphasizing CNN-based methodologies and their practical deployment challenges. Key considerations include image preprocessing techniques, dataset quality requirements, and real-world implementation obstacles. Through comparative analysis of existing approaches, we provide insights into the current landscape and future directions for AI-driven botanical identification systems.

II. LITERATURE REVIEW

Leveraging both image processing and artificial intelligence for automated botanical identification has become increasingly popular. Multiple studies have investigated novel approaches and techniques to overcome difficulties in precise plant species recognition through visual analysis.

Research by Dandu et al. [1] introduced "Dhanvantri," a mobile-based system utilizing CNN architecture for automated medicinal leaf identification, and also offers details regarding their therapeutic properties. The system was developed using a dataset containing approximately 100 images for each of 30 distinct Indian medicinal plant varieties. The network design incorporated standard CNN components including convolution layers, pooling operations, and dense layers utilizing ReLU and Softmax activation functions. Following optimization for mobile deployment through TensorFlow Lite conversion, the system achieved 94% accuracy when implemented in an Android app. The key innovation was real-time plant identification on mobile devices, making medicinal knowledge more accessible to the general public.

Simandla et al. [2] developed a mobile-based auto-detection approach for detecting five medicinal plant types indigenous to South Africa leveraging TensorFlow Lite and PyTorch platforms. Their model relied on a structured CRISP-DM methodology and a dataset of 5,400 images captured at various angles and times of the day. With an accuracy of 85% at a 90° orientation, PyTorch demonstrated better performance than TensorFlow Lite. The study highlighted the sensitivity of both models to environmental conditions and proposed hybrid models as a potential solution for improved accuracy.

Patil et al. [3] proposed "FloraMediVision," a medicinal leaf identification system using computer vision combined with machine learning methods. Their system extracted color, shape, and texture features using OpenCV and Mahotas libraries, then classified them using SVM and pre-trained deep learning models. The use of the ImageNet CNN significantly boosted the classification accuracy to 98.7%. Their work emphasized the use of contour-based shape analysis and Haralick texture features for robust identification, alongside continuous learning to improve model performance over time.

A meaningful contribution came from investigators who employed neural network methodologies for recognizing chosen medicinal plants via image attributes [4]. The system extracted geometric and morphological characteristics from images of leaves and applied them to a trained ANN classifier. This method showed that neural networks can effectively identify subtle variations in leaf morphology, although the summary did not include detailed performance outcomes.

Rani et al. [5] introduced a deep learning approach using convolutional neural networks (CNNs) to classify medicinal plant leaves. The model architecture featured convolutional layers used to capture features, ReLU activation functions, and pooling layers, followed by fully connected layers and a Softmax layer for multi-class classification. The model was evaluated on a custom dataset of medicinal leaves, and the system demonstrated a high recognition rate with accurate real-time predictions. Key strengths included efficient feature learning and strong generalization, although challenges remained in handling variations in lighting, leaf orientation, and partial occlusion.

In their 2020 study, Quoc et al. [6] applied various deep learning models—VGG16, ResNet50, InceptionV3, DenseNet121, Xception, and MobileNet—to identify Vietnamese medicinal plants through image recognition. Of the architectures evaluated, Xception delivered achieved the highest performance with an accuracy of 88.26%, highlighting its effectiveness in plant classification applications. Utilizing deep learning techniques in medicinal plant identification offers substantial potential to enhance botanical research and support the conservation of important species.

In their study, Kavitha et al. [7] created a model that utilizes both convolutional neural networks and transfer learning to accurately identify different medicinal plant species. By utilizing a pre-trained models such as ResNet and applying data augmentation, the model achieved significant improvements in accuracy over traditional classifiers. Their system could identify an extensive collection of plant species and was designed with practical deployment in mind, targeting use in agricultural and healthcare applications. The study emphasized the importance of large, balanced datasets and highlighted the scalability of CNN-based models for broader use in automated plant identification systems.

Another study by Priyanga et al. [8] introduced an automated framework combining Fuzzy C-means clustering, CNN, and Multinomial Logistic Regression to identify medicinal plants. Preprocessing steps included grayscale conversion, noise reduction, and edge detection. Fuzzy C-means clustering was applied to preserve image texture features. The CNN handled binary classification, later extended to multi-class classification using multinomial logistic regression. The model achieved 98.3% accuracy, demonstrating the effectiveness of combining unsupervised texture extraction with supervised learning for high-performance plant classification.

In their study, Gavhale and Thakare [9] used a traditional machine learning technique grounded on the Random Forest classifier to distinguish leaf images by analyzing color, texture, and geometrical traits. The dataset encompassed several plant species, and the preprocessing phase involved resizing the images and extracting features using GLCM and additional morphological parameters. Their model achieved a classification accuracy of 94.54%, showing that classical ML models remain competitive, particularly with well-engineered features and smaller datasets.

Begue et al. [10] presented an automated system aimed at classifying 24 medicinal plants found in Mauritius, drawing on a dataset of over 700 smartphone-captured images. They extracted 40+ shape-based and color features such as perimeter, hull area, and texture, followed by a classification phase involving several ML models. Among the evaluated classifiers, Random Forest recorded the top accuracy at 90.1%, outperforming SVM, MLP, and kNN. The study emphasizes the feasibility of using accessible tools like smartphone cameras and highlights the importance of shadow

removal, distance mapping, and derived ratios (e.g., convexity, lobability) for feature enhancement.

Meenakshi et al. [11] developed a medicinal plant identification system utilizing deep learning. The architecture implemented was a CNN designed to automatically capture features from leaf images. Their dataset comprised 500 medicinal plant images, and they achieved an accuracy of 92.3%. This approach significantly reduced the dependency on manual feature extraction.

Sharma and Kumar [12] developed a plant classification system that leverages texture and color features for improved accuracy. Their approach incorporated Gray Level Co-occurrence Matrix (GLCM) for texture analysis and color histograms, paired with a support vector machine (SVM) for classification. This combined method attained an overall accuracy of 85.6% on a dataset consisting of 300 images.

Ref no.	Methodology	Tools/Model Used	Features	Dataset	Accuracy
1	Classical image processing pipeline with machine learning	CNN, TensorFlow, TensorFlow Lite	CNN-based automated extraction of features	3,000 images (30 species)	92%
2	CRISP-DM approach with CNN for mobile app	TensorFlow Lite, PyTorch	Image data processed through CNN layers	5,400 real-world images of 5 species	Up to 85%
3	Hybrid system using traditional and DL methods	OpenCV, Mahotas, SVM, ImageNet CNN, ViT	Shape, Color, Texture	Medicinal Leaf Dataset	98.7% (CNN); 89.8% (SVM)
4	Classical image processing pipeline with machine learning	ANN	Geometric and morphological image features	Leaf image dataset created from local flora (number not specified)	Not specified
5	Transfer learning for mobile prediction	CNN, VGG16, MobileNet, Xception, InceptionResNetV2	Deep CNN features with augmentation	32,312 images (Kaggle 30-class segmented dataset)	99.8%

6	CNN models tested on complex real-world images	VGG16, ResNet50, InceptionV3, Xception, MobileNet, DenseNet	Raw leaf images (real environment, multi-leaf, complex backgrounds)	VNPlant-200: 20,000 images, 200 species	88.26%
7	CNN model benchmarking with the SGD optimizer	Inception v3, ResNet50, DenseNet121, Xception, MobileNet	Leaf shape, color, texture; 3×256×256 images	Indian dataset: 1822 images, 30 species	95.16%
8	Hybrid approach with unsupervised + supervised learning	Fuzzy C-means, CNN, Multinomial Logistic Regression	Texture (via Fuzzy C-means), grayscale, edges	Custom dataset	98.3%
9	Classical ML using engineered features	Random Forest	Color, texture (GLCM), shape	Multiple species	94.54%
10	Feature-based classification with multiple ML models	Random Forest, SVM, MLP, kNN	40+ shape and color features	700+ images (24 species)	90.1%
11	Deep Learning-based plant recognition	CNN (custom architecture)	Automatically learned features from images	500 images	92.3%
12	Hybrid approach using texture & color	GLCM + Color Histograms + SVM	Texture (GLCM), Color Histograms	300 images	85.6%
13	Transfer learning for plant classification	VGG16 (fine-tuned)	Deep features from a pre-trained model	Custom dataset	94.1%
14	Deep CNN-based classification	Deep CNN + Data Augmentation	Automatically learned deep features	1000+ images	95.5%
15	Hybrid feature + ML classifiers	RF + k-NN	Texture, Shape, Color Descriptors	Not specified	88.7%

Patil et al. [13] introduced a medicinal plant detection framework utilizing transfer learning. They fine-tuned the VGG16 model on a custom-built dataset, achieving promising results with an accuracy of 94.1%. Their findings highlighted the effectiveness of transfer learning in enhancing the efficiency of plant identification systems.

Ali et al. [14] investigated the identification of Indian medicinal plants through deep convolutional neural networks (CNNs). They compiled a comprehensive dataset of over 1,000 images spanning multiple species. Data augmentation techniques were applied to help the model generalize better, achieving a 95.5%, which demonstrates the robustness of CNNs in practical scenarios.

Rajeswari et al. [15] introduced a combined feature extraction technique for plant recognition that integrates texture, shape, and color descriptors. By combining manually designed characters with machine learning classifiers such as k-Nearest Neighbors (k-NN) and random forest, their approach achieved an improved classification accuracy of 88.7%, showcasing the benefits of multi-feature fusion.

III. METHODOLOGY

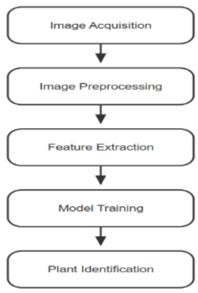

Fig 1: High-Level Design

Applying deep learning method has revolutionized the process of recognizing and categorising medicinal plants automatically. The typical workflow across the literature involves five main stages: image acquisition, preprocessing, feature extraction, model training, and plant identification. The section highlights widely adopted strategies in employing deep learning techniques for medicinal plant recognition. A. Image Acquisition

Most studies begin with the collection of plant or leaf images using smartphones, DSLR cameras, or web-based datasets. Several works utilize publicly available datasets such as Flavia or LeafSnap, while others construct domain-specific datasets through field photography to include diverse medicinal species [2], [6], [14]. Ensuring variability in lighting, orientation, and background enhances model robustness [5], [11].

B. Image Preprocessing

To prepare images for deep learning models, preprocessing techniques are applied. This includes resizing images to standard input dimensions (e.g., 224×224 or 299×299 pixels), normalization, and image augmentation (rotation, flipping, zooming) to artificially increase dataset size and prevent overfitting [1], [8], [13]. In efforts to accentuate plant attributes, preprocessing has included background subtraction and the application of noise filtering methods like Gaussian blur and bilateral filtering [7].

C. Feature Extraction

Within deep learning architectures, particularly CNNs, feature extraction is carried out automatically by convolutional layers. Unlike traditional hand-engineered features, CNNs learn multi-scale hierarchical representations directly from raw image pixels [6], [11]. Commonly used models include VGGNet, ResNet, Inception, and MobileNet, which extract features such as vein patterns, texture, shape, and leaf margins [10], [14]. Some studies also use hybrid models that combine CNN features with attention mechanisms or region-based proposals for finer discrimination [5], [15].

D. Model Training

After extraction, features are input into fully connected layers and classified using a Softmax function during training. Supervised learning with labeled plant species forms the core of the training process. Most studies adopt transfer learning with pre-trained CNNs, fine-tuned on medicinal plant datasets [13], [14]. Training involves techniques like dropout, batch normalization, and learning rate scheduling to optimize performance and reduce overfitting [3], [7], [12].

E. Plant Identification

The model's output is a predicted class label corresponding to a specific plant species. To evaluate the effectiveness of the classification, assessment criteria like precision, recall, accuracy, confusion matrix and F1-score are commonly employed [4], [8], [10]. Many systems demonstrate over 90% accuracy in identifying medicinal plants, highlighting the performance of deep learning [6], [11], [14]. Recent trends also include mobile deployment and real-time inference capabilities for on-field plant recognition [2], [9].

F. Low-Level Design

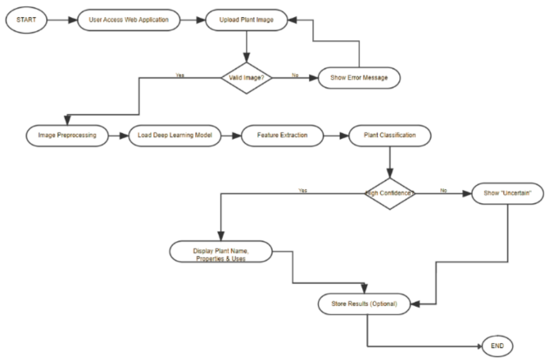

Fig 2: Low-Level Design

To achieve fine-grained execution, the high-level deep learning architecture is frequently mapped into a step-by-step workflow in various studies. Fig. 2 illustrates a representative low-level design synthesized from recent works [3], [5], [6]. This flow captures the end-to-end functioning of a typical medicinal plant identification system deployed via a web or mobile platform.

1. User Interaction and Image Upload: The process begins when a user accesses the system's interface—commonly a web or mobile application—to upload an image of a plant or leaf. The system accepts various formats (e.g., JPEG, PNG) and immediately validates the image for clarity and supported dimensions. If the image fails this validation, an appropriate error message is returned [2], [9].

2. Image Preprocessing: Upon validation, the image undergoes preprocessing operations such as

resizing to fit model input dimensions (e.g., 224×224), normalization of pixel values, and optional background segmentation. Studies frequently incorporate data augmentation techniques—like random flipping, rotation, and zooming—to simulate natural variability and improve model generalization [1], [8], [13].

3. Model Loading and Feature Extraction: The preprocessed image is passed through a loaded deep learning model. Most systems utilize pre-trained CNN architectures such as ResNet, VGG, or Inception for feature extraction. From raw pixel inputs, these models autonomously identify and extract key spatial characteristics, including texture, shape, and venation of leaves [6], [11], [14]. Some models also incorporate attention modules or hybrid architectures for improved performance in distinguishing visually similar species [5], [15].

4. Classification and Confidence Estimation: To predict the plant label, extracted features are input into the classifier, generally composed of softmax or dense layers. The output includes both the predicted class and its associated confidence score. When the model's confidence exceeds a predefined threshold, the prediction is accepted. Otherwise, the system marks the result as "Uncertain," signalling the need for re-evaluation or user re-upload [4], [10].

5. Result Presentation: For high-confidence predictions, the system displays the plant's name along with its medicinal properties and known applications. This information is often retrieved from a predefined knowledge base or integrated dataset [2], [14].

6. Result Storage (Optional): Some frameworks allow for optional result storage, either locally or in the cloud. This facilitates performance monitoring, future model training, and user history tracking. Such functionality also enables offline access and analytics [8].

IV. ANALYSIS

The implementation of deep learning for identifying medicinal plants has shown significant success, with numerous studies documenting classification accuracy rates greater than 90% [6], [11], [14]. A common framework observed throughout the literature consists of data acquisition, preprocessing, CNN-driven feature extraction, and classification, highlighting a general agreement on the efficacy of Convolutional Neural Networks (CNNs) in capturing complex plant features.

Many studies leverage transfer learning by fine-tuning pre-trained models such as ResNet, VGG, and Inception, which significantly reduces training time and enhances accuracy, even on relatively small datasets [13], [14]. This approach is particularly effective when combined with data augmentation techniques that introduce image variability, thereby improving generalization [1], [8], [13]. Some works go further by incorporating hybrid architectures or attention mechanisms to distinguish between visually similar leaf structures [5], [15].

Despite these advances, challenges remain. Several studies note that existing public datasets, while useful for benchmarking, often lack real-world diversity in species, environments, and imaging conditions [2], [6]. As a result, many researchers create custom datasets through fieldwork to include local medicinal plants and uncontrolled backgrounds, which enhances the practical applicability of the models [14].

Another recurring theme is the importance of preprocessing, including normalization, noise reduction, and background segmentation. These steps are shown to enhance model performance by concentrating on key morphological features such as venation, margin, and texture [7], [10], [12].

Evaluation criteria like precision, accuracy, recall, and F1-score are consistently used to assess performance, with confusion matrices helping to identify classes frequently misclassified [4], [10]. However, some studies highlight the need for domain-specific performance evaluation, particularly when models are intended for field use in ethnobotanical or clinical contexts [9].

Additionally, there is an increasing shift toward real-time and mobile-based plant identification systems, facilitated by the adoption of lightweight architectures such as MobileNet and the implementation of CNNs within mobile applications [2], [9]. This development broadens access to medicinal plant knowledge, especially in rural and healthcare-poor regions.

In summary, although deep learning has significantly advanced the progress of medicinal plant recognition, future efforts should focus on building larger, more diverse datasets, exploring lightweight and explainable AI models, and integrating contextual information (e.g., geographical data or growth conditions) to improve classification in real-world scenarios.

V. CONCLUSION

Utilizing deep learning in medicinal plant classification offers considerable opportunities to enhance botanical research, safeguard traditional medicine, and facilitate biodiversity conservation. This survey has examined various methodologies, architectures, and datasets employed across recent studies in the domain. The core pipeline followed in most works includes image acquisition, preprocessing, CNN-based feature extraction, model training, and classification.

Built upon the analysis, it is apparent that convolutional neural networks, especially when combined with transfer learning and data augmentation, these models can deliver strong classification performance and improved reliability. in diverse image conditions. Techniques like resizing, normalization, and background removal are essential preprocessing steps that enhance the visibility of crucial morphological features. Furthermore, the shift towards real-time mobile applications is an encouraging trend that increases the accessibility and usability of these systems in field settings.

Despite notable progress, challenges such as dataset scarcity, species similarity, and generalization to wild environments persist. Future research should concentrate on enhancing region-specific datasets, incorporating explainable AI technologies to increase trust and interpretability, and optimizing models for low-resource deployment.

Overall, the fusion of deep learning with medicinal plant identifications is a promising direction that not only aids in automation but also contributes to the conservation and scientific understanding of valuable medicinal flora.

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