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# Automated Identification of Indian Medicinal Plants using Deep Learning

Potnuru Prasanthi[1], Rakesh Salakapuri[2], Panduranga Vital Terlapu[3], Voonna Sivakrishna[4],
Gembali Hari Santhosh[5] and Telukala Praneethkumar[6]
[1,3-6]Aditya Institute of Technology and Management, Kotturu, Tekkali, Srikakulam, Andhra Pradesh-532201, India
[2]Symbiosis Institute of Technology, Hyderabad Campus, Symbiosis International (Deemed University), Pune, India
Email: srakesh@sithyd.siu.edu.in

***Abstract*— Medicinal plant traditional knowledge is intricately embedded in the health care practices and culture of India's rural indigenous communities. These communities have used the identification, collection, and use of herbs to treat sickness for many generations. India possesses almost 10,000 plant species with known therapeutic value, many of which are serve as the foundation for Ayurveda, one of the most traditional and holistic systems of medicine in the world. Even with this rich biodiversity, most of these plants have not been incorporated into the official Ayurvedic Pharmacopoeia due to time-consuming and labor-intensive procedures required for standardization and scientific authentication. Conventional identification methods that are based primarily on visual examination can be serious health hazards and are susceptible to misclassification. To overcome these shortcomings, the current study suggests an automated, deep learning based image classification model for precise identification of medicinal herbs. Through model training using high quality images of leaves and plants, the strategy focuses on improving classification accuracy, reducing human error, and offering an efficient, intelligent solution to aid ethnobotanists, Ayurvedic physicians, and teachers working in the fields of traditional medicine and plant science.**

***Index Terms*— Medicinal Plants (India), Image Classification, Deep Learning, Computer Vision, Herbal Identification, Ethnobotany, Ayurveda.**

## I. INTRODUCTION

Correct identification of medicinal plants is crucial to public health, particularly in nations such as India, where over 10,000 plant species are recorded to contain the rapeutic potentials. As more attention is paid to herbal and traditional medicine, correct categorization of the plants is crucial to their safe and effective use. Plant identification has, in the past, depended on specialist knowledge and physical visual inspection. Yet, these approaches are open to human fallibility and subjective bias, which may result in misclassification and even jeopardize patient safety and treatment effectiveness.

Identification of plants can now be automated by virtue of some recent breakthroughs in computer vision and deep learning. An extensive study issued in early 2024 illustrates the deep learning models, particularly the ones based on convolutional neural networks (CNNs) in combination with transfer learning, commonly achieve classification results greater than 90% on medicinal plant collections, even when most of the systems presently operational prioritize leaf images predominantly [1].

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Leveraging this success, newer studies are exploring more complex architectures. Notably, Vision Transformers (ViTs) have been found very effective in plant and disease classification problems, even when run on low-resource devices [2]. Inspired by the limitation of traditional plant identifying methods and the growing need for efficient automated substitutes, this study proposes the development of an automated medicinal plant classifier using the Vision Transformer (ViT) architecture. The system seeks to increase the quality of classification and reduce the likelihood of human error by using leaf-level and whole-plant images for training. Botanists, teachers, and physicians' tasks will be simplified by the consistent and scalable solution provided by this method. Contrary to traditional methods, which are mostly subjective visual inspection, the above model has the advantage of a process-driven mechanism for guaranteeing standardized, effective, and equitable identification of medicinal herbs, thus making it easier to adopt and utilize in plant science and traditional medicine research fields. Such integration of deep learning and imaging technology also promises new directions in creating simple-to-use real-time applications in clinical, academic, and horticultural domains.

Key components that are essential in the creation of an automated high-performance plant identification system are: Extensive Image Dataset: A heterogeneous and high-quality dataset of varied Indian medicinal plant species. Robust Preprocessing Pipeline: Performance of augmentation steps for being robust in varied imaging conditions. Real-Time Classification Capability: Fast enough and accurate enough plant identification to support real-time decision-making in realistic application environments.

This study seeks to overcome the limitations of conventional plant identification by presenting a Vision Transformer-powered solution that emphasizes accuracy, scalability, and operational efficiency in classifying medicinal plant species.

## II. Literature Survey

Pushpa et al. [3] described a hierarchical framework for the classification of 100 Indian medicinal plant species by integrating shape descriptors, texture patterns, and multispectral imaging features. Their work adopts a two-stage process: the first stage categorizes plant images based on similar visual features, and the second stage applies the Random Forest classifier to classify each of the cluster. With a composite feature fusion method, their model performed better than single-feature input methods. With GSL100, it was shown that things could be categorized with 94.54% accuracy. It performed well on the real-world datasets as well, reaching 75.46% accuracy on RTL80 and RTP40. This method is strong in resisting the limitations introduced by high intra-class variation and inter-class similarity, and thereby improving generalizability over diverse data conditions and accuracy of classification. Jithisree et al. [4] designed the Anti Mtb Medicinal Plant Database (AMMPDB Ver. 1.1), a manually edited electronic database of 118 Indian medicinal plants that may help treat tuberculosis and 3374 related phytochemicals. The database accumulates information from the various sources to offer an integrated repository in terms of plant taxonomy, phytochemical compounds, and anti-tubercular activity. It also provides detailed information like $IC_{50}$ values, 2D and 3D molecular structure, and reported drug use profiles. They authenticated their findings through the use of computational drug design case studies, demonstrating that AMMPDB is an effective drug discovery and in silico tuberculosis research tool. Subhash et al. [5] conducted a systematic review of Indian traditional medicinal plants and their bioactive compounds for the prevention and management of COVID-19 with a focus on their antiviral activity and immunomodulatory action. The results integrated classical medicine with information gained through in vitro, in vivo, and in silico tests to determine the prospective plant candidates. In particular, Zingiber officinale, Ocimum sanctum, and Withania somnifera were separated by their potent immune-nourishing, antiviral, and antioxidant properties. The results highlighted an ethnomedicine-upgraded pharmacology cohesiveness perspective to guide the creation of new treatment modalities to COVID-19. Sachin et al. [6] investigated the phenolic and flavonoid content and antioxidant activity in the extracts of 26 various medicinal plants. The analysis utilized methanolic and aqueous solvents to extract and estimate the bioactive compounds, determining their antioxidant activity using TAC (Total Antioxidant Capacity), DPPH (2,2-diphenyl-1-picrylhydrazyl), and FRAP (Ferric Reducing Antioxidant Power) assays. Among the samples screened, methanolic extracts of Terminalia chebula, Aloe vera, and Curcuma longa exhibited high phenolic content and high antioxidant activity, proving their significant application in medicinal uses. Their results show exactly how important phenolics are in improving the efficiency of antioxidants.Mohad et al. [7] showed a comprehensive review of the artificial intelligence techniques used for the identification of medicinal plants based on leaf image analysis. The work considered different algorithms, feature extraction, and benchmark datasets systematically. It also mentioned some usual issues and potential future directions. Despite significant advancements in this field, the issues of diversity in datasets and model scalability persist. This review provides pertinent information and sets a groundwork for further development in AI-based plant identification systems. Deepti et al. [8] conducted a systematic review that examined machine learning, image processing, and deep learning approaches to identifying plant species. The review integrates a wide variety of studies to emphasize developing trends in methodological techniques, including addressing the issues of interclass similarity and image occlusion. The review also delves into cutting-edge solutions, such as multi-feature fusion techniques and hybrid learning methods aimed at improving the accuracy and resilience of plant identification systems. It concludes that the application of hybrid models and feature combination significantly enhances recognition performance, which paves the way for more resistant plant identification frameworks. Pushpa B. R. and N. Shobha Rani [9] compiled an extensive dataset of 5,900 images corresponding to 40 Indian medicinal plant species and another 6,900 single-leaf samples obtained from areas in Karnataka and Kerala. The dataset is ideal for plant identification research based on AI due to the fact that it was captured using smartphone cameras in different environments. Being publicly available, its existence facilitates good machine learning and deep learning models that are beneficial to drug research and education. The dataset is made available with an aim to facilitate further research in medicinal plant taxonomy and therapeutic assessment.Kishore Chandra et al. [10] created a hyperspectral spectral repository for ten medicinal plant species through handheld sensor technology. Besides, they built a classification model from the Random Forest algorithm, which was also cross-verified with satellite-derived hyperspectral data.

They obtained 1,237 spectral signatures from leaves and canopies of plants in the Himalayas. Kappa value was 0.89 and the accuracy rate was 91.39%. Satellite validation for Saussurea costus was 81.31% correct. This hybrid of hyperspectral imaging and AI is an unobtrusive method to correctly identify plants and assist in conservation efforts. Tarikul Islam et al. [11] performed a large-scale virtual screening of 2,500 phytochemicals from 25 medicinal plants to find promising acetylcholinesterase (AChE) inhibitors for Alzheimer's disease treatment. They discovered three potential candidates: CID 102267534, CID 15161648, and CID 12441, using a combination of computational tools including molecular docking, MM-GBSA free energy calculations, pharmacokinetic and toxicity profiling, molecular dynamics (MD) simulations, and density functional theory (DFT) calculation.

The compounds exhibited good binding affinity, pharmacological characteristics, and chemical stability, putting their worthiness for experimental verification in Alzheimer's drug discovery into perspective. Rohini et al. [12] compiled a fine image dataset of Centella asiatica leaves for quality control and computer vision-based leaf health classification. The dataset includes 9,094 leaf images taken using Samsung Galaxy M21 smartphones and classifies them into three different classes: Healthy, Unhealthy, and Dried. After performing standard preprocessing techniques to have uniform image dimensions, the dataset is suitable for machine learning applications dealing with leaf health classification. It is a helpful research tool for quality assurance, herbal medicine, and ethnobotany.

## III. METHODOLOGY

### *A. Overview of Existing Systems*

Currently, image classification techniques are the primary method for identifying medicinal plants. Convolutional Neural Networks (CNNs) are the most widely used among these techniques. Researchers often utilize pre-trained deep learning models like InceptionV3, Xception, and DenseNet for classifying images of medicinal plants over a range of datasets. Transfer learning strategies are routinely used to improve model performance at a significantly reduced cost of training time and computational expense. Data augmentation methods are also typically utilized to enhance datasets artificially, and this makes models more resilient and provides better results for classification accuracy.

### *B. Issues with Existing Systems*

In spite of progress, current approaches towards medicinal plant classification are associated with a number of significant issues:

Limited Diversity of Datasets: Most current models are trained using relatively small or homogeneous datasets, which makes the likelihood of overfitting higher and their ability to generalize to new, unseen plant species or different environmental conditions lower.

Overfitting Issues: If there are not good mechanisms to include more data or multiple samples in training, models can overfit, and it would mean they learn superficial patterns rather than deep ones. It leads them to perform poorly on unseen data.

Geographic and Taxonomic Narrowness: Multiple studies focus on one area or a limited number of plant species, thus limiting the scope of application of their models to wider geographical, ecological, or taxonomic contexts.

Pipeline Complexity: The end-to-end implementation pipeline—ranging from image preprocessing to feature extraction and model training—can be technically complex, typically needing interdisciplinary expertise and high computational power.
Underutilization of Indigenous Knowledge: Numerous AI-based methods overlook conventional ecological and ethnobotanical knowledge systems that might provide rich contextual information to enhance accuracy and relevance of classification in culturally diverse environments.

*C. Research Objective*

This paper suggests the construction of a strong system named "Automated Identification of Indian Medicinal Plants Using Deep Learning," using the Vision Transformer (ViT) framework. The system is intended to classify medicinal plant species using leaf and whole-plant images. Through transfer learning and pre-trained models, the method is expected to have high classification accuracy without relying heavily on large manually labeled datasets.
Key Benefits are: Precise classification of medicinal plants,Efficient handling of large-scale image datasets, Support for diverse species and geographical variation, User-friendly integration with mobile or web applications and Valuable aid in botanical research, healthcare, and education through reliable plant recognition.

*D. Suggested Algorithmic Method*

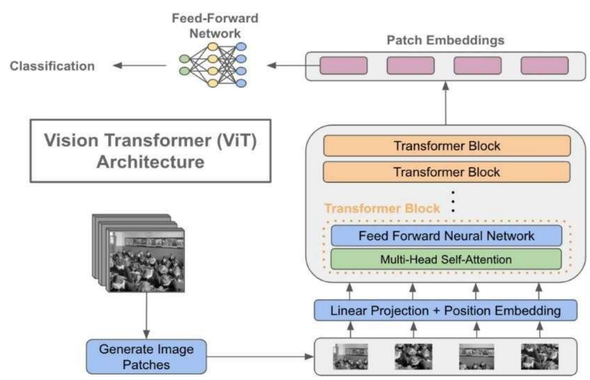


Fig 1: Vit algorithm

*Vision Transformer (ViT) for Plant Identification*
The foundation of the proposed system is the Vision Transformer (ViT) model, a new state-of-the-art image classification which is presented in figure 1. Unlike traditional CNNs, ViT divides input images into fixed-size patches and treats them as a sequence using a transformer model. This allows ViT to learn both global and local features by learning relations among various parts of an image. Its capacity for detecting subtle patterns and detailed textures makes it particularly well-equipped for the task of medicinal plant species classification, where subtle visual differences are critical. With the use of the ViT model's capability, the proposed system aims to set a new benchmark in computerized medicinal plant identification.

*Implementation Strategy*
Model Fine-Tuning: To optimize the model for Indian medicinal plant classification, we apply transfer learning to optimize a pre-trained Vision Transformer (ViT). This allows us to transfer the knowledge learned in the pre-trained model to the specific visual patterns within the medicinal plant dataset, thereby enhancing its accuracy and robustness.
Transfer Learning: Transfer learning enables us to harness the knowledge that models have been trained on large-scale image collections such as ImageNet. Using a pre-trained ViT model on such large-scale collections saves us significantly from the need for long training from scratch. This not only reduces training time but also improves performance, especially when we are working with quite small and domain-specific datasets like those of Indian medicinal plants.
Data Augmentation: To improve the model's generalization ability and to reduce the overfitting, we apply various data augmentation techniques during training phase. These include:

- Random Rotation – simulating different leaf orientations
- Horizontal and Vertical Flipping – introducing symmetry variations
- Color Jittering – adjusting brightness, contrast, and saturation to mimic varying lighting conditions

These augmentations ensure that the model is resilient to diverse environmental and visual inconsistencies encountered in real-world scenarios.
Performance Evaluation Metrics: We evaluate the model using standard classification metrics to ensure comprehensive performance assessment:

- Accuracy – the overall correctness of predictions
- Precision – the proportion of true positive identifications among all predicted positives
- Recall – the proportion of true positives identified among all actual positives
- F1-Score – the harmonic mean of precision and recall, offering a balance between the two

These metrics provide detailed insights into how effectively the model identifies and classifies different medicinal plant species.

*E. Sequential Process for Developing the Automated Identification of Indian Medicinal Plants System:*

The detailed flow chart is shown in figure 2 and the actual workflow is presented in figure 3.

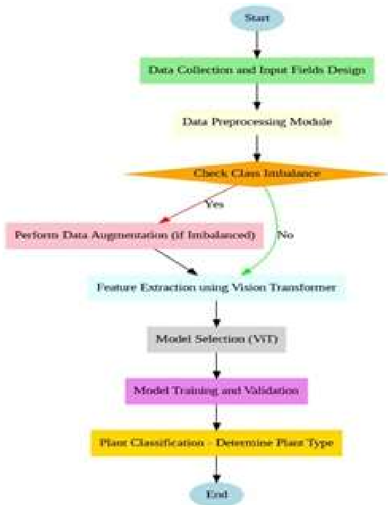


Fig 2: Flowchart

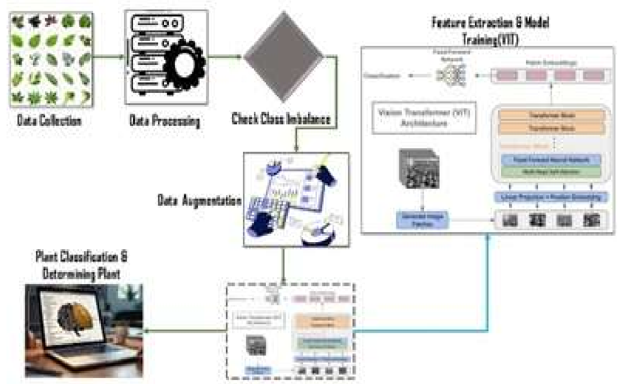


Fig 3: Actual Workflow

Data Collection and Input Fields Design: The system starts with the systematic gathering of images of different parts of Indian medicinal plants, i.e., leaves, herbs, and roots. For proper data management in an organized manner and correct labeling, a structured input form was created to gather crucial information on every plant entry. The form provides spaces for: Botanical Name – for correct scientific identification, Plant Part – indicating whether the image relates to a leaf, herb, root, etc. and Geographical Origin – specifying where the plant was originally found.
By implementing this systematic data entry method, the system not only provides consistency and accuracy in dataset creation but also annotates each image with their respective metadata. The added context information greatly helps in the process of classification and supports effective image retrieval during training and evaluation phases

*F. Data Preprocessing Module*

The preprocessing module is the initial step of raw image input preparation for the deep learning process. The process includes image resizing into the input specifications of the Vision Transformer (ViT) model, pixel value normalization into a standardized range, and format conversion to ensure the images are compatible with the model. In order to improve the generalization capacity of the model, data augmentation techniques like random rotation, horizontal/vertical flipping, and color jittering are applied. This module cleans, standardizes, and makes the input data varied, ready for feature extraction and successful training.

*G. Feature Extraction Using Vision Transformer (ViT)*

The Vision Transformer (ViT) model is utilized for detailed visual feature extraction from the plant images. In contrast to classical convolutional methods, ViT divides every image into patches of a fixed size and encodes the patch relationships with transformer encoders. This allows the model to extract fine-grained and global features, which is specially helpful in separating visually equivalent plant species. Based on transfer learning using pre-trained weights improves feature extraction performance even more, especially in situations where there is limited labeled data.

*H. Centralized Plant Species Database Integration*

A centralized, scalable database is used to hold plant images, feature vectors corresponding to those images, and metadata such as botanical classification and geographical location. The database serves as a complete reference for taxonomy and spatial data and facilitates both inference and training processes. Dynamic access to available data at any point in time through seamless integration with the classification pipeline enhances prediction quality and allows adaptive learning with the addition of new data.

*I. Model Training and Plant Classification*

After feature extraction, the preprocessed and annotated dataset is utilized to train the Vision Transformer model. Through repeated optimization over several epochs, the model adjusts its inner weights so as to reduce classification loss. A validation dataset is utilized in parallel to observe training performance, inform hyperparameter tuning, and avoid overfitting. The end-trained model can correctly classify plant species from new, unseen images—making it ready for real-world and real-time use.

*J. Output Generation and Data Sharing Module*

The output module presents the forecasted plant species and corresponding confidence scores. The module also offers visual comparisons of similar database entries, giving users better clarity of the results of the classification. The platform also supports safe sharing of classification outputs and reports across researchers, laboratories, and healthcare providers, enhancing inter discipline collaboration and knowledge transfer.

*K. Feedback Loop and Continuous System Improvement*

There is an integrated feedback system, through which misclassifications may be reported or supplementary data may be submitted. The latter is analyzed systematically to optimize model performance. This continuous feedback helps feed the database with new plant species and guides algorithmic development. Continuous observation of classification accuracy ensures that the system improves over time, becoming more dependable and versatile for increasing applications in botany, medicine, and ethnopharmacology.

## IV. Results and Discussion

Comparative analysis of existing research on medicinal plant identification indicates significant variation in accuracy, largely determined by the methodologies employed. The methods have varied from conventional machine learning and deep learning-based models to sophisticated methods based on hyperspectral imaging. Accuracies reported in previous research typically range from 75% to 94.54%, based on variables such as data quality, feature extraction approaches, and complexity of model.
By way of contrast, the system presented here with the Vision Transformer (ViT) architecture attained a remarkably higher classification accuracy of 99.49%, establishing a new baseline in this field. This dramatic improvement highlights the efficacy of transformer-based models to encode both fine-grained and contextual visual information required for precise classification of plant species. Future research may investigate incorporating larger and more varied datasets, as well as optimizing transformer architectures further, to make models more generalizable and robust across a wider range of plant types and growing conditions.

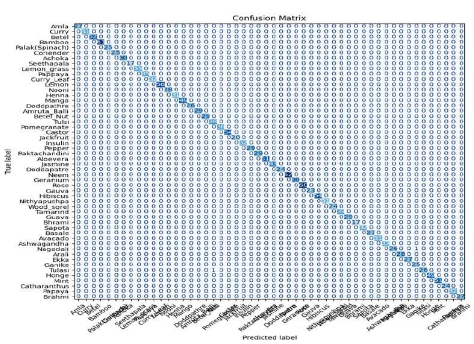


Fig 4: Confusion Matrix

Confusion Matrix Analysis: To evaluate the classification performance of the ViT model in detail, a confusion matrix was generated (refer to Figure 4). This matrix visualizes the alignment between the predicted labels and the actual ground truth across all plant classes. A dominant diagonal pattern in the matrix indicates that the vast majority of plant species were correctly classified, with minimal misclassification. This trend reflects the model's strong ability to extract discriminative features and accurately distinguish between visually similar species. The near-perfect alignment across most categories validates the model's precision and its capability to perform reliably under real-world conditions.

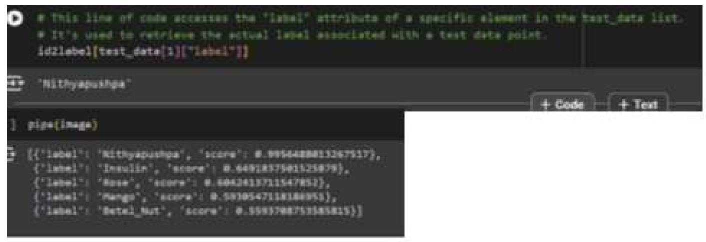


Fig 5: Selecting the image for testing

Fig 6: Predicted Image type

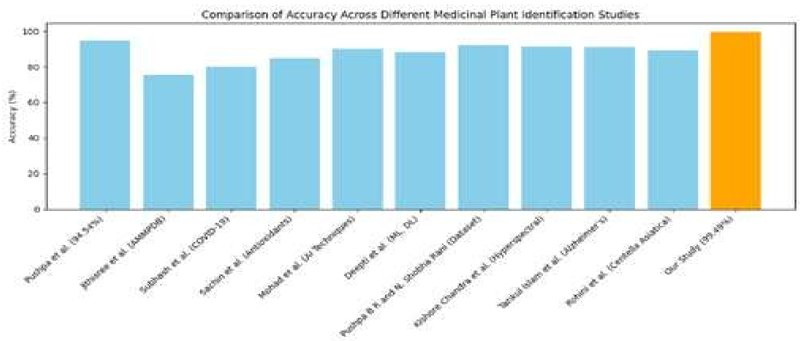


Fig 7: Comparison Graph

### A. Real-World Model Evaluation

To assess practical usability, a sample image from the test dataset was analyzed using the trained ViT model. As illustrated in Figure 5, the system successfully identified the species as Nithyapushpa, matching the ground truth label with high confidence. This result not only demonstrates the model's effectiveness in real-life applications but also confirms its robust generalization ability. Overall, the proposed Vision Transformer-based framework proves to be a highly accurate and operationally viable solution for automated medicinal plant classification. Moving forward, the system can be further enhanced by: Incorporating real-time prediction capabilities, Expanding the dataset with more geographically and visually diverse plant samples and Improving the model to achieve greater scalability and cross-domain adaptability. These advancements will ensure broader applicability in clinical, botanical, agricultural, and educational settings. The predicted image type for the selected test case is shown in figure 6. The proposed model outperforms all the existing models in terms of accuracy, which is shown in figure 7.

## V. CONCLUSION

Here, we proposed an automatic system for identifying Indian medicinal plants based on state-of-the-art deep learning methods with a focus on the Vision Transformer (ViT) architecture. The model was trained on a well-curated dataset of images of herbs and plant leaves with a high validation accuracy of 99.49%. To evaluate the model's robustness, important performance metrics were tested. The system maintained a 99.10% precision, 99.09% recall, and 99.16% F1-score, which shows its robust and effective capability to identify a broad range of plant species. These findings bring to the limelight the prowess of transformer-based models in dealing with intricate image classification tasks and show much promise for real-world applications in fields like botany, medicine, pharmacognosy, and traditional medicine. The model's superb performance is a result of combining transfer learning, preprocessing specific to the domain, and a well-organized, annotated dataset, all of which facilitated improved learning and generalization abilities.

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