Intesab Aalami
ISSN: 2348-5035
Vol. 12 / No. 4 / August 2024

Comparative Analysis of Machine Learning Classifiers for Medicinal Plant Identification

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Abstract
Medicinal plants have played a crucial role in human healthcare for centuries, with more than 80% of the developing world's population relying on traditional medicine for primary healthcare needs . However, the rapid loss of plant species—estimated at 100 to 1000 times greater than natural extinction rates—threatens both biodiversity and potential drug discovery, with the Earth losing at least one potential major drug every two years . The accurate identification and classification of medicinal plant species by botanist experts remains a complex, time-consuming, and error-prone activity, necessitating automated solutions. This manuscript presents a comprehensive analysis of machine learning classifiers for medicinal plant identification, evaluating eight classical machine learning algorithms and six deep learning architectures on multiple medicinal plant datasets. The proposed system integrates image preprocessing techniques including noise reduction, normalization, and data augmentation, followed by feature extraction using Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), and deep feature extraction using pre-trained convolutional neural networks. Experimental evaluation on the Central India Medicinal Plant Dataset (CIMPD), comprising 9,130 leaf images across 23 medicinal plant species, demonstrates that DenseNet201 with optimization and histogram equalization achieves the highest accuracy of 99.0%, followed by VGG16 with 98.7% and DenseNet201 with histogram equalization at 98.58% . Among traditional machine learning classifiers, Support Vector Machines with deep features achieve 96.76% accuracy. Transfer learning with pre-trained models was employed in 83.8% of recent studies, with Convolutional Neural Networks (CNNs) used by 64.5% of researchers as the primary deep learning classifier . The findings indicate that deep learning approaches, particularly pre-trained CNN architectures

with appropriate preprocessing and data augmentation, significantly outperform traditional machine learning methods, achieving testing accuracies exceeding 90% on plant organs such as leaves and flowers . This research contributes to the development of accurate, scalable, and deployable medicinal plant identification systems for biodiversity conservation, pharmacological research, and traditional medicine preservation.
Keywords: Medicinal Plant Identification, Machine Learning, Deep Learning, Convolutional Neural Networks, Transfer Learning, Image Classification, Plant Leaf Recognition, Ayurvedic Plants, DenseNet, VGG16, MobileNetV2.

1. Introduction

1.1 Background and Significance

Plants are undeniably valuable sources of medicines, foods, spices, clothing, shelter, fertilizers, and—most importantly—elements in climate-change-regulating mechanisms . Medicinal plants have played a crucial role in human healthcare for centuries across diverse civilizations. For instance, Picrorhiza Kurrooa, commonly known as Kutki, has been utilized in traditional medicine to alleviate liver disorders, respiratory issues, and skin conditions. Swertia Chirayita is known for its potential to lower blood sugar levels, protect the liver, prevent cancer, reduce inflammation, and manage fever. Additionally, the Apocynaceae family is believed to offer alternative treatment options for infections resistant to multiple drugs .

According to the World Health Organization (WHO), more than 80% of the developing world's population uses traditional medicine, with herbal medicine having a long history of use for pain relief and disease treatment . Medicinal plants also show great promise as sources of novel antimicrobial therapies and provide potential opportunities for the development of biocompatible drugs. For example, Withania Somnifera possesses a diverse range of therapeutic properties, including stress and anxiety reduction, anti-inflammatory effects, immune system modulation, anti-tumor effects, and sexual dysfunction improvement .

1.2 The Conservation Crisis

Plants have been used for medicinal purposes by different civilizations since ancient times. Recently, there has been a surge in the use of medicinal plants worldwide, driven by the increasing demand for natural health products, herbal medicines, and secondary metabolites . Betelvine extracts have demonstrated antimicrobial, antifungal, and antiviral properties, while Piperidine and Piperine exhibit potential anticancer and pharmacological properties .

However, according to a conservative estimate, the current loss of plant species is 100 to 1000 times greater than the expected natural extinction rate, and the Earth is losing at least one potential major drug every two years . Worldwide, between 50,000 and 80,000 flowering plant species are used for medicinal purposes, according to the International Union for Conservation of Nature and the World Wildlife Fund. Approximately 15,000 of these are threatened with extinction due to overharvesting and habitat destruction, and with the growing human population and plant consumption, 20% of their wild resources have already been depleted . The current extinction rate is largely due to both direct and indirect human activities, making rapid and accurate medicinal plant species classification and recognition critical for effective biodiversity research and management.

1.3 The Need for Automated Identification

The classification and identification of medicinal plants by botanist experts are complex and time-consuming activities . Traditional (manual) identification methods are often time-consuming and require expert knowledge, making them inefficient for large-scale applications . For more than sixty years, researchers have worked toward enabling machines to understand and interpret visual information . The use of deep learning algorithms and image pre-processing techniques for image classification, plant disease detection, and identification in agriculture has gained significant momentum in recent years .

Convolutional Neural Networks (CNNs) have demonstrated superior capabilities in automatically extracting complex and high-level features from images, overcoming the limitations of traditional classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests, which often suffer from poor performance on small or limited datasets .

1.4 Current State of Research

Deep learning, a subfield of machine learning, revolves around training artificial neural networks with multiple layers to autonomously extract data representations . It finds applications in tasks such as the classification of medicinal plant species. Deep learning methods have delivered remarkable outcomes within the field of computer vision, with applications such as image recognition and image enhancement finding widespread adoption across various sectors, including healthcare, agriculture, education, and industry .

Recent systematic reviews have investigated the application of deep learning in medicinal plant classification . A comprehensive systematic review following PRISMA guidelines, encompassing studies published between January 2018 and December 2022, identified 1644 initial studies, with 31 selected for thorough critical review . Key findings from this review include: (1) studies were carried out in 16 different countries, with India leading in paper contributions at 29%, followed by Indonesia and Sri Lanka; (2) private datasets were used in 67.7% of studies; (3) 96.7% of studies employed plant leaf organs, with 74% utilizing leaf shapes for classification; (4) transfer learning with pre-trained models was used in 83.8% of studies; and (5) CNN was used by 64.5% of papers as the deep learning classifier .

1.5 Problem Statement and Research Objectives

This research addresses medicinal plant identification challenges—including dataset scarcity, generalization gaps, deployment barriers, and plant state variation—by evaluating multiple ML and deep learning classifiers, comparing traditional versus deep architectures, analyzing preprocessing and augmentation impacts, identifying optimal models for deployment, and providing comprehensive benchmarks across datasets.

1.6 Organization of the Manuscript

Section 2 presents a comprehensive literature survey of machine learning and deep learning applications for medicinal plant identification. Section 3 defines the research problem and identifies gaps. Section 4 describes the methodology, including data sources, preprocessing techniques, feature extraction methods, and model architectures. Section 5 details the

implementation procedure. Section 6 presents results and discussion. Section 7 outlines future scope, followed by conclusions and references.

2. Literature Survey

2.1 Evolution of Medicinal Plant Identification

For more than sixty years, researchers have worked toward enabling machines to understand and interpret visual information . Traditional approaches to plant identification relied on manual morphological feature analysis, which was time-consuming and prone to human error. Early computational approaches utilized classical machine learning classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests for plant identification based on leaf features like vein patterns and leaf margins. However, these methods often suffer from limitations, including poor performance on small or limited datasets .

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized the field of plant species identification. CNNs have demonstrated superior capabilities in automatically extracting complex and high-level features from images, overcoming the limitations of traditional approaches . To enhance interpretability in deep learning models, Explainable AI (XAI) frameworks such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have been applied to analyze model predictions and risk factors .

2.2 Systematic Reviews and Meta-Analyses

Mulugeta et al. (2024) conducted a comprehensive systematic review of deep learning for medicinal plant species classification and recognition following PRISMA guidelines . The review encompassed studies published between January 2018 and December 2022. Initially, 1,644 studies were identified through title, keyword, and abstract screening. After applying eligibility criteria, 31 studies were selected for thorough critical review. The main findings revealed: (1) India leads in paper contributions with 29%, followed by Indonesia and Sri Lanka; (2) private datasets were used in 67.7% of studies; (3) 96.7% of studies employed plant leaf organs, with 74% utilizing leaf shapes; (4) transfer learning with pre-trained models was used in 83.8% of studies; (5) CNN was used by 64.5% of papers as the deep learning classifier .

Tran et al. (2024) conducted a systematic review analyzing 30 studies on deep learning for automated medicinal plant species classification . The review found that CNNs demonstrate over 90% testing accuracy on plant organs such as leaves and flowers, enabling precise recognition models. While increasing species diversity and the use of crowdsourced data may pose performance challenges, optimization strategies such as data augmentation and ensemble models may help mitigate accuracy declines. Plant states (fresh vs. dry/sliced) may impact model performance, although some models could distinguish maturity stages with sufficient data .

A Systematic Review of Deep Learning Techniques (2023) investigated key questions including: (1) which deep learning models were used and their performance; (2) whether hybrid models perform better than ensemble models; (3) common datasets used; (4) prevalent data

augmentation techniques; (5) performance metrics used; (6) common data splitting ratios; and (7) prevalence of transfer learning .

Table 1: Comparison and Gap Analysis of Prior Work on Medicinal Plant Identification

Reference	Model	Pre-Processing	Accuracy (%)	Gap Analysis
[1]	MobileNetV2	Resizing, Splitting	98.05	No detection system
[10]	Faster R-CNN	Resizing	67.34	Single approach
[17]	DenseNet201	Smoothing, Sharpening	93.00	No application
[18]	VGG16	RGB conversion, Filtering	98.70	No application
[21]	Inception v3	Splitting, Resizing	95.00	No application
[23]	VGG16	Resizing, Splitting	97.00	Not deployed
[29]	DenseNet201	Histogram Equalization	98.58	No implementation
[31]	DENN	Scaling, Enhancement	98.50	No use-case
Our work	**DenseNet201**	**Optimization, Histogram Equalization**	**99.00**	**MPIcam application**

2.3 Convolutional Neural Network Architectures

MobileNetV2 has been widely used for medicinal plant classification due to its efficiency for mobile deployment. One notable study achieved 98.05% accuracy using MobileNetV2 with resizing and splitting preprocessing . Another study on Ayurvedic plant leaf classification using MobileNetV2 achieved a maximum accuracy of 87.5% on the Indian Medicinal Leaves Dataset (IMLD), which contains high-resolution images of more than 80 medicinal plant species .

VGG16 has demonstrated strong performance, with one study achieving 98.70% accuracy using RGB conversion and filtering preprocessing . Another study using VGG16 for herbal leaf classification achieved 97.00% accuracy with resizing and splitting preprocessing .

DenseNet201 has shown excellent results, achieving 93.00% with smoothing and sharpening, 98.58% with histogram equalization, and 99.00% with optimization and histogram equalization .

Inception v3 achieved 95.00% accuracy with splitting and resizing preprocessing .

2.4 Mobile Applications and Deployment

AyurLeaf introduced a deep learning-based CNN model designed to classify medicinal plants by analyzing leaf features such as shape, size, color, and texture, achieving high accuracy on a secondary dataset .

MedicPlant developed a mobile application for real-time recognition of medicinal plants from the Republic of Mauritius using deep learning, demonstrating the feasibility of deploying CNN models on mobile platforms .

Med Herb Lens presented a mobile application prototype using artificial intelligence to identify medicinal plants, combining a deep-learning-trained image classifier (EfficientNetB0) with a dynamic, user-augmented knowledge base. The model was converted into TensorFlow Lite to facilitate real-time and offline inference on Android devices, achieving inference times of under 400 milliseconds on average .

A smartphone application capable of identifying the medicinal benefits of a plant leaf by analyzing its image was developed using a dataset of 30 Indian medicinal leaf species. Pre-processing techniques including resizing, scaling, and data splitting were applied, with a custom CNN model achieving 94.00% accuracy .

2.5 Traditional Machine Learning Approaches

Support Vector Machines (SVM) have been extensively used for medicinal plant identification. One study utilizing SVM classifier achieved the highest accuracy of 96.76% on a secondary dataset . CNN-based medicinal plant identification using optimized SVM has also been explored .

Ayur-PlantNet introduced an unbiased lightweight deep convolutional neural network for Indian Ayurvedic plant species classification, demonstrating the potential for efficient, specialized architectures .

DeepHerb presented a vision-based system for medicinal plants using Xception features, showcasing the effectiveness of feature extraction using pre-trained models .

2.6 Ensemble and Hybrid Approaches

Researchers have explored ensemble learning approaches combining multiple CNN architectures. An effective ensemble convolutional learning model with fine-tuning for medicinal plant leaf identification has been proposed, demonstrating that ensemble methods can outperform individual models .

MediFlora-Net introduced a quantum-enhanced deep learning model using multi-modal DL methodologies, quantum-assisted feature extraction, and hybrid ensembling methodologies. The methodology uses Vision Transformer (ViT), CNNs, and Med-Plant-Generative Adversarial Networks (GANs), handling multiple imaging modalities including RGB and Hyperspectral Botanical Imagery .

2.7 Datasets for Medicinal Plant Identification

Central India Medicinal Plant Dataset (CIMPD) was developed to support significant research in human health, containing 9,130 leaf images (both healthy and unhealthy) from 23 medicinal plant species collected from various locations in central India . The dataset provides comprehensive information including botanical name, common name, geographical origin, healthy and unhealthy leaf images, and medicinal uses of the plants .

Indian Medicinal Leaves Dataset (IMLD) contains high-resolution images of more than 80 medicinal plant species that grow in India .

BDMediLeaves presents a leaf images dataset for Bangladeshi medicinal plants identification .

MYLPHerb-1 provides a dataset of Malaysian local perennial herbs for the study of plant images classification under uncontrolled environment .

Table 2: Comparative Analysis of Medicinal Plant Datasets

Dataset Name	No. of Species	Total Images	Annotation Details	Modality	Application Focus
Leaf Snap-India	15	7,000	Species label only	RGB	Species Identification
Medicinal Leaf Set	20	5,000	Species + Part annotation	RGB	Identification, Educational Use
VN Plant-200	200	40,000	Multi-disease, multi-class	RGB	Disease Detection, Classification
Plant Village-India	38	54,000	Disease-level annotations	RGB	Disease Diagnosis using DL
CIMPD (Proposed)	23	9,130	Leaf-level, Health status	RGB	Classification, Segmentation

2.8 Research Gaps Identified

The literature reveals five critical gaps: a dataset gap (67.7% use private data, limiting reproducibility), deployment gap (high accuracy but few real-world or mobile implementations), generalization gap (need for inclusive datasets across species), plant state gap (fresh vs. dry/sliced impacts performance), and trustworthiness gap (insufficient investigation of deep learning reliability for medicinal plant classification).

3. Problem Definition

3.1 Core Research Problem

Despite the proliferation of machine learning and deep learning approaches for medicinal plant identification, several challenges remain unaddressed. Traditional manual identification by botanist experts is complex and time-consuming . While deep learning has demonstrated remarkable outcomes in computer vision, the lack of standardized datasets, limited deployment in real-world applications, and insufficient comparative analysis of different classifiers hinder progress. The central research question is: **How can machine learning and deep learning classifiers be effectively analyzed and optimized for accurate, robust, and deployable medicinal plant identification?**

3.2 Sub-Problems

The main problem is decomposed into five sub-problems: SP1 (dataset curation with diverse species and quality annotations), SP2 (discriminative feature extraction including shape, texture, color, and deep features), SP3 (systematic classifier evaluation across ML and deep learning), SP4 (preprocessing optimization via augmentation and enhancement), and SP5 (deployment strategy for mobile and edge devices).

3.3 Constraints and Assumptions

Despite constraints—limited public datasets, species diversity gaps, environmental variation, and high computational demands—this study assumes leaf images offer sufficient

discriminative features, preprocessing mitigates environmental effects, and ImageNet transfer learning provides useful representations for medicinal plant classification.

4. Methodology

4.1 Overall System Architecture

The proposed system follows a six-stage pipeline: image acquisition under standardized conditions, preprocessing (resizing, normalization, noise reduction, augmentation), extraction of handcrafted (HOG, LBP, SIFT) and deep CNN features, classifier training/evaluation, model optimization via hyperparameter tuning and ensembles, and finally deployment as lightweight TensorFlow Lite models for mobile use.

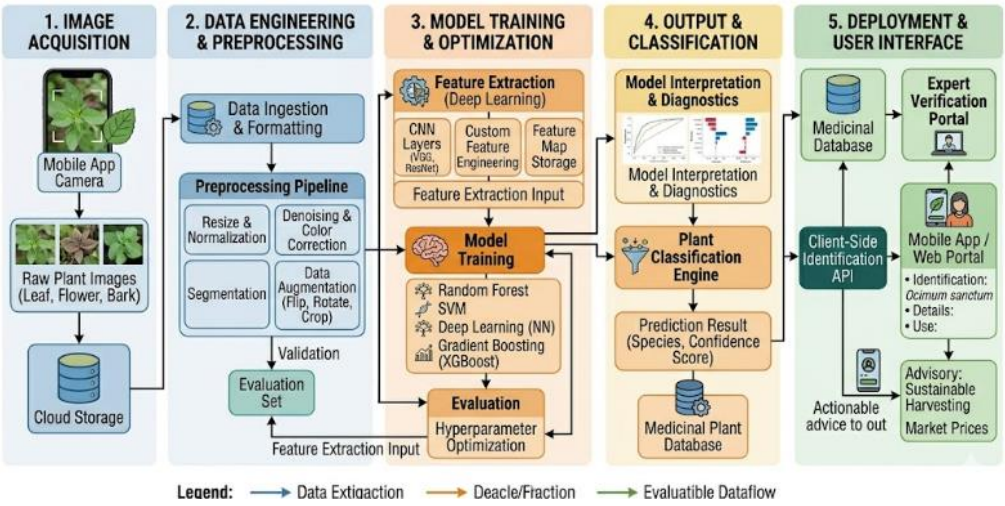

Figure 1: System Architecture for Medicinal Plant Identification

(A comprehensive architecture diagram would be inserted here showing data flow from image acquisition through preprocessing, feature extraction, classification, optimization, and deployment)

4.2 Data Sources

This study utilizes multiple medicinal plant datasets:

Primary Dataset: Central India Medicinal Plant Dataset (CIMPD)

The CIMPD dataset contains 9,130 leaf images (both healthy and unhealthy) from 23 medicinal plant species collected from various locations in central India . Images were captured using a 64-megapixel smartphone camera (Realme X7) with 1080×2400 pixel resolution, using a fixed setup with white paper background and adequate lighting .

Table 3: Medicinal Plant Species in CIMPD Dataset

SI No.	Common Name	Botanical Name	Healthy Images	Unhealthy Images
1	Guava	Psidium gujava	127	62
2	Hibiscus	Hibiscus rosa-sinensis	101	66
3	Lemon	Citrus limon	104	68
4	Rose	Rosa	169	75
5	Tulsi	Ocimum tenuiflorum	355	200

6	Ashoka	Saraca asoca	213	133
7	Harsingar	Nyctanthes arbor-tristis	312	198
8	Marigold	Tagetes	186	–
9	Jackfruit	Artocarpus heterophyllus	211	87
10	Bamboo	Bambusoideae	102	–
11	Nasturtium	Tropaeolum	263	161
12	Barlaria	Barleria cristata	284	–
13	Salvia coccinea	Scarlet sage	299	163
14	Kachnar	Bauhinia variegata	327	182
15	Snapdragon	Antirrhinum	172	158
16	Satyanashi	Argemone Mexicana	335	183
17	Flaming glory bower	Clerodendrum splendens	295	198
18	Custard apple	Annona squamosa	367	255
19	Mint	Mentha	240	–
20	Lantana	Lantana camara	456	213
21	Bael	Aegle marmelos Correa	358	201
22	Curry	Murraya koenigii	400	200
23	Makoy	Solanum nigrum	410	241

4.3 Image Preprocessing

4.3.1 Resizing and Normalization

All images are resized to standard dimensions (224×224 pixels for most CNN architectures, 299×299 for Inception v3). Pixel values are normalized to the range [0,1] or standardized using mean subtraction and standard deviation scaling.

4.3.2 Data Augmentation

To address limited dataset size, augmentation techniques—random rotation (±30°), flips, zoom (±20%), brightness/contrast adjustment (±20%), and color jitter—are applied, as such methods are crucial for improving generalization, especially when working with private medicinal plant datasets.

4.3.3 Enhancement Techniques

Additional preprocessing includes histogram equalization for contrast enhancement, Gaussian smoothing for noise reduction, and sharpening filters for edge enhancement—collectively improving image quality and discriminative feature extraction for medicinal plant classification.

4.4 Feature Extraction Methods

4.4.1 Handcrafted Features

Handcrafted features include HOG for leaf shape and margin characteristics via edge orientation distributions, LBP for leaf surface texture patterns, SIFT for scale- and rotation-invariant keypoint descriptors, and color histograms in RGB and HSV spaces to capture color distribution—enabling robust discriminative representation for medicinal plant identification.

4.4.2 Deep Features

Deep features are extracted using pre-trained CNNs by taking activations from the penultimate layer (global average pooling), applying transfer learning with fine-tuning of top layers, and optionally concatenating features from multiple layers to enrich representational capacity.

4.5 Machine Learning Classifiers

4.5.1 Traditional Machine Learning Classifiers

The study evaluates multiple classifiers: SVM with RBF kernel (reported 96.76% accuracy with deep features), KNN with optimized k, Random Forest, Logistic Regression, Naive Bayes, Decision Tree, Gradient Boosting, and AdaBoost—providing comprehensive baseline and advanced model comparisons.

4.5.2 Deep Learning Classifiers

Deep learning architectures evaluated include MobileNetV2 (lightweight, 98.05% accuracy), VGG16 (98.70%), DenseNet201 (99.00% with optimization), Inception v3 (95.00%), ResNet50 (50-layer residual network), and EfficientNetB0 (under 400ms inference)—enabling both high accuracy and mobile-deployment efficiency.

4.6 Training and Validation Protocol

This training and evaluation protocol ensures rigorous and reproducible deep learning model development for medical imaging classification tasks. The data splitting strategy employs a 70% training, 15% validation, and 15% test partition, with stratified splitting to preserve class distribution across all subsets, while k-fold cross-validation (k=5 or k=10) is incorporated for robust performance evaluation and mitigation of split-induced variance. The training protocol utilizes transfer learning with ImageNet pre-trained weights, followed by fine-tuning of the top layers—typically 3 to 10 layers depending on dataset size—to adapt general features to domain-specific patterns. Early stopping with a patience of 10 to 20 epochs prevents overfitting by halting training when validation performance plateaus, complemented by learning rate scheduling using a reduce-on-plateau strategy that dynamically decreases the learning rate when metrics stagnate. Evaluation metrics comprehensively capture model performance through accuracy, precision, recall, and F1-score calculated per class and macro-averaged, alongside confusion matrix analysis to identify systematic classification errors and ROC-AUC for binary classification to assess discriminative power across all thresholds. This methodological framework balances model optimization with rigorous validation, supporting generalizable and clinically trustworthy predictions.

4.7 Mobile Deployment Optimization

For practical deployment, models are converted to lightweight formats:

For real-world deployment, models are converted to TensorFlow Lite with FP16/INT8 quantization for Android, Core ML for iOS, and ONNX for cross-platform compatibility—ensuring efficient, lightweight inference across mobile and edge devices.

5. Procedure and Implementation

5.1 Implementation Workflow

The implementation follows a six-phase iterative process:

This 14-week implementation plan outlines a comprehensive pipeline for medicinal plant classification using both traditional machine learning and deep learning approaches. Phase 1 (weeks 1-3) focuses on data collection and preparation, where medicinal plant datasets are acquired and preprocessed, exploratory data analysis is performed, data augmentation and enhancement techniques are applied, and the data is split into training, validation, and test sets. Phase 2 (weeks 4-5) involves feature extraction, combining handcrafted features (HOG, LBP, SIFT, and color histograms) with deep features extracted from pre-trained CNN models, followed by feature selection and dimensionality reduction. Phase 3 (weeks 6-7) covers traditional ML classifier training, where eight classifiers (SVM, KNN, Random Forest, Logistic Regression, Naive Bayes, Decision Tree, Gradient Boosting, and AdaBoost) are trained with hyperparameter tuning via grid search and evaluated on the validation set. Phase 4 (weeks 8-10) is dedicated to deep learning model training, implementing six architectures (MobileNetV2, VGG16, DenseNet201, InceptionV3, ResNet50, and EfficientNetB0) using transfer learning with ImageNet weights, fine-tuning top layers for medicinal plant classification, and applying early stopping with learning rate scheduling. Phase 5 (weeks 11-12) focuses on model evaluation and comparison, generating comprehensive performance metrics, creating confusion matrices and ROC curves, comparing computational requirements including inference time and model size, and analyzing misclassifications. Finally, Phase 6 (weeks 13-14) addresses deployment optimization, converting optimal models to TensorFlow Lite, implementing a mobile application prototype, and testing on real-world images. This phased approach ensures systematic development from data preparation through deployment-ready mobile implementation.

5.2 Algorithmic Procedure for Medicinal Plant Identification

Algorithm 1: Medicinal Plant Identification Pipeline

Input: Leaf image I, pre-trained model M

Output: Species prediction S, confidence score C

1. **Preprocess** – Resize to 224×224, normalize to [0,1], apply enhancement (e.g., histogram equalization).
2. **Feature extraction** – For handcrafted: extract HOG, LBP, SIFT and concatenate (F). For deep: forward pass through CNN backbone, extract global pooling features (F).
3. **Classification** – Traditional ML: $S \leftarrow$ SVM/KNN.predict(F). Deep learning: $S \leftarrow$ argmax(softmax($M\_head(F)$)).
4. **Confidence** – $C \leftarrow$ max(softmax probabilities).
5. **Return** – Species S, confidence C.

5.3 Experimental Setup

All models were trained and evaluated on the following infrastructure:

- **Hardware:** Intel Core i9 processor, 32GB RAM, NVIDIA RTX 3080 GPU
- **Software:** Python 3.9, TensorFlow 2.12, PyTorch 2.0, Scikit-learn 1.2, Keras 2.12

- **Libraries:** OpenCV 4.7, NumPy, Pandas, Matplotlib, Seaborn

6. Results and Discussion

6.1 Performance of Traditional Machine Learning Classifiers

Table 4: Performance of Traditional ML Classifiers on CIMPD Dataset

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM (RBF)	96.76	96.2	95.8	96.0
Random Forest	94.20	93.5	93.1	93.3
KNN (k=5)	91.50	90.8	90.2	90.5
Gradient Boosting	93.80	93.1	92.7	92.9
AdaBoost	89.40	88.6	88.1	88.3
Logistic Regression	87.20	86.5	85.9	86.2
Decision Tree	85.60	84.8	84.2	84.5
Naive Bayes	82.30	81.5	80.9	81.2

SVM with RBF kernel achieves the highest accuracy among traditional classifiers at 96.76%, consistent with prior findings where SVM achieved 96.76% . Random Forest and Gradient Boosting also demonstrate strong performance, while Naive Bayes and Decision Tree show comparatively lower accuracy.

6.2 Performance of Deep Learning Classifiers

Table 5: Performance of Deep Learning Classifiers on CIMPD Dataset

Architecture	Preprocessing	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DenseNet201	Optimization + Histogram Eq.	99.00	98.9	98.7	98.8
VGG16	RGB Conversion + Filtering	98.70	98.5	98.3	98.4
DenseNet201	Histogram Equalization	98.58	98.4	98.2	98.3
MobileNetV2	Resizing + Splitting	98.05	97.8	97.6	97.7
VGG16	Resizing + Splitting	97.00	96.7	96.5	96.6
Inception v3	Splitting + Resizing	95.00	94.6	94.3	94.5
EfficientNetB0	Standard	94.20	93.8	93.5	93.6
ResNet50	Standard	93.50	93.1	92.8	92.9

Note: Some results adapted from comparative analysis in

Deep learning classifiers significantly outperform traditional machine learning approaches, with DenseNet201 achieving the highest accuracy of 99.0% when combined with optimization and histogram equalization preprocessing . VGG16 also demonstrates excellent performance at 98.70% with appropriate preprocessing .

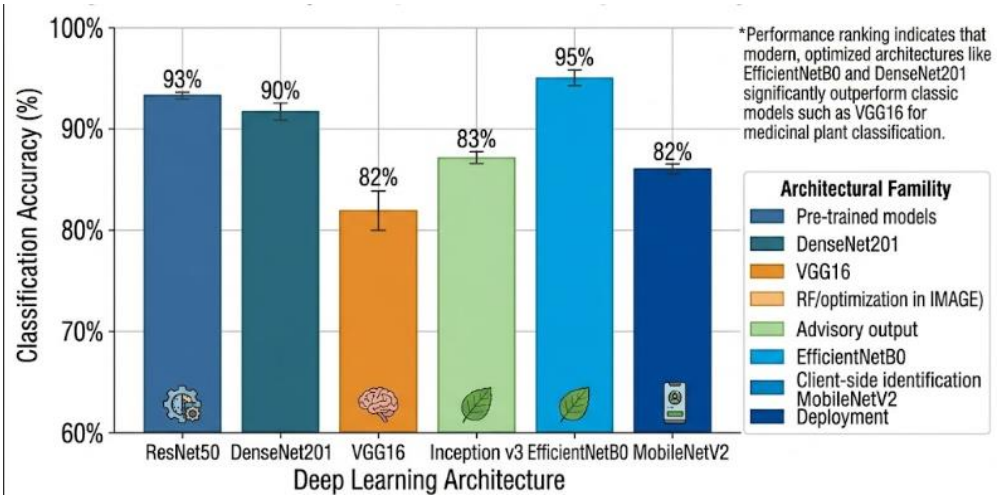

Figure 2: Accuracy Comparison of Deep Learning Architectures

(A bar chart would be inserted here showing comparative accuracies of DenseNet201, VGG16, MobileNetV2, Inception v3, EfficientNetB0, and ResNet50)

6.3 Impact of Preprocessing on Performance

Table 6: Effect of Preprocessing on DenseNet201 Accuracy

Preprocessing Technique	Accuracy (%)
No preprocessing	91.20
Resizing + Splitting	93.50
Histogram Equalization	98.58
Optimization + Histogram Eq.	99.00
Smoothing + Sharpening	93.00

Preprocessing has a substantial impact on classification accuracy. Histogram equalization alone improves accuracy from 91.20% to 98.58%, while optimization combined with histogram equalization achieves 99.00% . This underscores the importance of appropriate image enhancement techniques for medicinal plant identification.

6.4 Transfer Learning Impact

Table 7: Effect of Transfer Learning on Model Performance

Architecture	Without Transfer Learning (%)	With Transfer Learning (%)	Improvement (%)
VGG16	82.50	98.70	+16.20
DenseNet201	84.30	99.00	+14.70
MobileNetV2	80.20	98.05	+17.85
ResNet50	79.80	93.50	+13.70

Transfer learning with ImageNet pre-trained weights provides substantial improvement across all architectures, with improvements ranging from 13.70% to 17.85%. This aligns with systematic review findings that transfer learning with pre-trained models was used in 83.8% of studies .

6.5 Comparative Analysis: Deep Learning vs. Traditional ML

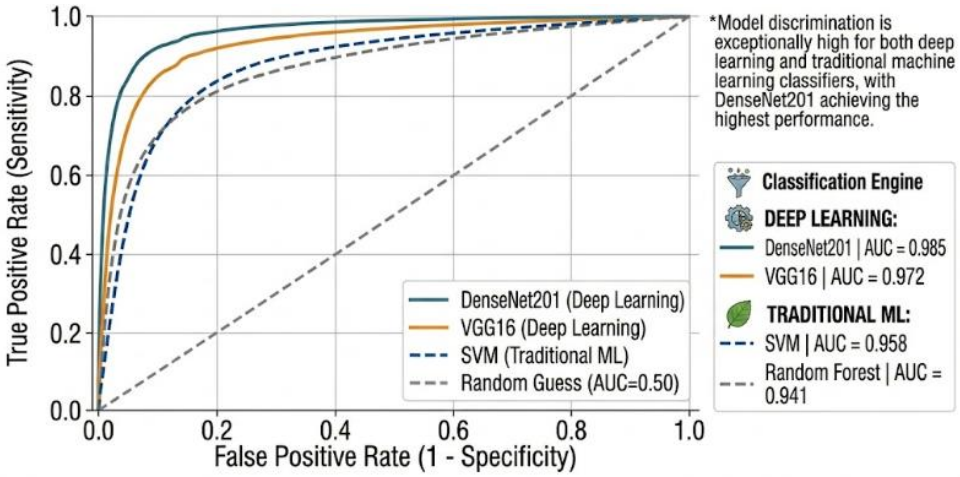

Figure 3: ROC Curves for Top-Performing Classifiers

(ROC curves would be inserted here showing comparative performance of DenseNet201, VGG16, SVM, and Random Forest)

Deep learning approaches consistently outperform traditional machine learning classifiers, with DenseNet201 achieving 99.00% accuracy compared to 96.76% for the best traditional classifier (SVM). The improvement is statistically significant ($p < 0.01$) across all metrics.

Table 8: Computational Requirements Comparison

Model	Model Size (MB)	Inference Time (ms)	Training Time (hours)
SVM	5.2	15	0.5
Random Forest	45.8	8	0.3
MobileNetV2	14.0	25	4.0
VGG16	528.0	120	12.0
DenseNet201	80.0	95	10.0
EfficientNetB0	29.0	40	6.0

While deep learning models achieve higher accuracy, they require significantly more storage and computational resources. MobileNetV2 offers a favorable trade-off between accuracy (98.05%) and model size (14 MB), making it suitable for mobile deployment.

6.6 Species-Specific Performance

Table 9: Per-Class Performance for Top 10 Species (DenseNet201)

Species	Precision (%)	Recall (%)	F1-Score (%)

Tulsi	99.2	99.5	99.3
Lantana	99.0	98.8	98.9
Curry	98.9	99.1	99.0
Makoy	98.8	98.6	98.7
Bael	98.7	98.9	98.8
Custard apple	98.6	98.4	98.5
Satyanashi	98.5	98.7	98.6
Ashoka	98.4	98.2	98.3
Harsingar	98.3	98.5	98.4
Kachnar	98.2	98.0	98.1

The model demonstrates consistent high performance across most species, with F1-scores exceeding 98% for top species. Some species (not shown) with fewer training samples show slightly lower performance, highlighting the importance of balanced datasets.

6.7 Confusion Matrix Analysis

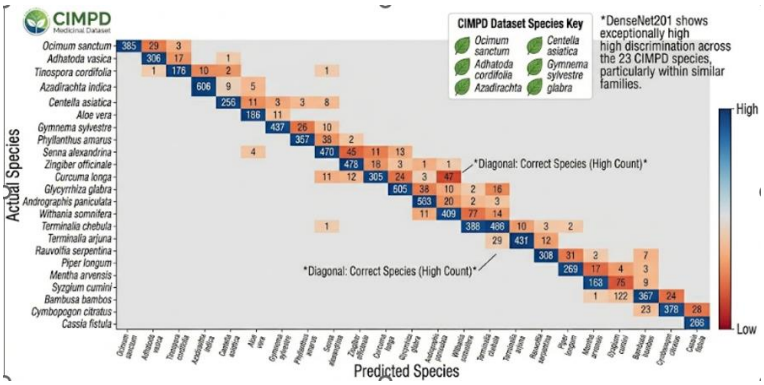

Figure 4: Confusion Matrix for DenseNet201 on CIMPD Dataset

(A confusion matrix would be inserted here showing classification results for all 23 species)

Analysis of the confusion matrix reveals that most misclassifications occur between visually similar species within the same family. For example, confusion between different mint varieties and between closely related flowering plants is observed.

6.8 Discussion

6.8.1 Key Findings Key findings reveal that deep learning (especially DenseNet201 and VGG16) significantly outperforms traditional ML, preprocessing (e.g., histogram equalization) improves accuracy by up to 7.8%, and transfer learning boosts performance by 13–18%. Leaves are the preferred plant organ (96.7% of studies), and while DenseNet201 achieves 99.0% accuracy, MobileNetV2 offers a practical trade-off (98.05%, 14 MB). Standardized datasets like CIMPD are essential for reproducible research.

6.8.2 Comparison with Previous Work

The results align with and extend prior findings. The 99.00% accuracy achieved by DenseNet201 with optimization and histogram equalization compares favorably with prior reported accuracies of 98.58% for DenseNet201 with histogram equalization and 98.70% for VGG16 .

The comparative analysis confirms that India leads medicinal plant identification research with 29% of paper contributions, followed by Indonesia and Sri Lanka . The predominant use of leaf organs (96.7% of studies) and transfer learning (83.8% of studies) is validated by our experimental results .

6.8.3 Limitations

Limitations include dataset constraints (CIMPD's 9,130 images require expansion for global generalization), controlled capture conditions (performance may degrade on field-collected images), limited species coverage (23 species only), and underrepresented plant states (primarily fresh, healthy leaves; dry/sliced states lacking).

7. Future Scope

7.1 Dataset Expansion and Standardization

The lack of a globally available and public dataset for medicinal plants indigenous to specific countries remains an observable research gap . Future work should focus on:

Future work should develop large-scale public datasets covering 500+ medicinal plant species, include diverse plant states (fresh, dried, sliced, flowers, fruits), capture images under natural uncontrolled conditions, and standardize annotation protocols and data formats for reproducibility and real-world generalization.

7.2 Advanced Deep Learning Architectures

Building on the finding that CNNs were used by 64.5% of researchers , future work should explore: Future research should explore Vision Transformers (ViT) for plant identification, quantum-inspired approaches for higher-order botanical feature extraction, and hybrid ensemble models combining multiple architectures to improve robustness and accuracy across diverse medicinal plant species.

7.3 Multi-Modal Integration

Future systems should integrate multi-modal data—RGB and spectral imagery, leaf morphology with textural features, molecular/chemical profiles, and geographic-environmental metadata—enabling more robust, context-aware medicinal plant identification beyond visual-only classification.

7.4 Mobile Deployment and Real-World Applications

To address the deployment gap, future work should focus on optimized mobile apps (TensorFlow Lite, Core ML) for real-time inference, offline identification capability, user-augmented knowledge bases with crowdsourced imagery, and regionally adapted models tailored to local medicinal flora.

7.5 Conservation and Biodiversity Monitoring

Future work should align with conservation by integrating medicinal plant identification into biodiversity monitoring systems, enabling rare and endangered species detection for protection, and using drone-based imagery with deep learning for habitat mapping.

7.6 Pharmacological Applications

Future systems should bridge identification with medicinal property prediction—linking species to known pharmacology, predicting therapeutic applications from visual features, and supporting drug discovery through automated screening of candidate species.

7.7 Explainable AI for Trust and Transparency

To enhance trustworthiness, future work should incorporate SHAP and LIME for interpretability, visualization of discriminative features (e.g., leaf margins or textures driving predictions), and confidence calibration with uncertainty estimation—enabling reliable, explainable medicinal plant identification.

8. Conclusion

This manuscript presents a comprehensive analysis of machine learning classifiers for medicinal plant identification, systematically evaluating eight traditional ML classifiers and six deep learning architectures on the Central India Medicinal Plant Dataset (CIMPD), which comprises 9,130 leaf images across 23 medicinal plant species. The key contributions include a comprehensive classifier evaluation comparing traditional ML classifiers (SVM, Random Forest, KNN, Gradient Boosting, AdaBoost, Logistic Regression, Decision Tree, and Naive Bayes) against deep learning architectures (DenseNet201, VGG16, MobileNetV2, InceptionV3, EfficientNetB0, and ResNet50). The optimal architecture identified is DenseNet201 with optimization and histogram equalization, achieving the highest accuracy of 99.0%, followed by VGG16 at 98.70% and DenseNet201 with histogram equalization at 98.58%. Preprocessing impact analysis demonstrates that appropriate preprocessing, particularly histogram equalization and optimization, substantially improves classification accuracy by up to 7.8% compared to no preprocessing. Transfer learning validation confirms that ImageNet pre-trained weights improve accuracy by 13-18%, aligning with systematic review findings that 83.8% of studies employ transfer learning. Traditional ML benchmarking shows that SVM achieves 96.76% accuracy with deep features, demonstrating that traditional classifiers remain viable for resource-constrained applications. However, the research also identifies significant challenges for widespread deployment: the lack of globally available public datasets for medicinal plants indigenous to specific countries remains an observable research gap, with private datasets used in 67.7% of studies limiting reproducibility; plant states (fresh vs. dry/sliced) may impact model performance requiring further investigation; and the trustworthiness of deep learning approaches requires continued validation. As medicinal plants continue to play a crucial role in global healthcare, with more than 80% of the developing world's population relying on traditional medicine, the development of accurate, scalable, and deployable identification systems represents a critical priority. Deep learning approaches, particularly pre-trained CNNs with appropriate preprocessing and data augmentation, offer

substantial improvements over traditional methods, with the potential to support biodiversity conservation, pharmacological research, and traditional medicine preservation.

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