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Medicinal Leaf Classifier Using MobileNetV2 and Deep Learning Techniques

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Abstract: *Medicinal plants play a vital role in traditional and modern healthcare systems, yet their accurate identification remains a challenging task due to morphological similarities among species and variations in environmental conditions. This paper presents a deep learning-based system for automated classification of medicinal plants using leaf images. A dataset of medicinal plant leaves was preprocessed through resizing, normalization, and augmentation to improve model generalization. MobileNetV2, a lightweight convolutional neural network architecture, was employed as the feature extractor with additional dense layers for classification. The model was trained and validated on a structured dataset, achieving a test accuracy of over 95%. Performance was evaluated using accuracy, precision, recall, and F1-score, confirming the robustness of the system. Furthermore, the trained model was deployed via a Streamlit web application, enabling real-time predictions through an interactive interface. The proposed approach demonstrates the potential of transfer learning for efficient medicinal plant recognition, bridging the gap between research models and practical usability.*

Keywords*:* Medicinal plants, Deep learning, MobileNetV2, Convolutional Neural Networks (CNN), Image classification, Transfer learning, Streamlit deployment, Plant identification

I. INTRODUCTION

The Medicinal plants have been central to healthcare systems for centuries, forming the foundation of traditional practices such as Ayurveda, Unani, and Traditional Chinese Medicine, and contributing significantly to modern pharmaceuticals. However, accurate identification of these plants remains a major challenge due to morphological similarities among species, seasonal variations, and environmental influences. Manual identification requires specialized botanical knowledge and is not scalable for large populations, often leading to misclassification and reduced reliability.

Advances in artificial intelligence (AI), particularly in computer vision, have opened new avenues for automated plant recognition. Deep learning models, especially Convolutional Neural Networks (CNNs), can automatically extract discriminative features from raw approaches that depend on handcrafted features. Among these, MobileNetV2 has emerged as a lightweight yet powerful architecture, offering high accuracy with reduced computational complexity, making it suitable for real-time applications and deployment on resource- constrained devices.

In this research, a MobileNetV2-based deep learning system is proposed for the classification of medicinal plants using leaf images. The approach leverages transfer learning to enhance feature extraction, combined with a structured preprocessing pipeline involving resizing, normalization, and augmentation to ensure robustness. The trained model is further deployed via a Streamlit web application, providing an accessible platform for real- time plant identification. This system not only improves classification accuracy but also bridges the gap between research prototypes and practical, user-friendly applications in healthcare, agriculture, and education.

II. LITERATURE SURVEY

Traditional Approaches For Plant Identification: Historically, medicinal plant identification has relied on manual observation of morphological traits such as leaf shape, venation, flower structure, and bark texture. Botanists often used

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herbarium samples and field guides to classify species. While effective to an extent, these methods suffered from several drawbacks, including subjectivity, dependence on expert knowledge, and susceptibility to environmental and seasonal variations. Furthermore, manual classification is time-consuming and does not scale well when dealing with large datasets. These limitations motivated the shift toward computational approaches for automated plant recognition. Machine Learning Approaches: Before the advent of deep learning, traditional machine learning algorithms were widely applied to plant classification tasks. Handcrafted features such as color histograms, texture descriptors, and geometric characteristics of leaves were extracted from images and fed into classifiers like Support Vector Machines (SVM), k- Nearest Neighbors (kNN), and Decision Trees. These models provided reasonable accuracy on small, structured datasets but faced challenges with scalability, noise, and inter-class similarity. Ensemble methods such as Random Forests improved robustness to some extent, but the reliance on manual feature engineering limited their adaptability and performance across diverse plant species. Deep Learning Approaches: The emergence of deep learning transformed plant recognition by eliminating the need for handcrafted feature extraction. Convolutional Neural Networks (CNNs) can automatically learn hierarchical representations directly from raw images, capturing subtle variations in leaf morphology that may be overlooked by human experts. Pioneering architectures such as AlexNet, VGGNet, and GoogLeNet demonstrated state-of-the-art performance in image recognition tasks, paving the way for their recent works have employed transfer learning with pretrained models like ResNet, DenseNet, and MobileNet, significantly boosting accuracy even with limited datasets. For example, Chowdhury et al. (2021) demonstrated the effectiveness of MobileNetV2 for herbal leaf classification, achieving high accuracy while maintaining computational efficiency. Similarly, Abdollahi (2022) applied MobileNetV2 to 30 classes of medicinal plants and reported classification accuracy above 98%. Despite these advances, many studies remained focused on model performance in controlled experimental setups without extending to real-world deployment. Current Limitations and Gaps: Despite notable progress, existing studies face several challenges that limit their applicability in practical scenarios:

• Dataset Size and Diversity: Many datasets contain a limited number of species or are geographically restricted, reducing model generalization.

• Deployment Gap: Most research stops at experimental validation, with few studies offering interactive systems accessible to non-specialist users.

• Explainability: Deep learning models often act as

―black boxes,‖ with limited interpretability of predictions, which may hinder user trust.

• Misclassification of Similar Species: Plants with closely resembling leaf structures, such as Mint and Basil, remain difficult to distinguish.

• Scalability: Lightweight, mobile-ready solutions are underexplored, restricting practical adoption in rural and field applications.

III. METHODOLOGY

1. Dataset and Data Preparation:

This study employs a dataset of medicinal plant leaf images collected from publicly available repositories and curated image banks. The dataset consists of multiple plant species, each organized into class-specific directories. To ensure effective training, the dataset was divided into three subsets: training (70%), validation (15%), and testing (15%), with care taken to maintain class balance.

To standardize the input, all images were resized to 224 × 224 pixels, consistent with the MobileNetV2 input requirements. Images were normalized to scale pixel values between 0 and 1, ensuring stable model convergence. Data augmentation techniques—including random rotation, flipping, zooming, and brightness adjustments—were applied to enrich the dataset and reduce overfitting. This preprocessing pipeline ensured that the model was trained on diverse input samples representative of real-world variability.

2. Data Pre-processing Pipeline:

Our preprocessing pipeline integrates multiple steps to prepare data for effective Deep learning classification.

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Image Standardization
• Conversion of raw images into RGB format.
• Resizing of all leaf images to 224 × 224 pixels.
• Normalization of pixel intensities within a 0–1 range.
• Removal of duplicate, low-quality, or corrupted samples.

Data Augmentation
To improve robustness and generalization, the following augmentation strategies were employed:
• Random rotations and horizontal/vertical flips.
• Cropping and zoom variations.
• Brightness and contrast normalization.
These augmentations increased dataset diversity, allowing the model to adapt to varying environmental conditions such as lighting, background, and leaf orientation.

3. Model Architecture Design Backbone Network
The proposed system leverages MobileNetV2, a lightweight convolutional neural network optimized for efficiency on mobile and embedded devices. Pretrained ImageNet weights were used to initialize the base model, enabling transfer learning and faster convergence. The convolutional layers of MobileNetV2 acted as the feature extractor while remaining frozen during initial training.

Classifier Selection
To adapt MobileNetV2 for multi-class classification, the top layers were replaced with a custom classification head comprising:
• A Global Average Pooling (GAP) layer.
• A fully connected dense layer with 128 units and ReLU activation.
• A Dropout layer (0.3) to mitigate overfitting.
• A final dense layer with softmax activation to generate probability scores across all plant species.

4. Training Pipeline Implementation Optimization Strategy
• Loss Function: Categorical Cross-Entropy for multi-class classification.
• Optimizer: Adam optimizer with an initial learning rate of 0.001.
• Batch Size: 32.
• Epochs: 20–30, with early stopping applied based on validation performance.

Train-Validation-Test Split
• Training Set (70%): Used to optimize model parameters.
• Validation Set (15%): Used for hyperparameter tuning and performance monitoring.
• Testing Set (15%): Used for unbiased evaluation of final model performance.
This structured split ensured generalization while preventing overfitting and data leakage.

5. Evaluation Methodology Classification Metrics
The trained model was evaluated using standard multi class classification metrics:
• Accuracy: Proportion of correctly predicted samples.
• Precision: Correctly predicted positives per class.
• Recall (Sensitivity): Correctly identified samples per actual class.
• F1-Score: Harmonic mean of precision and recall.
• Confusion Matrix: Visualization of class-wise misclassifications.

Performance Validation
• Cross-validation during training to assess robustness.
• Hyperparameter tuning (learning rate, batch size, augmentation intensity) to optimize results.

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• Comparative analysis with related studies to benchmark performance.

6. Experimental Setup and Implementation Technical Infrastructure

Hardware Configuration:

• CPU: Intel Core i7 (10th generation, 6 cores, 12 threads)
• RAM: 16 GB DDR4, sufficient for training and validation tasks
• Storage: 512 GB SSD for efficient read/write during image preprocessing and model training
• GPU: NVIDIA GTX 1650 (or higher), used to accelerate deep learning training; inference can also be executed on CPU during deployment

Software Environment:

• Programming Language: Python 3.10
• Frameworks and Libraries:
• TensorFlow/Keras (deep learning framework for model development)
• NumPy & Pandas (data handling and numerical operations)
• Matplotlib (visualization of accuracy and loss curves)
• Scikit-learn (performance evaluation metrics)
• Streamlit (web-based model deployment)
• Operating System: Windows 10 / Ubuntu 20.04 (64-bit)

Hyper parameter Configuration

The MobileNetV2-based model was fine-tuned with the following configuration:

Class	Precision	Recall	F1-Score	Support
Neem	0.96	0.95	0.96	500
Tulsi	0.93	0.91	0.92	450
Mint	0.91	0.89	0.90	400
Aloe Vera	0.92	0.90	0.91	380
Guava	0.95	0.94	0.95	370

7. Training Procedure Training Protocol:

• Data Splitting: The dataset was divided into training (70%), validation (15%), and testing (15%) subsets.
• Preprocessing: All images were resized to 224 × 224 pixels, normalized, and augmented to ensure robustness.
• Model Training: MobileNetV2 was initialized with ImageNet weights and fine-tuned on the medicinal plant dataset.
• Monitoring: Accuracy, loss, and validation metrics were tracked for every epoch to ensure stable learning.

Convergence Criteria:

• Training continued until validation accuracy plateaued.
• Early stopping was applied to avoid overfitting.
• The best-performing model weights were saved for deployment.

8. Results and Analysis Model Performance Overview

The proposed MobileNetV2-based pipeline demonstrated strong predictive performance, surpassing baseline models and effectively classifying medicinal plant species. The integration of preprocessing, augmentation, and transfer learning contributed to consistent accuracy and generalization.

Class	Precision	Recall	F1-Score	Support
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Tulsi	0.93	0.91	0.92	450

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Overall Model Performance Macro-Averaged F1: ~0.93 Micro-Averaged F1: ~0.94 Overall Accuracy: ~95%

Comparative Analysis:
Model Comparison
MobileNetV2 significantly outperformed classical models, validating the use of CNNs for medicinal image analysis.

Model	Accuracy	Macro F1	Training Time
Logistic Regression	78.2%	0.75	3 min
Random Forest	82.4%	0.79	7 min
MobileNetV2 (Proposed)	95.0%	0.93	25 min (GPU)

Ablation Study (Component Impact Analysis)
• Without augmentation, accuracy dropped by ~3%.
• Without transfer learning, accuracy reduced by ~5%.
• With a simple CNN vs MobileNetV2, MobileNetV2 achieved ~+7% higher performance.

Training Dynamics Analysis
• Training Accuracy: Reached ~97% after 20–25 epochs.
• Validation Accuracy: Stabilized around ~95%, showing minimal overfitting.
• Loss Curves: Demonstrated smooth convergence with no divergence.
• Early Stopping: Typically triggered after ~22 epochs.

IV. CONCLUSION.

This research presents a deep learning framework for medicinal plant classification using MobileNetV2 with transfer learning. The proposed pipeline achieved ~95% accuracy and demonstrated robust performance across multiple species, outperforming traditional machine learning methods.
The main contributions of this work include:
1. Technical Innovation: Application of MobileNetV2 with transfer learning for efficient and accurate medicinal plant recognition.
2. Dataset Engineering: Standardized preprocessing, augmentation, and stratified splitting for balanced evaluation.
3. Performance Advancement: Significant improvements in accuracy and F1-scores compared to baseline classifiers.
4. Practical Readiness: Lightweight architecture and rapid inference, enabling real-time deployment through a Streamlit-based web application.
While challenges remain—particularly in distinguishing morphologically similar species and handling dataset imbalance—this study establishes a foundation for scalable, accessible plant identification systems. Future enhancements, including advanced architectures, multimodal integration, and expanded datasets, will further strengthen the system's reliability and practical adoption in agriculture, healthcare, and education.

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