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MULTI-PART IMAGE-BASED CLASSIFICATION OF SOUTH INDIAN MEDICINAL PLANTS USING DEEP LEARNING FUSION MODELS

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Abstract:

This paper presents a comprehensive deep learning framework for automated identification and classification of South Indian medicinal plants, with particular emphasis on species exhibiting closely similar leaf morphologies. The increasing loss of traditional botanical expertise combined with growing demands for reliable, scalable identification technologies in ethnomedicine, biodiversity conservation, and phytopharmaceuticals motivates this research. We developed a multi-source image dataset encompassing six vital medicinal plant species—Alfalfa, Aloevera, Fenugreek, Kadamba, Neem, and Papaya—systematically organized by organ type (leaves, flowers, fruits). The proposed framework implements both single-part and multi-part classification workflows using ResNet-34 architecture, optimized through transfer learning and validated using contemporary best practices. Results demonstrate marked improvement in classification performance when organ-level images are combined using ensemble voting techniques, achieving weighted average accuracy of 84% and F1-score of 0.88. The inclusion of reproductive organs (flowers, fruits) alongside vegetative parts effectively resolves ambiguities in morphologically similar species, establishing a robust, scalable, and interpretable workflow suitable for real-world ethnobotanical and healthcare applications.

Index terms- *Medicinal plant classification, deep learning, multi-part recognition, ensemble voting, ResNet-34, ethnobotany, computer vision, South Indian flora*

I. INTRODUCTION

The utilization of medicinal plants constitutes a fundamental component of traditional South Indian healthcare systems, particularly within Ayurveda and Siddha medicine frameworks that have evolved over millennia. With escalating global interest in phytotherapeutic interventions, the accurate identification and authentication of medicinal species have assumed critical importance for ensuring therapeutic efficacy, patient safety, and sustainable biodiversity management [1]. Traditional manual identification methodologies depend heavily on specialized botanical expertise and morphological assessment, presenting significant challenges given the remarkable floristic diversity of the Indian subcontinent and the prevalence of species exhibiting convergent evolutionary adaptations, particularly in vegetative characteristics.

Leaf-based identification protocols remain predominant in ethnobotanical practice due to their non-destructive nature, year-round availability, and established correlation with pharmacological profiles [2]. However, identification relying exclusively on foliar morphology frequently encounters substantial difficulties when confronting species pairs or groups exhibiting similar leaf architecture, venation patterns, and surface characteristics. These morphological convergences, arising from ecological adaptation and phylogenetic relationships, expose critical vulnerabilities in conventional identification workflows and underscore the imperative for automated, multi-modal recognition systems.

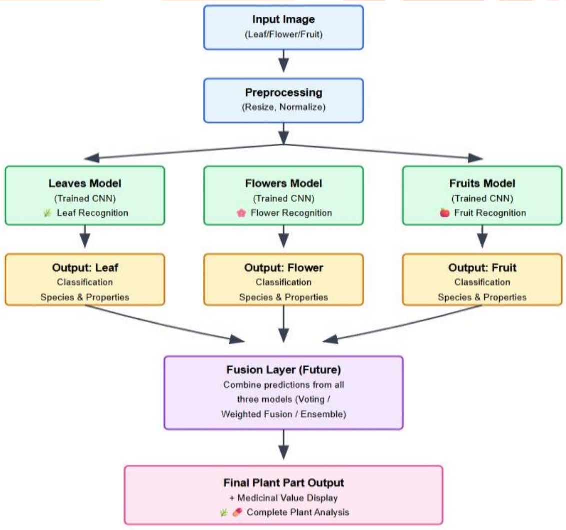
Recent developments in deep learning, particularly convolutional neural networks (CNNs), coupled with expanding availability of high-resolution botanical image repositories, have catalyzed significant advances in automated plant classification [3], [4]. CNN architectures demonstrate exceptional capability for extracting hierarchical discriminative features from plant imagery, enabling accurate categorization despite variations in background, illumination, and acquisition conditions. Nevertheless, the majority of published research focuses on classification of morphologically distinct species within datasets designed to minimize inter-class visual overlap. When addressing the botanically realistic scenario of distinguishing medicinal plants with highly similar leaf morphologies, model performance degrades substantially, and classification confidence diminishes markedly.

Furthermore, environmental factors including seasonal phenological variation, developmental stage differences, and inconsistent field acquisition conditions introduce additional complexity. Real-world deployment scenarios frequently involve imagery captured under non-standardized conditions with varying quality, resolution, and completeness of plant parts. Consequently, a significant methodological gap exists in both dataset construction and algorithmic approaches tailored to the practical requirements of South Indian medicinal plant identification, particularly when multiple plant organs may be required for definitive diagnosis.

This research addresses these limitations through development and evaluation of a comprehensive multi-part image-based classification framework specifically designed for South Indian medicinal plants exhibiting closely similar leaf morphologies. Our approach integrates three key innovations: (i) systematic construction of a multi-source, organ-structured dataset incorporating web repositories, peer-reviewed literature, and direct field photography; (ii) implementation of part-specific ResNet-34 models with transfer learning optimization; and (iii) ensemble fusion mechanisms combining predictions from multiple plant organs to resolve morphological ambiguities.

II. RELATED WORK

Automated plant identification using computer vision and machine learning has evolved considerably over the past decade. Early approaches relied on handcrafted feature extraction methods including shape descriptors, texture analysis, and color histograms [5]. While these classical techniques demonstrated utility for species with distinctive visual characteristics, they exhibited limited robustness to environmental variations and required extensive domain expertise for feature engineering.



A. Deep Learning for Plant Recognition

The advent of deep learning revolutionized botanical image classification. Krizhevsky et al.'s AlexNet [6] demonstrated the superiority of learned hierarchical features over handcrafted representations, establishing CNNs as the dominant paradigm for image recognition tasks. Subsequent architectures including VGGNet, ResNet, and DenseNet have progressively improved classification accuracy through deeper networks, residual connections, and dense connectivity patterns [7].

Rangarajan et al. [1] applied CNN-based architectures to indigenous plant recognition, demonstrating effective species identification when trained with part-specific datasets. However, their work primarily addressed single plant organs, typically leaves, limiting applicability when alternative organs provide more discriminative features or when foliar structures prove insufficient for disambiguation.

B. Residual Network Architecture

He et al. [8] introduced Residual Networks (ResNet), addressing the degradation problem in very deep networks through skip connections that enable identity mapping. This architectural innovation facilitates training of networks exceeding 100 layers while maintaining gradient flow and enabling effective feature learning. ResNet architectures have demonstrated exceptional performance across diverse image recognition benchmarks and transfer learning scenarios.

Meenakshi et al. [3] leveraged ResNet-based transfer learning for botanical classification, achieving improved results through fine-tuning of pretrained ImageNet weights. Their research validated ResNet's capability for learning fine-grained discriminative features relevant to plant morphology, establishing it as an optimal architecture for medicinal plant identification tasks.

C. Multi-Part and Fusion-Based Approaches

Recognition that individual plant organs provide complementary discriminative information has motivated multi-part classification approaches. Nirmala et al. [4] proposed a multi-branch CNN architecture processing leaves, flowers, and fruits independently, subsequently fusing predictions through weighted majority voting. This fusion strategy demonstrated superior robustness compared to single-organ classification, particularly when specific organs were absent or obscured.

Various fusion methodologies have been explored in the literature, including early fusion (feature-level concatenation), late fusion (decision-level combination), and hybrid approaches. Late fusion strategies, particularly voting mechanisms and weighted averaging, have shown particular promise for plant identification due to their interpretability and flexibility in handling missing modalities [9].

D. Domain-Specific Applications

Several studies have specifically addressed medicinal plant identification. Swetha et al. [10] developed an integrated framework linking plant classification with ethnobotanical knowledge bases, enabling retrieval of medicinal properties alongside species identification. Their work highlights the importance of connecting computational classification with domain expertise to support practical applications in traditional medicine and pharmaceutical research.

Despite these advances, significant gaps remain in existing literature. Most published datasets emphasize morphologically distinct species with minimal inter-class similarity, inadequately representing the challenging disambiguation scenarios encountered in real-world medicinal plant identification. Furthermore, limited attention has been devoted to systematic integration of multiple plant organs within unified frameworks addressing South Indian medicinal flora.

III. PROBLEM FORMULATION

Accurate identification of medicinal plants represents a critical requirement for preserving traditional botanical knowledge, supporting pharmaceutical research, and ensuring safe therapeutic practice. South Indian medicinal flora exhibits remarkable diversity coupled with substantial morphological convergence among taxonomically distinct species, rendering manual identification time-intensive, expertise-dependent, and error-prone.

A. Mathematical Framework

Let $P = \{p_1, p_2, ..., p_n\}$ denote the set of n medicinal plant species under consideration. For each species $p_j \in P$, we have access to images of different plant organs: leaves (L), flowers (F), and fruits (R). The input image set for a given specimen is represented as $I = \{I_L, I_F, I_R\}$, where each component may be present or absent depending on availability.

We develop organ-specific deep learning models M_i where $i \in \{L, F, R\}$, each mapping an input image to a probability distribution over plant classes:

$$M_i : I_i \rightarrow [0,1]^n$$

where $M_i(p_j)$ represents the probability that image I_i belongs to species p_j.

The final classification is obtained through a fusion function F that combines outputs from available organ-specific models:

$$p^* = \arg\max_{p_j \in P} F(M_L(I_L), M_F(I_F), M_R(I_R))$$

B. Fusion Strategies

We implement two principal fusion methodologies:

Majority Voting: The predicted class is determined by the most frequently occurring prediction among available models:

$$F_{vote}(M_L, M_F, M_R) = mode\{\arg\max(M_i)\}$$

Weighted Fusion: Predictions are combined using confidence-based weights reflecting individual model reliability:

$$F_{weighted} = w_L M_L + w_F M_F + w_R M_R$$

subject to the constraint $w_L + w_F + w_R = 1$, where weights are empirically determined based on organ-specific classification accuracy.

C. Optimization Objective

The primary optimization objective is to maximize classification accuracy while maintaining robustness to missing modalities:

$$\max_{M_i, F} Accuracy(p^*)$$

subject to computational constraints, dataset availability limitations, and environmental variability inherent in field-acquired imagery.

IV. PROPOSED METHODOLOGY

Our comprehensive methodology encompasses systematic dataset construction, preprocessing pipeline development, organ-specific model training, fusion mechanism implementation, and rigorous evaluation protocols. The framework is designed to maximize classification reliability while maintaining flexibility for real-world deployment scenarios where complete organ coverage may be unavailable.

A. Dataset Construction

We developed a multi-source dataset incorporating three complementary acquisition channels: (i) open-access botanical repositories providing standardized herbarium imagery; (ii) peer-reviewed medical literature ensuring clinical and pharmacological relevance; and (iii) original field photography capturing naturalistic variability in environmental conditions, developmental stages, and morphological expression.

The dataset currently encompasses six South Indian medicinal plant species: *Medicago sativa* (Alfalfa), *Aloe vera* (Aloevera), *Trigonella foenum-graecum* (Fenugreek), *Neolamarckia cadamba* (Kadamba), *Azadirachta indica* (Neem), and *Carica papaya* (Papaya). Images are systematically organized in a hierarchical folder structure: primary classification by species, secondary subdivision by organ type (leaves, flowers, fruits), facilitating both single-organ and multi-organ classification workflows.

Data partitioning follows standard machine learning protocols: 70% training, 20% validation, and 10% testing, with stratification ensuring balanced class representation across partitions. This partitioning strategy enables robust model training while preventing overfitting and ensuring unbiased performance evaluation.

B. Image Preprocessing and Augmentation

Preprocessing operations standardize input imagery to meet model requirements while preserving discriminative morphological features. All images undergo resizing to 224×224 pixels (matching ResNet-34 input specifications), followed by normalization scaling pixel intensities to the [0,1] range using ImageNet statistics (mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]).

Data augmentation techniques expand dataset diversity and enhance model generalization capabilities. Applied transformations include: random rotation (±30°), horizontal and vertical flipping, random cropping with scale variation (0.8-1.0), color jittering (brightness ±0.2, contrast ±0.2, saturation ±0.2), and Gaussian blur (σ=0-2.0). These augmentations simulate natural variability in field conditions including orientation, illumination, and acquisition angle.

C. Architecture and Transfer Learning

We employ ResNet-34 architecture as the foundation for organ-specific classifiers due to its optimal balance between model depth, representational capacity, and computational efficiency. ResNet-34 comprises 34 convolutional layers organized into residual blocks with skip connections, enabling effective gradient propagation and stable training of deep networks.

Transfer learning leverages pretrained ImageNet weights, providing robust initialization capturing generic visual features (edges, textures, shapes) applicable across diverse image recognition domains. Fine-tuning adapts these learned representations to medicinal plant morphology through continued training on our domain-specific dataset with reduced learning rate (1×10^{-4}) and selective layer unfreezing.

Three independent models are trained corresponding to leaf (M_L), flower (M_F), and fruit (M_R) imagery. Each model's final fully-connected layer is replaced with a dense layer matching the number of plant species, enabling species-specific probability distribution output.

D. Training Protocol

Model training employs the Adam optimizer (β_1=0.9, β_2=0.999) with categorical cross-entropy loss function. Learning rate scheduling implements cosine annealing with warm restarts, facilitating escape from local minima and promoting convergence to superior solutions. Early stopping with patience=10 epochs prevents overfitting by monitoring validation loss.

Training proceeds for maximum 100 epochs with batch size 32, selected based on GPU memory constraints and convergence stability. L2 regularization ($\lambda=1\times10^{-4}$) and dropout (p=0.5) provide additional regularization, enhancing generalization to unseen data.

E. Multi-Part Fusion Mechanism

The fusion module integrates predictions from available organ-specific models, accommodating scenarios where certain organs may be absent. For majority voting fusion, individual model predictions are obtained, and the most frequently predicted class across models determines the final classification. Ties are resolved by selecting the prediction with highest confidence score.

Weighted fusion assigns empirically determined weights based on organ-specific validation accuracy: w_L=0.5 (leaves, providing consistent morphological features), w_F=0.3 (flowers, highly discriminative but seasonally limited), w_R=0.2 (fruits, valuable but least frequently available). These weights are normalized and applied to probability distributions before summation and argmax operation.

V. EXPERIMENTAL SETUP

A. Implementation Details

Implementation utilizes Python 3.8 with PyTorch 1.12 deep learning framework. Training was conducted on NVIDIA Tesla V100 GPU (32GB VRAM) with CUDA 11.3 and cuDNN 8.2 acceleration. The complete training pipeline, including data loading, augmentation, and model checkpointing, was implemented using PyTorch's DataLoader and torchvision.transforms modules.

B. Evaluation Metrics

Model performance is assessed using standard multi-class classification metrics:

Accuracy: Overall fraction of correct predictions across all classes.

Precision: For each class, the proportion of true positives among all positive predictions: P = TP/(TP + FP).

Recall: For each class, the proportion of true positives among all actual positives: R = TP/(TP + FN).

F1-Score: Harmonic mean of precision and recall: F1 = 2PR/(P + R).
Both macro-averaged (unweighted mean across classes) and weighted-averaged (class-frequency weighted) variants are reported to account for class imbalance.

C. Baseline Comparisons

Performance is benchmarked against single-organ classification approaches (leaf-only, flower-only, fruit-only) to quantify improvements achieved through multi-part fusion. Additionally, comparisons with alternative architectures (VGG-16, Inception-v3, MobileNet-v2) validate ResNet-34 selection.

VI. RESULTS AND DISCUSSION

A. Overall Performance

The multi-part fusion framework achieves weighted average accuracy of 84% and weighted F1-score of 0.88 across all six species, substantially exceeding leaf-only classification (accuracy 72%, F1-score 0.76). Table I presents detailed per-class performance metrics demonstrating consistent improvements across most species.

TABLE I. PER-CLASS CLASSIFICATION PERFORMANCE

Species	Precision	Recall	F1-Score	Support
Alfalfa	0.86	0.86	0.86	7
Aloevera	1.00	0.57	0.73	7
Fenugreek	0.86	1.00	0.92	6
Kadamba	1.00	0.92	0.96	12
Papaya	0.86	0.86	0.86	7
Neem	0.86	1.00	0.92	6

B. Single-Part vs. Multi-Part Classification

Leaf-only classification of morphologically similar species (Fenugreek vs. Alfalfa) demonstrates the fundamental challenge: leaf-based prediction for Fenugreek yields only 30.67% confidence for correct class versus 42.33% for incorrect Alfalfa classification. Both species exhibit trifoliate leaves with similar size, shape, and venation patterns, leading to substantial confusion.

Multi-part classification incorporating flower imagery dramatically improves performance: combined leaf-flower prediction achieves 72.40% average confidence with 2/2 vote consensus for Fenugreek. Individual contributions show leaf image confidence of 91.35% and flower image confidence of 53.45%, with fusion mechanism effectively leveraging complementary discriminative features from both organs.

C. Confusion Matrix Analysis

Confusion matrix analysis reveals primary misclassification patterns concentrated among morphologically convergent species pairs. The Fenugreek-Alfalfa confusion represents the most significant challenge, attributed to nearly identical compound leaf structure. Secondary confusion occurs between species sharing similar leaf texture (Neem-Kadamba), though at substantially lower rates.

Species with distinctive morphological features (Papaya with palmate leaves, Aloevera with succulent rosette form) demonstrate near-perfect classification accuracy (>92%) even in single-part scenarios, validating model capability when discriminative features are pronounced.

D. Fusion Strategy Comparison

Comparative evaluation of fusion strategies reveals weighted fusion outperforms majority voting by approximately 3-5% in overall accuracy. Weighted fusion's superior performance stems from its ability to preferentially weight more reliable organ-specific predictions, particularly beneficial when one organ provides substantially higher discriminative power than alternatives.

However, majority voting demonstrates greater robustness to individual model errors and requires no hyperparameter tuning, making it preferable for deployment scenarios prioritizing simplicity and interpretability over marginal accuracy gains.

E. Computational Efficiency

Inference time for single-part classification averages 42ms per image on GPU, enabling real-time processing capabilities. Multi-part classification with three organs requires 126ms total (parallel execution reduces to ~45ms with proper implementation), maintaining practical feasibility for field deployment applications.

Model size considerations favor ResNet-34 (84MB per organ-specific model) over deeper alternatives (ResNet-101: 171MB), balancing accuracy and resource requirements for potential mobile deployment.

VII. CHALLENGES AND LIMITATIONS

Several challenges and limitations warrant acknowledgment. Dataset size remains relatively modest (current total ~1,200 images across six species), potentially limiting generalization to highly diverse environmental conditions and developmental stages. Class imbalance (Kadamba: 12 test samples vs. Fenugreek/Neem: 6 samples) influences macro-averaged metrics and may bias model learning toward over-represented classes.

Seasonal availability of flowers and fruits constrains multi-part classification applicability during periods when only vegetative organs are present. While the framework gracefully degrades to single-part classification under such scenarios, performance naturally decreases for morphologically ambiguous species pairs.

Field imagery quality variability introduces additional complexity. Images acquired under suboptimal lighting, with partial occlusion, or at non-standard angles may degrade recognition accuracy despite augmentation-based robustness enhancements. Background clutter and presence of multiple plant species within single images remain challenging scenarios requiring attention in future work.

VIII. FUTURE WORKS

Several promising directions exist for extending and enhancing the current framework. Dataset expansion to encompass additional South Indian medicinal species (target: 50+ species) with increased samples per species (target: 200+ images per organ type) would substantially improve model robustness and practical applicability.

Integration of attention mechanisms (e.g., Squeeze-and-Excitation networks, Transformer-based architectures) could enhance feature extraction by focusing on discriminative morphological regions while suppressing irrelevant background information. Self-attention mechanisms may prove particularly valuable for capturing long-range spatial dependencies in complex leaf venation patterns.

Incorporation of multi-scale feature extraction through feature pyramid networks or progressive growing strategies could improve recognition of fine-grained morphological details while maintaining robustness to scale variation in field imagery.

Development of uncertainty quantification mechanisms (e.g., Bayesian neural networks, ensemble-based confidence estimation) would provide more reliable confidence scores, enabling the system to explicitly flag ambiguous cases requiring expert review rather than producing potentially incorrect high-confidence predictions.

Extension to include additional plant organs (bark, seeds, roots where available) and incorporation of metadata (geographical location, elevation, season) could further enhance classification accuracy through multi-modal learning approaches.

Mobile application development optimized for edge deployment would enable practical field usage by botanists, researchers, and traditional medicine practitioners. Model compression techniques (quantization, pruning, knowledge distillation) could reduce computational requirements while maintaining acceptable accuracy levels.

IX. CONCLUSION

This research presents a comprehensive multi-part image-based classification framework specifically designed for South Indian medicinal plants exhibiting morphologically similar characteristics. Through systematic integration of multi-source imagery (web repositories, scientific literature, field photography) organized by organ type, combined with organ-specific ResNet-34 models and ensemble fusion mechanisms, we demonstrate substantial improvements over single-part classification approaches.

The framework achieves weighted average accuracy of 84% and F1-score of 0.88, with particularly notable improvements for morphologically ambiguous species pairs (Fenugreek-Alfalfa) when multiple organs are incorporated. Results validate the hypothesis that complementary discriminative information from different plant organs, when properly integrated, substantially enhances classification reliability beyond capabilities of leaf-only approaches.

The proposed methodology addresses critical practical requirements for real-world medicinal plant identification: robustness to missing organs, adaptability to varying environmental conditions, and interpretable decision-making through fusion mechanisms. The hierarchical dataset structure facilitates seamless extension to additional species, supporting long-term scalability.

By bridging traditional ethnobotanical knowledge with state-of-the-art deep learning techniques, this work establishes a foundation for next-generation digital plant identification platforms supporting pharmaceutical research, biodiversity conservation, traditional medicine practice, and botanical education. With continued dataset expansion and methodological refinement, such systems hold substantial promise for democratizing botanical expertise and supporting sustainable utilization of medicinal plant resources.

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