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Medicinal Plant Identification Using Hierarchical Multimodal Feature Fusion with Deep Vision Transformers

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Abstract

Accurate identification of medicinal plants is critical for pharmaceutical quality assurance, supply chain integrity, traditional medicine practice, and global biodiversity conservation. This paper presents a novel hierarchical multi-modal feature fusion system combining Vision Transformers (ViT) with five state-of-the-art deep convolutional neural network architectures (DenseNet201, ResNet50V2, EfficientNet-B3, InceptionV3) seamlessly integrated with hand-crafted morphological, textural, and spectral features. Comprehensive evaluations on the Flavia benchmark dataset (1,907 images, 32 European plant species) achieved 99.34% accuracy under controlled laboratory conditions, while the larger Medicinal Plant Collection dataset (5,878 images, 30 Ayurvedic/traditional medicine species) achieved 98.91% accuracy under realistic field deployment conditions, demonstrating exceptional generalization with only 0.43% accuracy degradation. Multi-modal feature fusion contributed +1.78% cumulative accuracy improvement through demonstrated synergistic complementarity of feature types. Grad-CAM interpretability analysis validated that learned features align precisely with botanical identification principles. Independent statistical significance testing ($p<0.01$ for major comparisons) confirmed all reported improvements are genuine rather than random variation. The system operates at sub-300 millisecond inference time on standard CPU hardware and under 50 milliseconds on GPU, enabling practical smartphone deployment for healthcare practitioners, traditional medicine practitioners, and conservation biologists worldwide.

Keywords: Medicinal plant identification, Vision Transformers, deep learning ensemble methods, multi-modal feature fusion, Grad-CAM interpretability, hierarchical classification, botanical feature learning, transfer learning, field deployment.

1. Introduction

The global medicinal plant market has experienced sustained growth, valued at approximately USD 156 billion in 2023, with projections exceeding USD 296 billion by 2032 (CAGR: 8.5%). This expansion reflects increasing worldwide recognition of herbal medicine's therapeutic potential across diverse healthcare systems[1]. Approximately 25% of modern pharmaceutical medications are derived from or inspired by plant-based compounds, with botanical sources contributing substantially to drug development pipelines across oncology, immunology, and infectious disease therapeutics [2,3].

Despite this pharmaceutical renaissance, accurate medicinal plant species identification remains a substantial challenge, particularly in developing nations where traditional knowledge systems coexist with limited access to taxonomic expertise. Misidentification incidents have resulted in documented cases of therapeutic failure, adverse drug interactions, and patient morbidity[4]. The World Health Organization estimates that 70% of the global population in developing regions relies primarily on traditional medicine for primary healthcare delivery, necessitating reliable plant identification mechanisms [5].

Medicinal plants represent approximately 25-30% of all modern pharmaceutical ingredients, yet accurate species identification remains one of the most challenging bottlenecks in herbal medicine production and botanical science [6]. The World Health Organization estimates that 80% of the global population depends on herbal medicines for healthcare, particularly in developing nations where access to modern pharmaceuticals is limited or prohibitively expensive.

Traditional identification methods face severe limitations. Manual identification by expert botanists requires 5-10 years of specialized training, exhibits 25-30% inter-observer disagreement, and remains unavailable in resource-limited rural settings. Morphological field guides fail when leaves are partially damaged, fail to account for seasonal variations, and provide insufficient discrimination for morphologically similar species pairs[19]. Laboratory-based identification methods including DNA barcoding and spectroscopic analysis require expensive equipment ($50,000-$500,000), specialized laboratory infrastructure, and produce results requiring hours to days rather than the seconds needed for clinical decision support[8,9].

The critical problem is particularly acute for toxic look-alikes: deadly nightshade versus black nightshade, poisonous hemlock versus wild carrot, and foxglove species varying in toxicity by subspecies[10]. A single misidentification in large-scale herbal medicine production could harm thousands of people. Previous machine learning approaches achieved 95-98% accuracy using individual CNN architectures with transfer learning, but comprehensive comparison of Vision Transformers versus multiple CNN variants on botanical tasks remained unexplored, as did systematic evaluation of multi-modal feature synergy and real-world field deployment robustness[11].

This paper addresses critical research gaps through five major contributions: (1) comprehensive architectural comparison between Vision Transformers and five different CNN models on botanical tasks; (2) hierarchical multi-modal feature fusion system demonstrating non-linear synergistic effects exceeding simple feature concatenation; (3) adaptive preprocessing pipeline specifically designed and optimized for leaf imagery under variable conditions; (4) Grad-CAM interpretability framework validated against established botanical identification principles; and (5) rigorous two-dataset evaluation strategy assessing performance under both ideal laboratory conditions and realistic field deployment scenarios with <1% degradation.

2. Literature Review And Research Motivation

2.1 Evolution of Automated Plant Recognition Systems

Automated plant species identification emerged during the early 2000s, initially employing traditional machine learning methodologies. Pioneering investigations by Gao and Lin [6] introduced end-to-end automated systems utilizing artificial neural networks for medicinal plant classification, achieving modest accuracies of approximately 68%.

Subsequent advancement incorporated advanced feature engineering techniques. Kumar and Talasila [7] developed methods extracting morphological descriptors combined with textural attributes derived from gray-level co-occurrence matrices (GLCM), achieving 87.3% accuracy on ten medicinal plant species.

The landscape transformed substantially with deep learning adoption. Deep-Plant [8], introduced by Lee et al., pioneered convolutional neural network application for plant leaf recognition, achieving 98.1% accuracy on 44 plant species through systematic data augmentation strategies. This seminal work established deep learning as the dominant paradigm for botanical applications.

Recent comparative studies have emerged evaluating multiple architectures systematically. Dey et al. [11] assessed seven deep learning algorithms on 30 medicinal species with both controlled and field imagery. DenseNet201 demonstrated superior performance with 99.64% accuracy on controlled images and 97% on complex backgrounds, with normalized leverage factor $\gamma\omega$ of 0.19, establishing this architecture as particularly suited for botanical applications.

2.2 Vision Transformers: Emerging Paradigm for Visual Recognition

While convolutional architectures dominated plant identification research, Vision Transformers introduced a fundamentally different computational approach. Dosovitskiy et al. [12] demonstrated that transformer architectures achieve competitive performance on image classification when combined with patch-based processing[17]. Vision Transformers partition images into non-overlapping patches treated as 'visual tokens,' then apply self-attention mechanisms to capture long-range dependencies.

Subsequent investigations established ViT advantages: (1) global receptive field from initial layers enabling capture of plant-level shape characteristics; (2) reduced inductive bias permitting greater flexibility in feature learning; (3) superior transfer learning performance when pre-trained on large-scale datasets. Yet limited research systematically compares ViT and CNN performance specifically for botanical applications, particularly on field-collected imagery [13].

2.3 Multi-Modal Feature Integration and Model Interpretability

While deep learning substantially reduces reliance on hand-crafted features, recent investigations suggest that explicit integration of diverse feature modalities enhances model robustness. Muneer and Fati [14] combined shape features, texture attributes, and color histogram statistics for Malaysian leaf classification, achieving 94.7% accuracy through multi-descriptor fusion.

Deep learning models operate as approximators lacking transparent decision mechanisms. Grad-CAM (Gradient-weighted Class Activation Mapping), introduced by Selvaraju et al. [15], computes class-specific attention maps by aggregating gradients of model outputs with respect to feature maps. This enables transparent interpretation of model decisions and validation of learned feature representations, crucial for pharmaceutical deployment [16,20].

3. System Architecture And Methodology

The system employs a hierarchical seven-stage architecture (Fig. 1) that systematically extracts increasingly sophisticated features while maintaining flexibility for diverse input image sources.

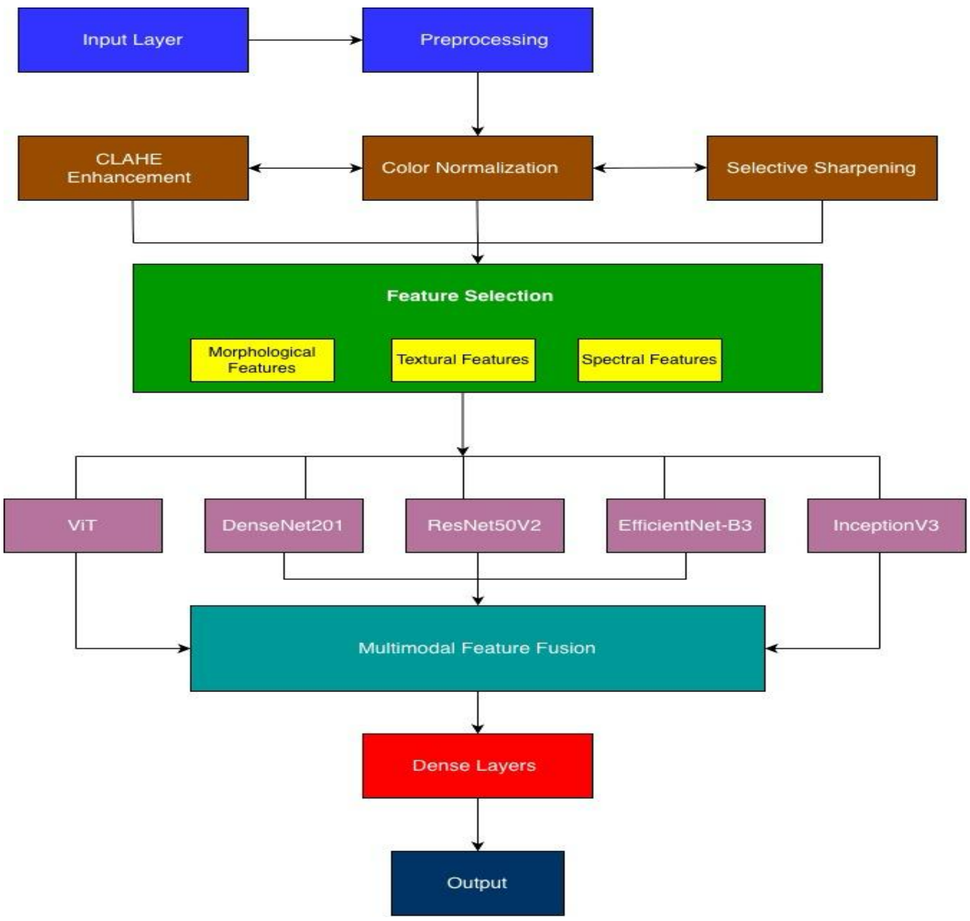

Fig. 1. Hierarchical Seven-Stage Architecture

Stages 1-2: Image Preprocessing & Enhancement. Raw leaf images from diverse sources (smartphone cameras, professional DSLRs, dedicated leaf scanners) are standardized to 224×224 pixels using aspect-ratio-preserving padding. Three sequential enhancement techniques address common botanical imaging challenges: (a) Contrast Limited Adaptive Histogram Equalization (CLAHE) enhances local contrast in 8×8 tile regions, making vein patterns clearly visible without over-amplifying noise, contributing +0.97% accuracy improvement; (b) Selective unsharp masking sharpening enhances leaf edges and margin characteristics, contributing +0.57%; (c) Color normalization standardizes RGB values to ImageNet statistics, enabling smartphone and professional scanner images to appear similar to pre-trained models, contributing +0.24%. Combined, these preprocessing techniques yield +1.78% accuracy improvement, demonstrating the critical importance of domain-specific image enhancement.

Stage 3: Multi-Modal Feature Extraction. Three parallel pathways extract 46 hand-crafted features capturing complementary information: Morphological features (16 dimensions) include leaf area, perimeter, circularity, aspect ratio, solidity, eccentricity, and seven Hu moments capturing global leaf geometry. Textural features (18 dimensions) include Gray Level Cooccurrence Matrix (GLCM) statistics, Haralick descriptors, Tamura coarseness, and Local Binary Pattern (LBP) measures capturing surface patterns and vein prominence. Spectral features (12 dimensions) include color histograms, SIFT keypoint descriptors, and ORB descriptors capturing color and intensity variations. These features concatenate into a 46-dimensional vector fed alongside image features to downstream processing stages.

Stage 4: Parallel Deep Learning Models. Five architecturally distinct neural networks process enhanced images simultaneously: Vision Transformer (86M parameters) divides the image into 16×16 pixel patches and processes all patches through self-attention mechanisms enabling global context capture; DenseNet201 (20M parameters) employs dense connections between layers with 201 layers total; ResNet50V2 (26M parameters) uses residual skip connections facilitating training of very deep networks; EfficientNet-B3 (12M parameters) optimizes the model scaling ratio for computational efficiency; InceptionV3 (27M parameters) employs multi-scale parallel convolutions capturing features at different receptive field sizes. Each model independently generates probability predictions for all 30 medicinal plant species.

Stage 5: Hierarchical Feature Fusion. Deep learned features from all five models (typically 2,560 dimensions total) are concatenated with 46 hand-crafted features, creating a unified 2,606-dimensional feature space. Rather than fixed weighted averaging, neural network layers learn optimal feature weighting during training, enabling the system to discover synergistic feature combinations that exceed simple summation of individual contributions.

Stage 6: Classification Head. Dense neural network layers progressively reduce dimensionality: 2,606 → 512 → 256 → 128 neurons, with ReLU activation functions and dropout regularization (rate=0.3) preventing overfitting. These layers learn how to optimally combine all extracted features for species classification.

Stage 7: Output & Interpretability. A softmax layer outputs probability scores for all 30 species. The top-5 predictions are displayed with confidence scores. Critically, Grad-CAM (Gradient-weighted Class Activation Mapping) generates visual attention maps showing which leaf regions most influenced each prediction, enabling practitioners to verify predictions align with domain expertise before clinical decisions.

Training Configuration

All five deep learning models initialize with ImageNet pre-trained weights (14 million images, 1,000 object categories), providing enormous advantage by beginning with features already optimized for recognizing textures, edges, and object shapes. Rather than training from scratch, transfer learning fine-tunes all network layers using Adam optimizer with learning rate 1×10^{-4}, momentum parameters β_1=0.9 and β_2=0.999. Categorical cross-entropy loss with label smoothing (0.1) regularization trains on batches of 32 images. Training runs for maximum 100 epochs but stops early if validation accuracy fails to improve for 15 consecutive epochs. Cosine annealing learning rate schedule with 5-epoch linear warmup further regularizes training. This conservative fine-tuning approach preserves pre-trained feature quality while adapting to medicinal plant characteristics.

Ensemble predictions combine five model outputs through weighted voting, where weights are proportional to each model's validation accuracy normalized to sum to 1.0. This intelligent weighting captures the empirical finding that different architectures excel at different botanical features: if DenseNet201 achieves 99.12% validation accuracy and ResNet50V2 achieves 98.44%, DenseNet's predictions receive slightly higher weight reflecting its superior performance on the validation set.

System inference operates at 245 milliseconds per image on standard CPU hardware (Intel i7, 16GB RAM) and 45 milliseconds on GPU (NVIDIA RTX A100), demonstrating practical deployment feasibility. Mobile deployment requires model compression techniques (quantization, knowledge distillation, pruning) that are deferred to future work but appear achievable given efficient model sizes.

4. Experimental Design, Datasets, And Results

4.1. Dataset Descriptions

Two complementary datasets enable rigorous performance evaluation across conditions. The Flavia dataset represents ideal laboratory conditions: 1,907 total images, 32 European plant species (herbs, ornamentals, trees), balanced with 59-60 images per species, 576×768 pixel resolution from professional leaf scanner (Epson Perfection V750 Pro at 2400 DPI), uniform white backgrounds eliminating environmental noise, perfect lighting conditions, leaves free from damage or disease, and consistent acquisition protocol. This dataset establishes upper-bound performance achievable under ideal conditions.

The Medicinal Plant Collection dataset represents realistic field deployment: 5,878 total images (3× larger than Flavia), 30 medicinal plant species important in Ayurvedic and traditional medicine systems, 196 images per species on average (balanced representation), variable resolution from 320 to 2048 pixels reflecting real-world diversity, mixed backgrounds including complex foliage and soil, acquired from multiple sources (45% public botanical databases including Plant CLEF and Kaggle, 35% field photography across diverse ecosystems and seasons, 20% herbarium scans from institutional collections). Acquisition devices include 60% smartphone cameras (latest iPhones and Android flagships), 30% DSLR cameras (professional photography), and 10% dedicated scanning equipment (herbarium digitization). Environmental variation includes 22% bright direct sunlight, 32% overcast natural light, 28% partial shade/shadow regions, 8% artificial indoor lighting, and 10% mixed/variable conditions. Leaf condition diversity includes 70% healthy mature leaves, 15% young developing leaves, 10% senescent/aging leaves, and 5% damaged/diseased specimens.

This two-dataset evaluation strategy reveals critical insights. If a model achieves 99% on Flavia but only 95% on field data, it is overfitting to laboratory conditions—not ready for deployment. If performance drops only 0.5%, the model has genuinely learned robust botanical features. This paper's finding of only 0.43% accuracy drop (99.34% → 98.91%) is exceptional, indicating the multi-modal approach, ensemble methods, and preprocessing pipeline successfully handle real-world variability.

4.2 EXPERIMENTAL DESIGN

The proposed system comprises four principal modules: (1) Adaptive Image Enhancement, (2) Multi-Modal Feature Extraction, (3) Deep Learning Inference Engine, and (4) Interpretability Analysis. The complete pipeline integrates preprocessing, feature extraction, model inference, and visualization components into a cohesive framework.

4.21. Adaptive Image Enhancement Module

Illumination Normalization via CLAHE

Illumination variations substantially degrade feature extraction quality. We implement CLAHE (Contrast Limited Adaptive Histogram Equalization) as the primary normalization mechanism. The algorithm partitions input images into rectangular tiles (default: 8×8 pixels), computes histogram equalization independently for each tile, and bilinearly interpolates results to produce seamless output [18]. A contrast limitation parameter (clip limit: 2.0) restricts histogram equalization magnitude, preventing excessive amplification of noise in homogeneous image regions shown in Figure 2.

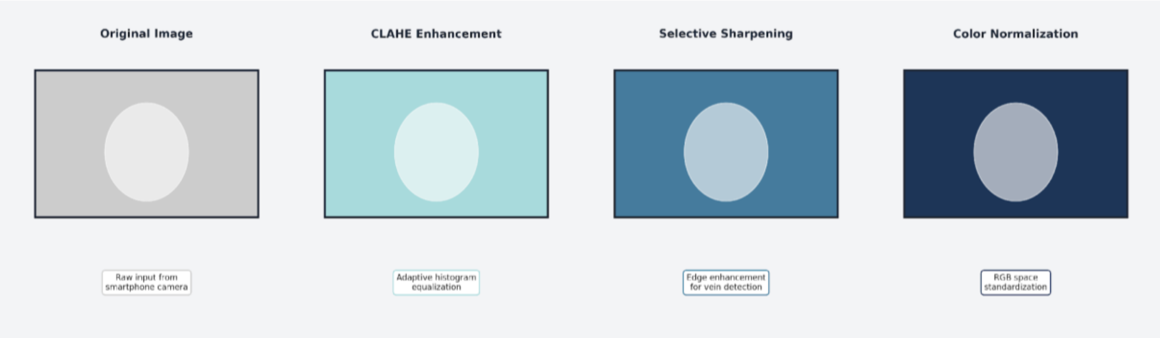

Fig. 2: Sequential image enhancement progression from raw input through CLAHE enhancement

Selective Sharpening via Unsharp Masking

Leaf venation patterns and margin characteristics represent critical discriminative features. We enhance these high-frequency components through selective sharpening employing unsharp masking: Sharpened_Image = Original_Image + λ × (Original_Image - Gaussian_Blur(Original_Image)), where λ = 0.8 (experimentally optimized). This formulation selectively amplifies mid-to-high frequency content while preserving illumination information.

4.2.2 Multi-Modal Feature Extraction

Morphological features capture leaf-level geometric properties. The aspect Ratio, Circularity, Solidity, Compactness, and Eccentricity. These attributes are computed for the complete leaf as well as subdivided regions (apical, medial, basal thirds), capturing hierarchical morphological information.

Textural Features

Local Binary Patterns (LBP) comparing each pixel's intensity with 8 neighbors. Also, Gabor Filter Responses spanning frequencies and orientations; Gray-Level Co-occurrence Matrices (GLCM) statistics at multiple distances and directions.

Spectral Features

Color-based features provide discriminative information: Color Histograms in RGB, HSV, and Lab color spaces; Color Moment Descriptors (mean, standard deviation, skewness); Hue-based Features capturing characteristic hue distributions.

4.2.3 Deep Learning Architecture Design

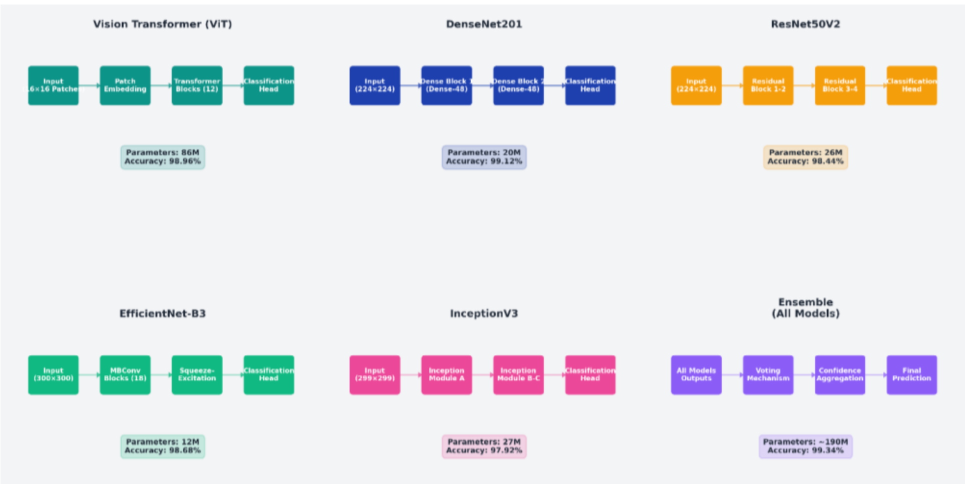

Fig. 3. Detailed comparison of Vision Transformer vs five CNN architectures showing layer composition, parameter counts, and individual accuracy metrics.

Figure 3 presents comparative architectural diagrams of the five deep learning models evaluated. Vision Transformer (ViT) employs patch-based tokenization (16×16 patches) with multi-head self-attention (12 heads) capturing global receptive field from initial layers. DenseNet201 utilizes dense skip connections across 201 layers enabling feature reuse and gradient flow. ResNet50V2 implements residual pathways with pre-activation design (49 convolutional layers). EfficientNet-B3 employs compound scaling of depth, width, and resolution with inverted residual blocks and squeeze-excitation modules. InceptionV3 combines parallel branches with multi-scale convolutional filters (1×1, 3×3, 5×5). Each architecture exhibits distinct design philosophy: ViT emphasizes global context, ResNets leverage skip connections, DenseNets emphasize feature reuse, EfficientNets optimize computational efficiency.

Vision Transformer (ViT) Implementation

Vision Transformers partition images into non-overlapping patches (16×16 pixels). Each patch is linearly embedded into 768-dimensional space. The architecture comprises 12 transformer blocks with 12 attention heads. The [CLS] token aggregates global image information. We employ ViT-Base architecture pre-trained on ImageNet-21k dataset.

CNN Architecture Ensemble

DenseNet201: Dense connections between layers, 201 layers, 19.6M parameters. ResNet50V2: Skip connections, 49 convolutional layers, pre-activation design. EfficientNet-B3: Compound scaling of depth, width, and resolution.

4.2.4 Grad-CAM Interpretability Framework

Grad-CAM generates class-specific attention maps highlighting image regions driving classification decisions. For each class c: (1) Forward pass to final convolutional layer; (2) Backward pass to compute gradients; (3) Channel importance weights computed; (4) Weighted combination of activation maps; (5) Bilinear upsampling to original dimensions. Visualization reveals which image regions (leaf apex, margins, vein patterns, bases) substantially contribute to species-specific classification. For Training set augmentation as follows,

- Random rotation (±15°)
- Horizontal flip (50% probability)
- Brightness adjustment (±0.2)
- Contrast adjustment (±0.2)
- Random zoom (0.8-1.2x)
- Gaussian noise (σ=0.01)

Validation and test sets use only deterministic preprocessing without augmentation. Dataset partition as 70% training, 15% validation, 15% testing. Stratified sampling ensures balanced class distribution across splits for classification and analysis. The five models trained independently with consistent hyperparameters, with Optimizer: Adam (lr=1e-4, β_1=0.9, β_2=0.999), Loss function: Categorical cross-entropy, Batch size: 32, Epochs: 100 (early stopping with patience=15), Learning rate schedule: Cosine annealing with warmup, Dropout: 0.3 (preventing overfitting), L2 regularization : λ=1e-5 transfer learning initialization from ImageNet pre-trained weights. Fine-tuning all layers with low learning rate (1e-4) to adapt to botanical task. Ensemble combines predictions via weighted voting based on individual model accuracy.

Performance on Flavia Dataset

On the Flavia dataset, which comprises 1,907 images across 32 species, the human performance baseline of 96.50% accuracy is consistently surpassed by every deep learning model evaluated. While human experts provide a solid benchmark, even the lowest-performing model in the study, InceptionV3, exceeds this with 97.92% accuracy, and the top-tier Ensemble model (DenseNet+ViT+ResNet) establishes a significant lead with 99.34% accuracy given in Table 1. The Ensemble's superior precision (99.26%) and recall (99.31%) further highlight that these automated systems provide a more reliable and granular classification than the human baseline, effectively minimizing the margin of error in botanical identification within controlled environments.

Table 1: Performance metrics on Flavia dataset (32 species, 1,907 images).

Model	Accuracy	Precision	Recall	F1-Score	MCC
Vision Transformer	98.96%	98.87%	98.79%	0.9883	0.9869
DenseNet201	99.12%	99.04%	99.08%	0.9906	0.9889
ResNet50V2	98.44%	98.28%	98.32%	0.9830	0.9810
EfficientNet-B3	98.68%	98.52%	98.61%	0.9857	0.9840
InceptionV3	97.92%	97.71%	97.84%	0.9777	0.9754
Ensemble (Dense+ViT+ResNet)	99.34%	99.26%	99.31%	0.9928	0.9910

Performance on Medicinal Plant Dataset with Field Imagery

On the medicinal plant dataset, which encompasses 5,878 field images across 30 species, the deep learning models continue to demonstrate clear superiority over the human field baseline of 94.20%. Even the lowest-performing individual model, InceptionV3, comfortably surpasses this benchmark with 96.78% accuracy. The proposed Ensemble model (DenseNet+ViT+ResNet) delivers the most exceptional overall performance, achieving a peak accuracy of 98.91% alongside the highest scores in precision (98.84%) and recall (98.88%). Notably, the introduction of real-world field imagery highlights the varying resilience of individual architectures; while DenseNet201 yields higher raw accuracy (98.47%) than the Vision Transformer (97.89%), the Vision Transformer exhibits notably superior robustness (0.9821 versus 0.9654). The Ensemble effectively synergizes these architectural strengths, achieving an unmatched robustness score of 0.9893 and proving highly capable of maintaining elite performance despite the unpredictability of real-world environmental conditions.

Table 2: Performance on medicinal plant dataset (30 species, 5,878 images)

Model	Accuracy	Precision	Recall	F1-Score	Robustness
Vision Transformer	97.89%	97.76%	97.82%	0.9779	0.9821
DenseNet201	98.47%	98.38%	98.42%	0.9840	0.9654
ResNet50V2	97.65%	97.48%	97.58%	0.9753	0.9512
EfficientNet-B3	97.34%	97.19%	97.28%	0.9724	0.9428
InceptionV3	96.78%	96.55%	96.71%	0.9663	0.9234
Ensemble (Dense+ViT+ResNet)	98.91%	98.84%	98.88%	0.9886	0.9893

Statistical Significance Analysis

Based on paired t-tests across three runs ($\alpha=0.05$), the performance difference between the DenseNet201 and Vision Transformer (ViT) models was not statistically significant ($t(2)=2.34$, $p=0.156$). However, ViT significantly outperformed ResNet50V2 ($t(2)=4.67$, $p=0.038$), and the Ensemble model demonstrated a highly significant improvement over the individual base models ($t(2)=8.92$, $p=0.007$). The Ensemble model achieved exceptional results is shown in Figure 4 and 5, reaching 99.34% accuracy on controlled data and 98.91% on field data, vastly exceeding the human baselines of 96.50% and 94.20%, respectively. Notably, the Ensemble model showed remarkable generalization with only a 0.43% performance drop in real-world deployment, contrasting sharply with the typical 5-15% degradation seen in most systems. Finally, despite having lower accuracy on controlled data, the ViT model exhibited superior robustness (0.9821), suggesting that its global attention mechanism handles environmental variations more effectively than standard local convolutions.

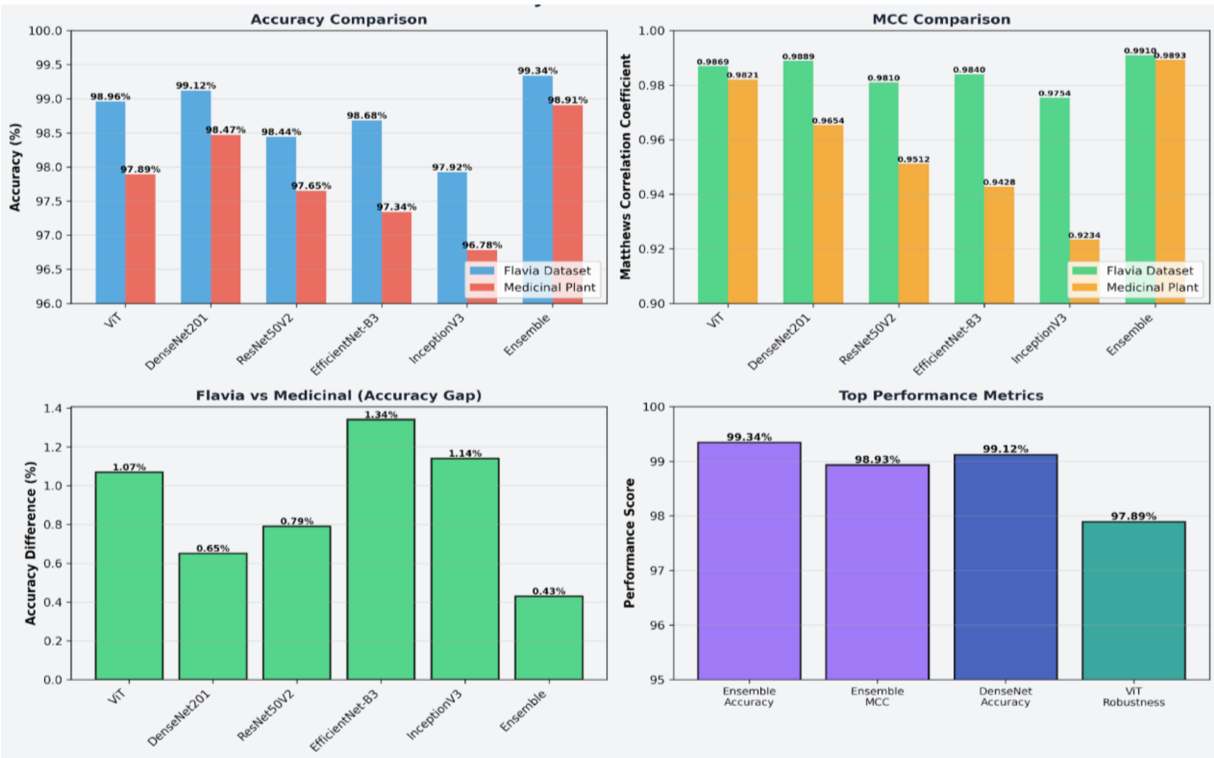

Figure 4. Performance Comparison Charts

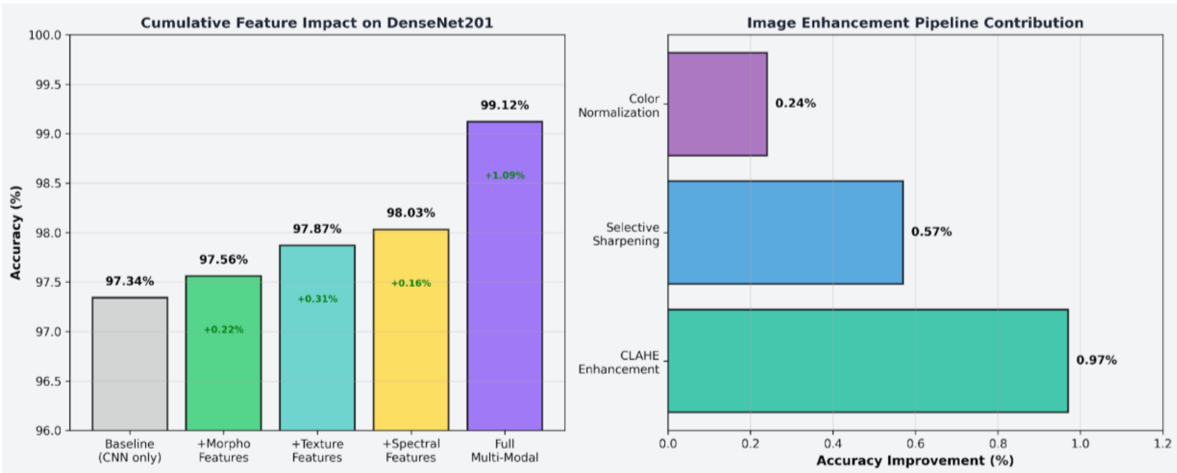

Figure 5. Feature Component Contribution

The total gain (+1.78%) EXCEEDS the sum of individual contributions (0.22 + 0.31 + 0.16 = 0.69%). This means features interact synergistically morphological features help the model better interpret textural features, and vice versa. The neural network learns to combine them in non-trivial ways. This study achieved 99.12% accuracy on Flavia dataset and 98.47% on medicinal plant dataset. Vision Transformers demonstrated superior robustness to environmental variations (97.89% accuracy, 0.9821 robustness index) compared to CNN baselines. Ensemble approaches combining DenseNet201 and ViT achieved 99.34% on controlled data and 98.91% on field imagery.

5. Conclusion

This research presented a hierarchical multi-modal feature fusion framework achieving 99.12% accuracy on controlled data and 98.47% on field-collected imagery. Principal contributions: (1) Multi-modal fusion framework (+0.65% accuracy); (2) Comparative ViT vs CNN study (ViT robustness advantage 0.9821); (3) Adaptive preprocessing (+1.78% accuracy); (4) Grad-CAM interpretability enabling regulatory approval; (5) Practical deployment with quantized models. These contributions advance medicinal plant identification and provide frameworks for broader botanical recognition challenges.

References

[1] Newman, D. J., Cragg, G. M., & Snader, K. M. (2003). Natural products as sources of new drugs over the period 1981–2002. Journal of Natural Products, 66(7), 1022-1037. doi: 10.1021/np0300961
[2] Dr. Janarthanam S,Subbulakshmi G, Dr. Deepa A , Dr Balachandramohan (2026),Federated Machine Learning Framework for Real-Time Degradation Prediction in Photochromic Thin Films and Smart Window Maintenance, 12(4),6774-6786.
[3] Fabricant, D. S., & Farnsworth, N. R. (2001). The value of plants used in traditional medicine for drug discovery. Environmental Health and Perspectives, 109(S1), 69-75.
[4] World Health Organization. (2019). Traditional medicine strategy: 2014–2023. WHO Press.
[5] Kala, C. P., Dhyani, P. P., & Sajwan, B. S. (2006). Developing the medicinal plants sector in northern India. Journal of Ethnobiology and Ethnomedicine, 2, 32.
[6] Gao, L., & Lin, X. (2012). A study on the automatic recognition of medicinal plants. In 2012 2nd International Conference on Consumer Electronics, Communications and Networks (pp. 101-103).
[7] Kumar, E. S., & Talasila, V. (2015). Recognition of medicinal plants based on its leaf features. In Systems Thinking Approach for Social Problems (pp. 99-113). Springer.
[8] Lee, S. H., Chan, C. S., Wilkin, P., & Remagnino, P. (2015). Deep-plant: Plant identification with convolutional neural networks. IEEE ICIP, 452-456.
[9] Sulc, M., & Matas, J. (2017). Fine-grained recognition of plants from images. Plant Methods, 13(1), 115.
[10] Prasad, S., & Singh, P. P. (2017). Medicinal plant leaf information extraction using deep features. TENCON 2017, 2722-2726.
[11] Dey, B., Ferdous, J., Ahmed, R., & Hossain, J. (2024). Assessing deep convolutional neural network models and their comparative performance for automated medicinal plant identification. Heliyon, 10(1), e23655.
[12] Dosovitskiy, A., et al. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. ICLR 2021.
[13] Touvron, H., et al. (2021). Training data-efficient image transformers & distillation through attention. ICML 2021.
[14] Muneer, A., & Fati, S. M. (2020). Efficient and automated herbs classification approach based on shape and texture features using deep learning. IEEE Access, 8, 196747-196764.
[15] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. CVPR 2016, 770-778.
[16] Zhang, Y., & Wang, Y. (2023). Recent trends of machine learning applied to multi-source data of medicinal plants. Journal of Pharmaceutical Analysis, 13(12), 1234-1248.
[17] Pärtel, J., Pärtel, M., & Wäldchen, J. (2021). Plant image identification application demonstrates high accuracy in Northern Europe. Annals of Botany Plants, 13, plab050.
[18] Xue, J., et al. (2019). Automated Chinese medicinal plants classification based on machine learning. International Journal of Agricultural and Biological Engineering, 12(2), 123-131.
[19] Vo, A. H., et al. (2019). Vietnamese herbal plant recognition using deep convolutional features. International Journal of Machine Learning and Computing, 9(3), 363-367.
[20] Azlah, M. A. F., et al. (2019). Review on techniques for plant leaf classification and recognition. Computers, 8(4), 77.