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MEDICINAL PLANT IDENTIFICATION: A HYBRID APPROACH COMBINING MANUAL AND DEEP LEARNING FEATURES

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ABSTRACT

Aims: To develop an automated medicinal plant identification system using image processing and deep learning techniques to improve accuracy and reduce reliance on expert knowledge. **Study Design:** Experimental study involving the classification of medicinal plant species using deep learning and machine learning approaches. **Place and Duration of Study:** Conducted in an academic research setting over a specific period. **Methodology:** A dataset of leaf and whole-plant images from six medicinal plant species was created. The approach integrates manually extracted morphological and textural features with deep learning features from a pre-trained ResNet model. These features are classified using a Random Forest classifier to enhance accuracy and robustness. Performance evaluation was conducted based on classification accuracy. **Results:** The ResNet model achieved 95% accuracy, while the hybrid model combining deep learning and manually extracted features further improved classification performance. **Conclusion:** The proposed system enhances medicinal plant identification accuracy, preserving traditional knowledge and supporting applications in botanical research, pharmaceutical development, and herbal medicine quality control. Additionally, after identifying the plant, the system provides information about its medicinal benefits, helping users understand its therapeutic applications. Further validation is required to ensure its reliability across diverse datasets.

Keywords: Medicinal Plant Identification, Feature extraction, Deep Learning, ResNet50.

INTRODUCTION

A Accurate identification of medicinal plants is vital for pharmaceutical research, traditional medicine, and conservation. It ensures herbal medicine quality, prevents misidentification risks, and aids in monitoring endangered species. However, traditional visual inspection by botanists is time-consuming, expert-dependent, and prone to errors, especially in large-scale identification tasks.

Advancements in computer vision and machine learning (ML) have enabled automated plant identification using image-based analysis. Deep learning models, particularly CNNs, have shown high accuracy but primarily focus on high-level features, often missing fine-grained morphological details crucial for distinguishing similar species.

To address these limitations, this research proposes a hybrid medicinal plant identification system integrating manual feature extraction with deep learning-based feature representation using ResNet, followed by classification with Random Forest (RF). A dataset of 659 images spanning six medicinal plant species (from Kaggle and self-collected data) is used for training and evaluation. This hybrid approach enhances classification by combining handcrafted features (leaf shape, venation, texture descriptors like GLCM, LBP, and Hu moments) with deep learning-based feature extraction from ResNet50, ensuring interpretable insights and improved accuracy. Additionally, after identifying the plant, the system provides detailed information on its medicinal benefits, offering valuable insights into its therapeutic applications.

By comparing ML and deep learning models, this study aims to determine the most effective approach for medicinal plant identification, enhancing accuracy, reliability, and accessibility for scientific research, herbal medicine, and conservation efforts.

LITERATURE REVIEW

In their 2017 study, Adams Begue, Venitha Kowlessur, Upasana Singh, and Fawzi Mahomoodally conducted research on the automatic recognition of medicinal plants using machine learning techniques in Mauritius. The researchers employed various feature enhancement methods, such as binary image processing, bounding boxes, contours, vertical and horizontal distance maps, and radical maps, to improve the recognition accuracy of medicinal plants. They tested multiple classifiers, including Random Forest, Probabilistic Neural Network (PNN), Support Vector Machine (SVM), Naïve Bayes, and k-Nearest Neighbors (k-NN), and reported accuracies of 90.1%, 88.2%, 87.4%, 84.3%, and 82.5%, respectively. The study utilized a dataset consisting of 720 images, which represented 24 different species of medicinal plants, demonstrating the effectiveness of machine learning approaches in this domain (Begue *et al.,* 2017).[1]
R. Upendar Rao, M. Sai Lahari, K. Pavana Sri, K. Yaminee Srujana, and D. Yaswanth (2022) conducted a study on the identification of medicinal plants using deep learning techniques. The study utilized DenseNet for feature enhancement and implemented a CNN classifier to achieve accurate results. The dataset comprised 1,500 images, with 30 leaf samples for each of the 50 species examined. Their approach yielded an accuracy of 91.6%, demonstrating the effectiveness of combining DenseNet with a CNN classifier.[2]

Electronics and Telecommunication Engineering students developed automatic recognition system for mango fruits using edge and color based segmentation methods. K-means clustering and canny edge detection methods used in image segmentation. Color based algorithm outperform and yield 85% than edge based algorithm.[3]

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Manojkumar P., Surya C *et al.,* [1] collected 20 random Ayurvedic front and back side leaves of 40 different species. The Weka tool is used for identification of medicinal plants using machine learning algorithms. Color and texture features of leaves are extracted from color and binary images. Support Vector Machine (SVM) and Multilayer perceptron (MLP) classifiers are used to identify the leaves based on following features Geometric, centroid-radii (CR) distances, colour features, texture features, HU invariant moments and Zernike moments. MLP (94.5%) out formed than Support Vector Machine (SVM).[4]

S. Kavitha, T. Satish Kumar, E. Naresh, Vijay H. Kalmani, Kalyan DevappaBamane, and Piyush Kumar Pareek (2023) conducted a study on medicinal plant identification using deep learning techniques. The study incorporated feature enhancement techniques such as image preprocessing, including resizing and normalization, to improve classification accuracy. Feature extraction was performed using MobileNetV2, a pretrained deep learning model, without applying data augmentation. The classification was carried out using MobileNetV2, which demonstrated superior performance, achieving an accuracy of 95%. The dataset comprised 1,784 images, with 1,428 images used for training and 357 for testing, covering six medicinal plant species: Aloe vera, Lemon, Mango, Neem, Tulsi, and Turmeric. Their approach highlighted the effectiveness of MobileNetV2 in accurately classifying medicinal plants.[5]

Sukanta Ghosh, Amar Singh, and Shakti Kumar (2023) conducted a study on medicinal plant identification using feature enhancement techniques and deep learning models. They employed Principal Component Analysis (PCA) for feature extraction and hybrid transfer learning. For classification, they used VGG16, a pre-trained model, and compared it with ResNet50, Inception V3, Xception, DenseNet121, and MobileNetV2. Their results showed an accuracy of 94% after 10 and 25 epochs, with the best accuracy of 95.25% achieved after 50 epochs. The dataset, which included 30 species, contained a total of 1,500 images, although the number of images per species was not explicitly mentioned.[6]

J. Samuel Manoharan (2021) conducted a study on herbal plant identification using machine learning techniques. The study employed feature enhancement techniques such as edge detection methods, including Prewitt, Canny, Laplace, and Sobel operators, to improve classification accuracy. Feature extraction was performed using the chi-square technique to enhance classification efficiency. The classification was carried out using a CNN-based model, incorporating a two-stage authentication (TSA) process with Ex-OR gate operations for improved recognition. The proposed method achieved an accuracy of 92%. The dataset consisted of 250 leaf samples, with an 80%-20% train-test split, covering herbal plant species such as Tulsi, Omavalli, Neem, VanaThulasi, Thudhuvalai, and Lime. The study demonstrated the robustness of the proposed approach in accurately identifying herbal plant leaves.[7]

A. Gopal, S. Prudhveeswar Reddy, and V. Gayatri (2012) conducted a study on plant identification using image processing techniques. The study utilized feature enhancement techniques such as segmentation, filtering, and feature extraction from plant leaves to improve classification accuracy. The classification approach was implemented using an unspecified method, achieving an accuracy of 92%. The dataset consisted of 100 leaf images for training and 50 leaf images for testing, covering ten different plant species. Their approach demonstrated the effectiveness of image processing techniques in identifying and classifying plant species accurately.[8]
B.R. Pushpa, S. Jyothsna, and S. Lasya (2025) conducted a study on medicinal plant identification using deep learning techniques. The study incorporated feature enhancement techniques such as image pre-processing, including resizing and normalization, to improve classification accuracy. Feature extraction was performed using MobileNetV2, a pretrained deep learning model, without applying data augmentation. The classification was carried out using MobileNetV2, which demonstrated superior performance, achieving an accuracy of 94%. The dataset comprised 1,784 images, with 1,428 images used for training and 357 for testing, covering six medicinal plant species: Aloe vera, Lemon, Mango, Neem, Tulsi, and Turmeric. Their approach highlighted the effectiveness of MobileNetV2 in accurately classifying medicinal plants.[9]

Kuldeep Vayadande, Premanand P. Ghadekar, Aparna Sawant, Maya P. Shelke, BhairaviShirsath, Bhakti Bhande, Harshada Sawai, SrushtiGawade, and Suraj Samgir (2024) conducted a study on medicinal plant classification using a CNN-based model. The study incorporated feature enhancement techniques such as image pre-processing, including noise reduction, contrast enhancement, pixel equalization, and reflection removal, to improve classification accuracy. The classification was performed using a Convolutional Neural Network (CNN), which achieved an accuracy of 91%. The dataset used for this study was sourced from Kaggle and contained 1,835 images covering 30 medicinal plant species, including Jamun, Tulsi, Neem, Rasna, Jackfruit, Basale, Indian Mustard, Karanda, Lemon, Peepal, Jasmine, Mango, Mint, Drumstick, Curry, Parijata, Betel, Mexican Mint, Indian Beech, Guava, Sandalwood, Rose Apple, Fenugreek, and more. Their approach demonstrated the effectiveness of CNN in accurately classifying medicinal plants.[10]

Rohan Kumar Verma, Prof. Syeeda, and Sagar M. Prajapathi (2024) conducted a study on medicinal plant identification using deep learning techniques. The study incorporated feature enhancement techniques such as image pre-processing, including resizing and normalization, to improve classification accuracy. Feature extraction was performed using MobileNetV2, a pretrained deep learning model, without applying data augmentation. The classification was carried out using MobileNetV2, which demonstrated superior performance. The dataset comprised 1,784 images, with 1,428 images used for training and 357 for testing, covering six medicinal plant species: Aloe vera, Lemon, Mango, Neem, Tulsi, and Turmeric. Their approach highlighted the effectiveness of Mobile NetV2 in accurately classifying medicinal plants.[11]

METHODOLOGY

Medicinal Plant Dataset

The success of any machine learning project depends on the quality and diversity of its training data. This medicinal plant identification project utilizes 659 images of 6 species, incorporating both leaf and full-plant images to enhance classification accuracy. Leaf images capture fine morphological details, while full-plant images provide broader structural context, aiding in distinguishing closely related species. Public datasets like Kaggle offer a strong foundation but may introduce biases, inconsistencies, and annotation errors. To address this, self-collected images are included, ensuring better species representation and model generalization. These images are captured under varied lighting, angles, and backgrounds to improve robustness. Multi-angle acquisition further minimizes over fitting by exposing the model to different viewpoints.

For efficient training, the dataset is organized into species-specific folders, streamlining data processing and evaluation. However, class imbalance remains a challenge, potentially affecting model fairness. Additionally, computational constraints influenced the selection of six species, as training deep learning models like ResNet and MobileNet demands high-performance GPUs (Graphics Processing Units) and extensive memory. Large datasets significantly increase training time, GPU load, and resource consumption, requiring access to powerful hardware or cloud-based GPU services. Furthermore, deploying the model on low-resource devices necessitates optimization for efficient inference without compromising accuracy.

Following are some species with their local name, scientific name and images :

Table No. 1: Local Name and Scientific Name of 6 species with their Images

 Aloe barbadensis miller	 Citrus limon	 Mangifera indica
 Azadirachtaindica	 Ocimumtenuiflorum	 Curcuma longa

Image Preprocessing

The preprocessing pipeline is designed to enhance image quality and facilitate feature extraction. Resizing images to a uniform 224x224 pixels ensures consistency for deep learning models, while normalization to the 0-1 range improves model training stability. Gaussian blur reduces noise without significantly blurring important details, while bilateral filtering preserves texture details. The careful selection of filter parameters is critical to balancing noise reduction and detail preservation. Grayscale conversion simplifies the data when color is not critical, although this decision needs careful evaluation as color can be a significant distinguishing factor for some species.

Morphological operations (erosion, dilation, contour detection) refine leaf boundaries and extract shape features. These operations require careful parameter tuning to optimize results , and their effectiveness depends on the initial image segmentation quality. The segmentation step, isolating the leaf from the background, is crucial for both manual and deep learning feature extraction. While the description mentions segmentation, the specific techniques employed are not detailed. A variety of methods exist, including thresholding, region-growing, and more sophisticated approaches like U-Net , each with its strengths and weaknesses. The choice of segmentation technique should be explicitly stated and justified.

Finally, the dataset is split into training, validation, and testing sets for fair evaluation . The specific splitting strategy and proportions should be explicitly defined. Stratified sampling is preferred to ensure that the class distribution is maintained across the subsets.

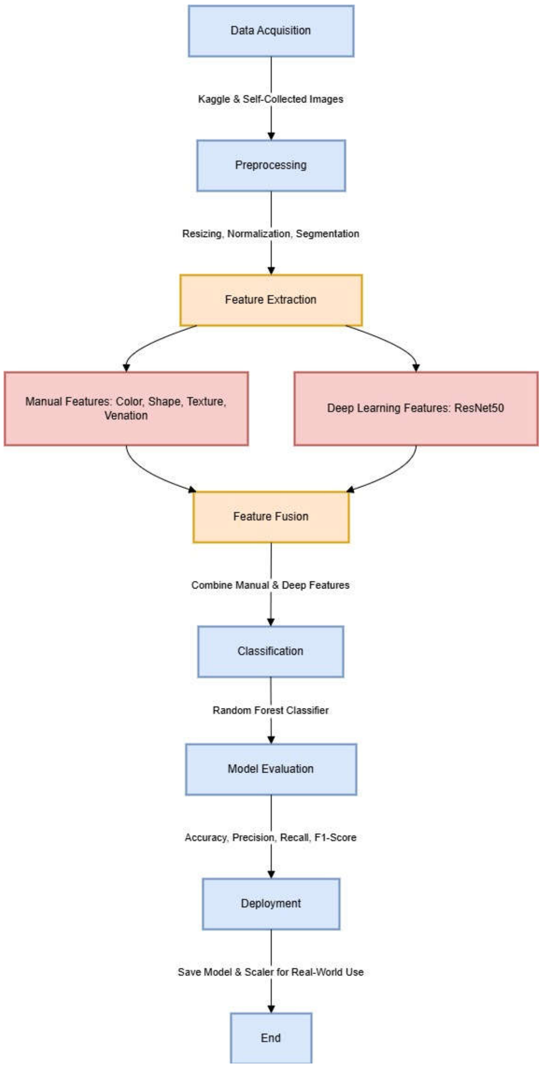

Fig 1 : Medicinal Plant Identification Workflow

Feature Extraction

The workflow employs a hybrid feature extraction approach, combining manual (handcrafted) features with deep learning features extracted from a ResNet50 model. This strategy aims to leverage the strengths of both approaches: the interpretability and domain-specific knowledge of manual methods, and the power of deep learning to capture complex patterns.

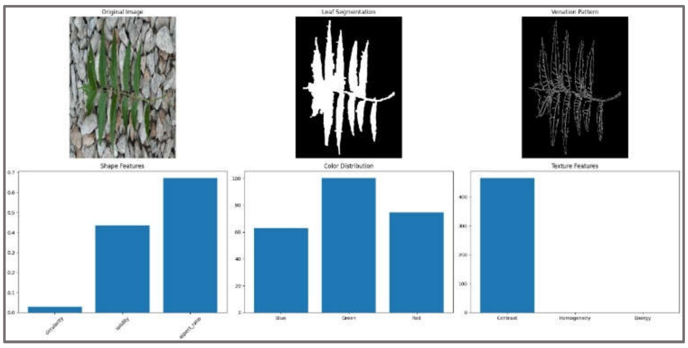

Fig 2 : Visualization of extracted features

Manual feature extraction involves the computation of color, shape, texture, and venation features. Color features (BGR, HSV, LAB color statistics) capture color variations, which can be significant for species differentiation. Shape features (area, perimeter, circularity, aspect ratio, solidity, eccentricity, Hu moments) quantify the leaf's geometry. Texture features (GLCM, Haralick, LBP) capture surface patterns, while venation features (Canny and Sobel edge detection) characterize leaf vein patterns. The selection of these features should be justified based on their relevance to plant morphology and established botanical knowledge. The use of multiple texture analysis techniques (GLCM, Haralick, LBP) is a strength as it allows for a more comprehensive representation of textural information. However, it also increases the dimensionality of the feature space, potentially leading to over fitting. Feature selection techniques should be considered to reduce dimensionality and improve model performance. Deep learning feature extraction uses a pre-trained ResNet50 model to extract a 2048-dimensional feature vector from the global average pooling layer. ResNet's deep architecture enables the learning of high-level features capturing subtle variations in morphology and texture. The use of a pre-trained model leverages knowledge learned from a large dataset (ImageNet), providing a strong starting point for feature extraction. Fine-tuning the ResNet50 model on the medicinal plant dataset further enhances its ability to capture species-specific features. The choice of ResNet50 is justified, but a comparison with other CNN architectures (VGG, Inception, EfficientNet) would strengthen the analysis and determine if ResNet50 is indeed the optimal architecture for this specific task.

Table 2: Extracted Features

Feature Type	Feature Count	Description
Manual Features	202	Color, Shape Texture, Venation
Deep Features (ResNet50)	2050	High-level extracted features
Total Features	**2250**	**Combined manual and deep features**

The dataset consists of 659 images representing six medicinal plant species, divided into training (80%) and testing (20%) sets. A total of 2250 features were extracted, combining 202 manually crafted features (e.g., texture, shape, venation) with 2050 deep learning features obtained using ResNet50. This fusion ensures the model captures both handcrafted and learned representations for better classification accuracy.

Feature Fusion & Classification

Feature combination merges the manual and deep learning features into a comprehensive feature vector. The exact method of fusion (concatenation, weighted averaging, or other techniques) is not specified, but this is a crucial aspect requiring careful consideration. The optimal fusion strategy depends on the nature of the extracted features, the dimensionality of the feature spaces, and the characteristics of the Random Forest classifier. Exploring different fusion techniques and evaluating their impact on classification performance would be beneficial.

The workflow uses a Random Forest classifier with 100 estimators and a stratified train-test split. Random Forest is a robust ensemble method suitable for high-dimensional data, offering feature importance ranking, which can provide insights into the most discriminative features. However, Random Forest's performance is sensitive to hyper parameter tuning, and optimization techniques like grid search or cross-validation are essential to find optimal settings. The description mentions a stratified train-test split, which is appropriate for handling class imbalances. The number of estimators (100) is a reasonable starting point, but the optimal number might vary depending on the dataset and computational resources. A hyper parameter optimization study is necessary to determine the ideal number of estimators for this specific application.

After classifying the plant species, the system retrieves relevant information about its medicinal properties from a database. The final output not only displays the plant's identity but also provides details on its benefits, including therapeutic applications and traditional uses. This feature enhances the practical utility of the system by offering users valuable insights into the medicinal value of the identified plant.

Table 3: Classification report of the proposed model

Species	Precision (%)	Recall (%)	F1-Score (%)
Aloevera	98	98	98
Lemon	86	100	92
Mango	100	91	95
Neem	100	91	95
Tulsi	97	91	94
Turmeric	100	100	100
Overall Accuracy	**95%**	**-**	**-**

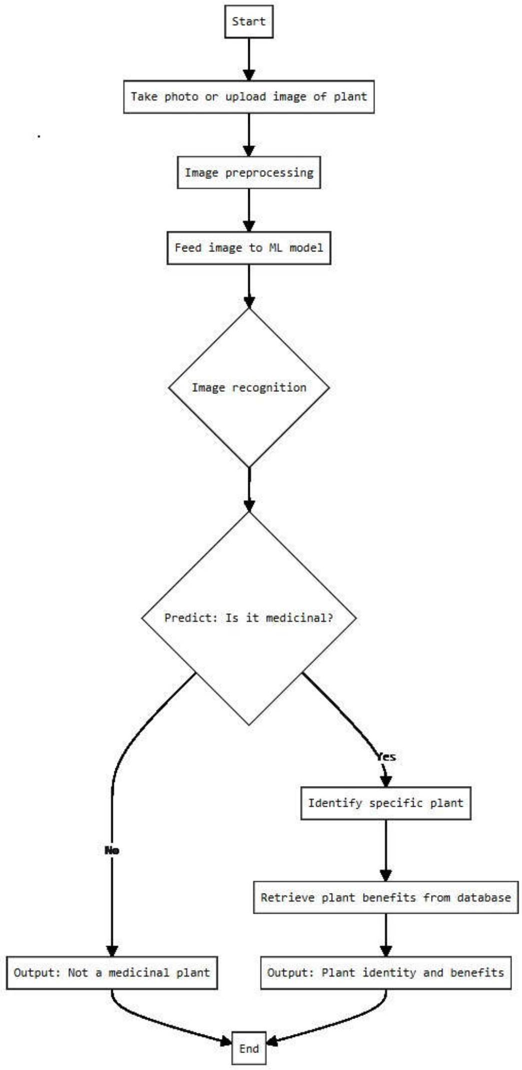

Fig 3 : Flow Chart

The process begins with the user either taking a photo or uploading an image of a plant. The image undergoes preprocessing to enhance its quality for better analysis. The processed image is then fed into the machine learning model for plant recognition. The model classifies whether the plant is medicinal. If the plant is medicinal, the system identifies the specific plant species and retrieves relevant benefits from a database. The output displays both the plant identity and its benefits. If the plant is not medicinal, the system outputs a message indicating that it is not a medicinal plant. This flow ensures accurate and efficient identification and classification of medicinal plants.

RESULTS AND DISCUSSION

To assess the performance of the proposed medicinal plant identification model, standard classification evaluation metrics are used, including Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive understanding of the model's effectiveness in correctly identifying medicinal plant species.

1. Accuracy: Measures the overall correctness of the model, calculated as:
   Accuracy = (TP+TN)/(TP+TN+FP+FN)
   It is useful for balanced datasets but may be misleading in imbalanced cases.
2. Precision: Indicates the proportion of correctly predicted positive instances out of all predicted positives:
   Precision = (TP)/(TP+FP)
   High precision reduces false positives, crucial in pharmaceutical applications.
3. Recall: Measures the model's ability to correctly identify actual positive instances:
   Recall = (TP)/(TP+FN)
   High recall minimizes false negatives, essential for accurate plant classification.
4. F1-Score: The harmonic mean of Precision and Recall, balancing both metrics:
   F1-Score = 2 * (Precision * Recall)/(Precision + Recall)
   It is effective when both false positives and false negatives need to be minimized.

The proposed hybrid medicinal plant identification model achieved an overall accuracy of 95%, outperforming traditional machine learning (ML) models and standalone deep learning (CNN) approaches. The feature importance analysis revealed that leaf area, texture-based Local Binary Pattern (LBP) bins, Hu moments, and perimeter were among the most significant features for classification. This highlights the importance of combining handcrafted and deep learning features to improve model performance.

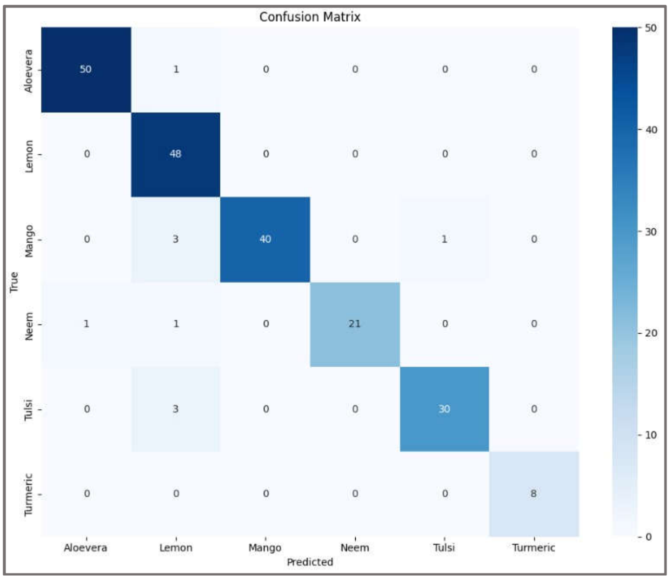

Fig 4 : Confusion Matrix

The confusion matrix analysis showed that Aloevera, Mango, Neem, and Turmeric had high classification accuracy, with minimal misclassifications. However, Lemon and Tulsi exhibited minor misclassifications, primarily due to similar morphological characteristics. These errors suggest the need for further feature engineering, such as higher-resolution vein segmentation or Fourier descriptors for shape differentiation. The classification report further supports this, with high precision and recall values across all species, while Lemon and Tulsi had slightly lower recall.

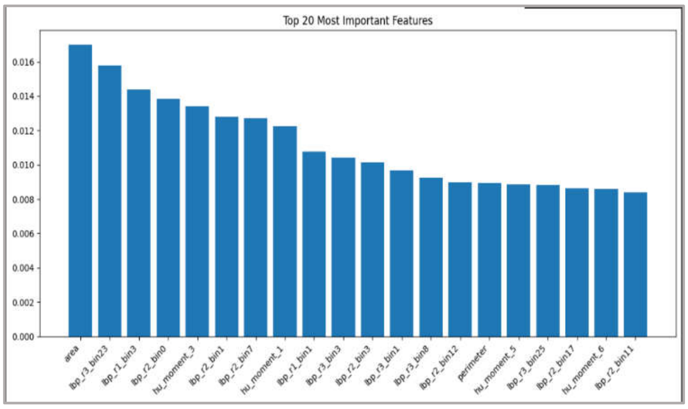

Fig 5 : Top 20 most important features ranked by the Random Forest model.

The feature importance ranking (Figure 6) highlights that leaf area, LBP bins, and Hu moments are the most influential parameters in plant classification. This suggests that texture-based and shape-based features play a crucial role in distinguishing species. The results validate the effectiveness of combining manual feature extraction with deep learning features to improve accuracy.

The table compares the performance of various Machine Learning (ML) and Deep Learning (DL) models for medicinal plant identification. Among traditional ML models, Random Forest (81% accuracy) outperforms SVM and KNN. The basic CNN model (79% accuracy) performs similarly to SVM. Pretrained models show superior performance, with ResNet model combined with Manual Feature Extraction achieving the highest accuracy (95%), outperforming MobileNet (92%), AlexNet (91%), and Visualizing CNN (86%). This highlights that ResNet is the most effective model, providing the best accuracy, precision, recall, and F1-score, making it the optimal choice for medicinal plant classification.

These results confirm that the proposed hybrid approach effectively improves medicinal plant classification. However, addressing dataset expansion, optimizing feature selection, and reducing misclassifications will further enhance the model's robustness and real-world applicability.

Table No. 4: Model comparison Which Were Obtained The Different Model

Types of Models	Model Application	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Machine Learning Algorithm	SVM	79	80	79	79
	Random Forest	81	81	84	82
	KNN	76	75	78	77
Deep Learning Algorithm	Convolution Neural Network	79	79	77	77
Pretrained	MobileNet	92	92	93	92

Model	ResNet(with Manual Feature Extraction)	95	96	95	95
	Visualizing CNN	86	89	85	87
	AlexNet	91	90	91	91

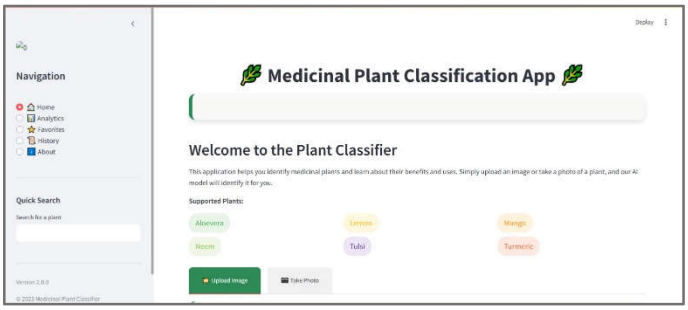

Fig 6 : Web Application Interface

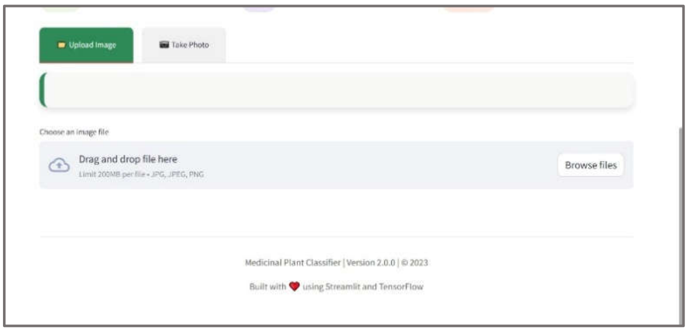

Fig 6 : Web Application Interface

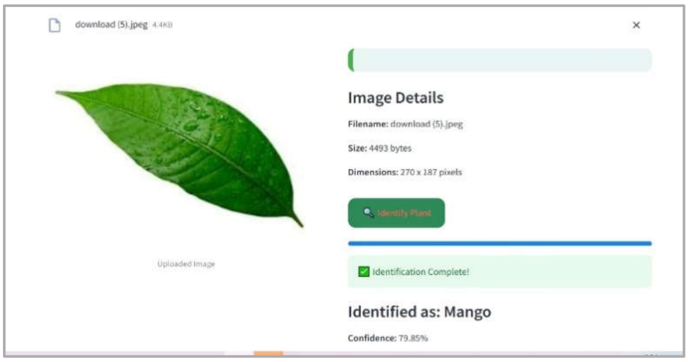

Fig 8 : Web Application Interface

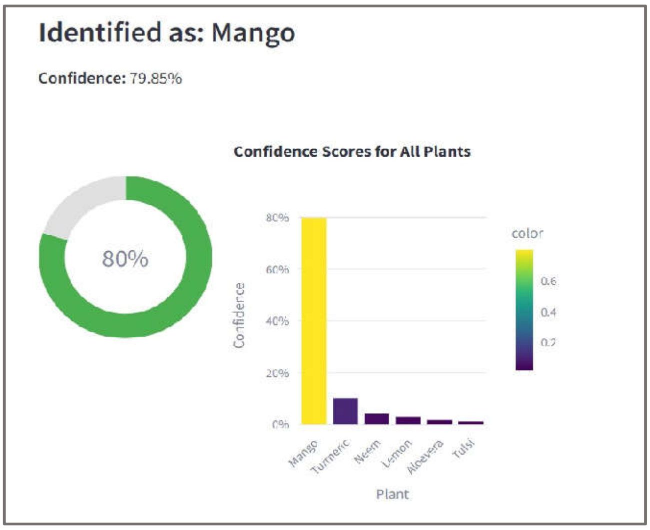

Fig 9 : Web Application Interface

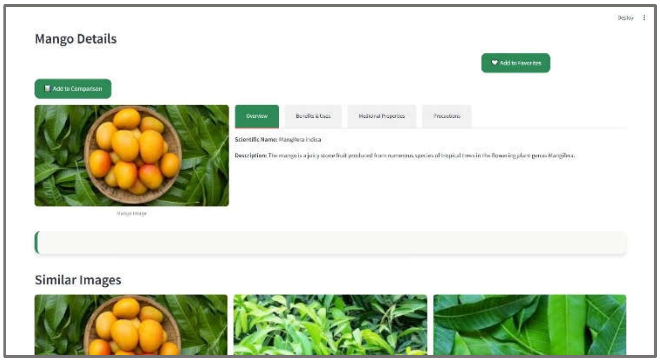

Fig 10 : Web Application Interface

Fig 11 : Web Application Interface

Fig 6, Fig 7, Fig 8, Fig 9, Fig 10, Fig 11 are Interface displaying the results of a medicinal plant identification, showing the species and its benefits.

CONCLUSION

The proposed hybrid medicinal plant identification model successfully integrates manual feature extraction with deep learning-based feature representation (ResNet50) to improve classification accuracy. By leveraging handcrafted features such as color, shape, texture, and venation, along with 2048-dimensional deep features, the model achieves a high classification accuracy of 95%, outperforming traditional machine learning (SVM, KNN, RF) and standalone CNN models. The Random Forest classifier, trained on the combined feature set, enhances performance by effectively capturing both low-level handcrafted features and high-level deep features.

The feature importance analysis confirmed that leaf area, texture-based LBP features, and shape descriptors (Hu Moments, perimeter) play a critical role in classification. The confusion matrix analysis revealed minor misclassifications in species with similar morphological characteristics (e.g., Lemon and Mango, Tulsi and Neem). However, the overall precision, recall, and F1-score remain consistently high across all species, validating the effectiveness of feature fusion in plant classification.

Despite the strong performance, several areas require further optimization. Expanding the dataset to include more species, implementing advanced feature selection techniques (PCA, RFE), and reducing computational costs through model optimization will enhance real-world applicability. Additionally, deploying the model as a mobile or web application can make it accessible for botanists, researchers, and the pharmaceutical industry.

This research demonstrates that combining manual and deep features significantly enhances medicinal plant identification, offering a scalable, accurate, and interpretable solution. Future work will focus on improving model generalization, optimizing feature fusion strategies, and enhancing interpretability using SHAP or LIME to make the system more transparent and adaptable for real-world deployment.

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Srushti Patil
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Tanvi Shendarkar
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