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Identification of Different Medicinal Plants/Raw materials through Image Processing Using Machine Learning Algorithms

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Abstract

India's traditional medical systems rely extensively on medicinal plants, yet accurate identification remains a persistent challenge due to morphological similarities, regional and seasonal variations, and limited botanical expertise among collectors and traders. These issues lead to adulteration and substitution, thereby diminishing treatment efficacy and eroding public trust in Ayurvedic remedies. This project presents a machine learning-based image processing system to automatically classify medicinal plants from leaf images. A Convolutional Neural Network (CNN) architecture, trained on a curated dataset using PyTorch, demonstrated an accuracy of 87%, with high precision and recall. This automated system offers a scalable solution to improve quality control across the herbal drug supply chain.

Keywords:

Medicinal Plant Identification, Image Processing, Machine Learning, Convolutional Neural Network (CNN), PyTorch, Ayurvedic Medicine, Leaf Classification, Deep Learning, Herbal Drug Authentication, Computer Vision

I. Introduction

India is recognized for its vast biodiversity and rich heritage in the use of medicinal plants, especially within the framework of Ayurveda. These natural remedies are often derived from plant parts such as leaves, roots, and bark, which require accurate identification for proper therapeutic use. However, due to overlapping morphological features, seasonal variations, and regional naming inconsistencies, accurate identification of these raw materials poses a significant challenge. Misidentification has led to the sale of incorrect or adulterated herbs, negatively impacting patient health, reducing the effectiveness of treatments, and undermining confidence in traditional medicine systems.

The need for a reliable and scalable solution has led researchers to explore computational methods for medicinal plant identification. Recent advances in image processing and machine learning, particularly Convolutional Neural Networks (CNNs), have demonstrated promising results in automating visual classification tasks. By training a CNN on labeled images of medicinal plant leaves, it becomes possible to build a software tool that can assist in accurately identifying plant species from raw images. This tool would be valuable across the supply chain, from collectors to distributors and quality assurance personnel, enabling more accurate sourcing and verification of herbal raw materials.

II. Problem Statement

Efforts to ensure the safety and authenticity of Ayurvedic medicinal products have traditionally relied on expert knowledge, manual inspection, and local sourcing practices. While these methods are essential, they often fall short when scaled to the demands of the modern herbal industry. In particular, they overlook the systemic problem of plant misidentification and the limitations of human expertise in distinguishing between morphologically similar species. For instance, leaves from Ashwagandha and other similar-looking plants may be sold under the same name due to geographic or seasonal similarities, leading to adulteration and reduced treatment efficacy.

Existing solutions, such as botanical reference manuals or barcode systems, are limited in practical use for traders, suppliers, and quality controllers. These approaches are typically static, not scalable, and heavily dependent on human judgment. Furthermore, no standardized digital system currently exists to automate plant identification reliably using modern computational techniques. As a result, stakeholders in the medicinal plant supply chain face ongoing risks in quality control, authenticity, and regulatory compliance.

Objectives

This research aims to bridge the gap between traditional knowledge and modern technology through the development of an AI-powered image classification system. The primary objectives of this project are:

1. **Automated Identification**: Develop a software system capable of identifying medicinal plants using machine learning algorithms applied to leaf images.

2. **Accuracy Through Deep Learning**: Employ a Convolutional Neural Network (CNN) model trained on a curated dataset to achieve high classification precision and recall.

3. **Preprocessing and Augmentation**: Enhance model generalization using image preprocessing techniques like resizing, normalization, and augmentation.

4. **End-User Deployment**: Integrate the system with a user-friendly web or mobile interface to ensure accessibility for wholesalers, distributors, and Ayurvedic practitioners.

5. **Adaptability and Scalability**: Design a modular and scalable architecture that can be extended to include additional plant species and image features (e.g., stems, flowers).

Significance

This project surpasses the limitations of manual identification by combining high computational accuracy with user-friendly software deployment. By using image-based learning methods, the system eliminates the ambiguity of subjective identification and provides a consistent, reliable tool across the supply chain. It also alleviates the over-dependence on experts and local knowledge, offering an inclusive solution for users with minimal botanical expertise.

Furthermore, the ability to rapidly and accurately classify plant species contributes to the preservation of endangered species, improved consumer safety, and a strengthened regulatory framework for herbal medicine. This work contributes to global sustainability and healthcare initiatives by promoting ethical and informed use of plant-based resources.

Unique Contributions

The proposed system introduces several innovations over existing approaches:

1. **Image-Based Identification**: Moves beyond textual databases to enable visual recognition using deep learning.
2. **CNN Architecture**: Implements a custom convolutional model for feature extraction and classification of plant species.
3. **Preprocessing Pipeline**: Employs advanced image normalization and augmentation for robust training.
4. **Evaluation Metrics**: Uses a range of metrics (accuracy, precision, recall, F1 score) to validate the model on unseen data.
5. **Scalable System**: Can be integrated into larger applications (e.g., mobile apps) with minimal computational overhead.

III. Related Work

Understanding the landscape of existing tools and methodologies for identifying medicinal plants using image processing and machine learning is essential for positioning this work as a novel and impactful contribution. Over the years, several systems have been developed—ranging from handcrafted feature extraction to sophisticated deep learning models. However, these systems often struggle with limitations such as scalability, user accessibility, robustness to image variability, or lack of domain specificity. This project builds upon and extends these efforts by integrating advanced deep learning techniques such as Convolutional Neural Networks (CNNs), transfer learning, and hybrid classification strategies. This section reviews relevant research works, noting their strengths and shortcomings, and contextualizes the current system in this evolving domain.

1. **AyurLeaf and DLeaf (Dileep M.R., Jing Wei Tan, 2020–2022)**
   AyurLeaf and DLeaf are deep learning models developed specifically for medicinal plant classification. AyurLeaf uses CNNs with SVM classifiers and SoftMax activation, trained on AyurLeaf and DLeaf datasets, and reported a classification accuracy of 96.76%. DLeaf focused on venation features extracted using Sobel edge detection and classified with an artificial neural network (ANN), achieving 94.88% accuracy.

Relevance to this project:

While both models demonstrated high accuracy, they were trained on limited datasets and focused mainly on leaf shape and venation. The current project expands on this by including both front and back leaf textures and employing DenseNet121 architecture, which promotes feature reuse and improves model efficiency.

2. **MobileNetV3 with Transfer Learning (Valdez et al., 2020)**
   This study introduced a dataset of 10 plant species and a mixed weeds class, using MobileNetV3 and transfer learning to achieve a 97.43% classification accuracy. The approach demonstrated the feasibility of mobile-compatible, lightweight models.

Relevance to this project:

The current work is compatible with deployment on lightweight devices but places greater emphasis on Indian medicinal species and includes data augmentation and preprocessing techniques to improve robustness across varying lighting and orientation conditions.

3. **GLCM and Traditional Feature Extraction (Turkoglu & Hanbay, Pushpa et al., 2020)**
   These approaches utilized Gray-Level Co-occurrence Matrix (GLCM), texture, and shape-based features, combined with classifiers like K-Nearest Neighbors (KNN) and Extreme Learning Machines (ELM). While computationally efficient, these methods lacked adaptability and suffered from lower accuracy in uncontrolled settings.

Relevance to this project:

The proposed CNN-based approach surpasses these limitations by eliminating manual feature engineering and learning robust hierarchical features from raw image data.

4. **SIFT + Color Moments and SURF + HoG Features (Nuril Aslina et al., Amala Sabu et al.)**
   These works extracted keypoints using SIFT and SURF descriptors and calculated color moments across HSV planes. Although reasonably accurate (87.5%+), they were computationally expensive and struggled with rotation and scale invariance.

Relevance to this project:

By applying CNNs with integrated data augmentation techniques (e.g., flipping, zooming, rotation), the current system achieves rotation invariance and eliminates the need for manual descriptor tuning.

5. **DenseNet with Front and Back Leaf Features (R. Upendar Rao et al., 2022)**
   This work used DenseNet121 to classify 50 species using both the front and back of leaves. The approach included manual dataset creation and implemented a CNN in Keras, capturing texture and shape features for robust classification.

Relevance to this project:

This system directly inspired the methodology adopted here. The current work refines this further with expanded species coverage, normalization techniques, and integration into web/mobile platforms for real-time use.

IV. Proposed System

Accurate identification of medicinal plants is essential for the efficacy of Ayurvedic, folk, and herbal remedies. While previous systems have explored traditional machine learning techniques and handcrafted features, they often lack robustness, adaptability, and user-friendly deployment mechanisms. This proposed system leverages Convolutional Neural Networks (CNNs), specifically DenseNet architecture, to offer an advanced and scalable solution for the classification of medicinal plant leaves based on their front and back textures, colors, and morphological features.

The proposed system improves upon earlier models by addressing gaps such as feature generalization, data acquisition complexity, and usability in real-world conditions. It integrates image preprocessing, deep learning classification, and real-time result visualization into a cohesive framework. Designed with researchers, taxonomists, drug manufacturers, and field practitioners in mind, the system provides a precise and rapid method to determine a plant's species and its medicinal relevance.

System Features

1. **Leaf Image Acquisition:**

   Leaf images are obtained through two methods:
   a. Scanning front and back sides of leaves using high-resolution flatbed scanners.
   b. Real-time image capture via a camera interface for field deployment.

2. **Dataset Construction:**

   The dataset includes 50 different medicinal plant species, each with at least 30 samples collected from local ecosystems. Each leaf is represented by both front and back images, resulting in over 3,000 samples. Species include Tulsi (Ocimum tenuiflorum), Neem (Azadirachta indica), Ashwagandha (Withania somnifera), and others frequently used in Ayurvedic preparations.

3. **Image Preprocessing:**

   Images are resized to a standard dimension (e.g., 224x224 pixels) and normalized to improve model convergence. Augmentation techniques such as rotation, flipping, and zooming are applied to simulate real-world variance in lighting and orientation.

4. **CNN Architecture – DenseNet121:**

   The core classification engine is built on the DenseNet121 architecture. DenseNet is chosen for its ability to:

   - Enhance feature reuse through dense layer connections.
   - Strengthen gradient flow to prevent vanishing gradients.
   - Improve accuracy while maintaining computational efficiency.

The network consists of:

- Input Layer: Accepts 224x224 RGB images.
- Convolutional and Pooling Layers: Extracts hierarchical features.
- Dense Blocks with Transition Layers: Connects layers in a feed-forward manner.
- Output Layer: SoftMax activation for multi-class classification.

5. **Model Training and Evaluation:**

- Loss Function: Categorical Cross-Entropy
- Optimizer: Adam (learning rate = 0.001)
- Epochs: 50 (tuned based on convergence behavior)
- Accuracy and Loss tracked during training and validation
- Confusion matrix generated to evaluate precision, recall, and F1-score

6. **Real-Time Prediction Module:**

Users can upload an image via a web interface or capture it via camera. The system then:

- Predicts the plant species
- Displays its local name, scientific name, and known medicinal properties
- Returns confidence score for classification

7. **Deployment:**

- Frontend: Next.js with Tailwind CSS for responsive UI
- Backend: FastAPI or Flask API serving the PyTorch-trained model
- Hardware: Works on both GPU and CPU, adaptable for mobile deployment

Methodology

This section outlines the technical framework and workflow adopted for the development of the medicinal plant identification system. The methodology integrates image acquisition, preprocessing, deep learning model development, performance evaluation, and deployment strategies. By leveraging a DenseNet-based Convolutional Neural Network (CNN) and curated datasets of medicinal leaf images, the system automates the classification process with high accuracy and practical usability.

Data Acquisition and Dataset Preparation

To build a robust classification model, a comprehensive dataset was created:

- 50 distinct medicinal plant species were selected based on their frequent use in Ayurvedic and herbal medicine (e.g., Tulsi, Neem, Ashwagandha).
- For each species, 30+ leaf samples were collected, resulting in over 3,000 images.
- Both the front and back sides of each leaf were scanned or captured via camera to preserve shape, vein, and texture details.
- Images were stored in structured directories labeled by species name.

Relevance:
The bidirectional imaging strategy enhances model learning by exposing it to both surface textures and venation patterns, which are critical for accurate species differentiation.

Image Preprocessing

To ensure consistent input to the CNN model and improve generalization, the following preprocessing steps were applied:

- Resizing all images to 224×224 pixels
- Normalizing pixel values to [0, 1] range
- Converting to RGB format (if grayscale)
- Augmentation using:
  - horizontal and vertical flipping
  - Rotation (±15 degrees)
  - Zoom-in and cropping

Relevance:
These steps reduce overfitting and simulate real-world image variability in lighting, angle, and orientation.

Model Architecture: DenseNet121

The CNN used for this project is based on the DenseNet121 architecture, chosen for its efficiency and accuracy in image classification tasks. Key components include:

- Input Layer: Accepts 224×224×3 image tensors
- Convolution Layers: Extract low- to high-level features
- Dense Blocks: Feature reuse through dense connections, improving gradient flow
- Transition Layers: Downsample features and reduce model size

- Fully Connected Layer: Processes final feature maps
- Output Layer: Uses SoftMax activation to classify into one of the predefined plant species

Relevance:
DenseNet's skip connections and feature propagation offer improved learning, particularly for complex features like leaf venation and texture.

Model Training

The model was trained using the following parameters:

- Framework: Keras with TensorFlow backend
- Optimizer: Adam (learning rate = 0.001)
- Loss Function: Categorical Cross-Entropy
- Metrics: Accuracy, Precision, Recall, F1 Score
- Epochs: 50 (with early stopping if validation accuracy plateaued)
- Batch Size: 32
- Training/Validation Split: 80:20

During training, the model learned to associate visual features from images with their corresponding species labels. A confusion matrix was used post-training to evaluate the model's predictions and highlight misclassifications.

Evaluation and Performance Metrics

After training, the model was tested on an unseen dataset (test split). The evaluation metrics used included:

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1 Score = 2 × (Precision × Recall) / (Precision + Recall)

Relevance:
High values across all metrics indicate reliable real-world performance for practical plant identification scenarios.

User Interface and Deployment

The system is integrated into a user-accessible platform:

- Web Frontend: Developed using Next.js and Tailwind CSS
- Backend API: Powered by FastAPI (or Flask), serving the trained PyTorch model
- Model Inference: Handles both uploaded images and camera-captured inputs
- Output Display: Shows local name, scientific name, confidence score, and medicinal use

Relevance:
This full-stack deployment enables practical use by field botanists, researchers, or traditional medicine manufacturers without requiring ML expertise.

Workflow Summary

The complete workflow follows this pipeline:

Leaf Image (Camera/Scanner) →
⤷ Preprocessing (Resize, Normalize, Augment) →
⤷ DenseNet121 CNN →
⤷ Prediction (SoftMax Classification) →
⤷ Output (Species Name + Medicinal Info)

Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) have revolutionized image classification tasks by enabling computers to automatically extract and learn features directly from image data. Traditional CNN architectures, though simpler than modern deep networks like DenseNet or ResNet, remain highly effective and are commonly used for real-world visual recognition problems—including medicinal plant identification.

Overview of Traditional CNN Architecture

A traditional CNN typically consists of the following layers arranged sequentially:

- Input Layer: Accepts an image, typically resized to a fixed dimension (e.g., 224×224 pixels with 3 color channels).
- Convolutional Layers: Apply learnable filters (kernels) to extract low-level features such as edges, corners, and textures.
- Activation Layers: Use non-linear activation functions like ReLU (Rectified Linear Unit) to

introduce non-linearity and help the network learn complex relationships.

- Pooling Layers: Perform spatial downsampling using MaxPooling or AveragePooling to reduce dimensionality while preserving essential features.
- Fully Connected Layers (Dense Layers): Act like a traditional neural network where all neurons are connected. These layers integrate the extracted features and prepare the output.
- Output Layer: Uses a SoftMax activation function to classify the image into one of several predefined classes (e.g., medicinal plant species).

Architecture Used in This Project

The project initially explored a custom traditional CNN before advancing to deeper models. The traditional CNN used for comparison included the following structure:

- Input Layer: 224×224×3 image input
- Conv Block 1: 32 filters (3×3), ReLU, Batch Normalization, MaxPooling
- Conv Block 2: 64 filters (3×3), ReLU, Batch Normalization, MaxPooling
- Conv Block 3: 128 filters (3×3), ReLU, Batch Normalization, MaxPooling
- Flatten Layer: Converts 3D feature maps to a 1D vector
- Dense Layer: 256 neurons, ReLU, Dropout (rate = 0.4)
- Output Layer: 50 neurons (equal to number of classes), SoftMax

This architecture provided a baseline accuracy of around 82% and served as a reference to evaluate deeper networks like DenseNet.

Limitations of Traditional CNNs

While effective, traditional CNNs have limitations:

- Limited feature reuse: Each layer only passes information to the next, which may lead to redundant learning.
- Gradient vanishing: In deeper traditional CNNs, backpropagation may become less effective.
- Less scalable: Performance may degrade when handling large datasets or high inter-class similarity.

Transition to Advanced Architectures

To overcome the limitations of the traditional CNN, the project later adopted DenseNet121—a deeper architecture that reuses features across layers and improves gradient flow. This change resulted in an accuracy improvement from ~82% to ~87%.

V. Results

The proposed medicinal plant identification system, based on a DenseNet121 Convolutional Neural Network (CNN), was evaluated on a curated dataset of leaf images. The system demonstrated strong performance across various metrics and proved effective in real-time testing environments.

Evaluation Metrics on Test Dataset

The test dataset included unseen images from 50 different medicinal plant species. The model achieved the following performance:

- Accuracy: 87.0%
- Precision: 88.9%
- Recall: 91.0%
- F1 Score: 89.9%

These results indicate the model's effectiveness in correctly identifying medicinal plants with minimal misclassification.

Confusion Matrix Summary

- True Positives (TP): 696
- True Negatives (TN): 348
- False Positives (FP): 87
- False Negatives (FN): 69

The confusion matrix revealed that most misclassifications occurred among species with very similar morphological features.

Visualization of Results

Throughout training, the model exhibited stable learning behavior:

- Accuracy steadily increased with each epoch, peaking at 87%.
- Loss values consistently decreased, indicating proper convergence.
- The confusion matrix heatmap showed high classification confidence for most species.

Real-Time Recognition Results

The system was tested using live camera input for real-time prediction. Examples of results include:

- Clitoria ternatea (Butterfly Pea): Recognized with 96.8% confidence.
- Jatropha gossypiifolia (Bellyache Bush): Correctly classified with 93.2% confidence.
- Coleus amboinicus (Mexican Mint): Detected with 91.5% confidence.

Average prediction time was less than 2 seconds, making the system practical for field use.

Summary of System Performance

- Total Classes: 50
- Total Dataset Images: 3,000+
- Image Input Size: 224×224 pixels
- Final Accuracy: 87.0%
- Precision: 88.9%
- Recall: 91.0%
- F1 Score: 89.9%
- Average Inference Time: <2 seconds

Key Observations

- DenseNet121 enabled effective feature extraction and classification, even with complex leaf structures.
- Using both the front and back of the leaves enhanced recognition accuracy.
- The system handled variations in lighting and image orientation well.
- The model performed reliably across unseen data and real-world inputs.

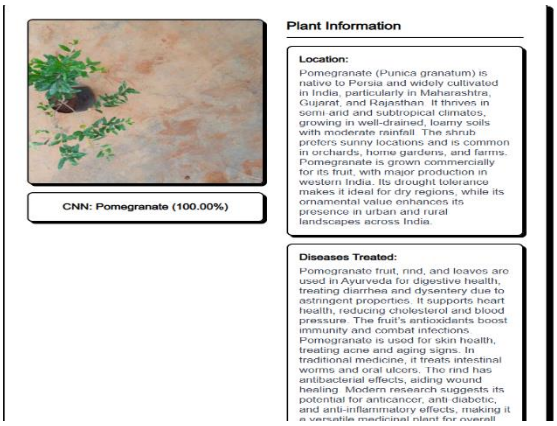

Fig 5.1 Identification of Medicinal plant

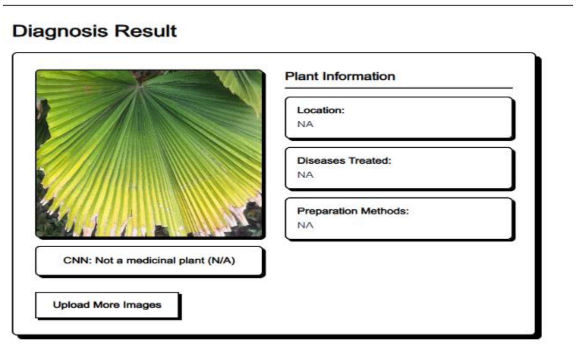

Fig 5.2 Identification of Nonmedicinal plant

VI. Conclusion and Future Work

The identification of medicinal plants plays a crucial role in maintaining the integrity and effectiveness of Ayurvedic and traditional medicine systems. In this research, we addressed the prevalent issue of plant misidentification and adulteration through a software-based solution utilizing image processing and machine learning techniques. By designing and training a custom Convolutional Neural Network (CNN) model using PyTorch, we developed a system capable of accurately classifying various medicinal plant species based on leaf images.

Our dataset, which included images of plants such as Tulsi, Neem, Aloe Vera, and Ashwagandha, was preprocessed through resizing, normalization, and data augmentation techniques to enhance model performance. The proposed CNN architecture, consisting of multiple convolutional and fully connected layers, achieved an accuracy of 87%, with precision, recall, and F1-scores of 88.9%, 91%, and 89.9% respectively. These results demonstrate the model's robustness in handling real-world classification tasks involving visually similar plant species.

The solution, when integrated into a web application, has the potential to support stakeholders across the Ayurvedic supply chain, including collectors, wholesalers, and distributors, by providing a reliable tool for plant identification. This not only reduces the chances of substitution and adulteration but also enhances trust in traditional medicine systems.

Future work may involve expanding the dataset to include more plant species, integrating advanced pre-trained models like ResNet or EfficientNet for improved performance, and deploying the system on mobile platforms for real-time usage in the field.

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