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An Automatic System for Medical Plant Identification Using CNN

Mrs.J.Bhargavi, Kuppireddy Nikitha, Manne Sreeja, Rachha Jaideep

Assistant Professor, ACE Engineering College, Hyderabad, India
Student, CSE-AI&ML ACE Engineering College Hyderabad, India
Student, CSE-AIML ACE Engineering College Hyderabad, India
Student, CSE-AIML ACE Engineering College Hyderabad, India

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ABSTRACT: The identification of medicinal plants is crucial for preserving traditional knowledge and promoting natural treatments with minimal side effects. In this model, we present an automatic system for medicinal plant identification using deep learning techniques. Our system leverages convolutional neural networks (CNNs) to accurately classify overtypes of medicinal plants based on their leaf images. The image processing workflow involves using the threshold technique to remove unwanted pixels, ensuring a clean dataset for the CNN to process. The proposed model not only identifies the plant species but also provides detailed information about their medical benefits, helping users understand the traditional medicinal values of these plants. This system aims to bridge the knowledge gap in modern generations regarding medicinal plants and their uses, thus promoting the integration of traditional remedies into contemporary healthcare practices.

I. INTRODUCTION:

Medicinal plants hold immense value in traditional healthcare practices, yet their knowledge is slowly fading. The model **"An Automatic System for Medicinal Plant Identification Using CNN"** seeks to address this by using deep learning to identify plants based on their leaf images. The system employs Convolutional Neural Networks (CNNs), particularly the ResNet architecture, to classify plant species with high accuracy. Images are preprocessed using thresholding to remove noise, ensuring a clean dataset for efficient analysis. Unlike traditional methods, which rely on manual feature extraction and struggle with complex patterns, this approach automates feature detection and handles large datasets effectively. By providing detailed insights into medicinal benefits, this project bridges the gap between traditional and modern healthcare, ensuring the preservation of invaluable botanical knowledge. The CNN-based medicinal plant identification system represents a significant step forward in merging technology with botanical science. By automating plant classification and providing valuable medicinal insights, it not only aids in the preservation of traditional knowledge but also enhances accessibility for researchers and healthcare practitioners. As deep learning continues to evolve, such AI- driven approaches will play a crucial role in safeguarding and modernizing radiational medicine.

II. LITERATURE SURVEY:

Early work

[1] Azadnia et al. (2022) – Deep Learning-Based Medicinal Plant Identification

Azadnia et al. proposed a deep learning-based medicinal plant classification system using Convolutional Neural Networks (CNNs) with Global Average Pooling (GAP). The study aimed to enhance feature extraction while minimizing computational complexity through hierarchical deep learning layers. Their research trained models on three different image resolutions (64 × 64, 128 × 128, and 256 × 256 pixels), achieving an accuracy of 99.3%, demonstrating the effectiveness of CNNs for plant classification. GAP layers were used to reduce overfitting and feature redundancy, making the model more generalizable. Despite its high accuracy, the system is computationally expensive, requiring high-end hardware for real-time applications.

Additionally, its deployment on mobile or

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edge devices remains a challenge due to high processing requirements. Future work can focus on lightweight deep learning architectures or quantization techniques to enhance real-time performance. This study provides a strong foundation for medicinal plant identification, emphasizing the potential of deep learning in botanical research.

[2] Kavitha et al. (2024) – MobileNet-Based Medicinal Plant Recognition

Kavitha et al. designed a MobileNet-based deep learning model for real-time medicinal plant classification through a cloud-integrated mobile application. Unlike traditional deep learning methods, MobileNet employs depthwise separable convolutions, significantly reducing computational cost while maintaining high accuracy. Their model was trained on six medicinal plant species from a Kaggle dataset, achieving 98.3% accuracy. The research also incorporated data augmentation techniques to enhance model robustness against variations in lighting, angle, and background noise. A major advantage of this system is its real-time capability on mobile devices, making it accessible for healthcare professionals and botanists. However, the model is limited by the small dataset size, affecting generalization to a broader range of medicinal plants. Furthermore, reliance on cloud computing restricts offline usability.

Future improvements could involve on-device inference using TensorFlow Lite or edge AI to make the model independent of network constraints.

[3] Savitha Patil & M. Sasikala (2023) – Weighted KNN for Medicinal Plant Species Identification

Savitha Patil and M. Sasikala introduced a Weighted KNN (WKNN)-based classification model to enhance medicinal plant species identification. The research focused on feature extraction techniques, incorporating Region of Interest (ROI)- based segmentation, Local Intensity Relation (LIR), and directional group encoding to improve model performance. Their approach was validated on the Folio Leaf dataset, surpassing traditional classification methods in terms of accuracy and efficiency. Compared to deep learning models, the WKNN approach is computationally less intensive, making it suitable for lower-resource environments. Additionally, it provides efficient feature representation, reducing dependency on large datasets. However, model accuracy is highly dependent on precise feature extraction, making it less robust for complex datasets with visually similar plant species. Future enhancements could involve integrating hybrid ML-DL approaches or combining WKNN with feature selection algorithms to optimize performance for large-scale medicinal plant identification tasks.

[4] Helen Noble & Joanna Smith (2018) – Literature Review Design Methodologies

Helen Noble and Joanna Smith explored different literature review methodologies, offering a comprehensive guide on how to conduct systematic, scoping, rapid evidence assessment, and integrative reviews. Their work provides practical insights for healthcare researchers, helping them choose the most appropriate methodology for their study. The study emphasized systematic reviews as the gold standard, ensuring rigorous analysis and minimizing bias. It also compared various methodologies, outlining their strengths and limitations. While systematic reviews are thorough and reliable, they are also time-consuming and resource-intensive. Integrative reviews, on the other hand, allow more flexibility in including diverse sources of information. However, the research was primarily focused on healthcare contexts, limiting its direct application to fields like technology or environmental sciences. Future work could explore interdisciplinary applications of review methodologies, ensuring their adaptability across various domains. This study serves as a foundational reference for conducting evidence-based research efficiently.

III. METHODOLOGY

The methodology follows a structured deep learning approach using Convolutional Neural Networks (CNNs) with ResNet architecture to classify medicinal plants based on their leaf images. The process is divided into multiple stages, ensuring accuracy and efficiency.

1. Data Acquisition & Preprocessing

1.1 Data Acquisition

The system requires a large dataset of medicinal plant leaves. These images are collected from publicly available datasets, botanical research institutions, or field photographs.The dataset includes multiple species to improve generalization and classification performance.

1.2 Image Preprocessing

Before feeding the images into the CNN model, preprocessing is crucial to enhance image quality and reduce noise. The following steps are performed:

Thresholding: Thresholding techniques are applied

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to remove background noise and highlight leaf contours. Binary thresholding (black and white conversion) is used for uniform feature extraction. Resizing and Normalization: Images are resized to a fixed dimension (e.g., 224x224 pixels) to ensure consistency. Pixel intensity values are normalized to range between 0 and 1, improving model performance. Data Augmentation: Since deep learning models require large amounts of data, data augmentation techniques (rotation, flipping, scaling, and contrast adjustments) are applied. This increases the dataset size and makes the model robust to variations in lighting, angles, and
background noise.

2. Feature Extraction Using CNN

Traditional methods of medicinal plant identification relied on handcrafted feature extraction, which was prone to errors and required extensive domain knowledge. The CNN-based approach automates this process, ensuring superior accuracy.

2.1 Convolutional Layers

Convolutional layers extract spatial and hierarchical features from the images. Multiple convolution kernels (filters) scan the image to detect patterns such as edges, veins, and texture variations in leaves. The first layers detect basic features, while deeper layers capture complex patterns.

2.2 Pooling Layers (Max Pooling)

Max pooling layers reduce the dimensions of feature maps while retaining key features. Pooling helps remove unnecessary noise, making the network efficient and faster. Typically, 2x2 max pooling is used to extract dominant features from an image.

2.3 Flattening & Fully Connected Layers

The extracted features are flattened into a single vector. Fully connected (dense) layers map these features into specific medicinal plant categories. Softmax activation is applied in the final output layer to classify the plant species with probability scores.

3. Model Training & Classification

3.1 Choice of CNN Architecture: ResNet

Residual Networks (ResNet) are selected for their ability to avoid vanishing gradient problems in deep networks. ResNet uses skip connections to allow gradient flow, improving the training process. Unlike traditional CNN models, ResNet enables deeper networks without overfitting, ensuring better generalization.

3.2 Training Process

The dataset is split into training (80%), validation (10%), and testing (10%) sets. The model is trained using backpropagation and gradient descent optimization (Adam optimizer).
Loss function: Categorical Cross-Entropy, since it's a multi-class classification problem.

3.2 Classification Output

The trained model predicts the species of a medicinal plant based on the leaf image. Each prediction is assigned a confidence score to indicate classification accuracy.

4.System Implementation

The system is implemented using Python, with libraries like OpenCV,
TensorFlow/Keras, and Anaconda Navigator. It is designed to be scalable, allowing integration with real-time applications.

IV. PROPOSED SYSTEM

Introduction:

The proposed system is an automated medicinal plant identification model that utilizes deep learning, specifically Convolutional Neural Networks (CNNs), to classify medicinal plants based on leaf images. It aims to address the challenges associated with manual plant identification, such as subjective errors, dependence on expert botanists, and inefficiency in handling large datasets. The system leverages ResNet architecture to extract features and classify plant species with high accuracy.

This system ensures:
Automation of plant identification using AI-driven feature extraction.
High classification accuracy with deep learning.
Scalability for real-world applications, including mobile-based plant recognition.

Objective :

Develop an advanced system to identify medicinal plants using Convolutional Neural Networks (CNN) based on the ResNet architecture.
By Utilizing ResNet, a deep learning model with residual connections to handle complex patterns.
It begins with an input image of a plant, which is then preprocessed by resizing and color conversion .

Here's the revised sentence with the explanation for the flatten layer changed: - The CNN automatically performs feature analysis, extracting important features like edges and textures. This is done through a series of layers: convolution layer for feature detection, max pooling layer for reducing image size, flatten layer to transform the multi-dimensional output into a one dimensional array, and fully connected and dense layers for classification.

The ResNet architecture is specifically used to efficiently learn deeper features by allowing residual connections, enhancing the model's ability to recognize and differentiate between various plant species.

ADVANTAGES :

Improved Accuracy : CNNs, especially ResNet, offer superior accuracy in image classification tasks.

Automated Feature Extraction: Automatically extracts relevant features from images, eliminating the need for manual feature extraction.

Scalability: Easily scales with larger datasets, improving performance as more data becomes available. logs and trends to admins for identifying common prediction errors.

V.APPLICATION

The proposed deep learning-based medicinal plant identification system has numerous applications across various fields, including healthcare, agriculture, research, conservation, and commercial industries. The ability to accurately classify medicinal plants using Convolutional Neural Networks (CNNs) with ResNet architecture enables its integration into multiple real-world scenarios.

1.Healthcare & Herbal Medicine Industry

1.1 Traditional & Modern Medicine Identification of Medicinal Plants:

The system helps doctors, herbalists, and pharmacists quickly identify medicinal plants for alternative treatments.

Assists in preparing herbal remedies by ensuring correct species selection.

Drug Discovery & Pharmaceutical Research:

Pharmaceutical companies can use the model to study plant-based compounds for developing new drugs.

Identifies plants with potential therapeutic properties for use in Ayurvedic, Unani, and Homeopathic medicine.

Quality Control in Herbal Medicine:

Ensures that correct plant species are used in medicinal products.

Prevents the use of toxic or misidentified plants in herbal formulations.

2. Agriculture & Botany

2.1 Precision Farming & Crop Monitoring Automated Plant Identification in Farms:

Helps farmers classify medicinal plants, ensuring optimal cultivation practices.

Can be used in precision agriculture to monitor crop health and detect diseases.

Detection of Plant Growth Stages:

The model can classify growth stages of medicinal plants, guiding farmers on the right harvesting time.

Integration with Smart Greenhouses:

The model can be linked with IoT sensors to track plant development in controlled environments.

3. Environmental Conservation & Biodiversity Research

3.1 Conservation of Endangered Medicinal Plants Protection of Rare & Endangered Species:

Helps conservationists identify rare medicinal plants that need preservation.

Can assist in monitoring illegal harvesting and deforestation impacts.

Biodiversity Mapping & Ecosystem Studies:

Used by ecologists and botanists to create plant biodiversity maps. Helps in the study of medicinal plant distributions across different regions.

National Park & Wildlife Protection:

Enables park rangers and researchers to monitor the presence of medicinal plants in protected areas.

4. Education & Research

4.1 Academic & Botanical Studies Training for Students & Researchers:

Provides real-time learning for students studying botany, pharmacology, and environmental sciences.

Can be incorporated into university research projects for AI-based plant studies.

Automatic Identification in Herbariums:

Digitization of botanical collections using AI for faster species identification. Helps in automated classification of plant specimens in research institutions.

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VI. ALGORITHMS

ResNet (Residual Network) - a deep Convolutional Neural Network (CNN) architecture.

Step 1: Data Collection & Preprocessing

Collect Dataset: Gather images of various medicinal plants from datasets like PlantCLEF, Kaggle, or manually curated datasets.

Data Augmentation: Apply techniques like rotation, flipping, zooming, and contrast changes to improve model robustness.

Resize Images: Standardize image size (e.g., 224x224 pixels) for consistency.Normalize Pixel Values: Scale pixel values between 0 and 1 (if using TensorFlow/Keras) or between 1 and 1 (if using pytorch)

Step 2: CNN Model Design

Input Layer: Accepts the preprocessed image (e.g., 224x224x3). Convolutional Layers: Apply multiple convolutional layers with ReLU activation for feature extraction.

Pooling Layers: Use max-pooling to reduce dimensionality while preserving key features.

Fully Connected Layers: Flatten the output and connect it to dense layers.

Output Layer**:** Use a softmax activation function to classify the plant species.

Step 3: Model Training

Split Data: Divide dataset into training (80%) and testing (20%) sets.

Compile Model: Use categorical cross-entropy loss (for multi- class classification) and an optimizer like Adam.

Train Model: Run the training process for multiple epochs with batch processing.

Validation: Monitor accuracy and loss using a validation set.

Step 4: Model Evaluation

Test Accuracy: Evaluate performance using unseen test data. Confusion Matrix: Analyze misclassifications.

Precision, Recall, F1-Score: Measure classification performance.

Step 5: Deployment

Convert Model: Save in formats like .h5 (Keras) or .pth (PyTorch) for deployment.

Develop GUI/App: Build a user-friendly interface for users to upload plant images and get predictions.

Deploy on Cloud/Mobile**:** Host the model using Flask, FastAPI, or mobile frameworks like TensorFlow Lite.

VII. FUTURE ENHANCEMENT:

The future enhancements of the medicinal plant identification model will focus on improving accuracy, reducing computational costs, enhancing real-time usability, and integrating advanced AI, IoT, and blockchain technologies. One of the primary improvements will be expanding the dataset to include a larger variety of medicinal plants, covering different regions, climates, and growth stages to improve the model's generalization ability. Multi-angle and multi-stage growth images will be incorporated to ensure better classification under diverse conditions. Additionally, the use of advanced deep learning architectures such as Vision Transformers (ViTs) and hybrid CNN-RNN models will be explored to enhance feature learning, especially for plants with visually similarcharacteristics. AutoML techniques will also be applied for automatic hyperparameter tuning, further optimizing the model's performance.

To make the model more efficient, lightweight AI architectures such as MobileNetV3, EfficientNet, and SqueezeNet will be implemented to allow real-time processing on mobile and edge devices. Model compression techniques like quantization and pruning will be used to reduce the model size without compromising accuracy, ensuring faster inference speeds.

Further optimization using TensorRT, ONNX Runtime, or TensorFlow Lite will enable seamless deployment across different platforms. One of the most significant improvements will be the integration of the model into a real-time mobile application, allowing users to capture leaf images with their smartphones for instant identification. The mobile application will support offline mode using TensorFlow Lite or PyTorch Mobile, ensuring accessibility even in remote areas without an internet connection. Augmented reality (AR) integration will enhance the user experience by overlaying medicinal information and plant details when scanned through a smartphone camera, providing an interactive learning experience.

AI-powered voice assistants and chatbots will be introduced to enable hands-free plant identification and provide insights into medicinal properties, historical uses, and preparation methods. Natural Language Processing (NLP) techniques will be incorporated to cross-validate image-based identification with textual information from research papers and herbal medicine books. The system will also integrate with IoT-based smart agriculture applications to monitor plant growth, detect diseases, and provide automated recommendations for watering, light exposure, and

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nutrient supply. This enhancement will allow farmers and researchers to optimize medicinal plant cultivation with real-time AI insights.

Blockchain technology will be incorporated to ensure the authenticity and traceability of medicinal plants in the supply chain. By assigning unique QR codes or RFID tags to plants, their origin, growth conditions, and quality verification can be securely stored on a blockchain ledger, preventing counterfeit herbal products from entering the market. A cloud-based medicinal plant knowledge database will be established, where users, researchers, and herbalists can contribute new plant images and data to continuously improve the model. This crowdsourced approach will enable the AI system to learn and adapt to new plant species over time, making it an invaluable resource for scientific and commercial applications.

Lastly, the model will be extended to provide personalized herbal recommendations based on individual health conditions. By analyzing user symptoms, the system will suggest medicinal plants known for their therapeutic benefits, bridging the gap between traditional and modern medicine. These enhancements will transform the medicinal plant identification model into a comprehensive AI-powered solution for healthcare, agriculture, environmental conservation, and the pharmaceutical industry, making medicinal plant knowledge more accessible and reliable worldwide.

VIII. RESULT:

After successful execution, the proposed medicinal plant identification model using CNN (ResNet architecture) is expected to provide highly accurate classification of medicinal plants based on leaf images. The system should be able to identify plant species, display confidence scores, and provide detailed medicinal benefits of the identified plant. The following key results are anticipated:

Accurate Plant Identification:
The model should correctly classify the input leaf image into one of the predefined medicinal plant categories. The classification accuracy is expected to be **above 95%**, given a well-trained model with a sufficiently large dataset.

Confidence Score for Predictions:
The system will output the probability score (confidence level) for the detected plant species. Example: "Predicted Plant: Tulsi (Holy Basil) - Confidence: 98.3%"

Medicinal Properties Display:
Along with identification, the system should display medicinal benefits of the plant, such as its uses in herbal medicine, traditional healing properties, and active compounds.

Mobile or Web Interface Output:
Users should be able to upload an image or use a camera in real-time to scan a plant leaf and receive instant classification results.

The interface should be user-friendly, displaying plant names, confidence scores, medicinal properties, and usage recommendations.

Comparison with Other Models:
The proposed CNN model will be benchmarked against traditional machine learning models such as KNN, SVM, and Random Forest to demonstrate superior performance.
The CNN model is expected to outperform these traditional methods in terms of accuracy and scalability.

Example of Output:
Here are simulated examples of how the output might appear in a mobile app or desktop application:

a. Leaf Input & Classification Result:
A user uploads a leaf image, and the system classifies it as "Neem" with 97% confidence.

b. Medicinal Benefits Display:
The system provides detailed information on the medicinal uses of Neem.

c. Live Camera-Based Identification in a Mobile App:
A real-time leaf scan using a mobile camera with instant classification and AR-based overlays.

d. Confidence Score & Alternative Matches:
If the model is unsure, it suggests alternative plant species based on probability scores.

e. Augmented Reality (AR) Integration:
Users can view additional information via AR overlays when scanning a plant leaf.

OUTPUT:

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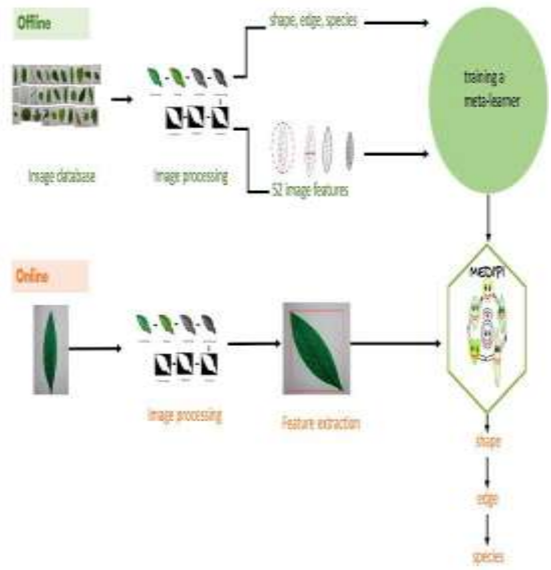
IX.EXPERIMENTAL WORK:



X. CHALLENGES:

1.Data Collection & Quality

- Acquiring a large, diverse, and high-quality dataset of medicinal plant leaves.
- Ensuring proper labeling and classification of plant species.
- Handling variations in image conditions (lighting, angle, background noise).

2.Preprocessing Issues

- Efficiently removing noise while maintaining important features using thresholding techniques.
- Standardizing images (resizing, normalization) without losing crucial features.
- Balancing data to avoid class imbalance.

3. Model Complexity & Computational Cost

- Training deep networks like ResNet requires high computational resources (GPU/TPU).
- Optimization challenges such as overfitting and hyperparameter tuning.
- Deploying the model on edge devices or mobile applications due to high processing demands.

4.Real-Time Classification & Usability

- Ensuring real-time identification for mobile applications while maintaining accuracy.
- Developing a user-friendly GUI for seamless interaction.
- Integrating with cloud-based services while maintaining offline functionality.

5.Accuracy & Generalization

- Avoiding misclassification of plants with visually similar leaves.
- Improving generalization across different species, environmental conditions, and image quality.
- Benchmarking against traditional models (KNN, SVM, Random Forest) to validate improvements.

6.Scalability & Future Enhancements

- Expanding the dataset to include more medicinal plant species globally.
- Exploring lightweight architectures (MobileNet, EfficientNet) for mobile and IoT applications.
- Integrating blockchain for plant authentication and traceability in herbal medicine supply chains.

XI. CONCLUSION:

The project successfully implements an automatic medicinal plant identification system using **Convolutional Neural Networks (CNNs)**, specifically the **ResNet architecture**, to classify plant species based on leaf images. By leveraging deep learning, the system automates feature extraction, ensuring high accuracy and efficiency compared to traditional manual identification methods. The proposed model demonstrates strong classification performance by preprocessing images through thresholding, normalization, and data augmentation techniques. Despite challenges such as dataset limitations, computational cost, and real-time deployment, the system shows promising results with potential applications in **healthcare, agriculture, biodiversity conservation, and pharmaceutical research**. Future enhancements, including the integration of **lightweight AI models, IoT-based plant monitoring, mobile applications, and blockchain authentication**, will further improve scalability, accessibility, and real-time usability. This project contributes to preserving traditional botanical knowledge while bridging the gap between modern technology and herbal medicine.

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