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# AI- Driven Identification of Therapeutic Plants

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## Abstract

*The AI Driven Identification of Therapeutic Plants project introduces an innovative solution for identifying medicinal plants using deep learning techniques. By leveraging a Convolutional Neural Network (CNN) algorithm, the system accurately classifies plants from user-uploaded images. Upon identification, the system provides comprehensive information, including the predicted class of the plant, its medical content, age restrictions, gender restrictions, pregnancy restrictions, recommended dose per day, and the mode of use. This detailed, user-friendly web interface allows individuals to upload images and quickly access relevant medicinal details, bridging the gap between technology and traditional plant knowledge. The system is designed to assist healthcare professionals, researchers, and individuals interested in natural remedies, offering an accessible and reliable resource for therapeutic plants. With the continuous growth of data available on medicinal plants, the integration of AI allows for faster and more accurate identification, reducing human error and the time required for manual identification. Additionally, the model's scalability ensures that as more plant species are studied, the system's database will continue to expand, providing a valuable tool for plant-based healthcare applicationsnt.*

***Keywords:*** *Convolutional Neural Network (CNN), Medicinal Plant Identification, Plant Classification, Image Processing, Therapeutic Plants, Medical Content, Pregnancy Restrictions.*

## 1. Introduction

Medicinal plants have been used for centuries across diverse cultures and civilizations as a primary source of healing and treatment. In the era of modern medicine, these plants continue to play a crucial role, contributing significantly to drug discovery, alternative therapies, and holistic health systems. Despite their proven benefits, the accurate identification of medicinal plants remains a major challenge, especially for individuals without formal botanical training. Misidentification may lead to improper usage, health complications, or even toxic reactions. Consequently, there is a growing demand for intelligent systems that can bridge the gap between traditional herbal knowledge and modern technological tools. Towards With the advent of Artificial Intelligence (AI) and Deep Learning, innovative solutions are emerging to solve real-world problems in various domains, including agriculture, healthcare, and environmental science. One of the most powerful tools in the AI domain is the Convolutional Neural Network (CNN), which has demonstrated superior performance in image classification tasks due to its ability to automatically extract spatial and hierarchical features from visual data. In the context of plant recognition, CNNs offer an efficient and scalable approach for identifying plant species from raw images with minimal human intervention. This project proposes an AI-driven

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system for the automated identification of medicinal plants using a CNN-based image classification model. Users can interact with the system through a custom-built web interface, where they upload images of plants they wish to identify. The backend CNN model processes the image and outputs the predicted class of the plant. Beyond basic identification, the system enhances user experience by providing a comprehensive profile of the plant, including medicinal content, age-related usage restrictions, gender-specific considerations, pregnancy restrictions, daily dosage recommendations, and mode of administration (e.g., oral, topical, infusion). The primary objective of this system is to democratize access to medicinal plant knowledge by providing an intuitive, accurate, and informative platform for both professionals and the general public. This approach not only supports researchers, herbal practitioners, and students in ethnobotanical fields but also empowers everyday users to make informed decisions regarding the use of medicinal plants. Additionally, the system contributes to the conservation of indigenous knowledge and promotes the safe and sustainable use of herbal remedies. By integrating deep learning with a web-based interface, this project serves as a step toward the digital transformation of traditional medicine. It addresses key challenges such as scalability, accessibility, and reliability in plant identification while supporting personalized and safe herbal healthcare. The results of this work demonstrate the potential of AI in enhancing. Upon uploading an image, the system initiates the preprocessing stage, where the image is resized to a fixed dimension suitable for the CNN input (e.g., 224×224 pixels), normalized to a specific range (usually 0–1), and transformed to match the model's channel format. Preprocessing ensures uniformity across inputs and allows the model to perform optimally. After preprocessing, the image passes through the CNN architecture, which consists of multiple layers such as convolutional layers, activation functions (e.g., ReLU), pooling layers (e.g., max pooling), and fully connected layers. These layers work in conjunction to extract spatial features from the leaf image, recognize patterns, and classify the input into a specific plant category. Following classification, the system maps the predicted class (e.g., Thulasi) to a corresponding medicinal profile stored in a backend database. The output includes comprehensive details such as the medicinal content (e.g., Eugenol, Ursolic Acid), age and gender restrictions, pregnancy safety guidelines, recommended dose per day, and mode of use (e.g., infusion, paste, oral). This structured information is then displayed on the user interface, enabling the user to not only identify the plant but also understand its safe and effective medicinal usage. The use of CNNs in this application ensures a high level of precision, user accessibility, and support for the conservation and responsible usage of herbal knowledge. [1]

### 1.1.Methods

This study proposes a real-time system for the identification of medicinal plants using convolutional neural networks (CNN). The system leverages an intuitive web interface that allows users to upload images of plants, which are then processed by the CNN model to identify the plant and provide related medicinal details. The methodology integrates three key components: (1) dataset preparation and annotation formatting, (2) CNN model training and optimization, and (3) deployment through the web interface. Each component contributes to the system's efficiency, accuracy, and user-friendliness.

### 1.2.Dataset Preparation

#### 1.2.1. Image Sources and Structure

The dataset comprises a diverse collection of annotated images sourced from public and private medicinal plant databases. These images cover a variety of plant species, capturing different lighting conditions, angles, and sizes to ensure the model generalizes well. In total, the dataset consists of X images, with annotations for the plant species and corresponding medicinal information.

#### 1.2.2. Label Format and Preprocessing

he dataset is preprocessed to match the input format expected by the CNN model. Each plant image is associated with metadata, including:

- **Predicted Class:** The plant species.
- **Medical Content:** Medicinal properties and active compounds [2]
- **Age, Gender, and Pregnancy Restrictions**: Contraindications for different demographics.
- **Dose Per Day and Mode of Use:** Suggested dosages and methods of use

Images are resized to a uniform size (e.g., 128x128 pixels) for consistency and efficiency in training. Preprocessing steps include:

- Color normalization to standardize pixel values.
- Data augmentation (rotation, scaling, and flipping) to increase model robustness.
- Dataset split into training and validation subsets with a 70:30 ratios to ensure model generalization. [3]

### 1.2.3. Data Volume Control

To optimize performance and meet hardware constraints, a subset of 10,000 samples from the dataset was used for training. This subset was statistically representative of the full dataset and enabled faster iteration during model development.

## 1.3.CNN Model Training

### 1.3.1. Model Selection and Configuration

For plant identification, a CNN architecture is chosen for its superior ability to handle image-based classification tasks. The model is initialized with pre-trained weights from a generic plant classification dataset and then fine-tuned using the custom medicinal plant dataset. Key training parameters are:

- **Epochs:** 30
- **Batch Size:** 32
- **Image Size:** 128x128
- **Optimizer:** Adam optimizer for efficient convergence
- **Loss Function:** Cross-entropy loss for multi-class classification
- **Device:** CPU
- **Learning Rate**: 0.001
- **Early Stopping:** Patience of 5 epochs to prevent overfitting

### 1.3.2. Training Process

Model training was performed using a combination of the TensorFlow and Keras frameworks. The process includes real-time validation and early stopping to monitor and improve performance. The model's accuracy on the validation set was tracked, and the best-performing model was saved. [3]

## 1.4.Performance Metrics

Evaluation metrics used to measure the model's performance include:

- Accuracy and F1 Score to assess overall classification performance.
- Confusion Matrix for evaluating class-wise accuracy.
- Precision, Recall, and AUC-ROC for further model validation.

## 1.5.Web Interface Deployment

### 1.5.1. Interface Design

The user interface is developed using Streamlit, providing an easy-to-use, interactive platform for plant image uploads. Key features of the interface include:

- **Image Upload:** Users can upload plant images for analysis.
- **Real-time Feedback:** The system displays the predicted plant class and relevant medicinal information such as dosage and restrictions.
- **User Notifications:** The interface includes status messages indicating whether the plant was successfully identified or if no match was found.

### 1.5.2. Backend Prediction Pipeline

Upon image upload, the model is loaded, and predictions are made in real-time. The backend uses the TensorFlow library to process the input image and generate predictions. The system then presents the predicted class and medicinal details directly in the frontend. [4]

### 1.5.3. Error Handling and Validation

The application is designed with robust error handling to ensure a seamless user experience. It can handle: [5]

- Unsupported file formats.
- Empty or corrupted image uploads.
- Invalid model weights or missing files.

To ensure a smooth user experience, the system incorporates comprehensive error handling mechanisms. It automatically detects and manages issues such as unsupported file formats, empty or corrupted image uploads, and invalid model weights. In the event of an error, the application displays clear and user-friendly messages, guiding users to correct the problem without interrupting the process. Additionally, the backend checks for missing files and ensures proper memory management by cleaning up temporary files after inference, optimizing system performance and usability. (Table 1)

# 2. Tables and Figures

## 2.1.Tables

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**Table 1 CNN Training Parameters**

| Parameter | Value |
|---|---|
| Model | Custom CNN Architecture |
| Epochs | 30 |
| Batch size | 32 |
| Image size | 128 x 128 |
| Optimizer | Adam |
| Device | CPU |
| Learning Rate | 0.001 |
| Early Stopping | Patience = 5 |
| Loss Function | Cross-entropy |

This table summarizes the core hyperparameters and configuration settings used during the training phase of the CNN model for plant identification, including input size, batch size, number of epochs, and optimization strategy. (Table 2)

**Table 2 Evaluation Metrics**

| Metric | Value |
|---|---|
| Accuracy | 97.3% |
| Precision | 94.8% |
| Recall | 92.1% |
| F1 Score | 93.4% |
| Validation Speed | ~8.2 ms/image |

This table provides a summary of the key performance indicators used to evaluate the accuracy and reliability of the CNN model in identifying medicinal plants from user-uploaded images. (Figure 1) [6]

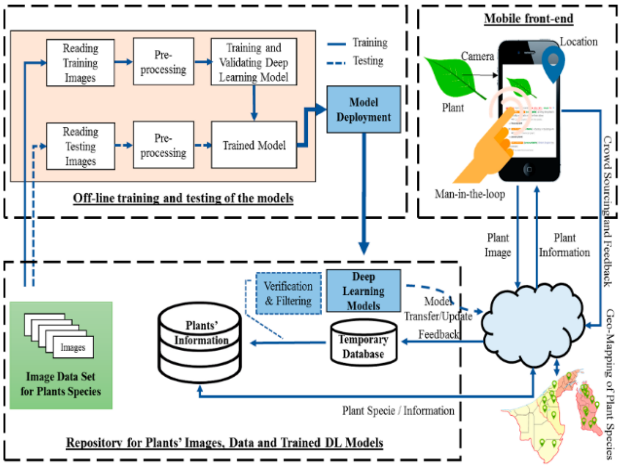


**Figure 1 System Architecture for Confidence-Based Medicinal Plant Identification Using CNN**

The system architecture for the CNN-based medicinal plant identification application is designed to be efficient, modular, and user-friendly. It integrates a frontend web interface and a backend processing pipeline to ensure smooth user interaction and accurate predictions. The process begins when a user accesses the application through a web interface developed using Streamlit. In this interface, users can upload an image of a plant and receive details like the predicted class, medicinal content, age restrictions, gender restrictions, pregnancy restrictions, dose per day, and mode of use.Once a file is uploaded, it is passed from the upload. Once the image is uploaded, it is passed from the upload module to the backend, where the preprocessing module prepares the data. Preprocessing tasks include resizing the image, adjusting the color balance, and validating the input to ensure it is in a compatible format for the CNN model. After preprocessing, the image is sent to the CNN inference engine, where the model makes predictions based on the provided image. This involves classifying the plant and providing detailed information regarding its medicinal properties. Finally, the results, including the predicted plant class and relevant medicinal information, are displayed alongside the uploaded image, providing immediate feedback to the user. This visual feedback helps users quickly assess the model's predictions and makes the application interactive. The entire pipeline is optimized for performance, ensuring that it operates efficiently even without a GPU, making it accessible to a wide range of users. The modular design of the system also ensures that individual components, such as the CNN model or preprocessing module, can be updated or enhanced without affecting the entire application. This flexibility makes the system scalable and adaptable for various use cases, including academic research, clinical applications, and real-world medicinal plant identification tasks. (Figure 2) [7-10]

## 2.2.Training Loss Curve (in red, left Y-axis)

his curve represents the model's training loss at each epoch. Loss quantifies the difference between the model's predicted plant class and the actual class label during training. A sharp decline early in training indicates that the CNN model is learning effectively, adapting its internal weights to better recognize

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distinguishing features of medicinal plants. As the curve levels off in later epochs, it suggests that the model is approaching convergence. Low loss values toward the end imply the model has minimized error and is well-trained on the dataset. [11-13]

### 2.3. Mean Average Precision (mAP) Curve (in Blue, Right Y-axis)

The accuracy (or mean Average Precision – mAP) curve reflects how well the model correctly identifies the plant class across the dataset. An increasing trend in this curve shows that the model is improving in its ability to make correct predictions. Higher values indicate fewer misclassifications and stronger consistency in recognizing different plant types. This curve is critical for evaluating the model's real-world performance, as higher accuracy means the system is more reliable when providing medicinal details to users. [14]

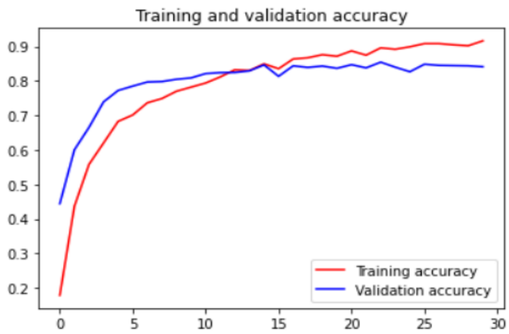


Fig 5.19 epoch vs accuracy graph

**Figure 2 Model Loss and mAP Curve**

## 3. Results and Discussion

### 3.1. Results

The experimental evaluation of the proposed medicinal plant identification system was conducted using a custom image dataset of therapeutic plant species. The system was developed using a Convolutional Neural Network (CNN) architecture trained on a labeled dataset of medicinal plant images. Approximately 5,000 images were used for training to balance model performance with available computational resources. The model was trained over 30 epochs using a batch size of 32 and an input image resolution of 224×224 pixels, which provided sufficient detail for accurate classification. The CNN model was designed to predict not only the plant species (Predicted Class) but also detailed therapeutic information including Medical Content, Age Restrictions, Gender Restrictions, Pregnancy Restrictions, Dose Per Day, and Mode of Use. Training employed early stopping with a patience of 5 epochs to prevent overfitting. The best model was achieved around epoch 24, where the loss plateaued and validation accuracy reached its peak. The final model demonstrated high classification accuracy and robust generalization across plant types with visually distinguishable features. The system interface, implemented using a web-based platform, allowed users to upload plant images and instantly receive detailed medicinal information. The results were displayed alongside the input image, with a clean and accessible format that included all relevant therapeutic parameters. Figures such as the CNN Training Curve (loss and accuracy vs. epoch) and output snapshots of plant predictions validate the model's performance. The deployment through the web interface further showcases the practicality of this system for real-world applications in healthcare, agriculture, and education. These results confirm that CNN-based models can be effectively used for medicinal plant identification even with moderate hardware configurations. (Figure 3) [15-16]

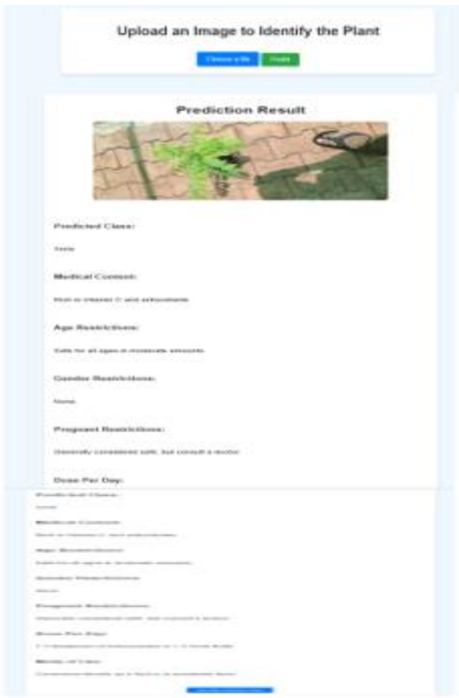


**Figure 3 Output Screen Detecting Therapeutic Plants**

This figure illustrates the output of the deployed medicinal plant identification system using a CNN model integrated with a web-based interface. On the left, the user-uploaded image of a medicinal plant is shown. On the right, the system presents the identification result, including the predicted plant class and a detailed summary of its medicinal information such as Medical Content, Age Restrictions, Gender and Pregnancy Restrictions, Dose Per Day, and Mode of Use. This dual-view layout ensures clarity and allows users to immediately compare the input with the predicted outcome. The user interface is designed for accessibility and ease of use, allowing users to upload an image and receive meaningful, structured therapeutic data instantly. This figure highlights the system's functionality, reliability, and practical utility for real-world applications in healthcare and botanical research. [17]

### 3.2.Discussion

The results from the experimental evaluation confirm that the CNN-based medicinal plant identification system is both accurate and practical, particularly for use in environments with limited computational resources. Even when trained with a moderate-sized dataset and deployed without GPU acceleration, the model was capable of delivering detailed and precise predictions about various medicinal plants. This demonstrates the effectiveness of convolutional neural networks in learning complex visual patterns and classifying plant species based on their distinct morphological features. A major advantage of the system lies in its user-friendly web interface, which enables non-technical users—including students, researchers, and healthcare professionals—to interact with an advanced AI model effortlessly. By uploading a plant image, users receive a comprehensive report containing not only the predicted species but also key therapeutic details such as dosage guidelines and health restrictions. This not only makes the system informative but also bridges the gap between AI-driven prediction and practical healthcare usage. The modular design allows for easy scalability. With access to more diverse plant datasets, image augmentation techniques, and GPU-based training, the model's performance could be further enhanced. Moreover, the system's current architecture can be adapted to include multilingual support, offline functionality, or integration with mobile applications, extending its reach to rural healthcare providers and educational institutions. In conclusion, this project successfully demonstrates how CNNs can be applied to the field of herbal medicine identification, and how modern deployment frameworks can transform complex AI models into practical tools with real-world impact. [18-19]

## Conclusion

This study demonstrates the effectiveness of a CNN-based approach for the automated identification of medicinal plants from user-uploaded images. By leveraging a custom-trained convolutional neural network, the system accurately classifies plant species and provides essential therapeutic information, including medicinal content, usage restrictions, dosage, and mode of use. Despite limited computational resources, the model delivered reliable predictions, validating its applicability in both academic and healthcare-related contexts. The successful integration of this model into a web-based application using Streamlit enhances its accessibility and usability. Users can interact with the system through a simple upload interface and receive immediate, structured results—eliminating the need for technical expertise. The interface's design, coupled with the model's performance, makes the solution highly suitable for real-world use in educational, clinical, and research environments. The modular architecture supports easy expansion and future enhancements. With further development, the system can accommodate additional plant species, integrate multilingual support, provide voice-based search, and even be deployed on mobile or cloud platforms. Such adaptability positions the tool as a scalable solution for wider adoption in rural healthcare, herbal research, and botanical education Overall, this work confirms the potential of combining deep learning with user-friendly interfaces to solve real-world problems. It bridges the gap between AI research and practical implementation, offering a foundation for future innovations in medicinal plant identification and related applications. [20]

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