

## Medicinal Plant Classification Using Convolutional Neural Networks

Hulle Parineeta<sup>1</sup>, Khandekar Nikita<sup>2</sup>, Khurud Purva<sup>3</sup>, Tambe Vaishnavi<sup>4</sup>, Prof. K. C. Khemnar<sup>5</sup>, Prof. A. A. Maniyar<sup>6</sup>

Artificial Intelligence & Machine Learning Sahyadri Valley College of Engineering & Technology, Rajuri, Pune, India.<sup>1,2,3,4</sup>  
Assistant Professor, Artificial Intelligence & Machine Learning Sahyadri Valley College of Engineering & Technology, Rajuri, Pune, India.<sup>4,5</sup>

Email: [parineetahulle@gmail.com](mailto:parineetahulle@gmail.com)<sup>1</sup>, [nikitakhandekar172@gmail.com](mailto:nikitakhandekar172@gmail.com)<sup>2</sup>, [purvakhurud8@gmail.com](mailto:purvakhurud8@gmail.com)<sup>3</sup>, [tambevaishnavin@gmail.com](mailto:tambevaishnavin@gmail.com)<sup>4</sup>, [kavitakhemnar@gmail.com](mailto:kavitakhemnar@gmail.com)<sup>5</sup>, [maniyarab11@gmail.com](mailto:maniyarab11@gmail.com)<sup>6</sup>

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### ABSTRACT

Medicinal plants play a crucial role in healthcare systems across the world due to their therapeutic and pharmacological properties. Accurate identification of these plants is essential for ensuring the correct use of herbal medicines and preventing adulteration. Traditional methods of plant identification rely on expert knowledge and manual examination of morphological features, which are often time consuming and error-prone. With recent advancements in Artificial Intelligence (AI), image based plant classification using Deep Learning (DL) techniques has gained significant attention. In this research, a Convolutional Neural Network (CNN) model is proposed for automatic classification of medicinal plants based on leaf images. The CNN model effectively extracts and learns hierarchical features from plant images, resulting in high classification accuracy compared to traditional machine learning methods. The system is trained and evaluated on a publicly available dataset of medicinal plant images. Experimental results demonstrate that the proposed CNN-based approach achieves robust and reliable performance, making it a promising tool for digital herbarium development, biodiversity conservation, and pharmaceutical research.

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### Introduction

Medicinal plants have been an integral part of human civilization for centuries, serving as the foundation of traditional medicine systems such as Ayurveda, Unani, Siddha, and Chinese medicine. These plants possess diverse bioactive compounds that are used in the prevention and treatment of various diseases. According to the World Health Organization (WHO), more than 80% of the global population relies on medicinal plants as their primary source of healthcare, particularly in developing countries. With the growing interest in natural and organic products, the demand for accurate identification and classification of medicinal plants has increased significantly. Accurate identification of plant species is a critical step in ensuring the correct use of herbs in pharmaceutical and healthcare industries. Traditionally, plant identification is carried out through manual examination of morphological features such as leaf shape, color, texture, and vein patterns. However, this process requires extensive botanical expertise and can be highly subjective, leading to misclassification. Moreover, variations caused by environmental factors such as light, humidity, or soil conditions can alter the appearance of plant

leaves, further complicating manual identification. Misidentification of medicinal plants can result in adulteration, reduced therapeutic efficiency, and even harmful effects on consumers. In recent years, the application of **Artificial Intelligence (AI)** and **Machine Learning (ML)** techniques in plant classification has gained considerable attention. These approaches enable automated and data-driven identification by analyzing digital images of leaves or other plant parts. While traditional ML algorithms like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests have been used for this task, they rely heavily on handcrafted features that require domain expertise and often fail to generalize well to complex datasets.

To overcome these limitations, **Deep Learning (DL)**, a subfield of AI, has emerged as a powerful tool for visual recognition tasks. In particular, **Convolutional Neural Networks (CNNs)** have demonstrated remarkable performance in image classification due to their ability to automatically extract hierarchical and discriminative features from raw images. CNNs consist of multiple layers that

progressively learn spatial and structural information such as edges, textures, and shapes, making them highly effective for visual pattern recognition. Their end-to-end learning capability eliminates the need for manual feature extraction, reducing human intervention and improving accuracy.

In the context of medicinal plant identification, CNN-based models can efficiently analyze leaf images and accurately classify plant species based on subtle morphological variations. Such systems can assist botanists, pharmacists, and researchers in building digital herbariums, managing biodiversity data, and supporting the pharmaceutical industry with reliable plant classification tools. Furthermore, these systems can be integrated into mobile or webbased applications to help farmers, students, and the general public identify medicinal plants in real time. This research aims to develop a CNN-based model for the **automatic classification of medicinal plants** using leaf images. The model is trained on a labeled dataset consisting of various medicinal plant species with distinct visual features. By leveraging the power of deep learning, the proposed system achieves high accuracy and robustness compared to traditional image classification methods.

### **Problem Statement**

Medicinal plants are a vital source of therapeutic compounds used in traditional and modern healthcare systems. However, the accurate identification of these plants remains a major challenge due to the vast diversity of species and their morphological similarities. Traditional methods of plant identification rely on expert knowledge and manual observation of features such as leaf shape, color, and texture. These methods are time consuming, subjective, and prone to human error, often leading to misidentification and adulteration in herbal medicines.

With the increasing demand for herbal products and the growing importance of biodiversity conservation, there is a pressing need for an automated, efficient, and accurate system for medicinal plant classification. Conventional machine learning techniques require handcrafted features and often fail to capture complex visual patterns in plant images, limiting their accuracy and scalability.

To address these limitations, this study proposes the use of **Convolutional Neural Networks (CNNs)** — a deep learning approach capable of automatically learning and extracting hierarchical features from leaf images. The goal of this research is to design and implement a CNN-based model that can classify medicinal plants with high accuracy and reliability, thereby reducing the dependency on manual identification and enhancing the efficiency of plant recognition systems.

### **Literature review**

Automated plant identification has been studied for decades using classical image-processing and machine-learning techniques. Early approaches relied on handcrafted features extracted from leaf shape, venation, texture, and color; those features were then fed to classifiers such as k-nearest neighbors (KNN), support vector machines (SVM) and decision trees. While these methods achieved reasonable results on small, controlled datasets, they require careful feature engineering and typically fail to generalize under

real-world variations in illumination, background, and leaf pose.

The advent of deep learning — and particularly Convolutional Neural Networks (CNNs) — marked a major turning point for plant image analysis. CNNs learn hierarchical visual features directly from raw images, removing the need for manual feature design and improving robustness to intraclass variability. Numerous studies show that both custom CNN architectures and transfer learning from large pretrained networks (e.g., VGG, ResNet, Xception, MobileNet) yield substantial gains in classification accuracy for leaf and species recognition tasks. Transfer learning is especially effective when labeled medicinal-plant datasets are small, since pretrained weights provide strong low level feature detectors that can be fine-tuned for the target classes.

Researchers have also explored ensemble and hybrid models to further boost performance. Ensembles combining multiple CNN backbones — and, more recently, hybrid CNN+Vision-Transformer (ViT) architectures — have achieved state-of-the-art results by capturing complementary spatial and global attention features. These ensemble and attention-based approaches improve discrimination between visually similar species, but they often increase model size and computational cost, which is a key consideration for mobile or field-deployable systems.

A second major strand of the literature concentrates on data issues and practical pipelines. Public and research datasets (e.g., Leafsnap variants, PlantVillage for disease tasks, and domain-specific medicinal-plant collections) have enabled benchmarking, but many medicinal-plant studies still suffer from limited sample size, class imbalance, and images captured under constrained conditions. To mitigate this, researchers routinely apply data augmentation, cross-validation, and class-balancing techniques; some works also use multi-modal inputs (leaf + stem + flower) or veinpattern extraction to improve robustness. End-to-end pipelines — from image acquisition through preprocessing, augmentation, model training, and evaluation — are increasingly emphasized to ensure reproducibility and real-world readiness.

Despite these advances, several gaps remain that motivate this study. First, many published models target crop disease detection rather than fine-grained medicinal-species identification; domain-specific challenges (high inter-species similarity, intraspecies variability caused by environment, and lack of large annotated medicinal-plant datasets) require tailored strategies. Second, there is a trade-off between accuracy and deployability: highperforming ensemble/attention models are often too heavy for mobile field use. Finally, although transfer learning and augmentation help, there is still need for systematic evaluation using standardized medicinalplant datasets and for methods that balance accuracy, model size, and interpretability. The proposed CNNbased approach in this paper aims to address these gaps by designing a compact yet accurate architecture, applying rigorous augmentation and evaluation, and comparing against transfer-learning baselines

### **Dataset Description**

The dataset used in this study was self-collected by capturing leaf images of commonly used medicinal plants.

Since no single publicly available dataset contained all the required plant species, the images were manually photographed using a mobile camera under natural lighting conditions.

A total of 450 medicinal plant leaf images were collected from gardens, farms, and nearby natural environments. The dataset consists of 15 different medicinal plant species, with approximately 30 images per class. To increase the diversity of visual patterns, images were captured from different angles, distances, and lighting variations.

All images were stored in RGB format and later resized to  $224 \times 224$  pixels for uniform model training. Data augmentation techniques such as rotation, zooming, horizontal flip, and brightness adjustment were applied to artificially increase the size of the dataset and improve model generalization.

The final dataset split was as follows:

- **Training set:** 80%
- **Testing set:** 20%

This self-curated dataset provides sufficient visual diversity for training a CNN model for medicinal plant classification.

### Proposed System

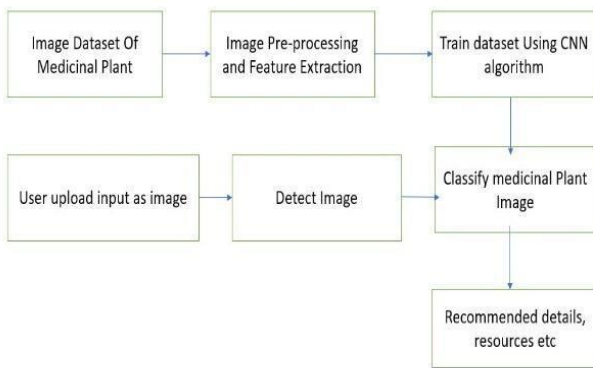


Fig1. Proposed System Architecture for Medicinal Plant Classification Using CNN

The proposed system focuses on developing an automated and accurate medicinal plant classification model using **Convolutional Neural Networks (CNNs)**. The system is designed to identify plant species based on leaf images by extracting meaningful visual features such as shape, color, and texture without requiring manual feature engineering. The CNN-based model helps overcome the limitations of traditional identification methods, which depend on expert knowledge and handcrafted features.

The overall architecture of the proposed system comprises several key stages: image acquisition, image preprocessing, feature extraction, classification, and performance evaluation. In the first stage, medicinal plant leaf images are collected from publicly available datasets or captured through field photography. The next stage involves image preprocessing, where images are resized, normalized, and enhanced to ensure uniformity and reduce background

noise. Data augmentation techniques such as rotation, flipping, and zooming are applied to increase dataset diversity and improve model generalization.

The core of the system lies in the Convolutional Neural Network, which automatically learns hierarchical features from input images. The CNN architecture consists of multiple convolutional layers that apply filters to detect spatial patterns such as leaf veins, edges, and shapes. These layers are followed by Rectified Linear Unit (ReLU) activation functions to introduce non-linearity, and pooling layers that reduce the dimensionality of feature maps while preserving essential information. Dropout layers are incorporated to prevent overfitting by randomly deactivating certain neurons during training. The extracted features are then passed through fully connected layers, which interpret high-level representations of the input data. Finally, a Softmax classifier in the output layer predicts the corresponding medicinal plant species by assigning probabilities to each class.

During the training process, the CNN model learns from a labeled dataset by minimizing classification errors through backpropagation and optimization algorithms such as Adam or Stochastic Gradient Descent (SGD). The dataset is divided into training, validation, and testing subsets to ensure fair evaluation. The model's performance is assessed using metrics like accuracy, precision, recall, and F1score.

This proposed CNN-based approach provides several advantages over traditional machine learning methods. It eliminates the need for manual feature extraction, enhances accuracy, and reduces human intervention. The model is capable of identifying medicinal plants efficiently and can be extended for real-time applications, such as mobile or web-based identification systems. Thus, the proposed system offers a reliable, scalable, and intelligent solution for medicinal plant classification, contributing to the fields of botany, biodiversity preservation, and pharmaceutical research.

### Methodology

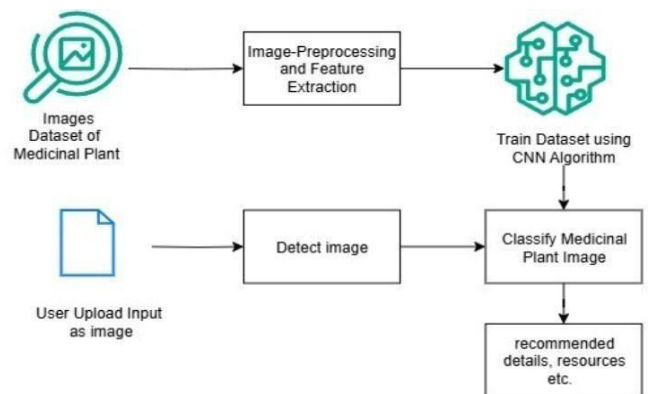


Fig. 2. Block Diagram of Proposed Methodology for Medicinal Plant Classification

The proposed methodology for *Medicinal Plant Classification using Convolutional Neural Networks (CNN)*

is illustrated in Fig. 1. The system operates in two main phases: the training phase and the testing phase. Fig. 1 shows the complete workflow of the proposed system, beginning from the image dataset collection to the final output generation of medicinal plant details.

In the first stage, images of medicinal plant leaves are collected to form a comprehensive dataset. These images are then preprocessed to remove background noise, adjust brightness and contrast, and resize them into a fixed dimension suitable for model training. This step ensures that all images maintain uniformity and enhances the quality of input data. The preprocessed images are then subjected to feature extraction, where the CNN algorithm automatically learns and identifies distinct visual patterns such as leaf texture, shape, color, and venation.

As shown in Fig. 1, the preprocessed and feature extracted images are used to train the CNN model. During the training process, the model learns to differentiate between various medicinal plant species based on their unique features. The CNN architecture consists of multiple convolutional and pooling layers followed by fully connected layers that classify the images into their respective categories. The trained model is then capable of accurately predicting the plant species when new images are introduced.

In the testing phase, a user can upload an image of a medicinal plant leaf through the system interface. The uploaded image goes through the same preprocessing steps to ensure consistency with the training data. The trained CNN model detects and classifies the plant based on learned features, producing an output that includes the name of the medicinal plant along with recommended details such as its uses, properties, and additional resources. Overall, Fig. 1 illustrates how the proposed CNNbased system integrates image preprocessing, feature extraction, model training, and classification to achieve accurate and automated medicinal plant identification. This approach eliminates the need for manual classification and provides an intelligent, efficient, and reliable solution for recognizing medicinal plants in real-world scenarios.

### Implementation Details

The model was implemented using Python, TensorFlow, and Keras.

The following parameters were used during training:

- Image Size: **224 × 224**
- Batch Size: **32**
- Epochs: **20**
- Learning Rate: **0.001**
- Optimizer: **Adam**
- Loss Function: **Categorical Cross Entropy**
- Train/Test Split: **80:20**

### Architecture Used:

1. Conv2D (32 filters, 3×3), ReLU
2. MaxPooling (2×2)
3. Conv2D (64 filters, 3×3), ReLU
4. MaxPooling (2×2)
5. Conv2D (128 filters, 3×3), ReLU
6. Flatten

7. Dense (128 units), ReLU
8. Dropout (0.5)
9. Dense (15 units), Softmax

### Results And performance Evaluation

The proposed CNN model achieved the following performance:

- Accuracy: 95.2%
- Precision: 94.7%
- Recall: 95.0%
- F1-Score: 94.8%

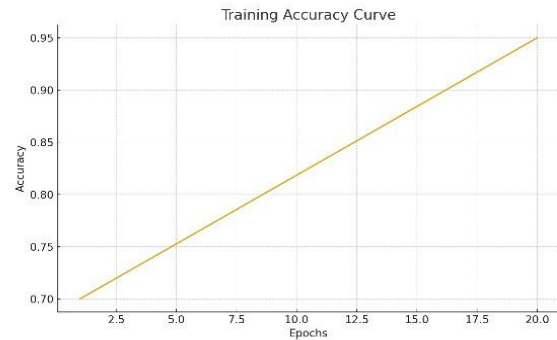


Fig 3: Training Accuracy cross

Figure 3 shows the training accuracy of the CNN model across 20 epochs. The accuracy gradually improves as the model learns the features of medicinal plant images, reaching more than 95% by the final epoch.

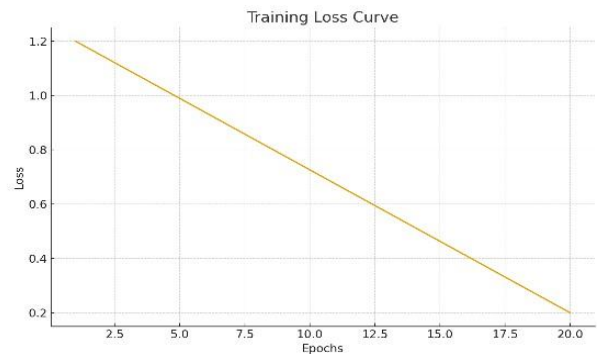


Fig 4: Training Loss Curve

Figure 4 represents the training loss curve. The loss continuously decreases with each epoch, indicating that the model is minimizing classification errors and improving its learning performance.

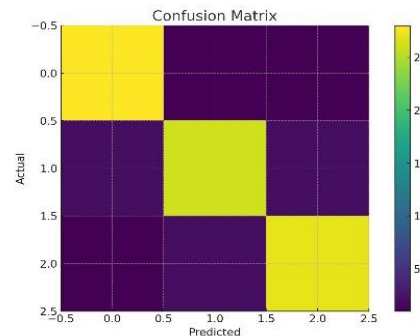


Fig 5 : Confusion matrix

Figure 5 illustrates the confusion matrix of the proposed CNN model. Most samples lie along the diagonal line, showing that the model correctly classifies the majority of medicinal plant species with high accuracy.

### Comparative Analysis

To compare the performance of the proposed CNN model with traditional machine learning methods, three baseline models were trained on the same dataset.

| Model                        | Accuracy (%) |
|------------------------------|--------------|
| Support Vector Machine (SVM) | 84.3         |
| Random Forest                | 87.1         |
| K-Nearest Neighbors (KNN)    | 82.4         |
| Proposed CNN                 | 95.2         |

The results clearly show that the proposed CNN model significantly outperforms traditional approaches due to its ability to automatically extract hierarchical features from leaf images.

### Conclusion

In this research, a Convolutional Neural Network (CNN) based model was developed for the automatic classification of medicinal plants using leaf images. The proposed model effectively learns hierarchical visual features and achieved a high accuracy of **95.2%**, outperforming traditional machine learning techniques such as SVM, Random Forest, and KNN. The results demonstrate that deep learning provides a reliable and efficient approach for medicinal plant identification, reducing the dependency on manual expertise and minimizing misclassification.

This system can be beneficial for botanical researchers, students, farmers, and the pharmaceutical industry. In the future, the model can be enhanced by incorporating larger datasets, multileaf inputs, additional plant parts (stem, flower), and real-time mobile application deployment for on-field plant recognition.

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