

# Artificial Intelligence-Based Approaches for Plant Leaf Disease Detection

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Received: 19 November 2025, Accepted: 17 December 2025, Published: 19 December 2025

**Abstract:** Medicinal plants have long been central to traditional healing systems, especially in Ayurveda, which promotes balance between body, mind, and environment. Accurate identification of these plants is essential for safe use, yet conventional methods often rely on subjective human judgment. This study explores how artificial intelligence can support plant recognition by using machine learning (ML) and deep learning (DL) techniques to classify medicinal leaves. A diverse image dataset was analyzed based on visual features such as color, texture, shape, and size. ML models—including Support Vector Machines, Decision Trees, and Random Forests—were compared with advanced DL architectures like VGG16, InceptionV3, and Vision Transformers. To improve model generalization and reduce overfitting, data augmentation and transfer learning were applied. Results showed that DL models consistently outperformed ML approaches, with the transformer-based model achieving the highest classification accuracy. These findings suggest that AI-powered systems can make medicinal plant identification more reliable and scalable. The study offers practical insights for digital health applications and contributes to the modernization of traditional medicine through technology-driven solutions.

**Keywords:** Medicinal Plants, Machine Learning, Deep Learning, Leaf Classification, Health Informatics

## 1. Introduction

The recognition of medicinal plants holds vital importance in public health, pharmacology, and natural product research. Among different plant organs, leaves are particularly valuable for species identification because their shape, color, venation, and texture patterns serve as essential visual markers for classification (Kumar, Singh, & Sharma, 2019). Conventional identification techniques typically rely on expert observation and manual comparison of morphological features (Sharma, Singh, & Gupta, 2020). Such methods require specialized botanical expertise and are often supported by static reference materials, such as field guides and herbarium samples.

However, manual identification presents several challenges. It is time-consuming, limits large-scale processing, and heavily depends on human judgment, which increases the likelihood of inconsistency and error (Verma, Kumar, & Singh, 2021). Furthermore, traditional reference datasets may be incomplete or regionally restricted, making it difficult to identify rare or geographically specific species (Patel, Mehta, & Joshi, 2022).

In recent years, the use of computer vision and artificial intelligence (AI) has brought significant progress to the automated identification of medicinal plants. Machine Learning (ML) and Deep Learning (DL) methods now allow for the extraction and interpretation of leaf characteristics—such as shape, texture, and structure—without the need for manual analysis. Algorithms like Support Vector Machines (SVM) and Convolutional Neural Networks (CNNs) have shown strong performance in identifying plant species and differentiating between healthy and diseased samples (Li, Zhang, & Wang, 2009; Bakhshipour & Jafari, 2018). Beyond classification, these AI-based approaches have also proven useful in detecting visual signs of pest damage, nutrient imbalances, and environmental stress factors (Lottes et al., 2020; Negrete, 2018), offering valuable support for plant health monitoring and precision agriculture. Automated systems for leaf recognition not only enhance the efficiency of medicinal plant research but also contribute to sustainable agriculture and biodiversity conservation. The integration of high-resolution imaging, large-scale datasets, and Unmanned Aerial Vehicle (UAV) technologies has further strengthened the accuracy and scalability of these systems.

This study performs a comparative evaluation of ML and DL techniques for medicinal leaf identification, aiming to determine the most effective algorithms for automated classification. By bridging existing

research gaps, this work contributes to the development of intelligent, data-driven systems that facilitate the reliable recognition of medicinal plant species.

## 2. Literature Review

In recent years, artificial intelligence (AI) has become increasingly prominent in the field of plant disease detection, with machine learning (ML) and deep learning (DL) standing out as the most widely adopted techniques. Deep learning models—particularly Convolutional Neural Networks (CNNs)—have shown exceptional performance in identifying and classifying diseases based on leaf imagery. For example, ResNet50 achieved an accuracy close to 97% on the well-known PlantVillage dataset, highlighting the strength of deep architectures in detecting plant-related pathologies (Kumar et al., 2022). Likewise, Bayesian CNNs have demonstrated impressive generalization capabilities, reaching approximately 99% accuracy when distinguishing between diseases affecting tomato and potato leaves (Singh et al., 2022). These results underscore the potential of AI-driven approaches to support more accurate and scalable plant health diagnostics.

Hybrid and ensemble-based models have also been widely explored. The combination of color and texture-based features with CNN architectures—using Support Vector Machines (SVMs) for classification—has proven effective for multi-disease detection in rice plants (Zhang et al., 2021). Likewise, k-means clustering combined with multi-class SVMs produced reliable results in the classification of soybean leaf diseases (Patel et al., 2023). Approaches based on few-shot learning and Siamese Networks have further expanded the potential of DL in domains with limited training data, enabling accurate predictions even with small datasets (Ghosh et al., 2023).

In addition to disease detection, DL models have been applied to plant species differentiation. Discriminative CNN frameworks have achieved high accuracy in the classification of bean cultivars (Ranjan et al., 2022), while hybrid CNN–SVM systems demonstrated strong performance in identifying tea leaf diseases (Khan et al., 2024). Moreover, the integration of Histogram of Oriented Gradients (HOG) feature extraction with Random Forest classifiers has been shown to enhance the reliability of plant disease identification (Sharma et al., 2019).

Recent advances in transfer learning and UAV-based imaging have further extended the scope of AI in agriculture. UAV imagery has been effectively employed for the recognition of palm and banana trees (Nguyen et al., 2024), and pre-trained CNN architectures such as VGG16 and EfficientNet have achieved outstanding results in classifying maize and legume crops (Liu et al., 2021; Ahmed et al., 2024). Hybrid methods combining CNNs with histogram-based features or other neural network architectures have also yielded promising results (Rebetez et al., 2016). Multi-layer CNN models have successfully analyzed rice crop phenology (Yang et al., 2020), while two-layer CNNs demonstrated accurate detection of tobacco plants from UAV images (Fan et al., 2018).

AI technologies have also played an essential role in weed detection and crop pattern recognition. CNN-based frameworks have been successfully used for identifying crop rows in maize fields (Dian Bah et al., 2018), while CRowNet, a hybrid of the Hough transform and CNNs, improved row detection accuracy (Bah et al., 2020). U-Net–based architectures achieved excellent results in counting corn plants from aerial imagery (Kitano et al., 2024). Moreover, traditional ML models such as SVMs, when enhanced with texture and color features, have remained competitive in differentiating weeds from crops (Li et al., 2009; Bakhshipour & Jafari, 2018). Fully Convolutional Networks (FCNs) have further improved plant–weed discrimination by incorporating stem and spatial context data (Lottes et al., 2020).

Overall, research across multiple agricultural domains confirms the transformative impact of AI-based methods in automating disease diagnosis, crop monitoring, and plant classification. These findings collectively establish a strong foundation for developing AI-assisted tools in medicinal plant identification, which this study aims to extend and refine.

### 3. Methodology

This study focuses on developing an effective automated system for identifying and classifying medicinal plant leaves. To support this goal, the publicly available Medicinal Leaf Dataset compiled by R. & J. (2020) was used. The dataset includes a rich variety of species such as sandalwood (*Santalum album*), Jamaican cherry (*Muntingia calabura*), Indian and Mexican mint (*Plectranthus amboinicus*, *Coleus amboinicus*), and Oriental mustard (*Brassica juncea*), along with over thirty other medicinal herbs collected from botanical gardens in India. Each species is represented by roughly 1,500 images, with 60 to 100 high-resolution samples per plant type.

To prepare the data for model training, all images were resized to  $180 \times 180$  pixels for consistency. Data augmentation techniques—such as flipping, rotating, zooming, and shifting—were applied to increase dataset diversity and reduce overfitting. The dataset was then split into training and testing sets.

For classification, both traditional machine learning methods (SVM, Decision Tree, Random Forest) and deep learning models (VGG16, InceptionV3, and Vision Transformer) were used. Pre-trained networks were fine-tuned through transfer learning to suit the dataset's characteristics. Model performance was assessed using accuracy, precision, recall, and F1-score, offering a balanced evaluation especially in cases of class imbalance.

The formulas used are as follows:

$$\text{Accuracy (Acc)} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

Measures the proportion of correctly classified instances across all predictions.

$$\text{Precision (P)} = \frac{TP}{(TP + FN)} \quad (2)$$

Indicates the reliability of positive predictions.

$$\text{Recall (R)} = \frac{TP}{(TP + FP)} \quad (3)$$

Reflects the model's ability to identify all relevant positive cases

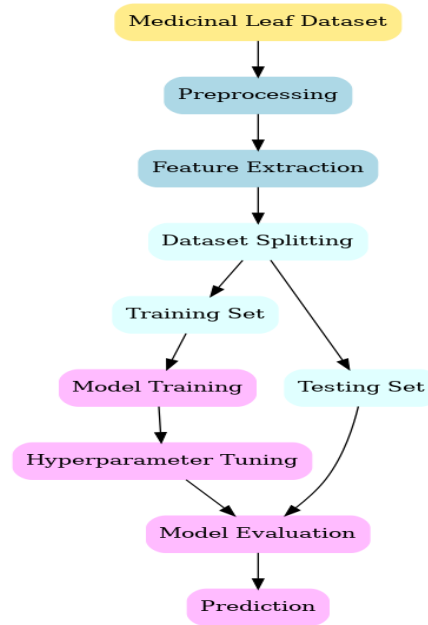
$$\text{F1 - Score} = \frac{2 * \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Provides a harmonic mean of precision and recall, balancing both metrics.

These evaluation criteria were selected to ensure a thorough and balanced comparison of the models, accounting for both overall predictive accuracy and sensitivity to class distribution. By systematically analyzing the performance of each algorithm, the study contributes a comparative framework that may inform future research in automated medicinal plant identification and classification.

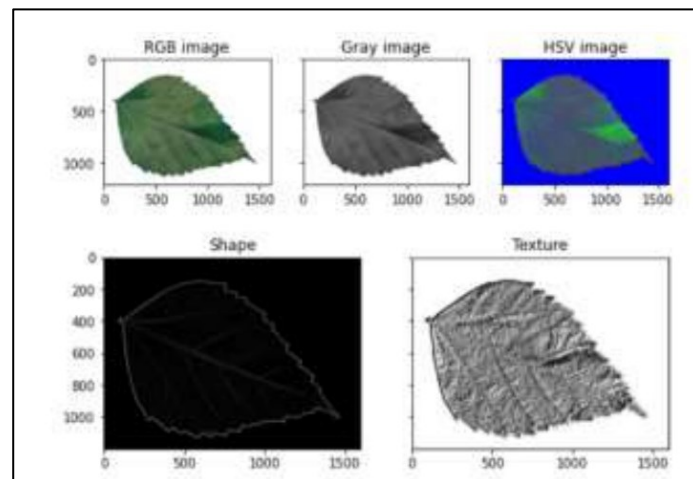
#### 3.1. System Architecture and Feature Extraction

The overall system architecture is illustrated in Figure 1. The system workflow begins with user interaction, where a user uploads an image of a leaf. The system then classifies the image using the pre-trained model and presents the prediction results. Additionally, a database is integrated to provide supplementary information about the identified leaf species and their morphological characteristics.



**Figure 1.** System architecture of the proposed model

In this study, four distinct techniques were employed to extract features from leaf imagery: RGB and HSV color representations, Sobel edge detection, and Local Binary Patterns (LBP). The RGB and HSV color models were utilized to encode chromatic attributes of the leaves, which are instrumental in distinguishing species based on visual cues. The Sobel operator facilitated the identification of edge structures, thereby capturing shape-related features critical for object delineation. Meanwhile, LBP was implemented to quantify textural characteristics, enabling a nuanced analysis of surface patterns that enhance classification fidelity. Representative samples of these extracted features are illustrated in Figure 2.



**Figure 2.** Examples of extracted leaf features

Subsequent to feature extraction, three supervised machine learning classifiers were deployed to perform the categorization task: Linear Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF). The SVM algorithm was selected for its capacity to construct optimal separating hyperplanes in high-dimensional spaces, thereby achieving effective class discrimination. Decision Trees offer a transparent and interpretable framework, allowing for intuitive visualization of decision boundaries.

Random Forest, as an ensemble-based approach, aggregates multiple decision trees to bolster predictive accuracy and reduce variance, thereby improving generalization across unseen data.

Model performance was assessed using a suite of standard evaluation metrics, including accuracy, precision, recall, and F1-score. To further refine model efficacy, hyperparameter optimization was conducted via grid search, ensuring the systematic identification of parameter configurations that yield optimal results during both training and validation phases.

This methodological framework was designed to maximize both the precision and robustness of the classification models, thereby supporting reliable automated identification of medicinal plant species based on leaf imagery.

The upper row in Figure 2 illustrates the original RGB image (left), its grayscale version (middle), and the HSV representation (right).

The lower row presents the image after Sobel edge detection (left) and the texture representation obtained via the LBP method (right).

#### 4. Results

In the deep learning stage of the classification pipeline, a hybrid approach combining data augmentation and transfer learning was adopted to enhance model performance. Data augmentation techniques were employed to synthetically increase the diversity and volume of the training set, thereby improving the model's ability to generalize and minimizing the likelihood of overfitting. The augmentation process involved a series of geometric transformations, including horizontal and vertical flips, rotations, zoom operations, and spatial translations along both axes.

Two convolutional neural network (CNN) architectures, pre-trained on large-scale image datasets, were fine-tuned using the augmented medicinal leaf dataset. The first architecture, VGG16, comprises 16 layers and was adapted by substituting its terminal fully connected layer with a global average pooling layer, followed by a custom dense layer utilizing a softmax activation function. This modification allowed the model to better align with the specific classification task and improved its discriminative capacity.

The second architecture, InceptionV3, features a deeper structure with 48 layers. In this configuration, the original classification head was replaced with two fully connected layers activated by ReLU functions, followed by a softmax layer for multi-class prediction. Both models were optimized using the Adam optimizer with a fixed learning rate of 0.0001, and categorical cross-entropy was selected as the loss function to guide the training process.

To identify the most effective model configuration, a systematic hyperparameter tuning process was conducted. Parameters such as the number of neurons in the dense layers and the number of training epochs were iteratively adjusted to maximize classification accuracy. This methodology leveraged the strengths of transfer learning while tailoring the models to the unique characteristics of the medicinal plant dataset, ultimately enhancing predictive performance.

**Table 1.** Performance Comparison of Machine Learning Algorithms

| No. | Machine Learning Algorithm   | Accuracy (%) | Precision | Recall | F1-Score |
|-----|------------------------------|--------------|-----------|--------|----------|
| 1.  | Support Vector Machine (SVM) | 88.42        | 0.88      | 0.88   | 0.87     |
| 2.  | Decision Tree                | 61.85        | 0.62      | 0.62   | 0.61     |
| 3.  | Random Forest                | 81.19        | 0.83      | 0.81   | 0.81     |

Table 1 shows how well each machine learning method performed when classifying medicinal plant leaves. Among them, the Linear SVM stood out by reaching 88% accuracy, which suggests that the way features were extracted played a big role in the success—and with some fine-tuning, even better results might be possible.

**Table 2.** Accuracy of Deep Learning Models Across Different Epochs

| No. | Deep Learning Model | Epochs | Accuracy (%) |
|-----|---------------------|--------|--------------|
| 1.  | VGG 16              | 20     | 96.73        |
|     |                     | 25     | 90.19        |
|     |                     | 30     | 96.46        |
| 2.  | Inception v3        | 20     | 94.01        |
|     |                     | 25     | 94.55        |
|     |                     | 30     | 95.64        |

Table 2 summarizes the accuracy results obtained for the VGG16 and Inception v3 models across different epoch values.

It can be observed that VGG16 reached the highest accuracy of 96.73% at 20 epochs, while Inception v3 achieved 95.64% at 30 epochs.

**Table 3.** Performance of Vision Transformer Model

| No. | Deep Learning Model | Epochs | Accuracy (%) |
|-----|---------------------|--------|--------------|
| 1.  | Vision Transformer  | 5      | 99.71        |

As shown in Table 3, the Vision Transformer (ViT) model achieved the highest classification accuracy of 99.71% in the medicinal leaf identification task, even with a relatively low number of epochs.

This result highlights the superior performance and efficiency of transformer-based architectures in feature representation and classification compared to traditional CNN models.

## 5. Discussion and Conclusion

This research conducts a comparative analysis of machine learning (ML) and deep learning (DL) techniques applied to the classification of medicinal plant foliage. Within the ML category, the Linear Support Vector Machine (SVM) emerged as the most effective model, attaining an accuracy rate of 88%. This outcome underscores the critical role of feature extraction in shaping classification performance and indicates that further optimization of these techniques may lead to improved predictive accuracy.

Within the DL category, the VGG16 model demonstrated superior performance, achieving an accuracy of 96.73%. This finding indicates that deep learning architectures are more effective than traditional ML algorithms in handling image-based datasets, particularly those involving complex morphological and textural characteristics. The Vision Transformer (ViT) model exhibited the best overall performance, attaining an accuracy of 99.71%, which clearly demonstrates the advantage of transformer-based architectures in capturing intricate and context-aware visual representations.

One notable advantage of deep learning models is their ability to perform end-to-end learning without requiring manual feature extraction. However, when working with smaller datasets, these models are more susceptible to overfitting, which can lead to reduced performance in real-world applications. The

results of this study suggest that, given the characteristics of the dataset, deep learning approaches—especially transformer-based models—are more suitable for the automatic classification of medicinal plant leaves. Nonetheless, the performance of each algorithm may vary depending on dataset diversity, size, and image quality.

The proposed medicinal leaf detection system can accurately and rapidly identify plant species, making it useful even for users without specialized botanical knowledge. This approach not only supports the broader field of medicinal plant classification research but also provides a foundation for developing data-driven decision support systems in digital health and herbal medicine applications.

For future work, it is recommended that the models be tested on real-time image datasets captured under varying environmental conditions. Moreover, integrating the proposed system into a mobile application could enhance its accessibility, enabling real-time identification and classification of medicinal leaves in the field.

In contrast to conventional plant identification techniques, the developed system provides a flexible and scalable framework that can be incrementally enhanced with newly acquired data, thereby facilitating more efficient research workflows and broadening access to botanical information across both traditional and contemporary medical contexts.

### Acknowledgments

This study was presented at the 12th International Conference on Management Information Systems (ICMIS 2025), held at Ankara Medipol University, Ankara, Türkiye, between October 23–25, 2025.

### Author Contributions

All authors made equal contributions to the conception, design, and writing of the manuscript.

**Funding:** This research received no external funding.

**Conflicts of Interest:** The authors declare no conflict of interest.

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