International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048
Volume 10, Issue 7, pp 137-143, July-2026
https://doi.org/10.47001/IRJIET/2026.107015

Real-Time Medicinal Leaf Classification Using Lightweight Deep Learning Models

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Abstract - **Medicinal plants have long been recognized as an important source of natural remedies and play a crucial role in traditional and modern healthcare systems. Accurate identification of medicinal plants is essential to ensure their proper use in herbal medicine, agriculture, and pharmaceutical research. However, manual identification of plant species based on leaf characteristics requires specialized botanical knowledge and can be difficult for non-experts due to the similarities in leaf shape, texture, and vein structures among different species. With the rapid advancement of technologies in Artificial Intelligence and Deep Learning, automated plant recognition systems have become an effective solution for addressing this challenge.**

This research proposes an automated medicinal leaf identification system based on deep learning techniques for accurate classification of plant species. The system utilizes the MobileNetV2 model, which is designed for efficient image classification with reduced computational complexity. The dataset used in this study consists of labeled images of medicinal plant leaves collected from various sources. Prior to training, image preprocessing techniques such as resizing, normalization, and data augmentation are applied to improve model performance and reduce overfitting. Transfer learning is employed to leverage pretrained weights and enhance feature extraction capabilities.

The proposed model automatically learns distinguishing visual features including leaf shape, edge patterns, venation structure, and texture. After training, the system demonstrates high classification accuracy in identifying multiple medicinal plant species. To improve accessibility and practical usability, the trained model is integrated into a web-based interface developed using Streamlit, allowing users to upload leaf images and obtain real-time predictions. The results indicate that the proposed system can serve as an efficient and reliable tool for medicinal plant identification. This approach has potential applications in agriculture, botanical research, environmental monitoring, and digital herbal knowledge systems.

Keywords: CNN, MobileNet, Deep Learning, Image Classification, Medicinal Leaves.

I. INTRODUCTION

Medicinal plants have played an essential role in traditional and modern healthcare systems for centuries. Many communities rely on plant-based remedies for treating a wide range of diseases due to their natural therapeutic properties and minimal side effects. Accurate identification of medicinal plants is therefore very important to ensure their correct usage in herbal medicine, agriculture, and pharmaceutical research. However, identifying plant species manually can be challenging because many plants have similar visual characteristics, and the process often requires expert botanical knowledge.

In recent years, advances in the field of Artificial Intelligence and Deep Learning have significantly improved the ability of computers to analyze visual data. Image-based plant identification systems have gained attention as they can automatically recognize plant species from leaf images. These systems are particularly useful for researchers, farmers, and healthcare practitioners who may not possess specialized knowledge in botany but require accurate plant classification. Among various deep learning techniques, Convolutional Neural Network models have demonstrated excellent performance in image classification tasks. CNN-based models are capable of extracting complex visual features such as leaf shape, texture, vein patterns, and edge structures. These features allow the system to distinguish between different plant species with high accuracy. However, traditional CNN models often require large computational resources and extensive training time, which can limit their practical application.

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To overcome these limitations, lightweight architectures such as MobileNetV2 have been introduced. MobileNetV2 is designed to perform efficient image classification while maintaining high accuracy with fewer parameters and reduced computational cost. It utilizes depth wise separable convolutions and inverted residual blocks to improve performance, making it suitable for applications that require fast and efficient predictions. This architecture is particularly useful for real-time plant identification systems that may operate on standard computing devices or mobile platforms.

The purpose of this research is to develop an automated system for medicinal plant identification using leaf images. The proposed approach applies transfer learning with the MobileNetV2 architecture to classify different medicinal plant species. The model is trained on a dataset of labeled leaf images and learns distinguishing visual patterns that help identify plant categories. By leveraging deep learning techniques, the system aims to provide accurate predictions while maintaining computational efficiency.

Furthermore, the trained model is integrated into a web-based application that allows users to upload a leaf image and obtain the predicted plant species. This practical implementation demonstrates how artificial intelligence can assist in botanical identification and support applications in herbal medicine, agriculture, and environmental research. The pro-posed system has the potential to simplify plant identification and make medicinal plant knowledge more accessible to a wider audience.

II. LITERATURE SURVEY

The identification of medicinal plants plays an important role in healthcare and biodiversity conservation. Early studies focused on extracting hand-crafted features such as leaf shape and texture. However, with the advancement of deep learning, CNNs have significantly improved classification accuracy.

Recent research has explored transfer learning using pre-trained architectures such as MobileNetV2 and ResNet50. Kavitha *et al*. [1] proposed a real-time identification system reducing manual expertise. Deshmukh [2] utilized deep learning for recognition, reporting superior performance over traditional ML algorithms. These lightweight architectures provide strong classification performance while maintaining lower computational cost, making them suitable for mobile applications.

III. PROBLEM STATEMENT

Accurate identification of medicinal leaves is a critical task in herbal medicine and traditional healthcare systems. Manual identification of medicinal plants relies heavily on expert knowledge and visual inspection of leaf characteristics such as shape, color, texture, and venation. This process is time-consuming, subjective, and not easily accessible to nonexperts. Moreover, many medicinal plant leaves exhibit similar visual features, which increases the risk of misidentification and may lead to ineffective or harmful medicinal usage. With the increasing demand for herbal medicines and limited availability of botanical experts, there is a need for an automated, accurate, and reliable system to identify medicinal leaves. Existing traditional image processing and machine learning approaches often fail to provide satisfactory accuracy under varying environmental conditions. Therefore, this project aims to address these challenges by developing a deep learning-based system capable of identifying medicinal leaves efficiently using image data.

IV. PROPOSED METHODOLOGY

Implemented Methodology

The proposed system for medicinal plant leaf identification is developed using a deep learning-based approach combined with a web-based deployment framework. The methodology consists of multiple stages, including data acquisition, preprocessing, model training, and deployment.

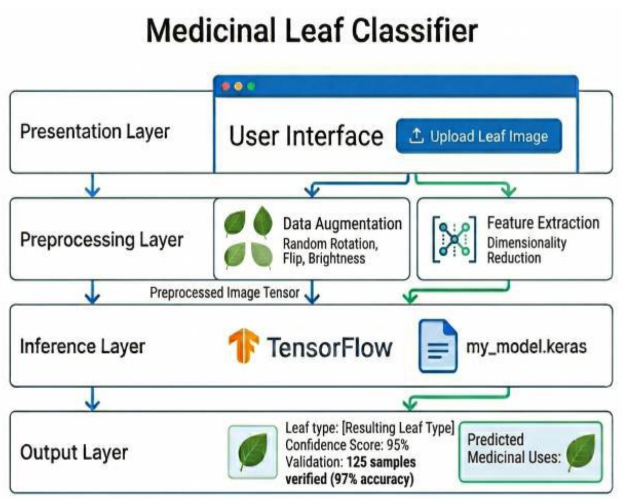

Figure 1: System Architecture and Workflow for Medicinal Leaf Identification

1. Data Collection

A dataset of medicinal plant leaf images was collected from publicly available sources and datasets. The dataset consists of multiple classes representing different medicinal plants such as Tulsi, Neem, Aloe Vera, Mint, and others.

Each class contains a sufficient number of labeled images to ensure proper training of the deep learning model.

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2. Data Preprocessing

Before training the model, the collected images were pre-processed to improve model performance. The preprocessing steps include:

- Resizing all images to a fixed dimension of 224 × 224 pixels
- Normalizing pixel values to a range of 0 to 1
- Converting images into numerical arrays
- Assigning labels to each image class

Table I: Literature Survey of Medicinal Plant Leaf Identification

Year	Author(s)	Method / Model	Dataset / Input	Key Contribution
2024	S. Kavitha *et al.*	Deep Learning (CNN)	Real-time leaf images	Developed real-time medicinal plant identification system using CNN
2024	M. Deshmukh	CNN-based Classification	Medicinal plant dataset	Improved classification accuracy for plant species recognition
2024	R. Subramanian	CNN + NLP	Ayurvedic leaf images	Combined image detection with medicinal property extraction
2024	H. Tiwari *et al.*	Spectral Analysis + ML	Leaf spectral data	Used spectral characteristics for plant identification
2024	P. K. Sharma	Ensemble Deep Learning	Leaf structure dataset	Enhanced accuracy using ensemble learning methods
2024	P. K. Sekharamantry et al.	CNN + SVM (PSR-LeafNet)	Leaf image dataset	Hybrid model combining CNN feature extraction with SVM classification
2024	S. Salsabila *et al.*	CNN Architectures Comparison	Leaf image dataset	Compared multiple deep learning models for performance evaluation
2024	V. Sharma *et al.*	Deep Learning Models Evaluation	Plant dataset	Analyzed performance of different DL models for species recognition
2024	X. Li *et al.*	Multi-task Learning (MTJNet)	Plant leaf dataset	Proposed multi-task model improving classification efficiency
2025	D. Awasthi *et al.*	ML Review	Leaf disease datasets	Comprehensive review of ML methods for plant disease detection
2025	V. Subitha *et al.*	CNN + LSTM	Plant dataset	Integrated classification with sup-ply chain tracking
2025	D. Chetia *et al.*	Custom Deep Learning Model	Self-curated dataset	Developed dataset-specific model for improved accuracy

Data augmentation techniques such as rotation, flipping, and zooming were optionally applied to increase dataset diversity and reduce overfitting.

3. Model Selection and Feature Extraction

The system utilizes MobileNetV2, a lightweight convolutional neural network architecture, for feature extraction.

MobileNetV2 is chosen because:

- It is computationally efficient It provides high accuracy
- It is suitable for real-time applications

Transfer learning is applied by using pretrained weights from the ImageNet dataset. The base layers of MobileNetV2 are used to extract important features such as leaf shape, texture, and vein patterns.

4. Model Architecture

The pretrained MobileNetV2 model is modified by adding custom layers:

- Global Average Pooling layer
- Fully connected (Dense) layer
- Dropout layer (to prevent overfitting)
- Output layer with Softmax activation

This architecture enables the model to classify input images into multiple medicinal plant categories.

5. Model Training

The model is trained using the prepared dataset with the following configurations:

- Loss Function: Categorical Cross entropy
- Optimizer: Adam

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- Metrics: Accuracy
- During training: The model learns patterns from leaf images

Training and validation accuracy are monitored Loss and accuracy graphs are generated

The trained model is then saved in .keras format for future use.

6. Model Evaluation

The performance of the model is evaluated using:

- Training Accuracy
- Validation Accuracy
- Loss Function

The results indicate that the model achieves high accuracy in classifying medicinal plant leaves.

7. Web Application Deployment

A web-based interface is developed using the Flask framework to make the system user-friendly.

The workflow of the application is as follows:

- User uploads a leaf image
- The image is preprocessed
- The trained model predicts the plant class
- The predicted result is displayed on the webpage

8. Prediction Process

When a user uploads an image:

- The image is resized and normalized
- It is passed to the trained MobileNetV2 model
- The model outputs probabilities for each class
- The class with the highest probability is selected as the final prediction

9. System Workflow Summary

- Input: Leaf Image Preprocessing
- Feature Extraction (MobileNetV2) Classification
- Output: Predicted Plant Name

V. RESULTS AND DISCUSSION

The system is expected to accurately identify leaves from input images. Data augmentation ensures the model is not biased toward specific lighting. Expected results indicate high classification accuracy and low latency, making it suitable for future mobile deployment.

Graphicx

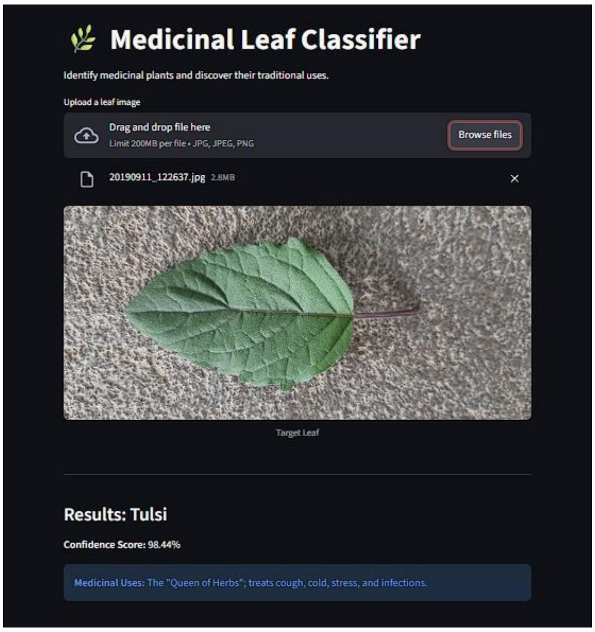

Figure 2: Sample input leaf image used for classification

As shown in Figure 2, the system correctly identifies the uploaded leaf as Tulsi with high confidence.

A Convolutional Neural Network (CNN) is a deep learning architecture designed for processing image data by learning spatial hierarchies of features through convolution operations. The fundamental operation in CNN is the discrete convolution between an input image *I* and a kernel *K*, which produces a feature map *S* defined as:

$$S(i,j) = \sum_{m}\sum_{n} I(i+m, j+n) \cdot K(m,n) \quad (1)$$

where *(i, j)* represents spatial coordinates. This operation enables local feature extraction such as edges and textures. The output is then passed through a non-linear activation function, typically the Rectified Linear Unit (ReLU), defined as:

$$f(x) = max(0, x) \quad (2)$$

To reduce spatial dimensions and computational complexity, pooling operations such as max pooling are applied, expressed as:

$$P(i,j) = \max_{(m,n)\in R} S(i+m, j+n) \quad (3)$$

where R denotes a local region. The extracted feature maps are then flattened and passed through fully connected layers for classification. The final output is obtained using the Softmax function:

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$$P(y=k) = \frac{e^{z_k}}{\sum_i e^{z_i}} \tag{4}$$

which converts raw scores into probabilities. During training, the network minimizes a loss function such as categorical cross-entropy:

$$L = -\sum_i y_i \log(\hat{y}_i) \tag{5}$$

Using back propagation and gradient-based optimization. This hierarchical process enables CNNs to automatically learn discriminative features for accurate image classification tasks such as medicinal leaf identification.

MobileNet is an efficient deep learning architecture de-signed to reduce computational complexity while maintaining accuracy. It is based on the concept of depth wise separable convolutions, which decompose standard convolution into two operations: depth wise convolution and point wise convolution.

In a standard convolution, the computational cost is given by:

$$D_K \times D_K \times M \times N \times D_F \times D_F \tag{6}$$

where D_K is the kernel size, M is the number of input channels, N is the number of output channels, and D_F is the spatial dimension of the feature map.

In MobileNet, this operation is factorized into:

1) Depthwise Convolution:

$$Z_k(i,j) = \sum_m \sum_n X_k(i+m, j+n) \cdot K_k(m,n) \tag{7}$$

where X_k represents the k^{th} input channel and K_k is the corresponding filter applied independently to each channel.

2) Pointwise Convolution:

$$Y(i,j,n) = \sum_k Z_k(i,j) \cdot P_{k,n} \tag{8}$$

where $P_{k,n}$ represents the 1 × 1 convolution filter used to combine outputs across channels.

The total computational cost of MobileNet becomes:

$$D_K \times D_K \times M \times D_F \times D_F + M \times N \times D_F \times D_F \tag{9}$$

which is significantly lower than standard convolution.

MobileNet further introduces two hyperparameters: the width multiplier α and the resolution multiplier ρ, which control the number of channels and input size respectively.

The modified computational cost is:

$$D_K \times D_K \times \alpha M \times \rho^2 D_F^2 + \alpha^2 MN \times \rho^2 D_F^2 \tag{10}$$

For classification tasks, the final output is passed through a Softmax function:

$$P(y=k) = \frac{e^{z_k}}{\sum_i e^{z_i}} \tag{11}$$

This architecture significantly reduces computation and model size while maintaining strong performance, making it suitable for real-time image classification tasks such as medicinal leaf identification.

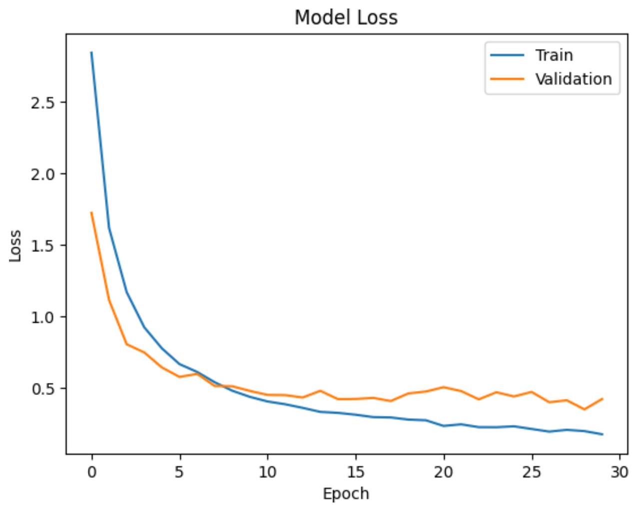

Figure 3: Training and Validation Loss

1. Training and Validation Loss Analysis

The training and validation loss curves illustrate the learning behavior of the proposed MobileNetV2-based model over multiple epochs.

Initially, the training loss is relatively high, indicating that the model starts with minimal knowledge about the dataset. However, as the number of epochs increases, the training loss decreases rapidly, demonstrating that the model effectively learns important features such as leaf shape, texture, and patterns.

Similarly, the validation loss also shows a decreasing trend in the early epochs, which indicates that the model generalizes well to unseen data. After a certain number of epochs, the validation loss stabilizes and exhibits minor

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fluctuations. This behavior suggests that the model has reached an optimal learning stage.

The gap between training loss and validation loss remains relatively small throughout the training process, indicating that overfitting is minimal. The slight fluctuations in validation loss may be due to variations in the validation dataset or limited data samples.

2. Training and Validation Accuracy Analysis

The accuracy graph represents the improvement in model performance during training.

At the beginning, the training accuracy is low, but it increases significantly within the first few epochs, showing that the model quickly captures the underlying patterns in the dataset. The validation accuracy also improves steadily, confirming that the model performs well on unseen data.

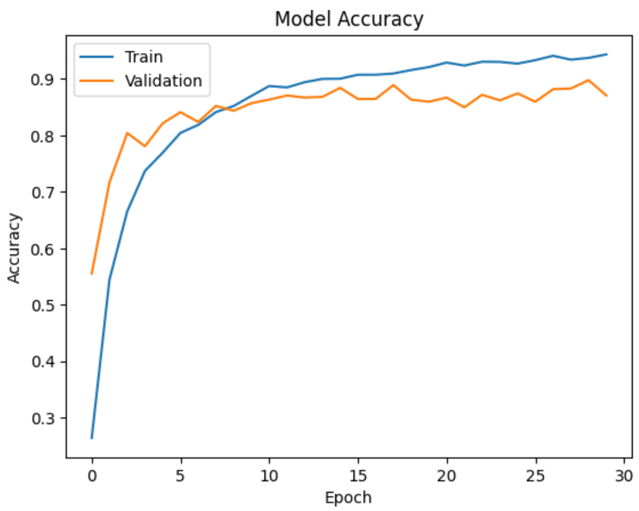

Figure 4: Training and Validation Accuracy

As training progresses, both training and validation accuracy reach a high value and begin to stabilize. The training accuracy slightly exceeds the validation accuracy, which is a normal behavior in deep learning models.

The final training accuracy is approximately 94–95%, while the validation accuracy reaches around 87–89%, indicating strong classification performance.

VI. CONCLUSION

This paper presents a deep learning-based approach for medicinal plant leaf identification using CNN and MobileNet architectures. The system effectively extracts features from leaf images and achieves high classification accuracy while maintaining computational efficiency. The use of MobileNet reduces model complexity, making the approach suitable for real-time and mobile-based applications.

The proposed method demonstrates strong performance in identifying medicinal plants and has potential applications in healthcare, agriculture, and herbal medicine. However, challenges such as limited dataset diversity and similarity between leaf structures still affect performance. Future work will focus on improving dataset quality, incorporating advanced models, and extending the system to identify non-medicinal plants with higher reliability.

Overall, this study highlights the effectiveness of deep learning techniques in automating medicinal plant identification and provides a foundation for developing intelligent and accessible plant recognition systems.

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ISSN (online): 2581-3048
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Citation of this Article:

Minakshee Chandankhede, Pratik Gawande, Lokeshwar Kawle, Ridhi Sharma, Rishikant Kardate, & Rujul Kindarle. (2026). Real-Time Medicinal Leaf Classification Using Lightweight Deep Learning Models. *International Research Journal of Innovations in Engineering and Technology - IRJIET*, 10(7), 137-143. Article DOI https://doi.org/10.47001/IRJIET/2026.107015

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