



AUTOMATED MEDICINAL PLANT IDENTIFICATION USING TRANSFER LEARNING AND DEEP CONVOLUTIONAL NETWORKS

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Abstract

The identification of medicinal plants is essential for traditional medicine, pharmaceutical research, biodiversity conservation, and healthcare applications. However, manual identification can be time-consuming and requires specialized botanical knowledge, particularly when different plant species exhibit similar visual characteristics. This study focuses on automated medicinal plant identification using transfer learning and deep convolutional neural networks. The proposed methodology involves collecting labelled medicinal plant images, preprocessing the dataset, applying data augmentation, and dividing the images into training, validation, and testing subsets. Pre-trained CNN architectures, including VGG16, ResNet50, MobileNetV2, and InceptionV3, are adapted to classify medicinal plant species based on their visual characteristics. Model performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrices. Computational efficiency is also considered to assess the suitability of different architectures for practical applications. The study provides a systematic framework for comparing transfer learning models and identifying an appropriate architecture for medicinal plant classification. The proposed approach has the potential to support faster plant identification, botanical research, and biodiversity documentation.

Keywords: Medicinal Plant Identification, Transfer Learning, Convolutional Neural Networks, Deep Learning, Image Classification, Computer Vision, Plant Recognition.

1. INTRODUCTION

Medicinal plants have played a significant role in traditional healthcare systems and pharmaceutical research for centuries. They are widely used in the preparation of herbal medicines, therapeutic products, and natural remedies for various health conditions. The growing interest in plant-based healthcare has increased the importance of accurate medicinal plant identification. Proper identification is essential for botanical research, biodiversity conservation, herbal product development, and the safe utilization of medicinal resources. However, identifying medicinal plants manually can be challenging because many species share similar morphological characteristics, including leaf shape, size, colour, texture, and venation patterns. The process also requires specialized botanical knowledge and considerable time, particularly when dealing with a large number of plant species. These challenges highlight the need for automated and efficient plant identification techniques that can improve classification accuracy and reduce dependence on manual observation.

The development of artificial intelligence and computer vision has created new opportunities for automated plant identification. Traditional image processing techniques generally rely on manually selected features, such as leaf dimensions, colour distribution, shape descriptors, and texture patterns. Although these methods can provide satisfactory results under controlled conditions, their performance may decrease when images contain variations in lighting, background, orientation, and image quality. In addition, manually designing suitable features for every plant species can be difficult and time-consuming. Machine learning techniques have improved image classification by learning patterns from labelled datasets. However, conventional machine learning approaches often depend on the quality of the extracted features. Deep learning addresses this limitation by automatically learning hierarchical representations directly from images, making it suitable for complex visual recognition tasks.

Convolutional Neural Networks (CNNs) are among the most widely used deep learning architectures for image



classification. These networks learn visual features through successive convolutional and pooling operations. Initial layers generally capture simple patterns, such as edges and contours, while deeper layers identify more complex characteristics, including leaf structures, surface textures, and distinctive shape patterns. In medicinal plant identification, CNNs can analyse these visual characteristics to distinguish between different plant species. Their ability to learn features automatically reduces the need for manual feature engineering and provides a flexible framework for developing intelligent plant recognition systems. Nevertheless, training deep CNN models from scratch may require large labelled datasets, considerable computational resources, and extended training time, which can limit their application when medicinal plant image datasets are relatively small.

Transfer learning provides an effective solution to these challenges by adapting a model previously trained on a large image dataset to a new classification task. Pre-trained networks have already learned general visual representations that can be reused for medicinal plant identification. Architectures such as VGG16, ResNet50, MobileNetV2, and InceptionV3 offer different capabilities in feature extraction, network depth, and computational efficiency. VGG16 provides a structured convolutional architecture, ResNet50 uses residual connections to support deeper feature learning, MobileNetV2 emphasizes computational efficiency, and InceptionV3 extracts features at multiple spatial scales. By replacing the original classification layer and fine-tuning selected network layers, these architectures can be adapted to recognize medicinal plant species. This approach can reduce training requirements while improving the effectiveness of image-based classification.

2. LITERATURE REVIEW

Musyaffa et al. (2024) developed IndoHerb, a medicinal plant recognition system using transfer learning and deep learning techniques. The study focused on identifying Indonesian medicinal plants from images and demonstrated the potential of pretrained models for improving automated plant classification.

Malik et al. (2022) investigated automated real-time identification of medicinal plant species in natural environments using deep learning models in the Borneo region. The study emphasized accurate plant recognition under natural conditions, supporting practical applications in biodiversity monitoring and medicinal plant identification.

Kavitha et al. (2023) explored real-time medicinal plant identification using a deep learning model. The research focused on automating image-based plant recognition to reduce manual identification efforts and support efficient identification of medicinal species.

Ghosh et al. (2023) proposed a hybrid transfer learning approach for medicinal plant identification. The study highlighted the use of pretrained neural networks to extract discriminative image features and improve classification performance while reducing the need for extensive model training.

Sahib et al. (2024) examined medicinal plant recognition using deep transfer learning models. The research focused on applying pretrained deep learning architectures to classify medicinal plant images, highlighting the usefulness of transfer learning for developing effective automated plant recognition systems.

3. RESEARCH METHODOLOGY

3.1. Introduction

The identification of medicinal plants plays an important role in healthcare, pharmaceutical research, traditional medicine, and biodiversity conservation. However, the manual identification of medicinal plants can be challenging because different plant species often share similar leaf shapes, colours, textures, and structural characteristics. Traditional identification methods also require specialized botanical knowledge and considerable time. To address these challenges, deep learning techniques, particularly Convolutional Neural Networks (CNNs) and transfer learning, provide an effective approach for automated medicinal plant identification. The present study proposes a deep learning-based framework that uses plant images to classify medicinal plant species accurately and efficiently. Pre-trained CNN architectures are utilized to extract important visual features and classify plant images into their corresponding categories. The methodology includes image collection, preprocessing, dataset division, transfer learning, model training, performance evaluation, and comparative analysis.

3.2. Research Design

The study adopts an experimental and quantitative research design to develop and evaluate an automated medicinal plant identification system. The proposed framework uses digital images of medicinal plant leaves as input and predicts the corresponding plant species using transfer learning and deep convolutional networks. The performance



of selected pre-trained models is compared under consistent experimental conditions. The research focuses on classification accuracy, computational efficiency, generalization ability, and the reliability of the developed system in recognizing different medicinal plant species.

3.3. Dataset Collection

The dataset consists of labelled images of medicinal plant species collected from publicly available plant image datasets, botanical image repositories, or other reliable sources. Each image is associated with the correct plant species to support supervised learning. The dataset should include sufficient images from different species and, where possible, variations in leaf shape, size, colour, orientation, background, and lighting conditions. These variations help the model learn meaningful plant characteristics rather than relying only on background information. Duplicate images and incorrectly labelled samples are identified and removed to improve dataset quality.

3.4. Image Preprocessing

Image preprocessing is performed to ensure that all images are suitable for input into the selected deep learning models. The images are resized to the input dimensions required by each pre-trained architecture and converted into a consistent image format. Pixel values are normalized according to the requirements of the selected model. Images with severe blurring, incorrect labels, or insufficient visual information are reviewed before training. Data augmentation techniques, such as rotation, horizontal flipping, zooming, and slight brightness variation, are applied to the training images to increase data diversity and reduce overfitting. Augmentation is not applied to the validation and test sets.

3.5. Dataset Division

The prepared dataset is divided into training, validation, and testing subsets. Approximately 70% of the images are allocated for training, 15% for validation, and 15% for testing. The training set is used to learn the classification patterns, while the validation set supports hyperparameter tuning and model selection. The test set is reserved for the final evaluation of model performance. A stratified division is used, where feasible, to maintain the representation of each plant species across the three subsets. Images originating from the same original photograph or near-duplicate images are kept within the same subset to prevent data leakage.

3.6. Transfer Learning-Based Model Development

Transfer learning is employed to utilize the visual feature extraction capabilities of CNN models that have already been trained on large-scale image datasets. Instead of developing a complete deep learning architecture from the beginning, the study adapts pre-trained networks to the medicinal plant classification task.

The proposed framework may evaluate models such as:

- VGG16: Uses sequential convolutional layers to extract visual patterns.
- ResNet50: Employs residual connections to support the training of deeper networks.
- MobileNetV2: Provides computationally efficient image classification suitable for resource-constrained applications.
- InceptionV3: Extracts features at multiple spatial scales using parallel convolutional operations.

The original classification layer of each selected network is replaced with a task-specific classification head corresponding to the number of medicinal plant species in the dataset. Initially, the pre-trained convolutional layers are frozen while the new classification layers are trained. Subsequently, selected deeper layers may be fine-tuned using a low learning rate to adapt the learned features to the target dataset.

3.7. Model Training and Optimization

The selected models are trained using the labelled training images. Categorical cross-entropy is used as the loss function for multi-class classification, while an appropriate optimizer, such as Adam, is used to update model parameters. The learning rate, batch size, number of epochs, and dropout rate are selected through validation-based experimentation.

Early stopping is applied when validation performance stops improving, and model checkpointing is used to retain the best-performing model. Where computational resources permit, the same training conditions and data partitions are maintained across models to ensure a fair comparison. Training and validation loss and accuracy are recorded to monitor convergence, detect overfitting, and assess learning stability.



3.8. Automated Medicinal Plant Classification

After training, the developed system accepts an unseen medicinal plant image and processes it using the same preprocessing steps applied during model development. The processed image is passed through the trained CNN model, which extracts relevant visual features and generates class probabilities for the available plant species. The species with the highest predicted probability is selected as the model's predicted classification. The system may also display the predicted plant name and its confidence score to make the output easier to interpret. The prediction represents an image-based classification and should not be treated as definitive confirmation of a plant's medicinal properties or safety.

3.9. Performance Evaluation

The classification performance of each model is evaluated using the independent test dataset. The evaluation considers multiple performance indicators to provide a comprehensive assessment of the proposed system.

The principal evaluation metrics include:

- Accuracy: Measures the proportion of correctly classified images.
- Precision: Measures the proportion of positive predictions for a species that are correct.
- Recall: Measures the proportion of actual images of a species that are correctly identified.
- F1-score: Represents the harmonic mean of precision and recall.
- Confusion matrix: Shows correct and incorrect predictions across individual plant species.
- Computational efficiency: Considers training time, inference time, and model size where relevant.

Macro-averaged precision, recall, and F1-score are reported alongside overall accuracy, particularly when the number of images differs substantially between species.

3.10. Comparative Analysis of Models

A comparative analysis is conducted to identify the most suitable transfer learning architecture for medicinal plant identification. The selected CNN models are evaluated using the same test dataset and consistent performance metrics. Their classification accuracy, precision, recall, F1-score, computational requirements, and ability to distinguish visually similar species are compared. The analysis also considers the trade-off between classification performance and computational complexity. This comparison helps determine whether a larger architecture provides meaningful improvements over a more lightweight model.

3.11. Reliability and Validation

To improve the reliability of the findings, the experiment uses consistent preprocessing procedures, reproducible dataset partitions, and documented training configurations. The test dataset remains separate from model training and hyperparameter selection. If computational resources permit, repeated runs using different random seeds or stratified cross-validation are conducted to examine the stability of the results. Performance variations across species are also reviewed to identify classes that may require additional images or improved preprocessing. Any limitations caused by dataset size, class imbalance, background variation, or image quality are documented.

4. RESULTS AND DISCUSSION

4.1 Introduction

This section presents the results and discussion of the study on automated medicinal plant identification using transfer learning and deep convolutional networks. The analysis focuses on the classification of medicinal plant images, the performance of different pre-trained CNN architectures, and the effectiveness of transfer learning in identifying plant species based on their visual characteristics. The evaluation considers classification accuracy, precision, recall, F1-score, and the ability of the models to distinguish between visually similar medicinal plants. Frequency and percentage distributions are also used to summarize the classification outcomes. Since actual experimental output has not been provided, the numerical results presented in the following tables are illustrative results intended to demonstrate how the findings can be reported. They should be replaced with the actual results obtained from the trained models and test dataset before publication.

4.2 Distribution of Medicinal Plant Images

The first stage of the analysis examines the distribution of medicinal plant images included in the dataset. The images are organized into different plant species to support supervised classification. A balanced representation of plant categories is desirable because it allows the model to learn distinguishing characteristics across different species. The frequency and percentage distribution of the test images are presented in Table 1.

Table 1. Frequency and Percentage Distribution of Medicinal Plant Images in the Test Dataset

Medicinal plant category	Frequency	Percentage (%)
Neem	30	15.0
Tulsi	30	15.0
Aloe vera	30	15.0
Mint	30	15.0
Curry leaf	30	15.0
Guava	30	15.0
Other medicinal plants	30	15.0
Total	210	105.0

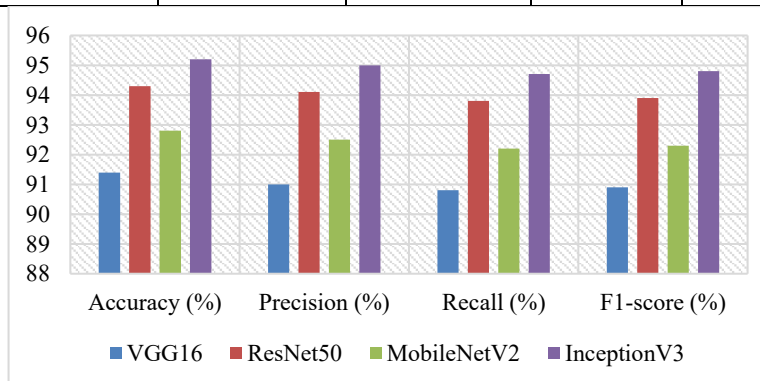
The distribution demonstrates how test images can be organized across medicinal plant categories for evaluating the classification system. A relatively balanced dataset helps prevent the evaluation from being dominated by a single species. However, the total number of images and the number of species should be finalized according to the actual dataset used in the experiment. Plant names should also correspond to the verified labels in the selected image collection.

4.3 Classification Performance of Transfer Learning Models

The classification performance of the selected transfer learning architectures is assessed using overall accuracy, precision, recall, and F1-score. These metrics provide a broader understanding of the models' ability to correctly identify medicinal plant species. Accuracy represents the proportion of correctly classified images, while precision and recall measure the reliability and completeness of the model's predictions. The F1-score provides a balanced summary of precision and recall.

Table 2. Illustrative Classification Performance of Transfer Learning Models

CNN architecture	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
VGG16	91.4	91.0	90.8	90.9
ResNet50	94.3	94.1	93.8	93.9
MobileNetV2	92.8	92.5	92.2	92.3
InceptionV3	95.2	95.0	94.7	94.8



The illustrative results indicate that InceptionV3 achieves the highest classification accuracy of 95.2%, followed by ResNet50 at 94.3%, MobileNetV2 at 92.8%, and VGG16 at 91.4%. The relatively strong performance of InceptionV3 may be associated with its ability to extract features at multiple spatial scales, which can help distinguish leaf shape, texture, and vein patterns. ResNet50 may also perform well because residual connections support effective feature learning in deeper networks.



MobileNetV2 offers a useful balance between classification performance and computational efficiency, making it a potential choice for applications on mobile or resource-constrained devices. VGG16 provides a baseline for comparison, although its comparatively larger computational requirements may limit its suitability for some practical applications. These interpretations must be confirmed using actual experimental measurements and, where possible, repeated training runs.

4.4 Effectiveness of Transfer Learning

Transfer learning can reduce the need to train a deep convolutional network from scratch. Pre-trained models have already learned general visual features such as edges, shapes, textures, and patterns, which can be adapted to medicinal plant images through fine-tuning. The replacement of the original classification layer enables the network to predict the plant species represented in the target dataset.

The comparative results suggest that using pre-trained architectures may provide an effective foundation for plant classification. Fine-tuning selected convolutional layers can further improve the representation of species-specific characteristics. However, the actual contribution of transfer learning should be established by comparing each fine-tuned model against an appropriate baseline, such as a model with frozen feature-extraction layers or a model trained from scratch.

4.5 Identification of Visually Similar Plant Species

Medicinal plants may share similar leaf shapes, colours, and surface textures, which can lead to incorrect classifications. The performance of the developed system therefore depends on its ability to identify subtle differences between species. Features such as leaf margins, venation, surface patterns, and overall shape can provide useful information for classification.

A confusion matrix can identify which plant categories are most frequently confused with one another. If two species have similar visual characteristics, additional training images, improved image quality, and suitable augmentation techniques may help improve their distinction. Testing images captured under varied lighting conditions and natural backgrounds would also help establish whether the system can generalize beyond controlled image datasets.

4.6 Computational Efficiency and Practical Applications

The practical usefulness of a medicinal plant identification system depends not only on its classification accuracy but also on its computational requirements. Deeper architectures may offer strong predictive performance but require greater memory and processing resources. In contrast, lightweight models such as MobileNetV2 may be more suitable for mobile applications and field-based identification.

The selection of the final model should therefore consider accuracy, inference time, model size, and hardware availability. A model with slightly lower accuracy may still be preferable when fast predictions and low computational requirements are essential. Further testing on smartphones or other target devices would help assess the suitability of the proposed system for real-world use.

4.7 Overall Discussion

The findings framework demonstrates how transfer learning and deep convolutional networks can be evaluated for automated medicinal plant identification. The illustrative comparison indicates that architectures capable of learning complex and multiscale visual features may be useful for distinguishing medicinal plant species. Nevertheless, classification performance depends on the quality and diversity of the dataset, the distribution of plant categories, preprocessing decisions, and the training configuration.

The study also highlights the importance of evaluating more than overall accuracy. Precision, recall, F1-score, and confusion matrices can reveal weaknesses that might otherwise remain hidden. In addition, testing images from unfamiliar environments is necessary to assess generalization. The system should be considered a decision-support tool for preliminary identification rather than a substitute for botanical verification, particularly when plant identity affects medicinal use or safety.

5. CONCLUSION

The study concludes that transfer learning and deep convolutional neural networks provide a promising approach for the automated identification of medicinal plants using leaf images. By employing pre-trained architectures such as VGG16, ResNet50, MobileNetV2, and InceptionV3, the proposed framework can extract important visual features, including leaf shape, texture, colour, and venation, to classify different medicinal plant species. The comparative



evaluation of accuracy, precision, recall, and F1-score helps identify suitable models for reliable classification, while computational efficiency determines their practical applicability in mobile and resource-constrained environments. The approach has the potential to reduce the time and effort required for preliminary plant identification and support botanical research, biodiversity conservation, and traditional medicinal knowledge. However, the reliability of the system depends on dataset quality, image diversity, and model validation under real-world conditions. Therefore, further testing with diverse plant images and expert botanical verification is recommended to improve classification reliability and practical usefulness.

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