A Deep Learning-based Framework for Detection and Classification of Ayurvedic Medicinal Plant Leaves

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ABSTRACT
Medicinal plants have long been recognized as essential sources of therapeutic compounds in both traditional and modern healthcare systems. However, accurately identifying specific plant parts with medicinal value remains a challenging task prior to laboratory-based extraction and analysis of bioactive components. This study presents a deep learning-based approach for the classification of medicinal plant parts using a Convolutional Neural Network (CNN) with a sigmoid activation function in the final layer for multi-label classification. The proposed method follows a supervised learning paradigm, where annotated image data establishes reliable ground truth for model training.The dataset primarily comprises high-resolution images of plant leaves, which are further utilized to infer and classify multiple plant components. To enhance performance and reduce training time, transfer learning is employed by fine-tuning pre-trained CNN models originally trained on ImageNet. The experimental implementation, including training and evaluation, was carried out using the Google Colab platform.Among the evaluated architectures, MobileNet demonstrated superior performance, achieving an accuracy of 99% on the training set and 98% on the testing set, along with an F1-score of 94%, indicating robust classification capability. Notably, the model maintained a high accuracy of 97% even without batch normalization in the fully connected layer. MobileNet also exhibited the fastest training time due to its efficient use of depthwise separable convolutions, which significantly reduce computational complexity. Furthermore, comparative analysis reveals that the inclusion of batch normalization enhances classification efficiency and model stability. Overall, the findings suggest that MobileNet is a highly effective and computationally efficient model for the classification of medicinal plant parts, offering significant potential for supporting automated plant-based medicinal research and applications.

Keywords
Deep Learning, Medicinal Plant Classification, Convolutional Neural Networks (CNN),Transfer Learning, Multi-Label Classification, MobileNet, Leaf Image Analysis.

1. INTRODUCTION
Plants play a fundamental role in sustaining life on Earth, serving as the primary source of oxygen and supporting ecological balance. Beyond their environmental significance, plants are widely utilized across various industries, including pharmaceuticals, biofuels, herbal products, and biomass production. Among these applications, the use of plants as traditional medicine has been practiced for centuries due to its cost-effectiveness and minimal side effects.

Despite the vast diversity of plant species, accurate identification remains a challenging task. Conventional plant identification is primarily performed manually by taxonomists, which is time-consuming and prone to human error. To address these limitations, researchers have increasingly focused on developing automated plant identification systems using computational techniques.

Medicinal plants, in particular, are crucial for the prevention and treatment of various diseases. However, much of the traditional knowledge related to herbal medicine, especially that preserved by rural communities and indigenous tribes, remains underutilized and is at risk of being lost. Factors such as deforestation, urbanization, and modernization are contributing to the displacement of these communities, leading to a gradual erosion of their valuable knowledge. Additionally, several medicinal plant species are becoming endangered and are classified as vulnerable due to environmental and anthropogenic pressures.

Preserving and promoting this traditional knowledge has become a critical priority. Much of this expertise resides with older generations, necessitating the development of effective strategies for its documentation and dissemination. In this context, automated plant identification systems can play a significant role in bridging traditional knowledge with modern technology.

This study proposes an automated approach for the classification of medicinal plant species using digital images of plant leaves. The methodology leverages deep learning techniques to analyze leaf characteristics for accurate identification. By integrating traditional knowledge with modern computational methods, the proposed system aims to contribute to the preservation and accessibility of medicinal plant information. Several approaches for automated leaf analysis have been explored in the literature, and this work builds upon those advancements to develop an efficient and reliable classification framework.

2. RELATED WORKS
Amala Sabu and colleagues (2017) [1] "Literature Review of Image Features and Classifiers Used In Leaf Based Plant Recognition Through Image Analysis Approach." Both our life and the lives of other creatures on the planet depend greatly on plants. Images of leaves are used to identify plants. Some systems make use of terminology employed by botanists. But transferring those traits to a computer automatically is challenging to extract. Digital cameras and handheld computers are widely available today, which has made the prospect of developing this system a reality. Researchers have been working on non-manual plant classification thanks to studies like image processing and machine learning. The identification of distinguishing characteristics for diverse species presents a problem in the development of this system.

E. Sandeep Kumar et al. (2018) [2] "Leaf Features Based Approach for Automated Identification Of Medicinal Plants" to identify medicinal plants in the Western Ghats. The kNN algorithm was used to classify the SURF and HoG features. An SURF feature descriptor is also used to depict the twenty different points of interest on the leaves as well as the leaf veins. To classify leaves with a k value of 1, this methodology uses the k-NN classification algorithm. The feature extraction method used in this model is computationally demanding despite having a high accuracy of over 96 percent.

A Gopal, R Janani, and others (2018) [3] "Identification Of Selected Medicinal Plant Leaves Using Image Fatures And ANN." - Geometric properties, colour characteristics, texture characteristics, HU invariant moments, and Zernike moments are used to categorise objects. The classification algorithms used are Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM), with the MLP classifier achieving a maximum accuracy of 99% for Geometric-Colour-Texture categorization. a Zernike combination of 38 properties.

A. Gummadi Divya Sree et.al (2019) [4] pioneered the use of a "Ayurvedic Leaf Identification Using Deep Learning Model" matrix segmentation, thinning, and visual assessment are the next steps in this process, which is a pioneer in its application. The testing and evaluation method makes use of 80 leaves altogether. Segmentation score methodologies were used in this process to evaluate the segmentation result. A segmentation value of 2 was given to 53.75 percent of the leaf photos, while a score of 1 was given to 42.5 percent of the images.

Amrutha M Raghukumar et.al (2020) [5] "Comparison of Machine Learning Algorithms For Detection Of Medicinal Plants" proposed a technique for categorising medicinal plant leaves and deriving their therapeutic characteristics. A probabilistic neural network classifier is used to determine the leaf class. The steps entail preprocessing, feature extraction, classification, and retrieval of therapeutic qualities. A crucial step in categorization is the calculation and comparison of feature vectors to other datasets.

Dr. Jai Ruby et.al (2021) [6] "Ayurvedic Leaf Classification Using Machine Learning Algorithm" showed techniques for both gathering leaves and converting the captured image to the device-independent l colour space. This feature map is reduced and optimised using principle component analysis (PCA). ImageNet served as the dataset. A 3x4096-pixel feature vector is produced when the model is routed through the Fully Connected layer. With the help of PCA approaches, SVM was applied to this feature set, and the accuracy was discovered to be 97.6 percent for lVGG-16 and 98.2 percent for l-VGG-16.

R. Upendar Rao et.al (2022) [7] "Identification Of Medicinal Plants Using Deep Learning" proposed an automated approach for classifying the leaves of medicinal plants. Utilising moment characteristics, boundary-based features, and colour characteristics, we may discriminate between several leaf types. The categorization effectiveness was 92% following training and testing on 100 and 50 leaves, respectively.

Sameer A et.al (2022) [8] "A Novel Approach To Classification Of Ayurvedic Medicinal Plants Using Neural Networks" based on the colour, texture, and form of the leaves. 36 training, 7 validation, and 20 test leaves were split from each leaf. In all, 63 leaves were used in the model. On the basis of eight hardly discernible properties among the twenty different characteristics of the leaves, the classification of leaves was made. The eight qualities are entropy, energy, correlation, skewness, kurtosis, and eccentricity. 94.4 percent of the time, this strategy works..

2. PROPOSED METHOD

In this study, CNN, the core of the deep learning algorithm, was utilised to automatically extract several distinctive properties from plant leaves. By adding batch normalisation to CNN's fully connected layer and adjusting weights and training hyperparameters, the study also used a transfer learning technique. In this study, we used the underside of leaves to create a model that would extract distinctive traits and properly identify various medicinal plant sections

2.1 Proposed System Architecture

The system consists of the following stages:

2.1.1 Data Collection

2.1.2 Data Annotation

2.1.3 Image Pre-processing

2.1.4 Feature Extraction

2.1.5 Model Training

2.1.6 Classification

Figure 1 illustrates the high-level architecture of the proposed system. The overall framework is systematically divided into multiple stages to ensure efficient processing and accurate classification. The initial stage consists of data collection and annotation, which together form the input layer of the system. In this phase, images are gathered from reliable sources and carefully labeled with the assistance of domain experts to ensure correctness and relevance.Following this, the pre-processing stage is applied to enhance image quality and standardize the dataset. This includes operations such as resizing, normalization, noise removal, and augmentation, which help improve model generalization and reduce overfitting.

The next stage involves feature extraction, where meaningful and discriminative features are derived from the input images. This is achieved using advanced techniques such as Convolutional Neural Networks (CNNs), which automatically learn hierarchical feature representations.Subsequently, the model training phase is carried out using the extracted features. During this stage, the model learns patterns and relationships within the data through iterative optimization and backpropagation. Hyperparameter tuning and validation strategies are employed to improve performance and ensure robustness.

Finally, the classification stage produces the output by assigning labels to the input images based on the learned model. The system’s performance is evaluated using appropriate metrics such as accuracy, precision, recall, and F1-score.Each component of the system is described in detail in the following subsections to provide a comprehensive understanding of the proposed methodology..

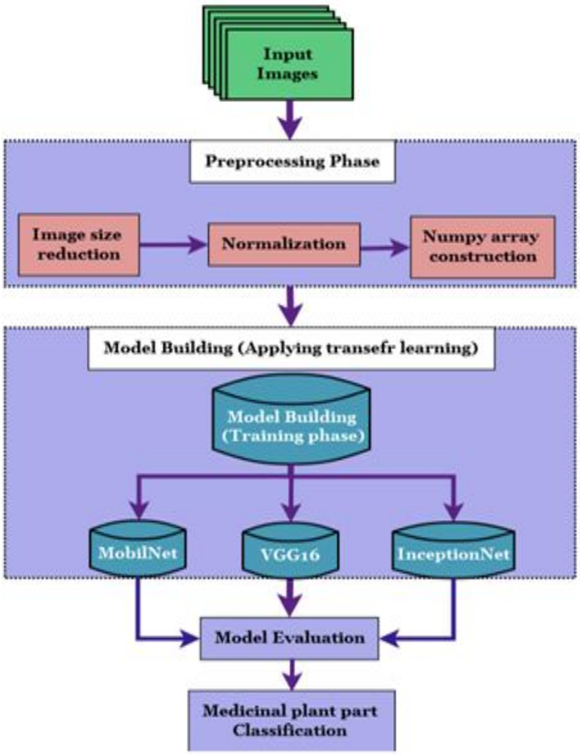

Fig 1 High-Level System Architecture

2.1.1 Data Collection

The dataset was collected from an online database. During image acquisition, variations in light intensity and leaf orientation were carefully considered to avoid the need for artificial data augmentation. To accurately capture vein characteristics, images were taken from the backside of the leaves. Additionally, the focal length was adjusted based on the size of the leaves to ensure clarity and consistency in the captured images. The dataset comprises 15,100 images of medicinal plant leaves. While each plant includes approximately 300 leaf images, the number of plant species under each class varies. Consequently, the dataset is imbalanced, with unequal representation across different categories.

Fig 2 Intensity variation of single leaf image

2.1.1.1 Visualizing Data Intensity Variation

By observing the vertical, left, and right sections of the image histogram, the frequency distribution of pixels across RGB channels, as well as the brightness and darkness levels of the images, can be visualized. Figure 2 presents images of a single leaf under different pixel intensity conditions, while Figures 3.3 and 3.4 (histogram plots) illustrate the variation in pixel intensity distribution across these images. The histogram of Sample 1 (S1) is shown in Figure 3 and differs from that of Sample 3 (S3). The primary distinction between S1 and S3 lies in the lighting conditions during image capture. This variation within images of the same leaf enhances the dataset's diversity, enabling the model to learn robust features and improve classification performance.

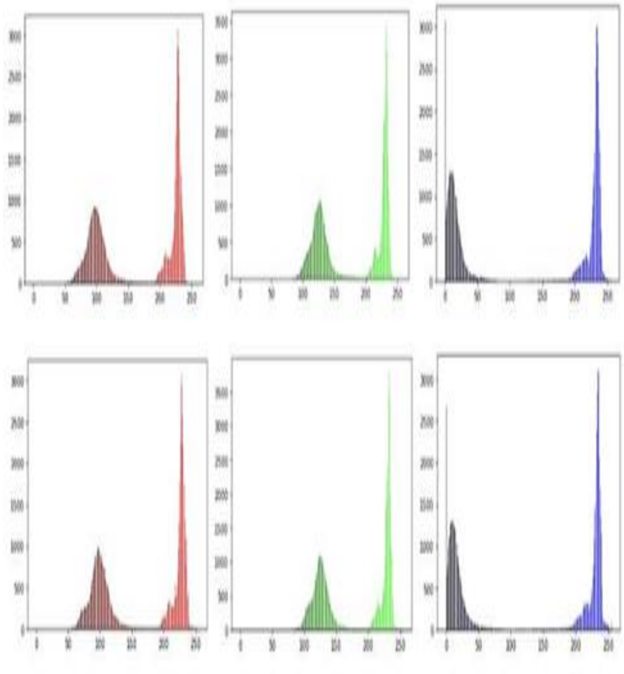

Fig. 3 Leaf image histogram (S1)

2.1.2. Data Annotation

Five experts involved in the preparation of traditional medicines, with 5, 10, 13, 28, and 30 years of experience, assisted in the labeling process. Initially, 72 plant species were selected; however, only 52 were included in the final dataset. Twenty plants were excluded because the experts could not consistently identify their distinguishing parts.

All plant parts were labeled (mapped) in the leaf images, as the system is based on a supervised learning approach, as shown in Table 1. The leaf image files are named sequentially as img_1, img_2, ..., img_n.

2.1.3. Image Pre-processing

The input images were resized to 128 × 128 pixels to reduce computational complexity and accelerate the training process. Pixel value scaling, commonly referred to as normalization, was applied as part of the system architecture. Since pixel intensities originally range from 0 to 255, directly using these large values can slow down or destabilize the CNN learning process. Therefore, all pixel values were normalized to a range between 0 and 1.

To further optimize performance, the processed image data were stored as arrays and saved as a single variable, enabling efficient reuse without repeated preprocessing. The target labels were selected and transformed into array format, followed by binarization using a label binarization function. This step ensures compatibility with the Sigmoid activation function. As a result, the system effectively treats each of the five target classes using a binary classification approach.

Although RGB images increase computational cost compared to grayscale images, they were retained to preserve essential color-based features that contribute significantly to model performance.

2.1.4. Feature Extraction

Pre-trained CNN models such as InceptionV3, MobileNet, and other optimized architectures are employed to extract meaningful features from leaf images and pass them to the classifier. As illustrated in Figure 5, feature extraction is carried out through the CNN's feature learning layers. This process involves the use of convolutional filters (kernels) that slide over the image pixels and compute dot products to generate diverse feature maps.

Subsequently, max pooling is applied to reduce the spatial dimensions of the extracted features, thereby lowering computational complexity and helping control overfitting. The ReLU (Rectified Linear Unit) activation function is used to introduce non-linearity, enabling faster and more effective learning while mitigating the vanishing gradient problem.

Through this automated feature extraction process, the deep learning model efficiently learns and captures the most relevant characteristics of plant leaves without the need for manual feature engineering.

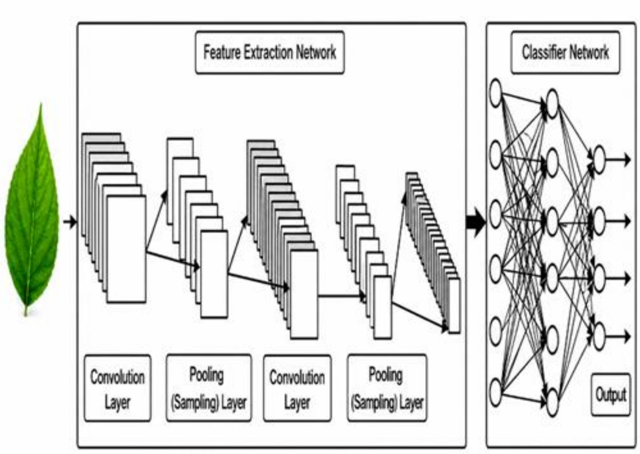

Figure 4 Convolutional neural network's structure.

Figure 5 illustrates how CNN extracts leaf features. The first patterns it finds are those that are easily recognisable, such the horizontal and vertical lines found in leaves. It attempts to determine the shape of the leaves by using the ability it has at the second layer to detect various corners on leaves. By extracting variously shaped veins on the surface of leaves, for example, it further computes more sophisticated feature map identification at the third layer. When it reaches the fourth layer, it has increased power to exploit every minute vein structure, and as it descends farther into the layers, it can recognise the structures that are present everywhere. CNN may therefore classify leaves by identifying their distinctive traits after completing this execution. The number of image features generated by the convolution technique is referred to in this study as the feature map. The number of features that the convolution layer produces will increase as the image size does. In the absence of padding, the convolution layer shrinks the size of the images.

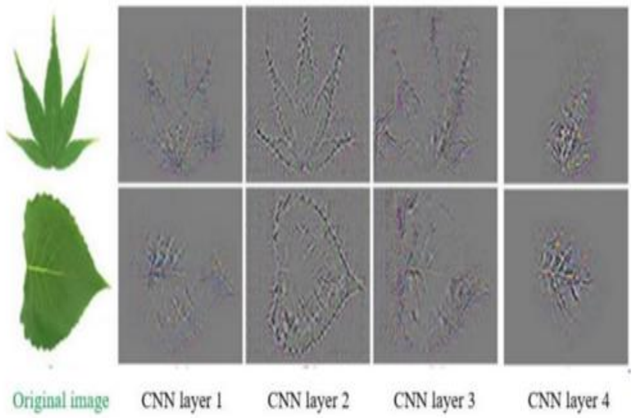

Figure 5 Feature extraction process in a CNN

3.1.5. Train the Model

Transfer learning techniques were applied to MobileNet, VGG16, and InceptionV3 to reduce computational cost and training time. These models were pre-trained on the ImageNet dataset, providing a strong foundation of learned features. During fine-tuning, selected layers were updated with new weights, while the remaining layers were frozen to preserve previously learned representations. The original dense layers were replaced, and batch normalization was introduced in the fully connected layers to improve training stability and performance. This approach offers several advantages, including faster training, fewer required epochs, and reduced dependency on large training datasets. To further customize the models, layer-wise fine-tuning was combined with hyperparameter optimization.

For MobileNet, the last four convolutional layers were unfrozen and retrained with updated weights, while earlier layers remained frozen. Two fully connected layers, each with 1024 units and ReLU activation, were added. As a result, the total number of layers increased from 28 to 30. Batch normalization was also incorporated to accelerate convergence and achieve better performance within fewer epochs.

In the case of VGG16, a similar modification strategy was followed. However, only one dense layer was added, along with a dropout layer (rate = 0.5) to mitigate overfitting.

For InceptionV3, all base convolutional layers were kept frozen, and a dropout rate of 0.9 was applied at the fully connected layer to further address overfitting. Apart from these differences, the overall methodology remained consistent with the other models.

The common hyperparameters across all models include batch size (number of training samples per iteration), number of epochs (total training iterations over the dataset), learning rate (step size for weight updates), dropout (to prevent overfitting by deactivating neurons), and optimizers (used to update model weights efficiently).

3.1.6 Classification

The final stage of the system is the classification step, where the extracted features are used to predict the class labels of plant leaves. The feature vectors obtained from the fine-tuned CNN models are passed through fully connected (dense) layers, which act as the classifier. A Sigmoid activation function is applied in the output layer to perform multi-label classification, enabling the model to assign probabilities to each target class. Based on these probabilities, the model determines the most relevant class for the given input image.

During this stage, the model learns the mapping between extracted features and corresponding labels through backpropagation and optimization techniques. The trained classifier is then used to predict unseen data with high accuracy. Performance metrics such as accuracy, precision, recall, and F1-score are used to evaluate the effectiveness of the classification model. This step ensures that the system can reliably identify and categorize plant leaves based on their learned features.

4. PERFORMANCE ANALYSIS

4.1 Performance Evaluation Metrics

The performance of the proposed framework was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score. In addition, confusion matrices and training-validation curves were analyzed to assess the robustness and generalization capability of the models are shown in table 1.

Table 1. Performance Evaluation Metrics

Model	Accuracy	Precision	Recall	F1-Score
MobileNet	98%	95%	93%	94%
VGG16	97%	88%	85%	86%
InceptionV3	95%	70%	66%	68%

4.2 Evaluation under Different Scenarios

The robustness of the proposed framework was evaluated under different image acquisition conditions, including variations in lighting intensity, leaf orientation, and background complexity.

Table 2. Scenario-Based Analysis Table

Scenario	Accuracy
Normal Lighting	98.2%
Low Lighting	96.8%
Rotated Leaves	97.1%
Complex Background	95.9%

Experimental observations indicate that the MobileNet architecture maintained stable classification performance across diverse environmental conditions are shown in table 2.

A comparative analysis was conducted to evaluate the proposed deep learning framework against existing approaches for medicinal plant leaf classification which is shown in table 3.

Table 3. Comparative Analysis of Existing Methods and Proposed Framework

Method / Reference	Technique Used	Accuracy
Sandeep Kumar et al. [2]	SURF + HOG + k-NN	~96%
Gopal et al. [3]	ANN (MLP) with handcrafted features	~99%
Raghukumar et al. [5]	Probabilistic Neural Network	~94–96%
Sameer et al. [8]	Neural Network with statistical features	~94.4%
Upendar Rao et al. [7]	Deep Learning + feature-based methods	~92%
Ruby et al. [6]	VGG16 + PCA + SVM	~98.2%
Proposed Method (MobileNet)	CNN + Transfer Learning (MobileNet)	**98% (Test), F1: 94%**
Proposed (VGG16)	Transfer Learning	~97–98%
Proposed (InceptionV3)	Transfer Learning	~95–96%

5. CONCLUSION

This study proposes a multi-label deep learning framework for the classification of medicinal plant parts, addressing the lack of publicly available datasets by constructing a domain-specific dataset based on expert knowledge and pathobiological insights. Experimental results demonstrate that leaf-based features, particularly vein patterns, play a critical role in accurate classification. The findings indicate that model performance is influenced not only by network depth and dataset size but also by the computational complexity of convolution operations. Despite having more layers, MobileNet achieves better generalization than VGG16 due to the use of depth-wise separable convolutions, which significantly reduce scalar multiplications and mitigate overfitting.

Among the evaluated models, MobileNet achieved the highest performance with an F1-score of 94%, outperforming VGG16 (86%) and InceptionV3 (68%) under consistent hyperparameters (learning rate: 1e-4, batch size: 32, optimizer: Adam). Additionally, MobileNet demonstrated superior efficiency in training and inference across extensive experimental evaluations.The study confirms the effectiveness of multi-label classification for medicinal plant part identification. However, limitations include the relatively small dataset and manual hyperparameter tuning. Future work should focus on dataset expansion, automated optimization techniques, and extending the framework to predict associated therapeutic applications for identified plant parts

6. REFERENCES

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