Medicinal Plants Identification Using Deep Learning

Rohan Kumar Verma[1] and Prof. Syeeda[2], Sagar M Prajapathi

[1-2] *Department of MCA, CMR University, Baglur, Bangalore, India*
Email: krv.rohan18@gmail.com

Abstract

Accurately identifying medicinal plants is crucial for their safe and effective use in various fields, including herbal medicine and biodiversity conservation. Manual identification methods are time-consuming, labor-intensive, and prone to errors. Recent advancements in machine learning and computer vision offer a promising solution by automating the identification process through the analysis of leaf images. This research presents a comprehensive study on the identification of various medicinal plants using a range of pre-trained deep learning models. We leverage the Indian medicinal leaves dataset from Kaggle, consisting of 80 species and approximately 6,900 leaf images. After preprocessing the dataset for image size and scaling, we explore multiple pre-trained models, including Xception, ResNet, VGG, and Inception, to evaluate their effectiveness in medicinal plant identification. The experimental results demonstrate the performance of each pre-trained model in accurately predicting the species of medicinal plants from leaf images. Furthermore, we develop a user-friendly interface that allows users to upload leaf images for identification. Upon analysis, the system provides detailed information on the predicted plant name, botanical name, common names, and medicinal uses. The implementation of this project has the potential to significantly benefit various stakeholders, including Ayurvedic practitioners, herbal medicine users, and researchers. By leveraging pre-trained deep learning models, this system streamlines the identification process and facilitates the safe and effective utilization of medicinal plants in healthcare and conservation endeavors.

Keywords—*Deep Learning, Plant Identification, Convolutional Neural Network, Pre trained Models, Image Processing, Medicinal Plants.*

I. INTRODUCTION

Accurately identifying medicinal plants is pivotal for various fields, including traditional medicine, pharmaceuticals, and biodiversity conservation. These plants serve as essential sources of therapeutic compounds, yet their identification often requires specialized knowledge and labor-intensive processes. Traditional methods, reliant on human expertise and morphological features, can be error-prone and time-consuming.

The intersection of deep learning and pre-trained models presents a promising avenue for automating and enhancing the accuracy of medicinal plant identification. Leveraging vast datasets and complex neural networks, deep learning models can effectively learn intricate patterns and features from plant images. Pre-trained models, initially trained on extensive datasets for general image recognition tasks, offer a foundation for identifying medicinal plants.

In this study, we investigate the application of pre-trained deep learning models for identifying medicinal plants. We explore the efficacy of various pre-trained models, such as ResNet, Xception and Inception, in accurately classifying medicinal plant species. Through transfer learning techniques, we adapt these models to recognize specific features relevant to medicinal plants, aiming to achieve high accuracy and robustness across diverse species and environmental conditions.

By harnessing the capabilities of deep learning and pre-trained models, we aim to overcome the limitations of traditional plant identification methods and provide a scalable, efficient, and accurate solution for identifying medicinal plants. This research has significant implications for healthcare, pharmacology, and conservation efforts, facilitating the discovery, utilization, and preservation of valuable medicinal plant resources.

II. EXISTING WORK

Paper [1] proposes an AI system using deep learning to identify indigenous ayurvedic medicinal plants from leaf images. It compares CNN, VGG16, and VGG19 models on a dataset of 64 medicinal plants from Kerala, achieving accuracy rates of 95.79%, 97.8%, and 97.6% respectively. This technology addresses the challenge of recognizing medicinal plants, potentially benefiting healthcare, botanical research, and ayurvedic studies, while fostering a collaborative approach to herbal medicine.

Paper [2] presents a study on Ayurvedic plant identification using machine learning and deep learning techniques. It focuses on classifying medicinal plants based on leaf images, achieving an accuracy of 98.7%. Various algorithms for preprocessing, segmentation, feature extraction, and classification are reviewed, highlighting the importance of leaves and flowers. The proposed method includes steps like image preprocessing, segmentation, feature extraction, and training/testing using a classifier, demonstrating promising results for medicinal plant classification.

Paper [3] proposes a deep learning approach for recognizing Indian medicinal plant species using CNN models, aiming to automate plant identification. It discusses the importance of medicinal plants in traditional medicine and the challenges in identifying them. Through dataset collection, data augmentation, and CNN architecture, the study achieves a promising accuracy of 93.75% on a balanced dataset of 10 plant species. Additionally, the paper outlines the methodology, results, and implementation of the model in a mobile application, showcasing real-world usability.

Paper [4] proposes an automated system using deep learning, specifically Convolutional Neural Networks (CNN), to classify Ayurvedic medicinal plant leaves based on images. The system achieved an accuracy of 94.10% on a dataset of 35 different species comprising 4390 images. The approach involves data collection, preprocessing, augmentation, and training the CNN model, showcasing the potential for technology to aid in Ayurvedic healthcare.

Paper [5] explores CNN-based methods for identifying Indian medicinal plants, crucial for biodiversity conservation. It evaluates ResNet101, InceptionV3, and VGG16 architectures using Transfer Learning on the Ayur Bharat dataset. Pre-processing with Canny edge detection enhances classification performance, with InceptionV3 achieving the best accuracy and F1-score. The study highlights the importance of accurate classification for preserving traditional medicinal plants.

Paper [6] presents a model called Medicinal Neural Networks (MNN) for identifying medicinal plants without relying on transfer learning. With a dataset of 8,259 images from four plant classes, MNN achieves an accuracy of 85.15%. The model's architecture includes convolutional layers, dropout, and image augmentation techniques to improve performance and prevent overfitting. Future work aims to expand the dataset and include more medicinal plant varieties.

Paper [7] proposes a deep learning-based approach using a VGG-16 model for recognizing and identifying medicinal plants. With a dataset of over 25,000 images, the CNN achieved a recognition rate of 98%. This method shows promise for accurate plant classification, providing a reliable tool for herbal medicine research and healthcare professionals.

Paper [8] proposes a machine learning-based approach using Support Vector Machine (SVM), Decision Tree, Multi-Layer Perceptron (MLP), and Bagging with J48 for recognizing and identifying medicinal plants based on their leaf characteristics. By building a database of leaf images from frequently used Ayurvedic medicinal plants and extracting feature vectors from both the front and back sides of the leaves, the study identifies the optimal combination of features for accurate plant classification. This method shows promise for improving the reliability and quality control of Ayurvedic medicine production, providing a valuable tool for both the pharmaceutical industry and healthcare professionals.

Paper [9] proposes an automated system for identifying medicinal herbs using computer vision and machine learning techniques. The study emphasizes the importance of accurately identifying medicinal plants used in Ayurveda, highlighting the challenges posed by manual methods reliant on human perception. The research aims to develop a robust system that combines image processing algorithms, pattern recognition, and feature detection methods to classify herbal leaves based on their unique characteristics.

Paper [10] investigates the classification of medicinal plants using Convolutional Neural Network (CNN) and Transfer Learning techniques. Conducted at the 2022 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET), the study addresses the increasing demand for automated plant identification leveraging computer vision advancements.

Paper [11] investigates the use of Convolutional Neural Networks (CNN) for identifying Vietnamese medicinal plants, emphasizing the application of deep learning in plant recognition within natural environments.

Paper [12] introduces a deep learning approach using the VGG-16 convolutional neural network (CNN) model for automated recognition of medicinal plants. A dataset comprising 25,686 images captured under diverse conditions was utilized to train the CNN, enabling it to learn intricate features and classify plants with high accuracy. The proposed method achieved a recognition rate of 98%, demonstrating the efficacy of deep learning in precise plant classification across different growth stages and lighting conditions.

III. CONVOLUTIONAL NEURAL NETWORKS (CNN)

A Convolutional Neural Network (CNN) is a deep learning algorithm specifically designed for processing structured grid-like data, such as images. It consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply learnable filters to input images, extracting features through sliding operations. These features become increasingly complex as they propagate through the network's layers. Pooling layers reduce spatial dimensions, aiding computational efficiency and enhancing robustness. Finally, fully connected layers aggregate information for classification. CNNs excel in tasks like image classification, object detection, and segmentation, making them a cornerstone of computer vision applications.

A .CNN Architecture

Figure 1 The architecture of CNN

Convolutional Layer

These layers apply learnable filters to input data, enabling the network to detect features like edges, textures, and patterns. Convolutional operations involve sliding the filters over the input data, performing element-wise multiplication, and summing the results to produce feature maps.

Pooling Layer

Pooling layers reduce the spatial dimensions of feature maps, which helps to decrease computational complexity and control overfitting. Common pooling operations include max pooling, where the maximum value within a region is retained, and average pooling, where the average value is computed.

Activation Layer

Activation layers introduce non-linearity into the network by applying an activation function to the output of convolutional and fully connected layers. Popular activation functions include ReLU (Rectified Linear Unit), sigmoid, and tanh, which introduce non-linear transformations to capture complex relationships in the data.

Fully Connected Layers

Fully connected layers, also known as dense layers, connect every neuron in one layer to every neuron in the next layer. These layers perform classification or regression tasks by combining the features learned from previous layers to produce output predictions.

Dropout Layers

Dropout layers randomly deactivate a fraction of neurons during training, which helps prevent overfitting by encouraging the network to learn more robust features.

Flatten Layers

Flatten layers reshape the output of convolutional layers into a one-dimensional vector, preparing the data for input into fully connected layers.

IV METHODOLOGY

A. Dataset

The dataset used for this project is named "Indian Medicinal Leaves" and is sourced from Kaggle, a widely recognized platform for datasets and machine learning competitions. This dataset comprises images of medicinal plants, specifically focusing on their leaves. It includes a total of 80 species of plants, each represented by a separate subfolder within the dataset directory. Across all species, there are approximately 6900 images, distributed among the respective subfolders based on plant species. The images feature varying backgrounds, capturing the plants in diverse environmental settings. This variability enhances the robustness of the dataset, allowing models trained on it to generalize better to real-world scenarios. The comprehensive nature of this dataset makes it a valuable resource for developing machine learning models aimed at identifying medicinal leaves in diverse conditions [13].

Figure 2 Sample Images of Dataset

B. Procedure

The procedure for developing and evaluating a deep learning model for medicinal leaf classification began with dataset preparation. The images were shuffled, and a batch size of 32 was used, with each image resized to 299x299 pixels. The class names were extracted from the dataset to identify the different categories of medicinal leaves.

To ensure effective training and evaluation, the dataset was partitioned into training, validation, and test sets. This was achieved using a custom function that split the data into 80% for training, 10% for validation, and 10% for testing, with the data shuffled to ensure randomness.

Data augmentation was implemented to improve model generalization, incorporating random horizontal and vertical flips and random rotations. Additionally, a preprocessing pipeline was established to resize the images to 299x299 pixels and rescale the pixel values to a range of 0 to 1.

For the model architecture, four different pre-trained models were utilized: Xception, Inception V3, ResNet152, and VGG19. Each model was pre-trained on the ImageNet dataset and was used as the base model with its top layers excluded and global average pooling applied. The base models were set to non-trainable to leverage their pre-trained weights effectively.

The architecture for each model included an input layer matching the image size, followed by data augmentation and preprocessing layers. The respective base model was used for feature extraction. Subsequently, a dense layer with 128 units and ReLU activation was added, followed by a dropout layer with a rate of 0.2 to prevent overfitting. The final layer was a dense layer with a softmax activation function to classify the images into the corresponding categories. This approach ensured a comprehensive evaluation of different architectures to determine the most effective model for medicinal leaf classification.

The model was compiled using the Adam optimizer and sparse categorical cross-entropy as the loss function, with accuracy as the performance metric. The training process involved using the training dataset with a validation dataset for monitoring performance over 25 epochs with a batch size of 32.

Finally, the performance of each model was evaluated using the test dataset, measuring loss and accuracy. The models demonstrated high effectiveness in classifying medicinal leaf images, with each achieving notable test accuracy. These high accuracies indicate the capability of the models to accurately identify medicinal leaves, making them valuable tools for medicinal leaf classification. The robust performance across multiple architectures underscores the potential of deep learning models in this domain.

V. RESULT AND ANALYSIS

The performance of three different models, Xception, ResNet152, and Inception V3, was evaluated on a dataset, and their precision, recall, and F1-score metrics were analyzed.

A. Models accuracy and Loss Comparision

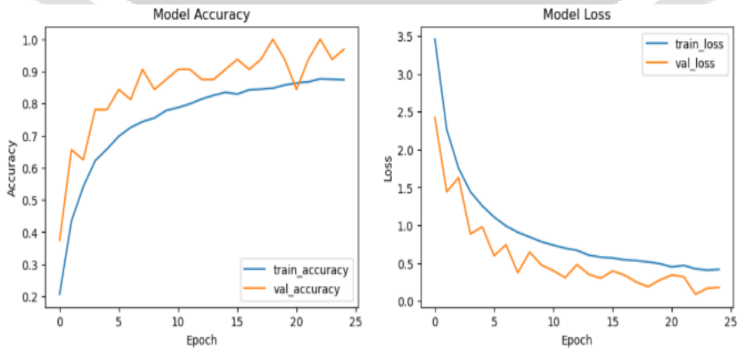

Figure 3 Xception Model Accuracy and Loss

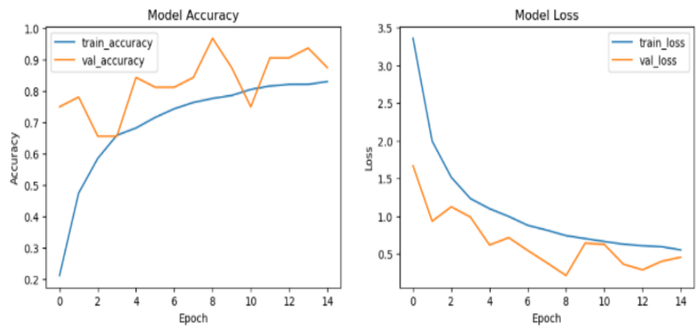

Figure 4 ResNet152 Model Accuracy and Loss

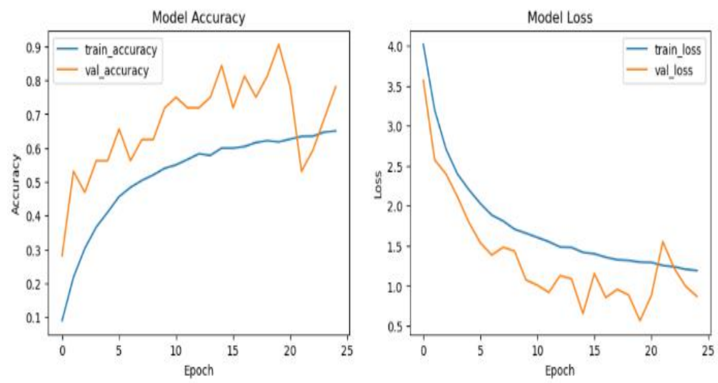

Figure 5 InceptionV3 Model Accuracy and Loss

The comparison of the three models—Xception, ResNet152, and Inception V3—reveals notable differences in accuracy and loss metrics. Xception consistently outperforms the others, achieving an accuracy range between 0.93 and 0.95 across various metrics, indicating robust performance and reliability as depicted in Figure 3. ResNet152, shown in Figure 4, follows with slightly lower accuracy scores ranging from 0.86 to 0.90, suggesting that while it is effective, it may not generalize as well as Xception. Inception V3, illustrated in Figure 5, lags behind with accuracy values between 0.76 and 0.80, reflecting a comparatively lower performance. This trend in accuracy is mirrored in the loss metrics, where Xception demonstrates superior optimization and lower error rates, followed by ResNet152 and then Inception V3. These results highlight Xception's strong capability in handling complex data and achieving higher predictive accuracy, making it the most suitable model among the three for this particular task.

Model	Test Accuracy	Precision	Recall	F1-Score
Xception	0.93	0.95	0.94	0.94
ResNet152	0.86	0.90	0.87	0.87
Inception V3	0.76	0.80	0.77	0.76

Table 1 Accuracy comparison of Models

The Xception model achieved the highest test accuracy of 93%, with precision, recall, and F1-score of 0.95, 0.94, and 0.94 respectively. It performed the best among the three models, indicating its effectiveness in classifying the given dataset. The ResNet152 model followed with a test accuracy of 86%, showing slightly lower performance compared to Xception. Its precision, recall, and F1-score were 0.90, 0.87, and 0.87 respectively. Lastly, the Inception V3 model had the lowest test accuracy of 76%, indicating its comparatively

weaker performance compared to the other two models. Its precision, recall, and F1-score were 0.80, 0.77, and 0.76 respectively.
Based on the evaluation metrics, the Xception model outperformed both ResNet152 and Inception V3 in terms of accuracy and overall performance. ResNet152 followed closely behind, while Inception V3 demonstrated the lowest performance among the three models. These results suggest that the choice of model architecture significantly influences the performance of image classification tasks, with more complex models generally yielding better results.

VI. CONCLUSION

In summary, the Identification of Different Medicinal Plants project marks a significant milestone in bridging traditional botanical knowledge with modern technology. Through the utilization of Machine Learning and Deep Learning approaches, this project offers an efficient means to accurately identify various medicinal plants. The integration of a user-friendly interface ensures accessibility for individuals of varying backgrounds, even those with no prior knowledge of the system's workings.

Through rigorous testing and validation, the project has demonstrated its reliability and effectiveness in delivering accurate identification results. The inclusion of features such as searching for medicinal plant uses and feedback submission further enhances the user experience.

Among the evaluated models, Xception emerges as the most effective, boasting the highest test accuracy of 93% and superior precision, recall, and F1-score metrics. ResNet152 closely follows, while Inception V3 lags behind with the lowest performance. These results underscore the importance of selecting appropriate model architectures in achieving optimal classification outcomes.

Looking ahead, the project holds significant potential for expansion and evolution. Future iterations could explore additional functionalities, such as developing mobile applications for on-the-go leaf identification or integrating with botanical databases for enhanced information retrieval. Collaboration with botanical experts and organizations could enrich the project's database and further improve the accuracy of identification results.

In conclusion, the Medicinal Leaf Identification study exemplifies the innovative fusion of conventional botanical knowledge with cutting-edge technology. With its dedication to accuracy, accessibility, and continuous improvement, the project is poised to make a lasting impact on the fields of botanical study, herbal medicine, and biodiversity conservation for years to come.

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