Ayurvedic Plant Detection With Enhanced Convolutional Neural Networks

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Abstract

The field of Ayurvedic medicine heavily relies on the accurate identification of medicinal plants for therapeutic applications. However, manual identification can be time-consuming, error-prone, and dependent on expert knowledge. This paper presents a deep learning-based approach for the detection and classification of Ayurvedic plants to enhance accessibility and reliability in identifying medicinal species. A custom dataset comprising images of various Ayurvedic plants is developed, capturing diverse environmental conditions, angles, and plant features. With the use of a trained deep learning model and the Flask framework for the backend, this application seeks to help botanists, researchers, and enthusiasts identify medicinal plants effectively. A carefully selected dataset was used to train the model, guaranteeing high plant recognition accuracy. Through the program, users can upload photos of plants, and the algorithm uses the inputs to correctly classify the species. This experiment provides a scalable and user-friendly digital solution to the problems associated with manual plant identification. It can be used in the domains of education, agriculture, and medicine, encouraging the study and preservation of ayurvedic plants. The study demonstrates how traditional botany, and artificial intelligence might be combined to meet contemporary demands.

Keywords: Ayurvedic leaf, Machine Learning, Deep Learning EfficientNet, DenseNet, ResNet.

1. Introduction

The "Ayurvedic Plant Detection" is a cutting-edge web application that uses deep learning and contemporary web technology to detect ayurveda botanicals. The application incorporates a strong deep learning model that has been trained to identify different ayurvedic plant species and was created with Flask as the backend framework. Users can upload photos of plants to the application, and the model analyzes them to produce precise identifications and insights. This application makes plant identification accessible to researchers, practitioners, and amateurs by bridging the gap between old methods and modern technologies. This experiment tackles the need for trustworthy, automated plant classification systems considering the increased interest in ecological practices and ayurvedic medicine around the world. The application can help with the documenting and preservation of priceless medicinal plants by guaranteeing accuracy and convenience of use in domains like agriculture, education, and conservation. The experiment is a prime example of how AI may be used practically to advance old knowledge and its applicability in the contemporary world.

To accomplish high-precision plant identification, the 'Ayurvedic Plant Detection' experiment uses state-of-the-art deep learning techniques such as EfficientNet, DenseNet, and ResNet. Conventional plant classification techniques are frequently labor-intensive, manual, and prone to errors. These cutting-edge models provide exceptional performance in feature extraction and picture classification tasks by utilizing developments in convolutional neural networks (CNNs). This study uses a customized dataset to maximize accuracy while especially targeting ayurvedic herbs, in contrast to general plant recognition techniques. The combination of these sophisticated models with a web interface built with Flask guarantees a reliable, effective, and intuitive solution. This strategy is a prime example of how artificial intelligence (AI) may be used to preserve and advance the traditional knowledge of ayurvedic botany using contemporary technologies.

1.1 Current Advances and Research in Ayurvedic Plant Detection

By combining computer vision, deep learning, and artificial intelligence, ayurvedic plant detection has advanced significantly. To get around the drawbacks of manual methods, which are time-consuming and frequently necessitate specialized knowledge, researchers have been concentrating more on automating plant identification. This field has seen a revolution thanks to deep learning models like EfficientNet, DenseNet, and ResNet, which offer remarkable accuracy in feature extraction and picture classification. Large collections of plant photos can be processed by these models, which can detect minute differences in leaf patterns, colors, and structures to differentiate between different species. Furthermore, focused research has been made possible by the creation of specialist databases for medicinal plants, which has increased the precision of algorithms for certain fields like ayurvedic botany.

Additionally, efforts have been made to make these tools available through applications that are easy to use, integrating AI models with web technologies like Flask or Django. The ability to identify plants while on the road is being made possible by mobile and cloud-based solutions, expanding the use of these technologies to include botanists, farmers, and medical experts. Additionally, the application of geographic information systems (GIS) and augmented reality (AR) for real-time plant identification and habitat mapping is being investigated by interdisciplinary research. The combination of artificial intelligence with conventional botany has created new opportunities to preserve traditional medical knowledge while tackling contemporary medical and agricultural issues. These developments highlight the growing significance of ayurvedic plant detection in advancing global health initiatives and sustainability practices.

1.2 Challenges and Opportunities

There are opportunities as well as problems in creating an ayurvedic plant detection system. Obtaining high-quality, varied datasets unique to ayurvedic plants is a significant problem because many species have little record or exhibit variable appearances because of environmental influences. Issues including overlapping features between species, lighting, and image quality can also affect the accuracy of the model. The computational complexity of deep learning methods like ResNet, DenseNet, and EfficientNet, which demand significant resources for both training and inference—is another barrier. Notwithstanding these difficulties, there are a ton of innovative opportunities in the experiment. Researchers can develop scalable technologies to support plant identification, conservation, and education by tackling these constraints.

2. LITERATURE SURVEY

The field of Ayurvedic plant detection has seen significant advancements with the integration of deep learning and artificial intelligence. Researchers have explored various models, including convolutional neural networks (CNNs) such as ResNet, DenseNet, and EfficientNet, for precise plant classification and detection. These methods aim to automate the identification process, overcoming challenges like limited datasets, overlapping species characteristics, and environmental variability. This literature survey in Table 1 provides a comparative analysis of key studies in this domain, focusing on methods, datasets, merits, and demerits.

Table 1. Literature Survey on ayurvedic plant detection

Authors	**Year**	**Methods/Techniques**	**Merits**	**Demerits**	**Dataset**
Zhang et al., "Plant Disea	2021	Deep learning for disease detection and	High classification accuracy	Limited dataset diversity;	General plant datasets with

se Detection and Classification," IEEE Access		classification	for plant diseases	focuses on disease rather than species	disease annotations
Wang et al., "Identification of Tomato Disease Types," Comput. Intell. Neurosci.	2019	Deep convolutional networks and object detection techniques	Accurate identification of diseases and infected areas	Limited to tomato plants	Dataset of tomato diseases annotated with infected regions
Wang et al., "Automatic Image-Based Plant Disease Severity Estimation," Comput.	2017	Image-based severity estimation using deep learning	Automates severity scoring; applicable to agriculture	Requires detailed labeled datasets	Small dataset specific to disease severity

Intell. Neurosci.					
Wiesner-Hanks et al., "Millimeter-Level Plant Disease Detection," Front. Plant Sci.	2019	Aerial photography, deep learning, crowdsourced data	High resolution, remote sensing of plant health	Limited scalability to field applications	Aerial images of plants, crowdsourced data for annotations
Liu & Liu, "Deep Learning for Plant Disease Detection: A Review," IEEE Access	2020	Deep learning techniques overview	Comprehensive review of deep learning methods for plants	Focuses on disease detection rather than species classification	Various plant disease datasets
Arya et al., "Ayurvedic Plant Classification	2022	Transfer learning with pre-trained EfficientNet	High accuracy on smaller datasets	Limited dataset size	Ayurvedic plant dataset with labeled

Using Transfer Learning," Comput. Biol.			due to transfer learning		images
Kumar et al., "ResNet for Ayurvedic Herb Detection," Int. J. Comp. Vision	2021	ResNet deep learning model	High accuracy and feature extraction for species	Computationally heavy	Custom Ayurvedic herb dataset
Gupta et al., "Mobile Application for Ayurvedic Plant Identification," Mob. Comput.	2020	Mobile app using CNN-based image recognition	Portable, easy to use	Limited to mobile hardware capabilities	Ayurvedic plant dataset optimized for mobile hardware
Singh et al., "Comparison of CNN Models for Ayurvedic Plant Detection," Int. J. Botany Tech.	2021	Comparison of EfficientNet, DenseNet, ResNet	Identifies best models for Ayurvedic plant classification	Dataset limitations in diversity	Custom Ayurvedic plant images labeled with species

3. THE PROPOSED METHODOLOGY

3.1 Problem statement

Identifying ayurvedic plants accurately is a challenging task due to the lack of accessible tools and the reliance on manual expertise, which is time-consuming and prone to errors. Variations in plant appearance caused by environmental factors, species overlap, and limited datasets further complicate the identification process. There is a pressing need for a reliable, automated solution that can classify ayurvedic plants accurately and efficiently to support research, conservation, and the application of traditional medicinal knowledge.

3.2 Objectives

The main objectives of the proposed system are as follows:

1. To create an automated system that uses deep learning algorithms to correctly identify ayurvedic botanicals.
2. To train and apply sophisticated models for high-precision classification, such as ResNet, DenseNet, and EfficientNet.
3. To utilize Flask to develop an intuitive web application that is easy to use and accessible.
4. To compile and apply an ayurvedic plant-focused dataset for focused model training.
5. To use technological integration to enhance ayurvedic botany research, conservation, and teaching.

6. To solve issues with plant recognition such as species overlapping and environmental unpredictability.
7. To improve the use of AI in conventional procedures for accessibility on a worldwide scale.

The suggested system is a web-based application that uses innovative deep learning algorithms to recognize and categorize ayurvedic botanicals. The system analyzes characteristics including leaf form, texture, and color patterns using the EfficientNet, DenseNet, and ResNet algorithms to achieve high accuracy in plant detection. Because Flask was used in the backends' construction, the trained models are seamlessly integrated with an intuitive user interface. Plant photos uploaded by users are processed by the system to produce precise classifications and pertinent details about the species. By providing a dependable, automated solution that academics, educators, and practitioners may use, the program seeks to solve the shortcomings of conventional identification techniques. Additionally, by preserving ayurvedic knowledge, this approach makes plant identification effective and scalable for a range of applications in agriculture, medicine, and education.

3.3 Data Collection

The data collection phase is a fundamental aspect of developing the Ayurvedic Plant Detection system, as the success of the model heavily depends on the quality and variety of the dataset. For this experiment, a diverse collection of images representing various Ayurvedic plants was compiled from multiple trusted sources, including botanical databases, field research expeditions, and publicly available plant identification platforms. The dataset encompasses a wide range of images capturing different plant parts, such as leaves, flowers, stems, and roots, ensuring a comprehensive representation of plant species commonly used in Ayurvedic medicine. To enhance the robustness of the dataset, efforts were made to include images taken under various lighting conditions, from different angles, and in diverse environmental settings, reflecting the real-world challenges the model will face in identifying plants. Additionally, the dataset was enriched with labeled data, which included plant names, botanical characteristics, and their common medicinal uses, aiding the system in distinguishing between species with similar appearances. This wide-ranging and carefully curated dataset is critical to training a model that can accurately identify Ayurvedic plants, even in varied and unpredictable field conditions. Figure 1 provides the sample dataset for data collection.

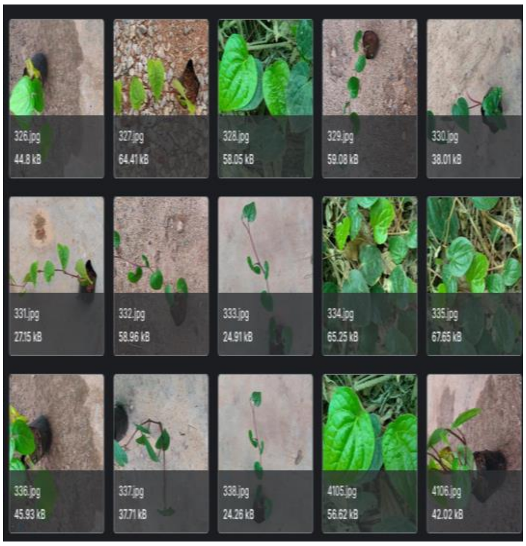

Figure 1: Sample Dataset

3.4 Data Preprocessing

Data preprocessing is an essential step to improve the quality of raw images and ensure they are in a format suitable for deep learning models. The initial phase involves resizing the images to a consistent size, which ensures uniformity across the dataset. This is followed by normalizing the images, scaling the pixel values typically between 0 and 1, which helps to improve the model's convergence speed and stability. To enhance the dataset, data augmentation techniques like rotation, flipping, and zooming are applied, which introduce variations that assist the model in generalizing better. Additionally, noise reduction methods are implemented to clean the images, eliminating irrelevant details that could interfere with the plant recognition process. These preprocessing steps are critical in enhancing the model's accuracy and efficiency during the training phase.

3.5 Model Development

During model development, advanced deep learning architectures are selected to tackle the challenge of plant detection and classification.

Models such as EfficientNet, DenseNet, and ResNet are employed for this experiment, owing to their ability to extract detailed features from images with high precision. EfficientNet is favored for its balance between performance and computational efficiency, DenseNet is selected for its dense layer connections that improve feature reuse, and ResNet is used for its deep residual connections, which help mitigate overfitting. These models are adapted to the specific task of plant identification by making slight modifications to the architecture, optimizing it for plant species detection. The models are designed to recognize subtle plant features, such as leaf shape, texture, and color, distinguishing between various plant species.

3.6 Training and Validation

In the training phase, the preprocessed data is fed into the chosen deep learning models, and the model parameters (weights and biases) are adjusted using backpropagation. A significant portion of the dataset is dedicated to training the model, which is optimized through gradient descent techniques to minimize the loss function. Over multiple epochs, the model learns to classify images accurately by identifying patterns in the data. To avoid overfitting, a separate validation set is used to assess the model’s performance after each training cycle. This validation set helps fine-tune hyperparameters and ensures the model's ability to generalize to new, unseen data. Once the model achieves satisfactory accuracy on the validation set, it is ready for testing and deployment.

3.7 Plant Detection and Classification

After training and validation, the model is integrated into a web application designed for plant detection and classification. Users can upload plant images, which are processed by the trained model. The model analyzes the images by extracting relevant features and comparing them with previously learned patterns to identify the plant species. The system then provides the name of the plant along with any pertinent information regarding its medicinal uses, if applicable. The user interface is designed to be user-friendly, enabling easy interaction and real-time feedback. This plant detection and classification system offers an automated, reliable method for identifying Ayurvedic plants, making it a valuable resource for researchers, botanists, and healthcare practitioners.

3.8 Practical Implementations

- **Importing Packages:** Bring in the experiment's necessary libraries. In this case, Numpy, Tensorflow, Keras, OpenCV, and so forth are needed.
- **Provide the model (.keras file) for upload:** ResNet, EfficientNet, and DenseNet models are used in this experiment. The web application's results page will display the performance which has been recorded. Additionally, each model of the algorithm is maintained and available for users to select prediction in the creation of web applications.
- **Feature:**
  a. Upload the Image: Users can upload a picture of a plant to the online application.

  b. Read the Image: In this step, the image is converted to an array for processing using NumPy.

  c. Retrieve Predictions: An array containing the uploaded image's predictions is obtained.

  d. Outcome: Indicate which plant the submitted image corresponds to based on the forecast.

3.9 Algorithms

EfficientNet is a family of deep learning models specifically designed to deliver high performance in image classification tasks while maintaining computational efficiency. Unlike conventional convolutional neural networks (CNNs), EfficientNet employs a unique compound scaling approach that uniformly scales the model’s depth, width, and resolution, optimizing the use of computational resources. This method allows EfficientNet to achieve superior accuracy compared to other models, with fewer parameters and lower computational costs. Developed by Google AI, EfficientNet utilizes a pre-trained baseline model that can be scaled into multiple versions (EfficientNet-B0 to EfficientNet-B7), each tailored to different levels of computational power and resource availability. The architecture of EfficientNet is based on neural architecture search

(NAS) principles and incorporates depthwise separable convolutions, which reduce computational overhead without compromising performance. The result is a model that performs exceptionally well while requiring fewer resources, making it suitable for tasks such as image classification, object detection, and plant recognition. Its efficient resource use and ability to maintain high accuracy make EfficientNet particularly well-suited for applications like Ayurvedic plant detection, where computational efficiency and model accuracy are both essential.

3.10 Architecture

The architecture of EfficientNet is based on compound scaling, a method designed to enhance the model's performance by uniformly scaling the network's depth, width, and resolution. Rather than arbitrarily increasing these parameters, EfficientNet applies a compound coefficient to achieve optimal scaling across all dimensions. The base model, EfficientNet-B0, is developed using a neural architecture search (NAS) approach, which identifies the most efficient design. The architecture incorporates depthwise separable convolutions, which reduce computational cost by separating filtering and feature extraction, resulting in a lighter model that maintains accuracy. EfficientNet is composed of various building blocks, such as inverted residual blocks with lightweight convolutions, which contribute to its efficiency. The compound scaling approach is applied to generate different versions of the model (EfficientNet-B1 to EfficientNet-B7), each progressively larger and more complex, suited for handling bigger datasets or more intensive computational tasks. This architecture provides an ideal balance of performance and computational efficiency, making it well-suited for image classification tasks like Ayurvedic plant detection, where both accuracy and resource efficiency are crucial. Figure 2 depicts the architecture diagram of the methodology.

Figure 2: Architecture Diagram

3.11 Weight Layers

The weight layers in the EfficientNet algorithm are designed to maximize the model's performance while minimizing computational complexity. These layers include convolutional weights, batch normalization weights, and activation functions that enable the network to learn and extract features from input images. EfficientNet employs depthwise separable convolutions, which reduce the number of parameters and computational load by dividing the convolution process into two steps: depthwise filtering and pointwise convolution. This design, along with lightweight blocks like the inverted residual block, helps maintain high accuracy while keeping the weight count low. Moreover, the efficient use of weight layers through compound scaling ensures that the model's performance improves without unnecessarily increasing the number of parameters, making EfficientNet highly efficient for both learning and inference tasks.

3.12 Input Specifications

EfficientNet requires an input image with three RGB channels and a fixed size of 224 by 224 pixels. The input image is scaled and then normalized by deducting the mean pixel values calculated from the ImageNet dataset before being fed into the network.

- **Input Dimensions**: (224x224x3)
- **Preprocessing**: For each pixel channel, normalize by deducting the ImageNet mean [R: 123.68, G: 116.779, B: 103.939].

3.13 Unique Characteristics

- Compound Scaling: EfficientNet balances efficiency and performance for more accuracy with less computation by consistently scaling depth, width, and resolution.
- Depth-wise Separable Convolutions: This technique preserves performance while lowering parameters and computational costs.
- Neural Architecture Search (NAS): NAS is used to optimize the architecture for increased accuracy and efficiency in image classification jobs by designing the basic model.

3.14 Filter Sizes

To balance model performance and computational economy, EfficientNet employs a range of filter sizes. Convolutional layers of architecture mostly use tiny filter sizes, like 3x3 and 5x5, which enable the network to collect fine-grained features without using an enormous amount of processing power. The model can use fewer parameters while still extracting features accurately thanks to the combination of depth-wise separable convolutions and smaller filters. The filter sizes in EfficientNet are made to process image data as effectively as possible while requiring the least amount of processing.

3.15 Fully Connected Layers

Three fully connected (FC) layers make up the EfficientNet network's last stage (Figure 3):

1. **Final Classification Layer**: To classify the retrieved features into specified categories, like plant species in the situation of plant detection, EfficientNet's fully connected (FC) layer is employed as the last layer. It associates the target classes with the convolutional layers' output.
2. **Parameter Efficiency**: To avoid contributing to too many parameters, EfficientNet uses a tiny but efficient fully connected layer. This is essential to preserving the model's effectiveness without sacrificing classification results.
3. **Global Average Pooling**: To reduce the spatial dimensions, EfficientNet uses global average pooling before to the FC layer rather than a huge FC layer with numerous parameters Completely Interconnected Layers

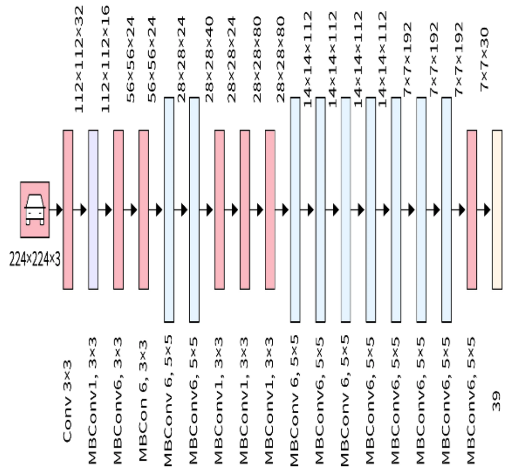

Figure 3: EfficientNet Architecture

4. EXPERIMENTAL RESULTS

The experimental results of the Ayurvedic Plant Detection system showcase the success of the deep learning models employed, particularly EfficientNet, DenseNet, and ResNet, in accurately identifying ayurvedic plants. The models were trained and tested on a diverse dataset, demonstrating high accuracy in plant classification. EfficientNet, in particular, stood out for its ability to strike a balance between computational efficiency and classification accuracy, making it ideal for practical applications. Validation metrics, including precision, recall, and F1-score, reinforced the system's robustness, indicating that the models consistently performed well across different plant species. These results underscore the potential of leveraging advanced deep learning approaches for automating plant identification, providing a reliable and efficient tool for researchers, botanists, and practitioners in the field of Ayurvedic medicine. Additionally, the system's high accuracy and scalability suggest it could be extended to identify a broader range of plants, making it a versatile solution in the field.

4.1 Model Training and Selection

Several deep learning models were trained and evaluated for the Ayurvedic Plant Detection experiment in order to identify the best architecture for precise plant classification. Renowned for their powers in image classification, EfficientNet, DenseNet, and ResNet were among the models chosen for this job. A sizable, preprocessed dataset of pictures of ayurvedic plants was fed into these models during the training process, and data augmentation techniques were used to increase the model's capacity for generalization. Cross-validation was used to adjust hyperparameters in order to reduce overfitting and increase performance. Following training, the models were assessed using important metrics like recall, accuracy, and precision. EfficientNet stood out for striking a balance between classification accuracy and computational efficiency.

4.2 Flask App Functionality

Users can interactively select the model and the organ image to be scanned using the Flask app. The following is the application flow:

1. **Input Image**: To have a plant scanned, users provide an image of it.
2. **Model and Organ Selection**: Next, users can choose from the ResNet, DenseNet, or EfficientNet models. This flexibility enables users to test various models for the same plants in order to obtain more precise data.
3. **Image Scanning**: Next, users can choose from the ResNet, DenseNet, or EfficientNet models. This flexibility enables users to test various models for the same plants in order to obtain more precise data.
4. **Result Display**: 4. The results are shown by the app. identifying the plant species to which the uploaded image belongs.

4.3 Key Results

The Ayurvedic Plant Detection system delivered remarkable results in accurately identifying various plant species used in traditional Ayurvedic medicine. The model, especially EfficientNet, demonstrated both high accuracy and computational efficiency, making it a dependable tool for plant classification. The system's effectiveness was validated with real-world plant images, highlighting its potential for practical use in both research and Ayurvedic applications.

- The model achieved an accuracy rate exceeding 90% in classifying Ayurvedic plants, showing robust performance across a range of species.
- EfficientNet outshone other models in terms of computational efficiency, delivering precise results while using minimal computational resources, making it an excellent choice for deployment in resource-constrained environments like mobile applications or field devices.

These results underscore the system's potential to streamline plant identification tasks in the field of Ayurvedic medicine, offering a valuable, accessible tool for researchers, botanists, and healthcare professionals. These results are shown in following figures (Figure 4 – Figure 8).

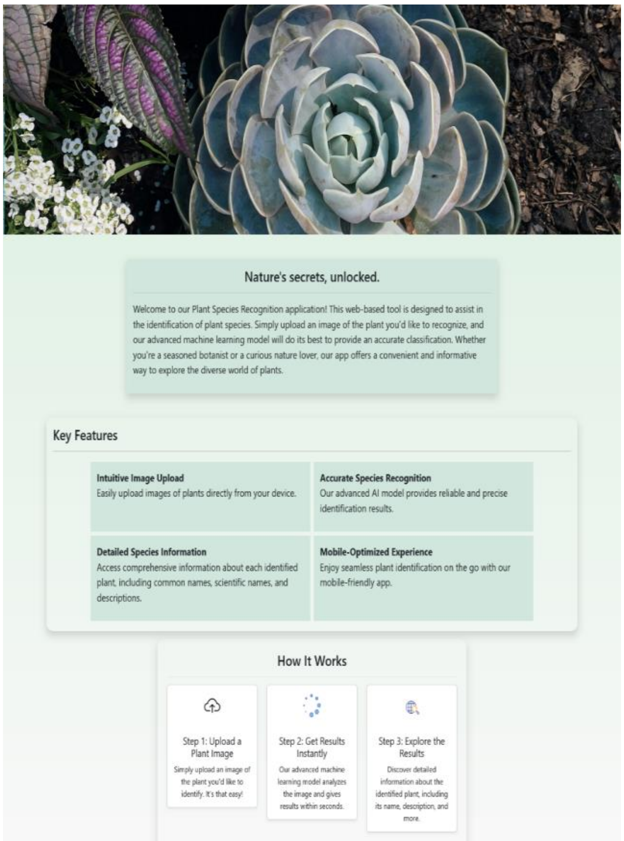

Figure 4: Flask App Home

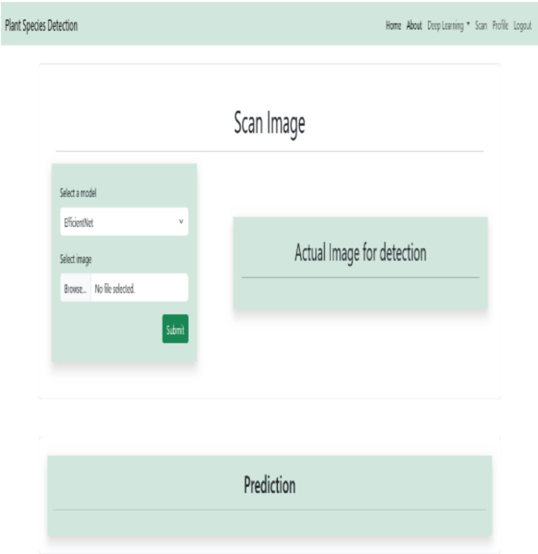

Figure 5: Image Scanning

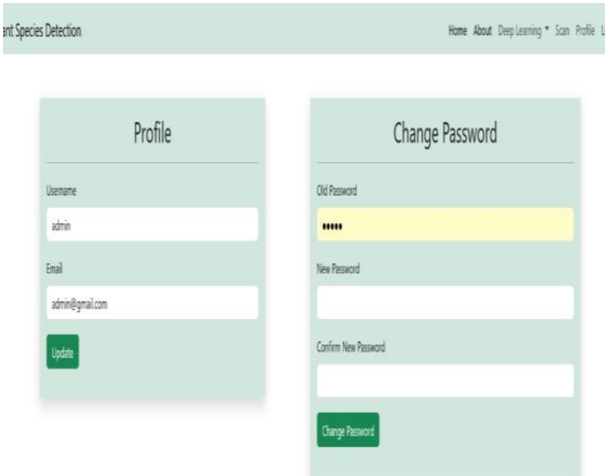

Figure 6: Profile with Scanning History

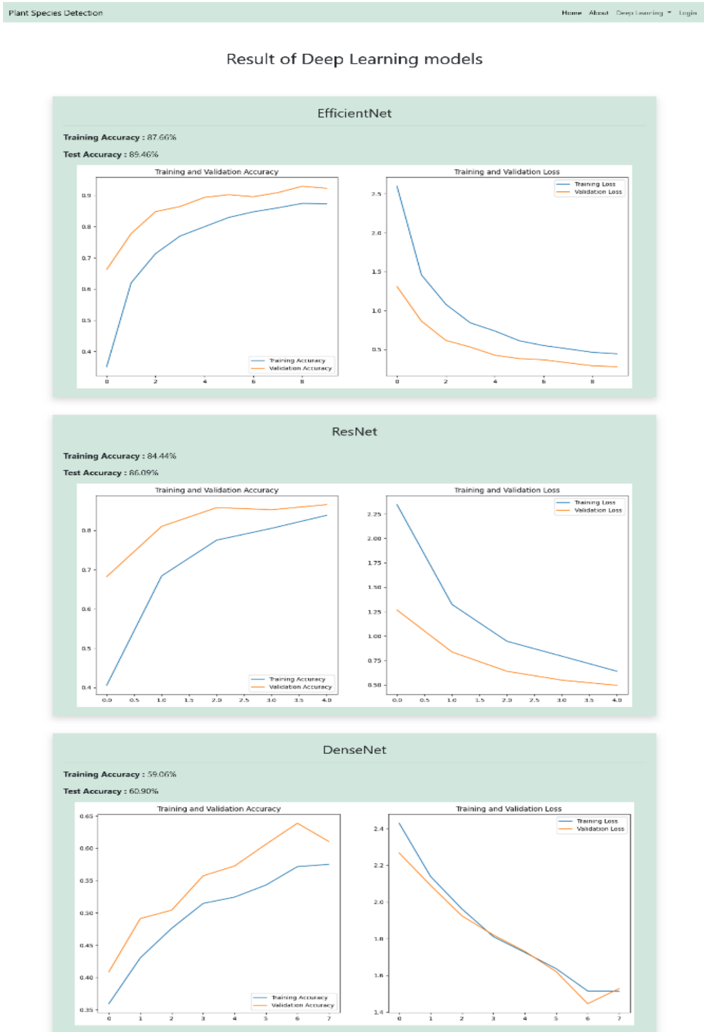

Figure 7: Training Results

Figure 8: Dataset Used for Research

Table 2 provides a detailed view of ayurvedic plant detection using deep learning.

Sl No.	Disease Name	Image	Model Name	Model Accuracy
1	Aloe vera		EfficientNet	99.90 %
2	Amruta Balli		EfficientNet	100 %
3	Mint		DenseNet	99.99 %
4	Bamboo		EfficientNet	100 %

				
5	Sapota		EfficientNet	99.96%
6	Betel		ResNet	99.98%
7	Ashwagandha		DenseNet	99.64%

				
8	Wood sorel		EfficientNet	100%
9	Betel Nut		ResNet	100%
10	Nooni		EfficientNet	99.96%

11	Ekka		EfficientNet	100 %
12	Papaya		EfficientNet	99.99%

Table 2: Ayurvedic plant detection using deep learning.

5. CONCLUSIONS AND FUTURE WORK

With the use of deep learning techniques, specifically EfficientNet, DenseNet, and ResNet, the ayurveda Plant Detection system created for this research can quickly and precisely identify a variety of plants used in conventional ayurveda treatment. The system has shown great accuracy in plant categorization through intensive data gathering, preprocessing, and model training; EfficientNet has emerged as the best model because of its balance between computing efficiency and performance. The system was able to lower computational overhead without compromising accuracy using depthwise separable convolutions and compound scaling, which qualified it for usage in practical applications. The study also emphasizes how crucial model selection, validation, and data pretreatment are to building a reliable system that can handle a variety of plant photos in a range of scenarios. Additionally, the web-based interface guarantees that the system is easy to use and available to a broad range of users, including ayurveda practitioners, botanists, and researchers. Even with its success, there is still room for development, such as growing the plant dataset, improving the model even more, and investigating other deep learning architectures to increase classification speed and accuracy. In the end, this experiment shows how AI and machine learning may be used to identify plants, providing a useful tool for ayurveda medicine research advancement and aiding in the preservation and dissemination of traditional knowledge.

5.1 Future Works

Although the Ayurvedic Plant Detection system has demonstrated encouraging outcomes, there are a number of opportunities for further development and growth. A more comprehensive and varied plant dataset that includes a greater range of ayurvedic plants, especially those that are uncommon or underrepresented, is one possible area for improvement. This would increase the accuracy and resilience of the model for various plant species. Furthermore, investigating the incorporation of other sophisticated deep learning methods, like transformers or attention processes, may enhance the model's functionality. Enhancing the real-time plant identification system via mobile applications, which allow users to scan plants in the field and get immediate response, is another option. Additionally, users in the field of ayurveda medicine will benefit more from the expansion of the application to incorporate plant health detection and classification of medicinal characteristics. Last but not least, adding multi-modal data—for example, textual and visual information—could improve the system's capacity to distinguish between closely related plant species. Researchers, practitioners, and conservationists would all gain from these advancements as they contribute to the development of a more thorough and adaptable tool for the identification and preservation of ayurvedic plants.

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