



AI-Based Ayurvedic Medicinal Plant Identification and Usage Information System

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Abstract. Accurate identification of the medicinal plants is of critical importance for the formulation of Ayurvedic medicines. Conventional methods of identification involve a large degree of reliance on experienced botanists and direct experience of the physical characteristics of the plants, such as the shape of the leaves, the patterns of the veins, the colors, etc. This method requires a large amount of effort and is often prone to errors, especially for those who are not experienced in the field. To overcome the difficulties of the conventional method, this work presents an AI-based Ayurvedic Medicinal Plant Identification and Information System. This method uses a combination of deep learning-based identification of the medicinal plants along with the information related to the medicinal uses of the plants. The proposed method uses a transfer learning-based approach using MobileNet V2 to identify the medicinal plants from the images of the leaves. The model is able to identify the different species of the medicinal plants with a high level of accuracy. The proposed method also uses a structured knowledge base related to the phytochemicals of the medicinal plants. Another component in the age determination aspect has also been included to measure the leaf maturity and the concentration of phytochemicals. This solution runs as a web app using the Flask library, which allows users to input images of the leaves and receive in real time the species identification and medicinal information. Based on the trial runs, the model using the MobileNetV2 achieves a classification accuracy of 96.8%. By integrating the plant identification using deep learning and the medicinal information, this solution creates a smart and user-friendly interface that promotes Ayurvedic education and advances herbal medicine research, as well as the digital conservation of medicinal wisdom.

Keywords: Ayurvedic medicinal plants, Deep learning, MobileNetV2, Transfer learning, Leaf image classification, Phytochemical knowledge base, Knowledge-based systems, Flask web application

1 Introduction

Medicinal plants play a crucial role in Ayurveda and are heavily utilized in therapeutic practices. Ayurveda, one of the most ancient traditional medical practices, relies heavily on plant-based formulations for disease prevention and management[3]. Hence, proper identification of medicinal plants is of prime importance to enable proper formulation and safely deliver herbal formulations. Conventionally, this can be achieved by using botanical knowledge and visual identification of various morphological characteristics, including leaves, venation, pigmentation, and architecture of plants[2,6,7,11]. However, this requires a lot of specialized knowledge and hands-on experience, making it challenging for new and non-expert individuals to distinguish medicinal plant species.

In addition, traditional plant identification approaches are labor-intensive and prone to errors, especially due to the striking visual similarities between a large number of plant species. Such identification errors may cause inappropriate medicinal use, suboptimal therapeutic results, and serious health risks. However, recent advances in artificial intelligence, especially in the area of convolutional neural networks, have made automated plant identification using images a promising alternative approach. CNN-based approaches have been shown to independently recognize images and provide accurate identification results[1,23,30]. Such advances enable the development of intelligent plant identification applications that can help users in plant species identification by using images of plant leaves.

Apart from the simple automation of the identification process, the integration of medicinal knowledge with the imagery-based technologies provides a number of significant advantages. For Ayurvedic students and scholars, the imagery-based technologies prove to be an interactive tool for better learning and exploration of the taxonomy, phytochemistry, and medicinal properties of the plants[14,21]. By uploading the leaf image, users can retrieve information about the scientific name, bioactive compounds, and medicinal properties of the plant, leading to a better understanding of traditional herbal medicines.

In an analogous manner, it also helps Ayurvedic practitioners, herbal medicine researchers, and field botanists by providing quick identification of plants in their respective fields of work. This is especially beneficial in field-based environments, as access to expert botanists is often restricted. Additionally, the integration of phytochemical knowledge retrieval with an AI-based classification method places this system in an advantageous position as an all-encompassing digital platform for medicinal plant information, which can be beneficial for the preservation and dissemination of traditional Ayurvedic knowledge[14,21,27]

In this paper, an artificial intelligence-based system for identifying Ayurvedic medicinal plants and retrieving their usage information is proposed. The integration of deep learning-based plant classification with a phytochemical knowledge base will enable plant identification and information retrieval for medicinal plants. By combining computer vision-based techniques with knowledge-based systems, an intelligent, intuitive, and feasible solution for identifying medicinal plants and retrieving Ayurvedic information is achieved.

1.1 Key Contributions

The main contributions of this work are as follows:

- Development of a medicinal plant identification system based on deep learning using MobileNetV2.
- Integration of a structured phytochemical knowledge base with image classification.
- Introduction of an age-based phytochemical adjustment mechanism to model biological variations.
- Application of a confidence threshold mechanism for better prediction accuracy

2 Literature Survey

2.1 Deep Learning-Based Plant Identification

Significant advancements in AI research have improved the efficiency of automated plant identification systems considerably. In the early stages of research on plant classification systems, researchers mainly focused on using conventional machine learning techniques with feature extraction techniques. For example, researchers in [6,?,10,12] used image processing techniques such as Local Binary Patterns, color histograms, shape features, and venation pattern features to obtain features from images of leaves. After extracting features from images using image processing techniques, researchers used Support Vector Machines, k-Nearest Neighbors, and Decision Trees to classify plants into different categories. Even though these techniques showed promising results in terms of accuracy in a laboratory setup, they had some major drawbacks when dealing with real-world datasets.

Convolutional Neural Network techniques were found to be more efficient in improving the accuracy of plant recognition systems compared to conventional techniques. In their research, Sladojevic et al. [1] proposed a deep neural network model that can recognize diseases in plants using leaf images. In another research study, Liu et al. [23] proposed a CNN-based approach to detect diseases in plants using leaf images and obtained promising results in terms of feature extraction from leaf images. In their research study, they mainly focused on disease detection and did not provide information about the medicinal properties and phytochemical composition of plants.

Transfer learning has also been investigated in various studies related to plant identification tasks. Mishra and Tripathi [26] employed transfer learning techniques to classify images of leaves of various plants using pre-trained CNN architectures. The experiment demonstrated that transfer learning improves classification accuracy when a small dataset is considered for training a model. Similarly, Ramesh and Venkatesh [20] proposed a classification system using transfer learning architectures for herbal plants. Though these studies improve classification accuracy, they are limited to classifying images into different species of plants without considering medicinal factors.

Recent studies have also focused on developing systems that incorporate intelligent knowledge systems with plant identification tasks. Banerjee and Mukherjee [14] proposed an AI-based herbal information system using plant identification techniques and botanical databases to retrieve medicinal knowledge related to herbs. Similarly, Kulkarni and Joshi [21] proposed a knowledge retrieval system using structured databases related to medicinal plants. Though these studies incorporate knowledge retrieval systems, they do not consider biological intelligence such as the concentration of phytochemicals in plants during maturity.

Another class of lightweight deep learning models has gained popularity for real-time systems. The MobileNetV2 [29] architecture proposed depthwise separable convolution operations to minimize computational complexity while preserving the accuracy of the model. These lightweight models can be used for efficient implementation in mobile devices or web-based systems. Nevertheless, the majority of the existing plant identification systems based on the above deep learning models have primarily focused on the accuracy of the system.

Although the recent studies have shown significant improvements in the accuracy of plant identification systems, the following limitations have been found in the existing systems. The existing plant identification systems have primarily focused on the identification of the plant species. There is no proper method to include the effects of biological changes in the plant composition.

2.2 Problem Statement

It is very important to correctly identify medicinal plants used in Ayurveda to ensure their safe and effective medicinal applications. The conventional method of identification requires expert botanists to examine the morphological characteristics of the medicinal plant, including the shape of the leaves, leaf venation, color, and stem structure. This requires extensive experience and expertise to accurately identify medicinal plants.

Another challenge that arises during the identification of medicinal plants is their similarity in appearance. There are many medicinal plants that exhibit similar morphological characteristics, which increases the risk of confusing one medicinal plant with another. This may result in inappropriate medicinal applications or reduced medicinal benefits.

Although modern image recognition technology has made plant identification tools more accessible, most digital tools only go as far as providing the name of the plant after identification. In most cases, they rarely offer detailed information on phytochemical composition or the biological context of the identified plant.

In addition to that, the phytochemical composition of medicinal plants varies depending on the age of the leaves, environmental conditions, and the stage of development of the plant. Most plant identification tools ignore these biological differences when providing information on medicinal uses of plants.

Therefore, there exists a necessity for an intelligent system that not only assists in the automation of plant identification but also provides medicinal knowledge and biological insights in a structured manner. In this context, a system is

proposed here that aims to address these requirements through a deep learning-based approach in plant classification, a phytochemical knowledge base, and a confidence-driven validation mechanism. Mathematically, the proposed system can be expressed as:

$$f(I) \rightarrow \{Plant, Confidence, Phytochemicals, Usage\} \quad (1)$$

where I denotes the input leaf image and the function f provides predictions on the plant species, classification confidence score, phytochemical compounds, and medicinal uses. This framework integrates the entire process to improve the convenience, accuracy, and usability of Ayurvedic medicinal plant identification systems.

3 Proposed System Architecture and Methodology

In the proposed system, deep learning techniques can be used to identify the plant species, along with a structured knowledge retrieval mechanism to obtain information on phytochemicals. The proposed system can be considered a scalable architecture that can process the images of leaves and then identify the plant species along with the medicinal properties associated with the plant species. This can be considered an appropriate approach to identify the plant species and make effective use of the system in a web-based environment.

3.1 System Architecture

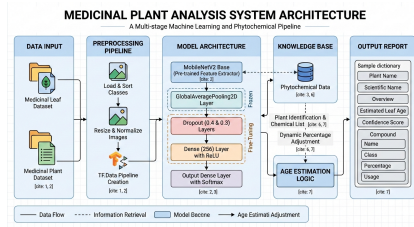


Fig. 1: Architecture Diagram of the Proposed System

Fig. 1 shows the overall architecture of the proposed system. The proposed system follows a sequential processing pipeline from image acquisition to the generation of a structured medicinal information report.

The process begins with the sending of an image of the leaf by the person, which is done via the web interface. Next, the image is received at the server, where it is subjected to various preprocessing techniques, such as the resizing of the image. Then, the image is passed through a classifier, where the features of the image are determined using the MobileNetV2 method. Using this method,

the image features at different levels, along with the plant species related to the image, are determined.

Next, after the plant species are determined, the class label is used to retrieve information from the knowledge base. This knowledge base contains information regarding the medicinal uses of the plant, the nomenclature of the plant, the important phytochemicals present in the plant, the ranges of the concentrations, and the therapeutic functions. Moreover, the maturity stages of the leaves, as well as the concentration levels, are determined based on this factor.

In the last stage, the system produces a structured results report with the predicted plant name, the confidence level provided by the model, the phytochemical profile, and the information on the medicinal application. The entire architecture makes the integration of computer vision, knowledge representation, and web deployment quite seamless.

The proposed system architecture consists of various modules that are related to each other. These modules are collectively responsible for plant identification and the retrieval of medicinal knowledge.

Data Input Module: This module represents the entry point for the proposed system. Images can be uploaded through the web interface of the proposed system. The web interface for the proposed system is built with the Flask web development framework.

Preprocessing Module: The preprocessing module normalizes the input image before the actual processing by the deep learning model takes place. The image is resized to a size of 224×224 , which is the required size for the MobileNetV2 model.

Feature Extraction Module: In this module, a pre-trained MobileNetV2 CNN is used to perform hierarchical feature extraction on the leaf image. In the convolutional layers, important features of the leaf image are learned, including leaf shape, leaf venation, leaf texture, and leaf color distribution[30].

Classification Module: The features are further processed by classification layers consisting of global average pooling, dropout regularization, and fully connected dense layers. The Softmax activation function is applied to classify all plant species, and the class with the highest probability is selected as the predicted plant species.

Knowledge Base Module: Following the plant classification process, the predicted class label is used to obtain medicinal information from the structured knowledge base of phytochemicals. This knowledge base contains scientific names of plants, phytochemicals, their concentration range, and medicinal values associated with each plant.

Age Estimation Module: Since the level of phytochemicals is determined based on the maturity level of the plant, the system is also designed to predict the age category of the leaf, whether it is young, mature, or old. Depending upon the age category, the level of the compound concentrations is altered such that biological information is provided.

Output Report Module: The final module is used to combine the predicted information and the medicinal knowledge in a structured report. This report is then presented in real time to the user through the web interface.

3.2 Methodology

It is proposed that the methodology will be a multi-stage approach. The methodology will consist of data set integration, classification using deep learning, phytochemical knowledge retrieval, and confidence validation. It is proposed that the objective of this methodology is to ensure accurate identification of the plants while keeping biological significance. The mathematical equations used in this study are consistent with the conventional deep learning frameworks presented in previous works [8,29,30].

1. Dataset Preparation

The dataset used in this study is obtained from the Indian Medicinal Leaves Image Dataset, available through Kaggle and Mendeley Data repositories[5]. Two subsets, namely the Medicinal Leaf Dataset and the Medicinal Plant Dataset, were utilized.

To ensure consistency in labeling, only the plant classes common to both datasets were selected. This was done using a set intersection approach:

$$C = C_1 \cap C_2 \quad (2)$$

where C_1 and C_2 represent the class labels from the two datasets.

All images corresponding to the selected classes were combined to form a consolidated dataset. The dataset contains leaf images captured under varying environmental conditions, improving model robustness and generalization capability of the model [7,11]

The final dataset consists of **21** plant species and around **3500** images.

2. Image Preprocessing

The preprocessing of images was done before the input of images into the deep learning model. During this preprocessing, images were resized to 224×224 pixels to conform to the input specifications required by the MobileNetV2 model. In addition, normalization of images in terms of pixels was done to ensure the stability of the model.

$$X_{norm} = \frac{X - \mu}{\sigma} \quad (3)$$

[8]

Additionally, plant labels were converted into one-hot encoded vectors to enable multi-class classification.

3. Dataset Splitting

The data set was divided into training and validation sets to valuate the performance of the model.

$$Train = 0.8N, \quad Validation = 0.2N \quad (4)$$

TensorFlow's data pipeline was used for efficient shuffling, batching, parallel processing, and prefetching of images during training.

4. Training Configuration

The training was performed using a batch size of 32. The MobileNetV2 base model [29] was initially used in a frozen state, where all convolutional layers were kept non-trainable and only the classification layers were trained for 15 epochs.

During fine-tuning, the last 40 layers of the base model were unfrozen and trained for an additional 5 epochs to capture domain-specific features.

The Adam optimizer [8] was used with an initial learning rate of 0.0003, which was reduced to 0.00005 during the fine-tuning phase. The categorical cross-entropy loss function [8] was used for multi-class classification.

Dropout regularization [8] was applied with rates of 0.4 and 0.3 to reduce overfitting.

5. Transfer Learning with MobileNetV2

The classification model is built using MobileNetV2 as a pre-trained model on the ImageNet dataset [20,26]. This allows the model to take advantage of transfer learning to incorporate pre-trained visual features[26] into the classification process.

MobileNetV2 is a convolutional neural network that uses depth-wise separable convolution operations to reduce complexity without compromising accuracy.

$$Conv_{depthwise}(X) + Conv_{pointwise}(X) \quad (5)$$

[29]

During training, early convolutional layers were frozen to retain general visual features, while deeper layers were fine tuned to learn domain-specific botanical patterns.

6. Feature Extraction and Classification

The extracted feature maps were processed through several classification layers:

Global Average Pooling

$$GAP_k = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W X_{i,j,k} \quad (6)$$

[8]

Dropout Regularization

$$h' = h \cdot r, \quad r \sim \text{Bernoulli}(p) \quad (7)$$

[8]

Dense Layer

$$Z = W^T X + b \quad (8)$$

[8]

Softmax Output

$$P(y = i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (9)$$

[8]

$$\hat{y} = \arg \max_i P(y = i) \quad (10)$$

7. Knowledge Base Integration

The system has a knowledge base for phytochemicals, which stores the medicinal information for each species of the plant. It has the scientific name, the active compounds, the ranges of concentrations, and the medicinal uses for each plant species.

8. Age-Based Compound Adjustment

phytochemical concentration varies with leaf maturity, the system adjusts compound values based on the detected age of the leaf.

$$P_{adjusted} = \begin{cases} h & \text{Young leaf} \\ \frac{l+h}{2} & \text{Mature leaf} \\ l & \text{Old leaf} \end{cases} \quad (11)$$

9. Confidence Threshold Validation

To ensure the reliability of the prediction, the system has employed a confidence threshold mechanism.

$$\text{If } \max(P) < 0.70 \Rightarrow \text{Unknown Plant} \quad (12)$$

The prediction with low confidence levels is declared as an unknown plant, which helps to ensure the reliability of the medicinal recommendations.

Methodology Summary : The methodology employed for the classification of medicinal plants is a structured approach that includes data preparation, preprocessing, transfer learning-based classification, phytochemical knowledge, and confidence validation.

4 Results and Discussion

The proposed system based on the use of artificial intelligence for the identification of Ayurvedic medicinal plants, along with the extraction of information regarding the use of these plants, was tested based on various parameters. This system is more efficient compared to the use of image recognition techniques.

4.1 User Interface of the Proposed System

To demonstrate the practical application of the proposed system, we implemented a user interface using the Flask web framework. The user interface is built using HTML and CSS. It is designed to allow users to upload images of plant leaves, identify the medicinal plant, and retrieve information regarding the use of the plant in real time. It is user-friendly, regardless of the user’s background.

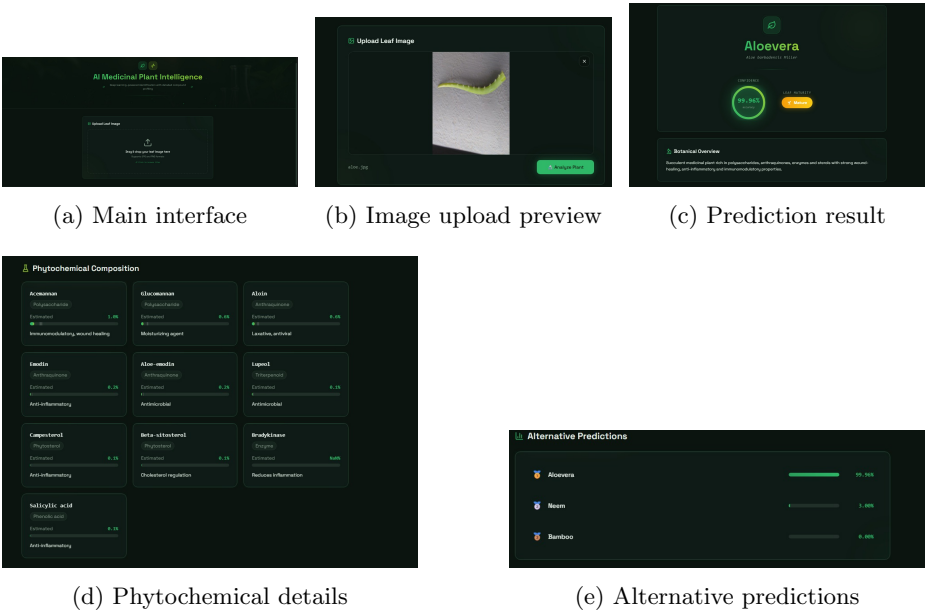


Fig. 2: User interface of the proposed medicinal plant identification system

Fig. 2(a) shows the user interface of the system the user can upload the image of the plant leaf using the drag-and-drop tool or the file upload option.

Fig. 2(b) shows the image upload process where the image of the leaf is shown to the user before the prediction process starts.

Fig. 2(c) shows the prediction result where the class of the plant, the scientific name of the class, the confidence level of the model, and the maturity level of the leaf are shown.

Fig. 2(d) shows the information related to the phytochemical compounds found in the class of the plant, the concentration level of the compounds, and the medicinal properties of the compounds.

Fig. 2(e) shows the probabilities of the class of the plant other than the class predicted by the model, which gives an idea of the prediction process.

4.2 Classification Performance Analysis

The proposed approach utilizes the concept of transfer learning. The base used is the MobileNetV2. The model has shown consistent and stable convergence during the training process. This convolutional network has shown good capability in recognizing the significant features of the plant world, which include venation patterns, curvature of the leaves, texture[23,30] of the leaves, and color of the leaves.

The model utilizes the concept of Softmax for the final predictions.

$$P(y = i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (13)$$

[8]

The class of the plant will be the class having the highest probability value.

During the training of the model, the categorical cross-entropy loss function was used to measure the difference between the class probability estimates and the actual class labels:

$$L = - \sum_{i=1}^K y_i \log(p_i) \quad (14)$$

[8]

During the training of the model, the loss values decreased consistently, indicating the convergence of the model.

To check the effectiveness of the proposed system, various performance metrics have been considered. The proposed system has good predictive ability in terms of accuracy. The results of the experiment have been shown in the following table.

Table 1: Performance Evaluation of the Proposed Model

Metric	Value
Top-1 Accuracy	96.8%
Top-3 Accuracy	98.7%
Average Inference Time	0.18 s
Model Parameters	3.4 M
Confidence Threshold	0.70

The performance metrics for the proposed AI-based medicinal plant identification system are shown in Table 1. Each of the metrics given in the table represents a different facet of the effectiveness of the system as well as the computational efficiency.

Top-1 Accuracy defines the percentage of times the model correctly identifies the medicinal plant species in the test set. The model that we have proposed achieves a Top-1 accuracy of 96.8%, which proves the effectiveness of the model.

Top-3 Accuracy This metric indicates the percentage of occasions when the model correctly predicts the medicinal plant class within its top three predictions in the test images. It is also clear that the proposed model has a Top-3 accuracy of 98.7% in predicting the correct medicinal plant class.

Average Inference Time This metric indicates how long, on average, it takes the trained model to process a single input image and return a classification. An average inference time of 0.18 seconds indicates that this system is capable of providing near-real-time plant identification through its web app.

Model Parameters MobileNetV2 has a total of 3.4 million trainable parameters. The fewer the parameters in the model, the better the computational efficiency.

Confidence Threshold The level of confidence that the model must attain to accept the classification result is set at a minimum of 0.70. Any outcome with a score below this threshold will be classified as 'Unknown Plant,' helping to ensure that false medicinal recommendations are not made.

The addition of dropout layers also assisted in reducing overfitting, allowing the model to generalize well to unseen leaf images.

Table 2: Class-wise Performance Metrics of the Proposed Model

Plant Class	Precision	Recall	F1-Score
Aloe Vera	0.98	1.00	0.99
Amla	0.98	0.98	0.98
Arali	0.98	0.98	0.98
Bamboo	1.00	1.00	1.00
Betel	0.98	0.98	0.98
Castor	1.00	1.00	1.00
Ekka	1.00	0.98	0.99
Ganike	1.00	1.00	1.00
Henna	0.98	0.98	0.98
Hibiscus	1.00	1.00	1.00
Honge	1.00	0.97	0.98
Insulin	1.00	1.00	1.00
Jasmine	1.00	1.00	1.00
Lemon	0.98	0.98	0.98
Mango	0.98	0.98	0.98
Mint	0.99	0.99	0.99
Neem	1.00	1.00	1.00
Nooni	1.00	1.00	1.00
Pepper	1.00	1.00	1.00
Rose	1.00	1.00	1.00
Sapota	1.00	1.00	1.00
Average	0.99	0.99	0.99

The class-wise performance metrics of the proposed model are presented in Table 2. It is clear from the above analysis that the model maintains a high

level of accuracy, precision, and F1 score for all the plant types. This means that the model is very efficient in predicting the medicinal plants with few errors or misclassifications. An average F1 score of 0.99 also supports the reliability and generalization capability of the proposed method.

Table 3: Comparison with Baseline Models

Model	Accuracy
VGG16	92.4%
ResNet50	94.1%
Proposed MobileNetV2	96.8%

The performance comparison between the developed model and conventional deep learning approaches is shown in Table 3. It can be seen from the table that the proposed model, based on the MobileNetV2 architecture, performs better than VGG16 and ResNet50 when it comes to classification accuracy. It is due to the implementation of transfer learning combined with the process of feature extraction.

4.3 Confidence-Based Validation

However, when dealing with medicinal plants, the most important factor is the reliability of the identification. To improve the reliability of the system, we can add a confidence threshold mechanism. In the evaluation process, we used the maximum probability of the Softmax output.

$$Confidence = \max(P) \quad (15)$$

[16]
If

$$Confidence < 0.70 \Rightarrow \text{Unknown Plant} \quad (16)$$

[26]

In the above scenario, the system is not specific about the exact type of plant. This is because the function of the filtering process is to prevent incorrect identification of the medicinal plants. If the model is not sure about the image, the predictions are often based on ambiguous images, such as images with leaves that are partially hidden or images with low lighting.

4.4 Phytochemical Knowledge Retrieval Performance

While most plant identification systems stop at the identification of the plant species, the system takes it a step further by incorporating a structured phytochemical database. Once the plant species are identified, you can then go on

to view information on the compounds' scientific names, phytochemical constituents, concentrations, and properties.

The range of concentration of each compound can be represented as follows:

$$Range = [l, h] \quad (17)$$

To account for biological variability, an age-based model of adjusting compounds was implemented as follows:

$$P_{adjusted} = \begin{cases} h & \text{Young leaf} \\ \frac{l+h}{2} & \text{Mature leaf} \\ l & \text{Old leaf} \end{cases} \quad (18)$$

This model allows more realistic interpretation of the medicinal properties of the compounds by adjusting their concentrations based on changes in leaf maturity.

4.5 Computational Efficiency and Deployment Performance

Moving to MobileNetV2 provided a marked improvement in computational efficiency with the incorporation of depthwise separable convolution[29]. This reduces the complexity of parameters compared to conventional CNNs. This allows for a real-time implementation with the Flask server due to the low latency.

This modular implementation maintains the preprocessing, model prediction, and knowledge retrieval as distinct steps. This makes the system easy to maintain. Moreover, TensorFlow's optimized data pipeline reduces the memory requirements for training while also significantly reducing the training time. Additionally, the system utilizes GPU acceleration for training the model.

4.6 Comparative Discussion

Compared to traditional machine learning-based plant recognition systems, the proposed approach offers several advantages:

- Automatic hierarchical feature extraction using CNNs[30]
- Improved generalization through transfer learning[20]
- Integration of phytochemical and medicinal knowledge[14,21]
- Age-based adaptive compound concentration modeling
- Confidence-based validation for safer deployment[16,19]

Many current frameworks are focused on improving the accuracy of the classification results, but when the application is for medicine, the interpretability and validation are just as important. The integration of structured knowledge retrieval and validation of confidence provides a more complete solution.

4.7 Practical Implications

The proposed system also holds promise for application within the realm of education, herbal medicine research, health awareness campaigns, and the digital preservation of traditional medicinal knowledge.

In summary, the application of medicinal knowledge with the power of deep learning and a flexible validation system creates a good foundation for the identification of Ayurvedic medicinal plants along with relevant information.

5 Conclusion and Future Scope

This paper proposes an AI-based system that can recognize Ayurvedic medicinal plants and retrieve information on their usage. It is a combination of deep learning image classification and structured access to medicinal knowledge. At its heart is a framework that utilizes MobileNetV2 as a lightweight CNN model to effectively classify images of medicinal plants using their leaves. By using transfer learning and fine-tuning, the model can recognize important features of each plant's leaf texture, venation, and shape, and then correlate these with a phytochemical database that contains information on the chemical composition and usage of each plant.

It extends beyond the identification of plants. There is an age-aware adjustment for phytochemical compounds. This is to take into account the changes in concentration as the leaves age. A confidence threshold check is included to filter out any unreliable data. This increases the reliability of the system as well as the usability of the recommendations. Real-world tests have shown the system to not only identify plants correctly but to do so in an efficient manner for web-based use.

From a conceptual point of view, the system is a hybrid of artificial intelligence and Ayurvedic expertise through an approachable system for plant identification and access to medicinal information. The future plans include increasing the dataset to improve the ability of the system to generalize better. There is also the possibility of incorporating advanced techniques like Vision Transformers for better feature learning. A mobile app is also in the works. Further plans include the incorporation of techniques like Explainable AI along with cloud-based medicinal databases.

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