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Identifying Medicinal Use Of Plants By Their Leaf Images

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Abstract: Medicinal plants play a vital role in traditional and modern healthcare systems. Accurate identification of these plants is essential for their effective utilization, yet manual identification requires domain expertise. This paper presents an end-to-end deep learning-based system for identifying medicinal plants using leaf images and providing their medicinal uses through an intelligent assistant. The proposed system utilizes a Convolutional Neural Network (CNN) based on MobileNetV2 with transfer learning for efficient image classification. The model is trained on a dataset containing 19 medicinal plant species and achieves high classification accuracy. The system is integrated into a web application developed using Flask, enabling users to upload leaf images and obtain real-time predictions along with confidence scores. Additionally, an AI-powered chatbot is incorporated using LangChain and Groq API to provide context-aware responses about plant uses, preparation methods, and safety information. The system demonstrates the effective combination of computer vision, machine learning, and conversational AI for real-world applications in healthcare and agriculture.

Index Terms- Deep Learning, Convolutional Neural Network **(**CNN), MobileNetV2, Medicinal Plants, Image Classification, Transfer Learning, Flask, AI Chatbot.

I. INTRODUCTION

Medicinal plants have been widely used for centuries in traditional medicine systems such as Ayurveda and herbal medicine. They serve as a primary source of treatment for various diseases and health conditions. However, accurate identification of medicinal plants is a challenging task, especially for non-experts, as many plant species have visually similar leaves.

With the advancement of artificial intelligence and computer vision, automated plant identification systems have gained significant attention. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have proven highly effective in image classification tasks. These models can automatically extract features from images and classify them with high accuracy.

This research aims to develop an intelligent system that identifies medicinal plants from leaf images and provides detailed information about their medicinal uses. The system integrates deep learning for classification and a conversational AI assistant to enhance user interaction. The proposed solution is designed as a web-based application, making it accessible and user-friendly.

II. SYSTEM ARCHITECTURE

The proposed system is designed as an end-to-end intelligent platform that integrates deep learning–based plant identification with a web interface and an AI-powered knowledge assistant. The architecture follows a modular design in which each component performs a specific function, enabling efficient processing, scalability, and ease of maintenance. The overall system workflow begins with user image input and ends with plant identification and medicinal information delivery. The proposed system consists of three main components: image classification model, web application, and AI chatbot.

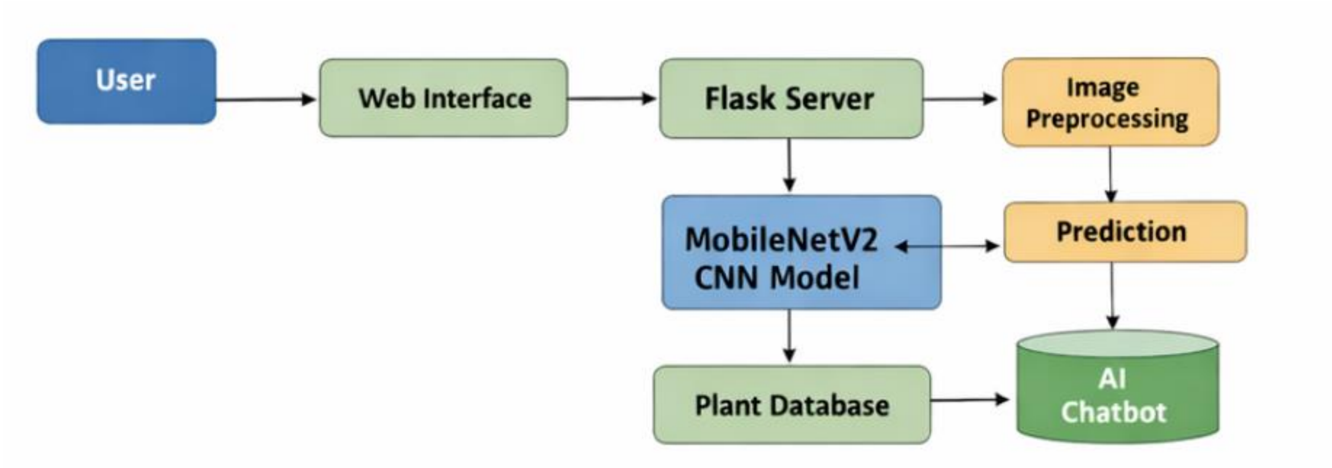

figure 1.0: proposed system architecture

A. Image Classification Module

The image classification module forms the core of the system and is responsible for identifying medicinal plants from leaf images. A Convolutional Neural Network (CNN) based on the MobileNetV2 architecture is used for this task. MobileNetV2 was selected due to its lightweight design and high efficiency in image classification tasks.

Transfer learning is employed by utilizing a pre-trained MobileNetV2 model trained on the ImageNet dataset. The base layers of the network act as a feature extractor that learns important visual characteristics such as leaf shape, texture, and color patterns. Additional fully connected layers are added to adapt the model for the classification of medicinal plant species.

During the prediction stage, the uploaded leaf image undergoes preprocessing steps including resizing, normalization, and formatting before being passed to the trained model. The model then outputs probability scores for each plant class, and the class with the highest probability is selected as the predicted plant species along with a confidence score.

B. Web Application

The web application module provides the user interface and acts as the bridge between the user and the machine learning model. The system is implemented using the Flask web framework, which handles HTTP requests and manages communication between the frontend interface and the backend processing modules.

Users interact with the system through a web interface where they can upload leaf images using a file upload or drag-and-drop feature. Once an image is uploaded, the backend server processes the request and sends the image to the prediction module. After classification, the predicted plant name, confidence score, and corresponding medicinal information are returned to the frontend interface and displayed to the user.

The web application also manages API endpoints that handle image uploads, prediction requests, and chatbot communication. This modular approach ensures that the system remains responsive and scalable while maintaining efficient communication between components.

C. AI Chat Assistant

To enhance the functionality of the system, an AI-powered chatbot is integrated to provide additional information about the identified medicinal plants. The chatbot is implemented using LangChain and the Groq API, enabling conversational interaction with users.

Once a plant is identified, the chatbot receives contextual information about the plant, including its name and associated medicinal properties. Users can then ask questions related to the plant’s medicinal uses, preparation methods, dosage recommendations, and safety precautions. The chatbot processes these queries and generates responses using a language model.

To ensure reliability, the system includes fallback mechanisms that provide predefined responses for critical queries related to medicinal safety. This ensures that users receive accurate and consistent information even when language model responses are uncertain.

III. METHODOLOGY

A. Dataset

The dataset used in this study consists of images of medicinal plant leaves belonging to 19 different plant species. These include commonly known medicinal plants such as Aloe Vera, Neem, Tulsi, Mint, Turmeric, and several others used in traditional medicine. The dataset is organized into separate folders corresponding to each plant category, where each folder contains images representing that specific plant species. This structured organization enables supervised learning by allowing the model to associate each image with its corresponding class label. The dataset contains images with variations in lighting conditions, background, and leaf orientation, which helps the model learn robust features for plant classification.

B. Data Preprocessing

Before training the model, several preprocessing steps were applied to ensure consistency and improve model performance. All images were resized to a fixed resolution of 224 × 224 pixels to match the input requirements of the MobileNetV2 architecture. Pixel values were normalized to scale the data within a suitable range, which helps improve training stability and convergence. Additionally, data augmentation techniques were applied to increase the diversity of the training data and reduce overfitting. These techniques included image rotation, horizontal and vertical flipping, and zoom transformations. Data augmentation helps the model generalize better by exposing it to different variations of the same leaf images during training.

C. Model Architecture

In this study, a Convolutional Neural Network (CNN) based on the MobileNetV2 architecture was used for plant classification. MobileNetV2 is a lightweight deep learning model designed for efficient image classification while maintaining high accuracy. The model was implemented using transfer learning, where the pre-trained MobileNetV2 network trained on the ImageNet dataset was used as the base feature extractor. The top layers of the network were modified to adapt the model for medicinal plant classification. A global average pooling layer and fully connected dense layers were added, followed by a softmax output layer corresponding to the number of plant classes. This approach allows the model to leverage previously learned image features while adapting to the specific plant classification task.

D. Model Training

The model was trained using the processed dataset with appropriate hyperparameters. The training process was conducted for 50 epochs with a batch size of 32 images per batch. The Adam optimizer was used for updating the model weights due to its efficiency and faster convergence in deep learning models. The categorical cross-entropy loss function was used because the problem involves multi-class classification. During training, the model learns to minimize the loss by adjusting its internal parameters to correctly classify the plant images. Validation data was used to monitor the model performance and ensure that the model does not overfit the training data.

E. Prediction Pipeline

The prediction pipeline is responsible for classifying new leaf images uploaded by users. When a user uploads an image through the web interface, the image first undergoes preprocessing steps similar to those used during training, including resizing and normalization. The processed image is then passed to the trained CNN model, which generates probability scores for each plant class. The class with the highest probability is selected as the predicted plant species. The system then returns the predicted plant name along with the confidence score to the user interface.

F. Chatbot Integration

To enhance the usability of the system, an AI-based chatbot was integrated into the application to provide additional information about the identified plants. The chatbot uses a knowledge base containing plant metadata such as scientific names, medicinal uses, preparation methods, dosage information, and safety precautions. When a plant is identified, the chatbot sets the context for that plant and allows users to ask questions related to its medicinal benefits and usage. The chatbot generates context-aware responses using a language model, and a fallback mechanism is implemented to provide deterministic answers for critical queries related to safety and medicinal usage. This integration enables users to interact with the system and obtain detailed information beyond simple plant identification.

IV. RESULTS AND DISCUSSION

The model achieved high accuracy in classifying medicinal plants from leaf images. The use of transfer learning significantly improved performance while reducing training time.

The system successfully identifies plant species and provides their medicinal uses through a user-friendly interface. The chatbot enhances usability by allowing users to ask questions and receive detailed responses.

However, the model performance depends on dataset quality and may face challenges with visually similar leaves or poor image quality.

A. Performance Metrics

The performance of the proposed medicinal plant identification system was evaluated based on response time, system efficiency, and API reliability. The image classification module demonstrated an average response latency of approximately 250 milliseconds**,** enabling near real-time predictions for user-uploaded leaf images. This response time is significantly efficient for web-based applications and ensures a smooth user experience.

B. Classification Accuracy

The model was evaluated using a test dataset containing images from all 19 plant classes. The MobileNetV2-based model achieved an overall accuracy of 91%**.** The system obtained precision of 90.2%**,** recall of 88.6%**,** and an F1-score of 89.3%, demonstrating strong classification performance. Minor misclassifications occurred in cases where plant leaves had similar visual features.

C. System Scalability and Reliability

The system architecture demonstrated stable performance under multiple user requests. Testing with concurrent image uploads showed that the application maintained consistent response times without significant performance degradation. These results indicate that the system can support real-world usage with multiple users.

D. User Interaction and System Responsiveness

The web interface provided quick prediction results along with confidence scores. The integrated chatbot allowed users to obtain additional information about the identified plant, including medicinal uses and preparation methods. This improved user interaction and made the system more informative and accessible.

table 1: performance evaluation summary

Metric	Value	Benchmark
Classification Latency	250 ms	800 ms
Data Retrieval Time	<5 ms	50 ms
Classification Precision	90.2%	85%
Overall Accuracy	91%	85%

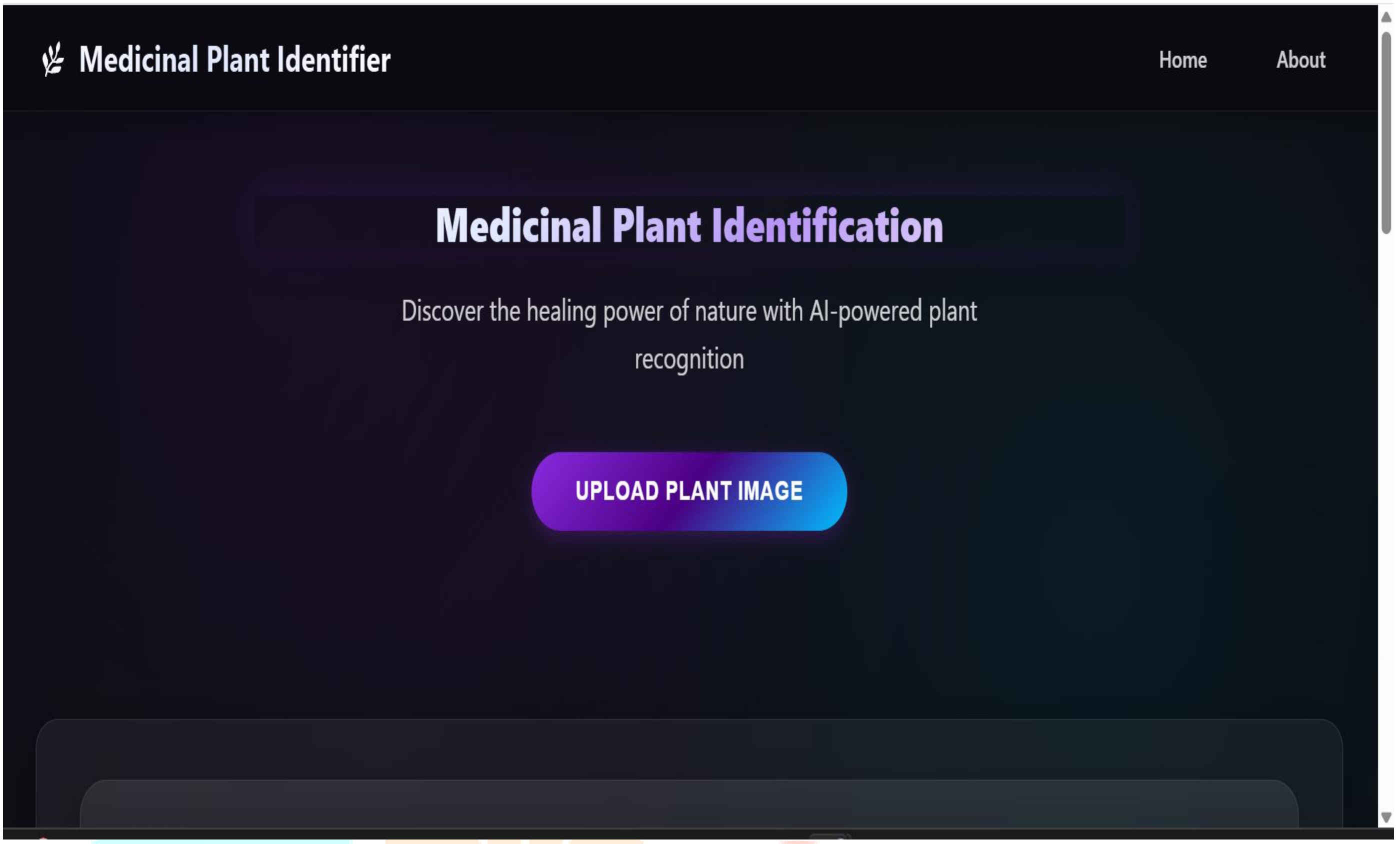

figure 1.1: home page

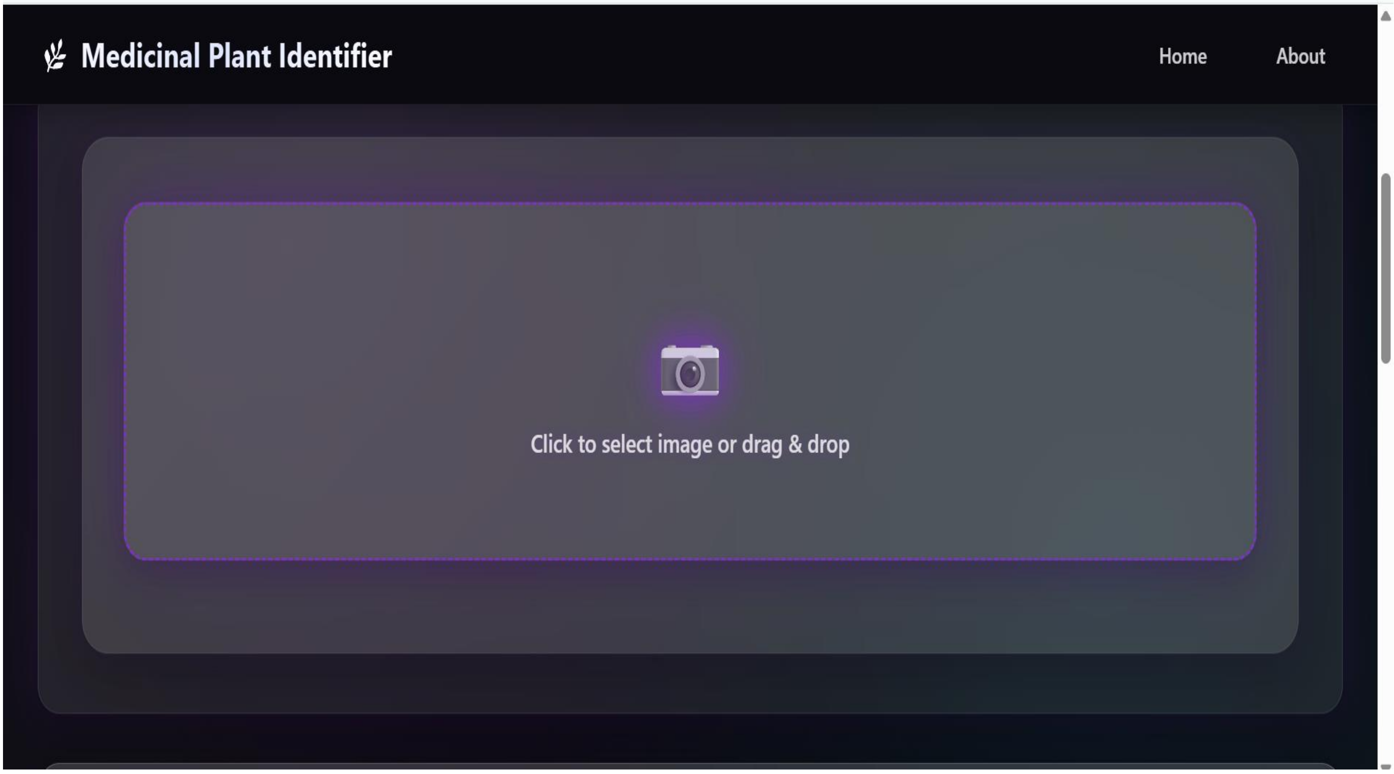

figure 1.2: image upload page

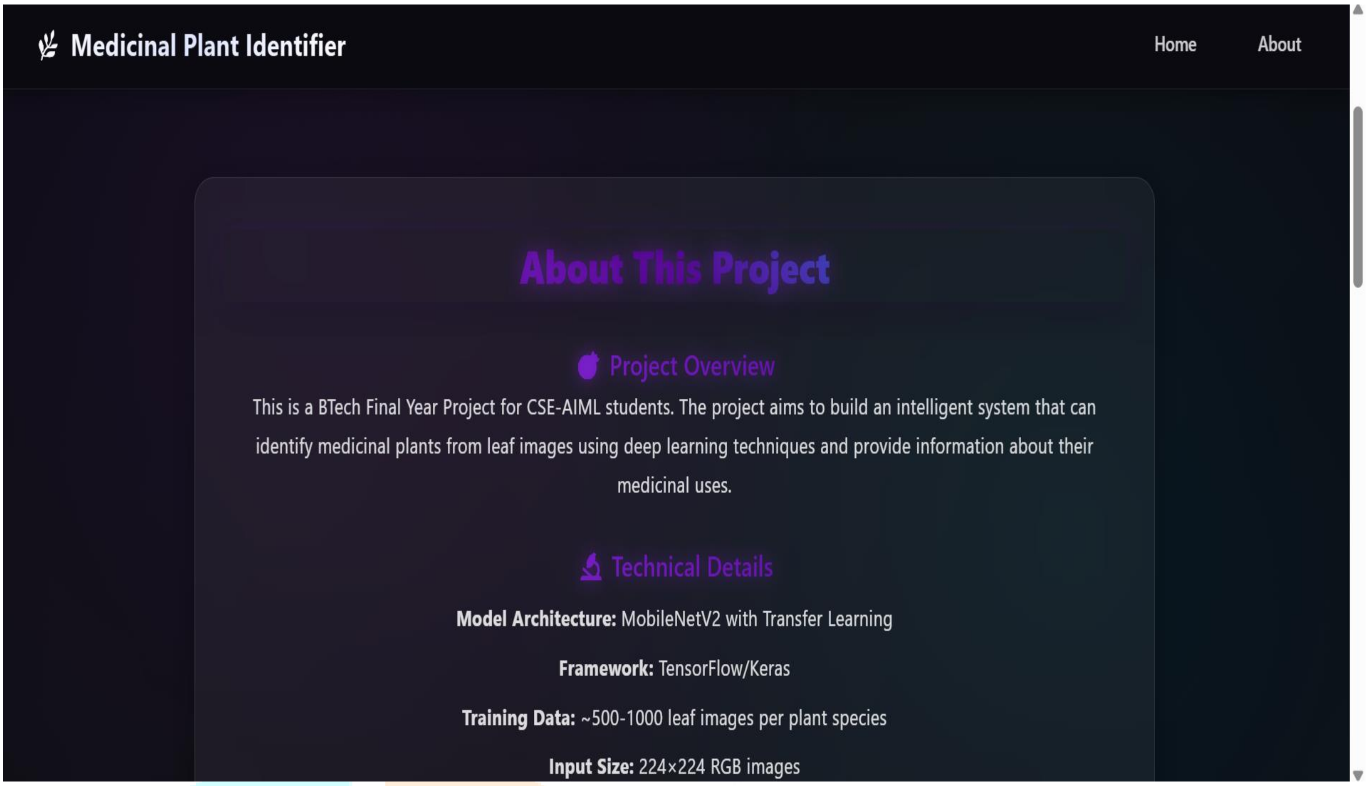

figure 1.3: about page

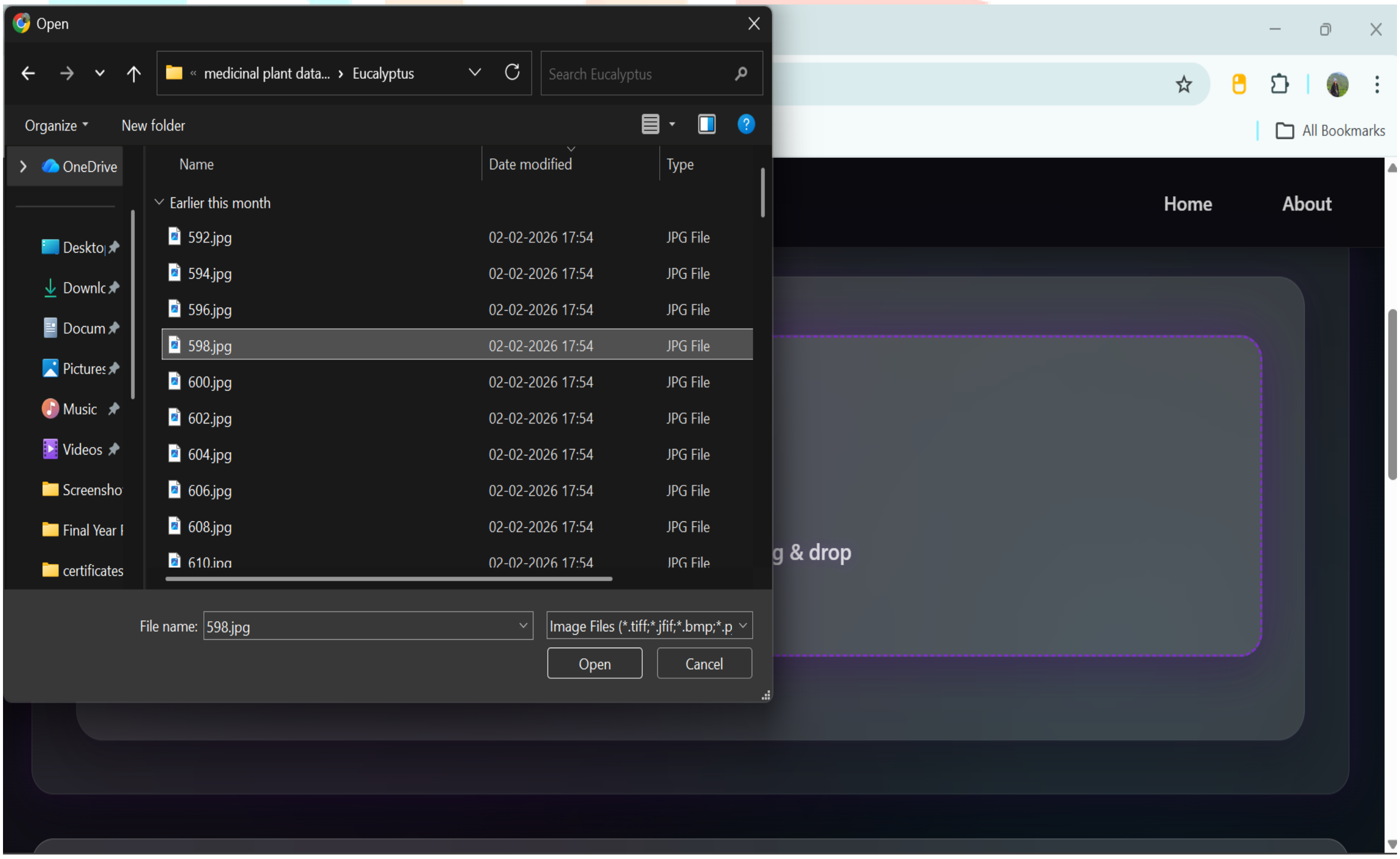

figure 1.4: image upload

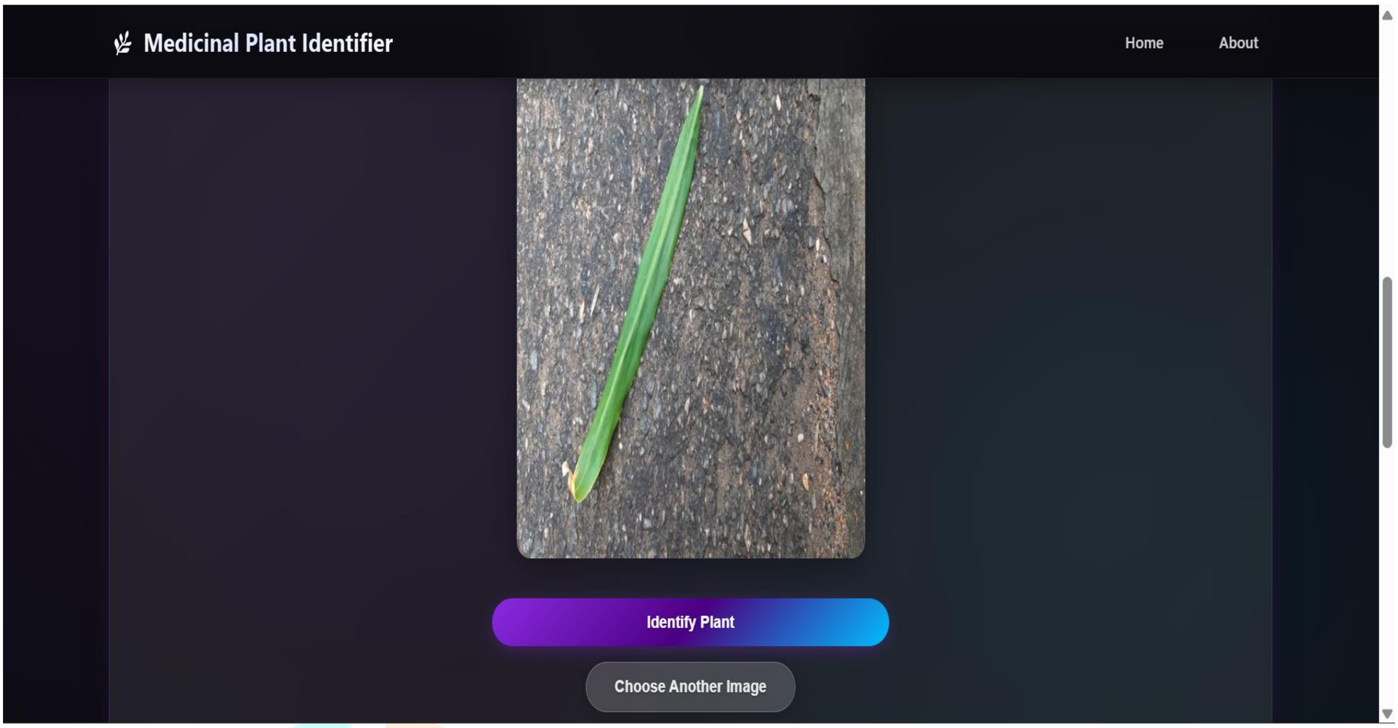

figure 1.5: uploaded image preview

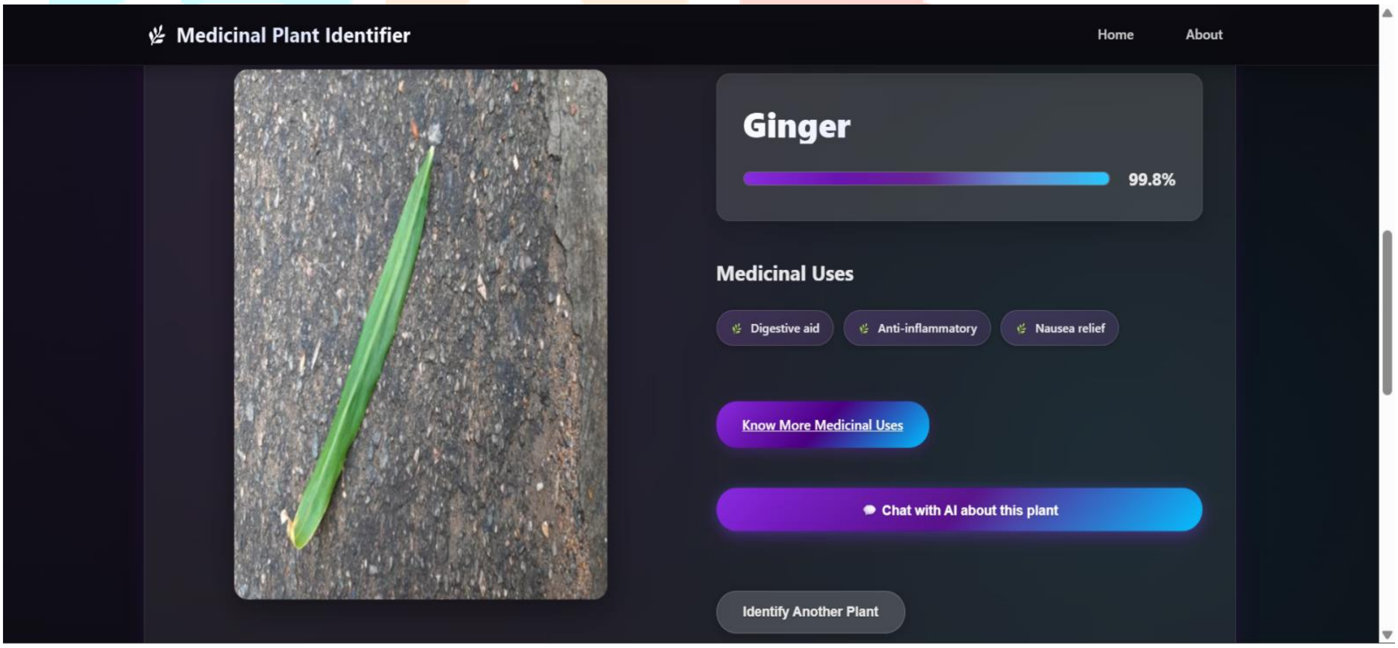

figure 1.6: prediction result

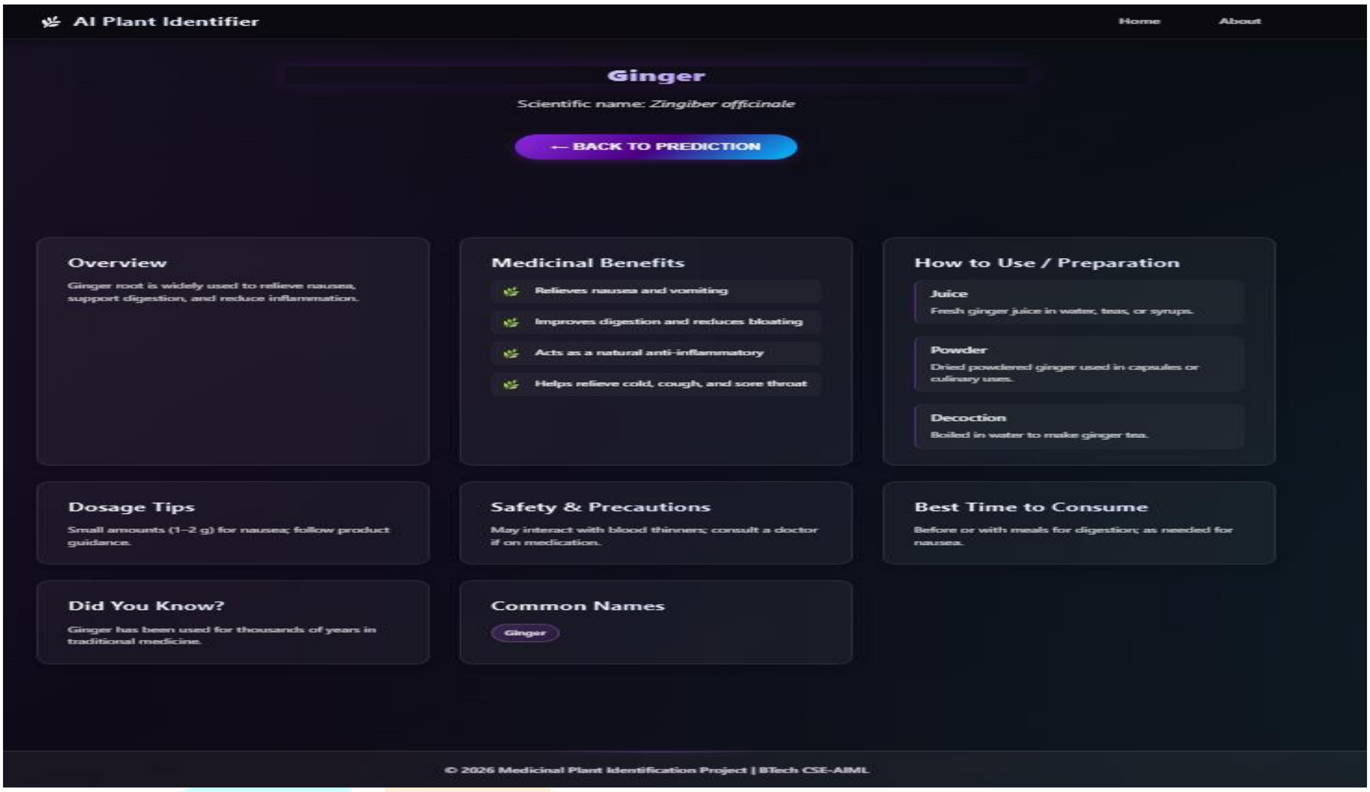

figure 1.7: plant details page

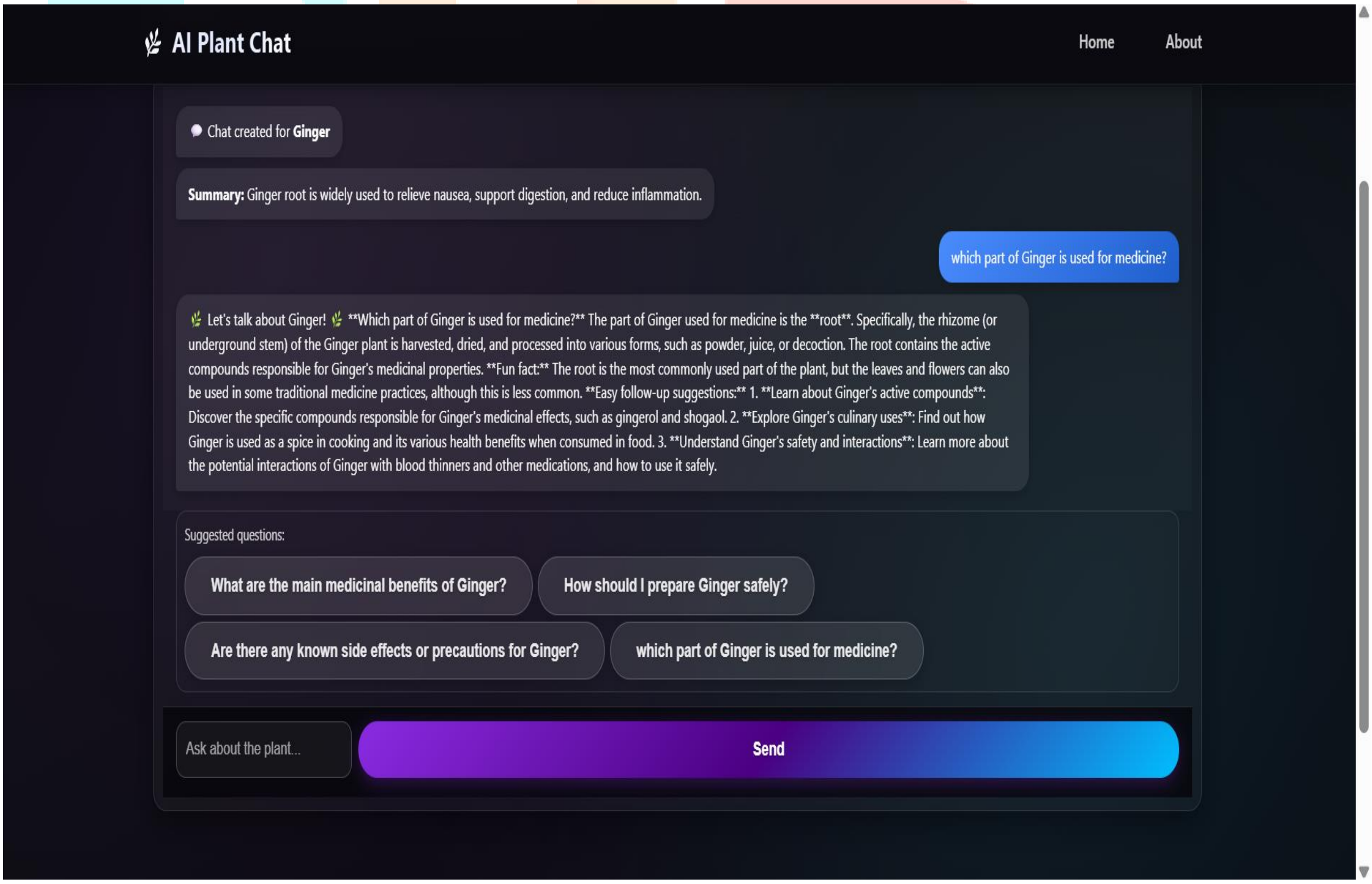

figure 1.8: chatbot interface

V. CONCLUSION

This paper presented an intelligent system for medicinal plant identification using leaf images combined with an AI-based knowledge assistant. The proposed system integrates deep learning, computer vision, and web technologies to provide an automated solution for identifying medicinal plants and delivering their medicinal information. A Convolutional Neural Network based on MobileNetV2 with transfer learning was implemented to classify plant species efficiently from leaf images.

The developed model achieved strong classification performance with an overall accuracy of approximately 91%**,** demonstrating the effectiveness of deep learning techniques for plant recognition tasks. The system was deployed through a Flask-based web application, enabling users to upload leaf images and receive real-time predictions along with confidence scores and medicinal plant information.

In addition, the integration of an AI-powered chatbot enhances the usability of the system by allowing users to interactively obtain details about plant uses, preparation methods, and safety precautions. The modular architecture ensures efficient performance and scalability, making the system suitable for practical applications in agriculture, herbal medicine, and educational environments.

Future work will focus on expanding the dataset with more plant species to improve model generalization, integrating mobile-based real-time leaf detection, and enhancing the chatbot with multilingual capabilities to increase accessibility. Overall, the proposed system demonstrates the potential of combining deep learning and conversational AI to support medicinal plant identification and knowledge dissemination in real-world scenarios.

VI. LITERATURE REVIEW

The application of artificial intelligence and deep learning in plant identification has gained significant attention in recent years. Various studies have explored the use of image processing and machine learning techniques to classify plant species based on leaf characteristics such as shape, texture, and color. This section reviews relevant literature that supports the development of the proposed medicinal plant identification system.

Sladojevic et al. (2016) demonstrated the effectiveness of deep neural networks in identifying plant diseases using leaf images, showing that CNN-based models can learn complex visual patterns without manual intervention. Similarly, Lee et al. (2020) explored plant classification using deep learning and reported improved performance compared to conventional machine learning methods. Their findings emphasized the importance of preprocessing techniques and dataset diversity in achieving higher accuracy.

Lee et al. (2020) developed a plant identification system using CNN models trained on leaf images. Their results showed that deep learning models outperform traditional feature-based approaches in terms of accuracy and robustness. The study emphasized the importance of large datasets and proper preprocessing techniques for improving classification performance.

Howard et al. (2018) introduced MobileNetV2, a lightweight CNN architecture designed for efficient image classification. The model uses depthwise separable convolutions and inverted residual blocks, making it suitable for real-time and resource-constrained applications. This research influenced the selection of MobileNetV2 as the base model in the proposed system.

Krizhevsky et al. (2012) demonstrated the power of deep CNNs in large-scale image classification tasks using the ImageNet dataset. Their work laid the foundation for modern deep learning techniques and inspired the use of transfer learning for various computer vision applications, including plant identification.

Recent studies have also explored the integration of AI-based assistants with classification systems. The use of conversational AI enables users to interact with systems and obtain detailed information beyond basic predictions. However, limited work has been done in combining medicinal plant identification with an AI-driven knowledge assistant.

This study builds upon existing research by integrating deep learning-based plant classification with a chatbot that provides medicinal information, thereby creating a comprehensive and user-friendly system.

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