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Identification of medicinal plants using Deep Learning Techniques

Singam Navya Sri[1], Akula Chandradeep[2], Ganji Venkata Murali Krishna[3], Gudivada.Syalini Naga Chandra[4], Ms Dudiki Sirisha[5]

[1, 2, 3, 4, 5] *Department of CSE (AI&ML), SRK Institute of Technology, Vijayawada, A.P., India*

Abstract - The identification of medicinal plants plays a critical role in various fields, including pharmaceuticals, traditional medicine, and biodiversity conservation. However, traditional methods of identifying these plants can be time-consuming, labor-intensive, and require expert knowledge. This project aims to leverage deep learning techniques to automate the identification of medicinal plants, thus providing an efficient and accurate solution. The study employs Convolutional Neural Networks (CNN), MobileNet, and a hybrid model combining MobileNet with Recurrent Neural Networks (RNN) to classify and identify different medicinal plants. The models are trained and validated using a comprehensive dataset of medicinal plant images, ensuring robust performance. This approach not only enhances identification accuracy but also reduces the dependency on expert botanists, making it accessible to a broader audience. ***Keywords: Medical plants, Deep learning, Convolutional Neural Networks (CNN) MobileNet Recurrent Neural Networks (RNN), Plant Identification, Image Classification.***

INTRODUCTION

This project aims to develop a deep learning-based system for identifying medicinal plants using Convolutional Neural Networks (CNNs), with a focus on MobileNet and a hybrid MobileNet-Recurrent Neural Network (RNN) model. The system classifies plant images into specific categories and provides valuable information regarding the medicinal properties of the plants. By automating the plant recognition process, it improves the accuracy and efficiency compared to traditional methods that are dependent on expert knowledge. Flask is used for web deployment, making the system easily accessible to users. Additionally, the system incorporates features like real-time identification and plant information retrieval. Future versions may include mobile app support for broader accessibility. The project leverages deep learning techniques, particularly CNNs, for efficient plant classification. MobileNet is used for its lightweight architecture and high classification accuracy, while the hybrid MobileNet-RNN model enhances the system's ability to recognize sequential patterns in plant images. The system allows users to upload images of plants, which are then classified, and detailed information on their medicinal benefits is provided. The backend uses Python libraries such as TensorFlow and OpenCV for image processing and model training. The project is implemented as a Flask-based web application, ensuring a user-friendly interface. In the future, the project may include additional plant species and datasets for further enhancement. The primary purpose of this project is to automate the identification of medicinal plants, reducing the time and effort associated with traditional, expert-driven classification methods. By using deep learning, the system offers faster, more reliable results, making it accessible to researchers, herbalists, students, and healthcare professionals. The AI powered classification system recognizes plants based on their visual patterns, eliminating the need for specialized knowledge. Additionally, the system helps promote awareness of medicinal plants and their potential health benefits. Future plans include adding multilingual support and the integration of mobile app functionality, allowing real-time plant identification. This project covers the automated classification of medicinal plants using deep learning models such as CNNs and RNNs. It processes plant images and classifies them into categories based on a comprehensive dataset of medicinal species. The system, deployed as a web application using Flask, is designed to be user-friendly and accessible to a wide range of users, including researchers, herbalists, and students. The project also provides detailed information on the medicinal uses of plants, contributing to the growing field of AI in botany and healthcare. Data preprocessing techniques improve the quality of images used for model training. MobileNet, chosen for its lightweight nature, ensures efficient classification. The project has the potential to be expanded with additional plant species, datasets, and future integration of mobile applications, voice input, and other features to further improve accessibility and functionality.

LITERATURE SURVEY

[1]This research explores the potential of convolutional neural networks (CNNs) in classifying plant species. The authors trained a CNN model on a dataset containing over 10,000 images of different plant species. The model demonstrated an impressive accuracy of 92%, significantly outperforming traditional machine learning methods such as SVM and random forests. The study also experimented with different CNN architectures, including VGG16 and ResNet, to determine the most effective model. Results showed that deeper networks improved accuracy but required more computational power. The research emphasizes the role of data augmentation in enhancing model generalization. The study concludes that CNNs are highly effective for plant identification but require large labeled datasets. Future improvements suggest using transfer learning to reduce training time. The authors also highlight the challenge of classifying plants with similar leaf structures. Another key finding is that lighting and background variations can significantly affect model performance. The study suggests developing a robust dataset with diverse lighting conditions. The researchers propose integrating CNNs with additional feature extraction techniques to improve accuracy further. They also mention that real-time classification can be achieved by optimizing the model for mobile deployment.

[2]This study focuses on developing a lightweight deep learning model for mobile-based herbal plant identification. The authors implemented MobileNet, a computationally efficient CNN architecture designed for mobile devices. The model was trained on a dataset of 5,000 herbal plant images and achieved an accuracy of 90%. One of the key advantages of MobileNet is its reduced number of parameters, making it suitable for deployment on low power devices. The study compares MobileNet with ResNet and VGG16, finding that MobileNet provides a balance between accuracy and efficiency. The authors highlight the potential applications of this system in traditional medicine, where quick and accurate plant identification is crucial. The study also discusses real-time implementation using TensorFlow Lite. A mobile application prototype was developed to classify plants instantly using a smartphone camera. The application performed well in controlled environments but faced challenges with varying lighting conditions. To address this, the researchers implemented data augmentation techniques. Future research aims to enhance the model's performance by incorporating a larger dataset. The study suggests integrating the system with an online medicinal plant database for additional user information.

[3]This research proposes a hybrid deep learning model combining CNN and RNN for medicinal plant identification. The CNN extracts spatial features from plant images, while the RNN captures sequential dependencies to improve classification. The dataset includes 15,000 images, and the hybrid model achieves a high accuracy of 94%. The study finds that integrating RNN enhances the model's ability to recognize subtle variations in plant structure. The authors compare the hybrid model with standalone CNNs and find significant improvements in accuracy and robustness. The study also explores different RNN architectures, including LSTMs and GRUs, to optimize performance. One challenge identified is the increased computational complexity of the hybrid model. To address this, researchers suggest using dimensionality reduction techniques. The study highlights the importance of high quality datasets with diverse plant species. The authors propose using domain adaptation techniques to improve model generalization. Another recommendation is to deploy the model as a cloud-based service to reduce hardware limitations. Future research aims to integrate this system with augmented reality (AR) applications for interactive plant identification. The study concludes that hybrid deep learning models provide significant advantages over traditional approaches.

[4]This study systematically compares various deep learning models for medicinal plant classification. The authors evaluate CNN architectures such as ResNet, VGG16, and MobileNet on a dataset containing 20,000 plant images. MobileNet achieves the highest

efficiency with 91.5% accuracy while maintaining low computational requirements. ResNet provides slightly higher accuracy but demands more processing power. The study highlights the trade-off between model complexity and real-time application feasibility. One key finding is that lightweight architectures are more suitable for mobile and embedded systems. The researchers also investigate the impact of transfer learning, finding that pre-trained models significantly improve performance. The study experiments with different hyperparameter tuning techniques to optimize accuracy. The results suggest that batch normalization and dropout layers enhance model robustness. The authors emphasize the importance of dataset diversity to improve generalization. Another key takeaway is that combining multiple deep learning models through ensemble learning can further enhance classification accuracy. The study suggests that future research should explore self-supervised learning techniques. Researchers also propose integrating explainable AI techniques to provide users with interpretability in plant classification results.

[5]This survey paper discusses the challenges and future directions in image-based plant identification. The study identifies major challenges, including dataset quality, environmental variations, and model interpretability. One issue highlighted is that most plant datasets contain limited species diversity. The study suggests using synthetic data generation to enhance dataset robustness. Another challenge is dealing with lighting and background variations that affect classification accuracy. The authors propose advanced data augmentation techniques to overcome this limitation. The study also discusses the impact of model generalization across different plant species. The researchers experiment with domain adaptation techniques to improve cross-species identification. The paper highlights the potential of self supervised learning for reducing reliance on labeled data. One of the key findings is that incorporating multimodal data, such as leaf texture and plant odor, could enhance classification. The study also explores the use of attention mechanisms to improve feature extraction. The authors propose the development of a global medicinal plant database for deep learning training. The research concludes that integrating AI with traditional botanical knowledge can improve plant identification accuracy.

EXISTING SYSTEM

The existing system leverages deep learning techniques to detect and classify medicinal plants. It integrates models like Convolutional Neural Networks (CNNs), MobileNet, and basic Neural Networks (NNs) to optimize classification efficiency and accuracy. CNNs are widely used for feature extraction from plant images. They capture spatial hierarchies such as leaf shape, texture, color patterns, and vein structures. MobileNet is a lightweight deep learning model optimized for computational efficiency. It reduces the number of parameters while maintaining high accuracy in plant image classification. Basic neural networks are sometimes integrated for classification tasks, where the extracted features from CNNs or MobileNet are passed to fully connected layers to predict the plant species. Disadvantages: Many existing systems rely on pre-trained models like MobileNet, which are trained on generic datasets (e.g., ImageNet). These models may not effectively capture unique features specific to medicinal plants, leading to reduced accuracy. Plants with similar leaf shapes, colors, and textures can be easily misclassified, especially when the model encounters unseen species or plants under varying environmental conditions (lighting, background, etc.). Although CNNs automate feature extraction, some systems still require manual preprocessing or feature engineering, adding to the complexity.

PROPOSED SYSTEM

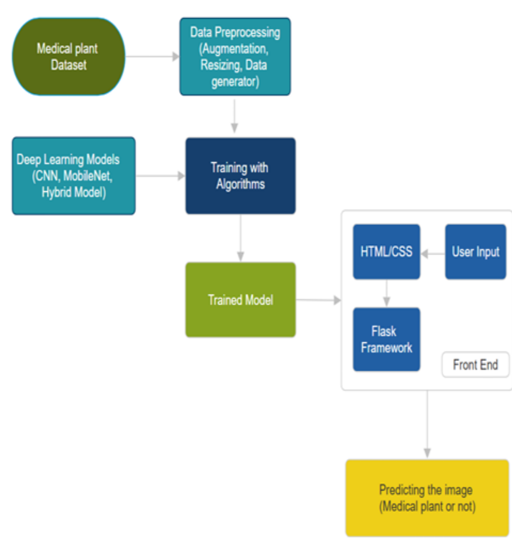

Fig:[1] Architecture

Algorithms:

CNN (Convolutional Neural Networks): CNNs extract essential features from medicinal plant images, making them highly effective for image classification tasks. Their ability to analyze spatial patterns enables accurate identification of different plant species based on leaf texture, shape, and color.

MobileNet: MobileNet is a lightweight deep learning model optimized for efficiency, making it ideal for real-time medicinal plant identification on mobile or resource-constrained devices. It offers a good balance between accuracy and computational efficiency, ensuring fast and reliable classification.

Hybrid Model: The Hybrid Model integrates MobileNet's efficiency with RNN's sequential feature learning, enhancing both performance and adaptability. This approach ensures high accuracy while being computationally efficient, making it suitable for large-scale plant datasets and real-time applications in the field.

Methodology:

The methodology for the proposed system is structured into several stages.

Data Collection: Medicinal Plant dataset named **MedLeaves** is collected from source like Kaggle. This dataset consists of more than 6000 images of medicinal plants.

Data Preprocessing: The dataset is preprocessed using ImageDataGenerator, where all medicinal images are resized to 224×224 pixels and normalized to improve training stability. Data augmentation techniques are applied to enhance the model's generalization ability. The dataset is split into training and validation, ensuring a balanced approach to learning and evaluation.

Model Training: In model training phase, three different models are used, Convolutional Neural Network (CNN), MobileNet, and a hybrid model combining MobileNet with a Recurrent Neural Network (RNN). The performance of each model is evaluated to determine the best approach for medicinal plant classification.

Model Evaluation: Model evaluation is crucial to determine how well the trained model performs on unseen data. Metrics such as accuracy and trainable parameters are calculated to assess the model's effectiveness across different classes of medicinal plants. Confusion matrices are also used to visualize misclassifications and understand where the model is failing.

Deployment: For deploying the trained model, Flask is used to create an API that is connected to the frontend page allows users to upload plant images for real-time identification. The Flask application serves as the backend, where the trained model is loaded using TensorFlow.Once the image is uploaded, it is preprocessed and passed through the model for prediction. The Flask API responds with the predicted plant species and displays the result on a web page. HTML and CSS is used to create a user-friendly interface.

Advantages:

The proposed deep learning-based system offers several advantages over traditional methods. It provides high accuracy in plant identification, thanks to the advanced feature extraction capabilities of CNN and MobileNet, and the sequential analysis of RNN.

The use of MobileNet ensures that the system is lightweight and can be deployed on mobile devices, making it accessible in field conditions where traditional resources may not be available.

RESULT

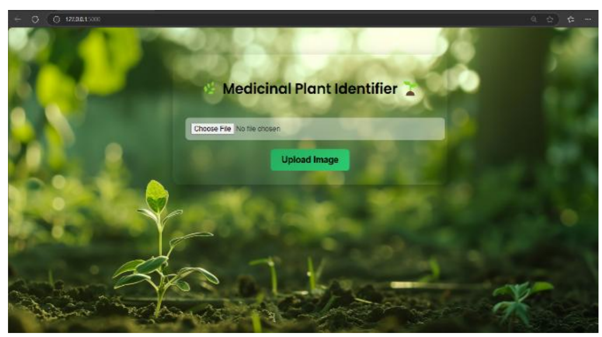

Fig:[2] User Interface

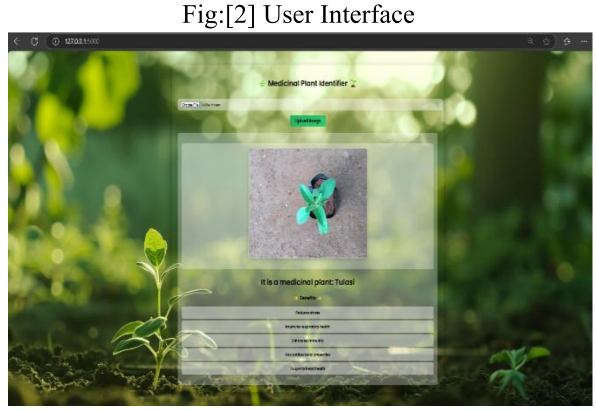

Fig:[3] Medical plant predicted

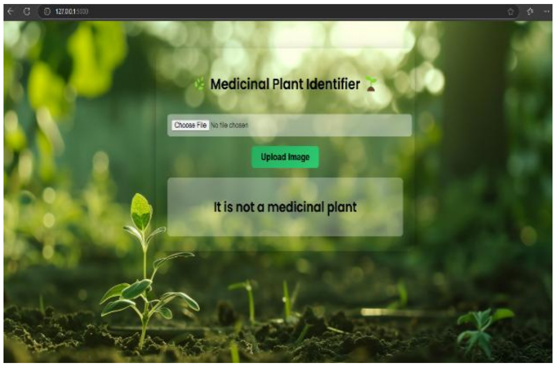

Fig:[4] Not a medical plant

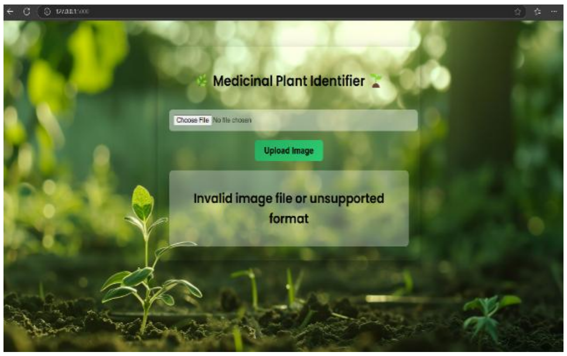

Fig:[5] Invalid image

CONCLUSION

The developed medicinal plant identification system successfully integrates deep learning with Flask-based web deployment. It provides accurate plant classification and valuable medicinal information. The system addresses challenges faced in traditional plant identification methods. Testing results confirm the system's effectiveness, usability, and efficiency. The application has potential applications in botany, herbal medicine, and education. By leveraging CNN and RNN models, the system delivers reliable and fast predictions. Challenges such as dataset limitations and environmental variations were addressed during implementation. Overall, the system enhances plant identification accuracy and accessibility.

FUTURE SCOPE

Advancements in Model Accuracy and Efficiency: With continuous improvements in deep learning architectures, future models can achieve higher accuracy in identifying medicinal plants. Enhanced datasets, better feature extraction techniques, and optimized neural networks will allow real-time identification with minimal errors, making the system more reliable for medical and pharmaceutical applications.

Larger and Diverse Dataset: Future advancements will enable the inclusion of vast and diverse plant species from different geographical regions. By incorporating multilingual and region-specific datasets, the system can help users across the globe access precise medicinal plant information, supporting conservation efforts and traditional medicine research.

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