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Plantify-Enhanced Medicinal Plant Identification Using Convolutional Neural Networks

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Abstract: Medical identification of plants serves important functions for healthcare systems as well as pharmaceutical development and protection of biodiversity. The identification process which depends on manual techniques demands extensive time from experts so automated solutions prove to be crucial. This paper investigates deep learning techniques for medicinal plant classification through combination of ResNet and EfficientNet structures. The training of our model utilized a large database consisting of medicinal plants which incorporated EfficientNet and ResNet architectures to extract complex leaf patterns together with their textual features and color schemes in the leaves.

Users can access Plantify system through its easy-to-use web interface which provides functionality for botanists and researchers along with healthcare professionals to submit plant images for instant classification. A collection of medicinal plant pictures served as input for model training and evaluation through which their main visual characteristics including leaf styles along with textures and color patterns were analysed. The experimental outcomes prove that EfficientNet surpasses traditional models both in accuracy performance and computational efficiency requirements which makes it appropriate for mobile application usage.

Keywords: Convolutional Neural Networks, EfficientNet, ResNet, Medicinal Plants, Image Processing,Machine Learning.

I. INTRODUCTION

Every medical practitioner from modern to traditional fields utilizes medicinal plants because of their therapeutic properties. Right recognition of medicinal plants proves vital for pharmaceutical care delivery and conservation programs during health services and medicines management. At present plants are identified through expert-driven manual inspection but this method requires a lot of time and produces inconsistent results.

Deep learning achieves its best outcomes in image classification through Convolutional Neural Networks (CNNs). Modern Artificial Intelligence research combines ResNet and EfficientNet architectural systems to develop the "Plantify" Enhanced Medicinal Plant Identification Using Artificial Intelligence System.

The "ResNet" residual network model detects hierarchical comprehensive features making it possible for EfficientNet to achieve higher accuracy performance with reduced resource requirements through compound scaling. These models allow the recognition of herbs through their leaf structure features together with their texture and color patterns.

The system undergoes evaluation using 6,900 samples from 80 different types of medicinal plant species which serve in the training process. The large quantity of data in this dataset represents a suitable basis for deep learning algorithm applications because extensive data provides enhanced accuracy across numerous plant species.

The main targets of this research project include developing an efficient neural network system which recognizes medicinal plants. The research determines how well ResNet and EfficientNet perform with regards to their accuracy and operational speed and model outcome capabilities.

An evaluation will be conducted on whether the model can function efficiently in real time as a mobile application and a cloud-based service. The identification system represents an efficient and simple classification system for medicinal botanists together with medical practitioners and research scientists.

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II. LITERATURE SURVEY

Nowadays, an increasing number of people have shown interest in deep learning systems for solving obesity problems as well as managing diets using food recognition systems.

S. Prasad and P. P. Singh (2017) introduced the ''Vision system for medicinal plant leaf acquisition and analysis,'' [1] a web application designed for identification of plant species. Utilizing 2 models: l$\alpha\beta$-CNN model and l$\alpha\beta$-CNN + PCA model. The application identifies the plant and gives information for that plant. The study underscores the accuracy of image-based recognition systems resulting to an accuracy of 92 % and 91% respectively.

Similarly, Santhi Daggubati (2024) proposed a comprehensive system for plant image recognition [2]. By using deep learning models such as Inception v3, VGG16, VGG19, Ensemble Model, the system achieves notable accuracy. However, the study acknowledges the challenge of incorporating recipies that can be formed from these plants which can be useful for curing many diseases.

In another research, Sulthana Habiba (2018) proposed another approach for plant species identification. Their study, titled ''Bangladeshi plant recognition using deep-learning based leaf classification'' [3] explores the use of a VGG 16 function which scores an accuracy of 96%.

All these studies emphasize the deep learning techniques as beneficial in transforming some facets of identification and classification of automated images of medicinal plants for the better. Nevertheless, they all stressed the necessity of more detailed research to solve problems, such as not only identifying a single leaf, but rather several leaves fused or a branch together and working with more sophisticated representation and text classification techniques.

III. METHODOLOGY

This project follows a systematic method beginning with collecting and preparing the data for use.The first process involves gathering images followed by standard input size resizing and normalization to improve model performance. Enhancing the dataset diversity through data augmentation techniques includes the methods of rotation along with flipping and contrast adjustment.

The feature extraction phase utilizes the EfficientNet and ResNet models that received training from large datasets before their application on the target dataset. The integration of batch normalization helps to enhance convergence while improving stability in the network.

DEEP LEARNING ARCHITECTURES

3.1 EfficientNet Architecture:

EfficientNet is an picture classification demonstrate that can be depicted as shocking due to the culminate agreement it keeps up between exactness and effectiveness. Its most special include is innovative compound scaling procedure, which EfficientNet's maker Google Brain created. It ideally combines demonstrate profundity (number of layers), width (number of channels per layer), and determination (input picture size). As restricted to old-fashioned models, EfficientNet at the same time scales all three with an shrewdly methodology. When compared to ResNet and Initiation, the EfficientNet demonstrate accomplishes predominant execution with a division of the parameters and lower computation costs.

The spine of EfficientNet are Versatile Altered Bottleneck Convolution (MB Conv) squares which have been said to start from MobileNetV2. These MB Conv squares utilize depth wise distinct convolutions, one of the most grounded strategies for include extraction, to decrease the required computation for acknowledgment. Also, Squeeze-and-Excitation (SE) layers are included into the show. Whereas this combination helps in capturing complex picture designs, it does so with negligible required computation.

In terms of effectiveness when put into hone, EfficientNet-B0 is the foremost effective with 237 layers and 5.3 million parameters, known as the baseline model. In spite of challenges, the complicated EfficientNet demonstrate is more effective than easier models as anticipated due to its lower floating point operations. The foremost exceptional highlight of EfficientNet is accomplished with moo precision and moo computational assets which makes this engineering exceptional for versatile or genuine time applications.

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Independent frameworks, question acknowledgment, and the restorative field are other divisions this demonstrate is successful in. EfficientNet's sweeping statement towards numerous image-based forms makes it broadly utilized with other models and a favoured choice for profound learning computer vision systems.

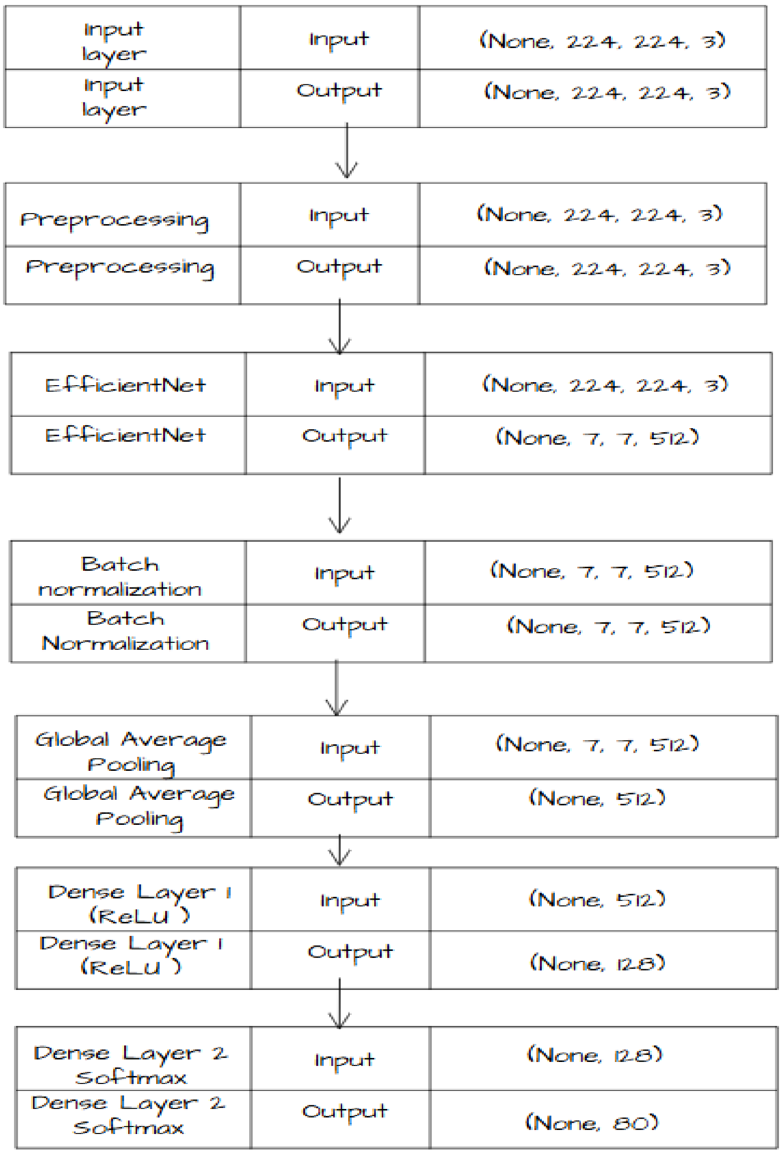

Fig 1: Architecture Image

3.2 ResNet Architecture:

Created by Microsoft in 2015, the ResNet (Leftover Arrange) engineering utilizes profound learning to fathom the vanishing angle issue frequently found in profound neural systems. With conventional profound systems, the more layers are included, the more prominent the execution decay gets to be which complicates the method of preparing.

Each remaining piece contains a set of multilayer convolution squares with a bypass personality alternate route that permits one or more layers to be skipped. Much obliged to the skip association, the show learns the leftover or contrast between the input and yield as restricted to coordinate mapping which incredibly streamlines the preparing handle for profound systems.

Variations of ResNet incorporate ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152, the number speaking to the full layers within the demonstrate. As anticipated, ResNet-50 has 50 layers counting convolutional, bunch normalization, ReLU actuation, and totally associated layers.

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Diverse layers in a ResNet design have diverse part sizes. The exceptionally to begin with convolution layer utilizes a 7x7 part to capture tall level highlights with the beginning step, afterward detail extraction is done utilizing 3x3 bits within the last mentioned steps of convolutions. Highlights are down examined through max pooling and stride-2 convolutional layers which capture vital information whereas diminishing the generally estimate.

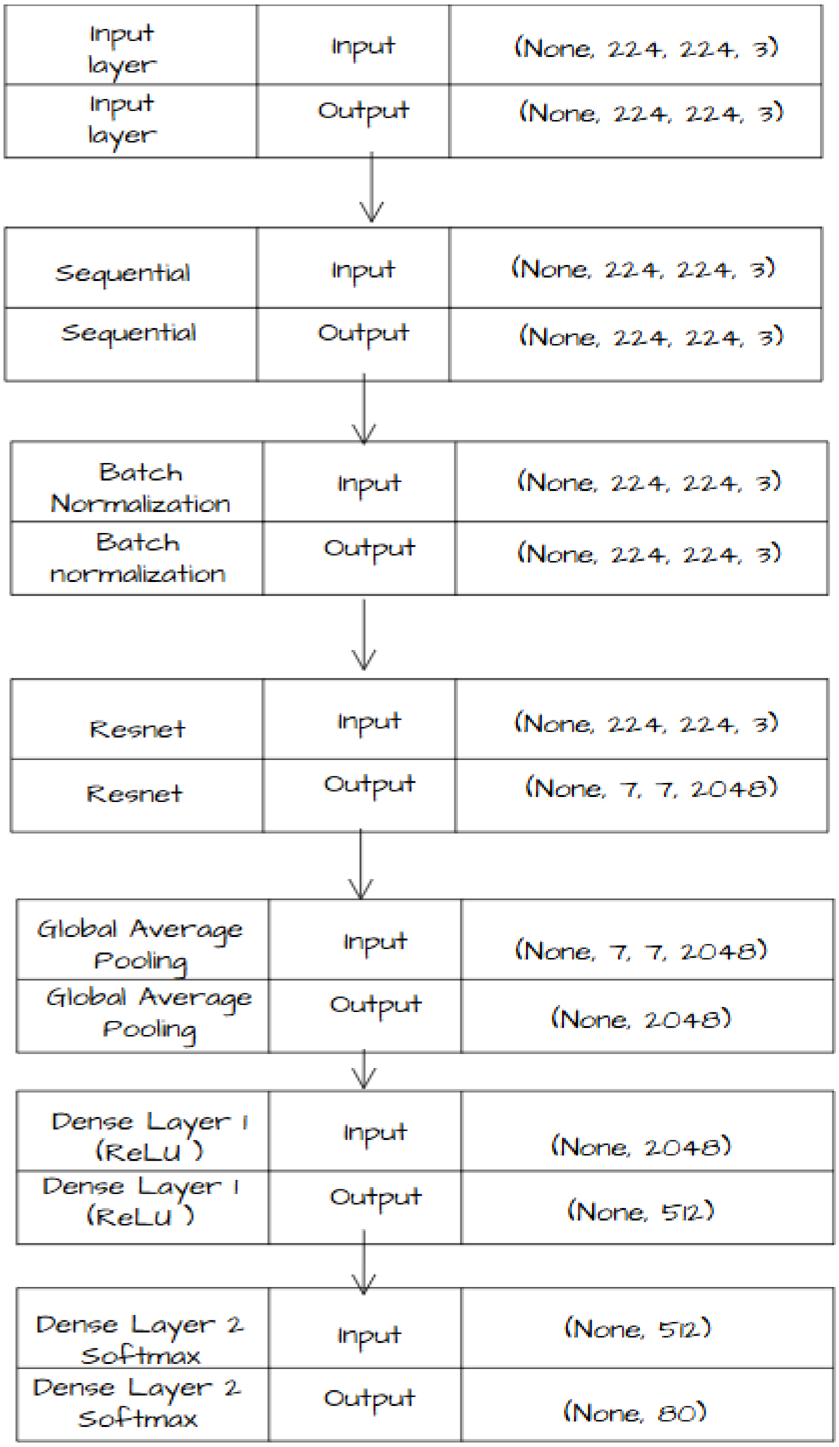

Fig 2: Architecture Image

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IV. RESULT AND DISCUSSIONS

The features extracted from the convolution layers of the source model using the ImageNet dataset aid to classify the target model. The target model is fed with the Plantify dataset to classify the 80 different Indian herbs.

	precision	recall	f1-score	support
Aloe vera	0.9916	1.0000	0.9958	118
Amla	0.9839	0.9104	0.9457	67
Amruthaballi	0.9670	0.9670	0.9670	91
Arali	1.0000	1.0000	1.0000	89
Astma weed	1.0000	0.9878	0.9939	82
Badipala	0.9231	0.9474	0.9351	76
Balloon Vine	1.0000	1.0000	1.0000	61
Bamboo	1.0000	0.9915	0.9957	118
Beans	0.9798	1.0000	0.9898	97
Betel	0.9912	0.9912	0.9912	114
Bhrami	0.9810	0.9904	0.9856	104
Bringaraja	0.9474	0.9863	0.9664	73
Caricature	1.0000	1.0000	1.0000	76
Castor	1.0000	0.9845	0.9922	129
Catharanthus	0.9925	0.9925	0.9925	134
Chakte	0.9444	1.0000	0.9714	68
Chilly	0.9583	1.0000	0.9787	69
Citron lime (herelikai)	0.9789	0.9394	0.9588	99
Coffee	0.9639	0.9639	0.9639	83
Common rue(naagdalli)	1.0000	1.0000	1.0000	67
Coriender	0.9914	1.0000	0.9957	115
Curry	1.0000	0.9762	0.9880	168
Doddpathre	0.9859	0.9859	0.9859	142
Drumstick	1.0000	1.0000	1.0000	56
Ekka	1.0000	0.9877	0.9938	81
Eucalyptus	1.0000	0.9875	0.9937	80
Ganigale	0.9868	1.0000	0.9934	75
Ganike	0.9831	0.9206	0.9508	63
Gasagase	0.9750	0.9873	0.9811	79
Ginger	0.9762	1.0000	0.9880	82
Globe Amarnath	0.9529	1.0000	0.9759	81
Guava	0.9683	0.9531	0.9606	128
Henna	0.9405	0.9875	0.9634	80
Hibiscus	1.0000	0.9915	0.9957	118
Honge	0.9912	1.0000	0.9956	113
Insulin	1.0000	0.9888	0.9944	89
Jackfruit	0.9630	0.9455	0.9541	110
Jasmine	0.9796	0.9796	0.9796	49
Kambajala	0.9831	0.9831	0.9831	59
Kasambruga	1.0000	1.0000	1.0000	48
Kohlrabi	1.0000	1.0000	1.0000	73
Lantana	1.0000	0.9342	0.9660	76
Lemon	0.9836	0.9756	0.9796	123
Lemongrass	1.0000	1.0000	1.0000	8
Malabar Nut	0.9273	1.0000	0.9623	51
Malabar Spinach	0.9512	0.9873	0.9689	79
Mango	0.9712	0.9806	0.9758	103
Marigold	0.9787	0.9892	0.9840	93
Mint	1.0000	0.9778	0.9888	135
Neem	0.9774	0.9848	0.9811	132
Nelavembu	0.9778	0.9778	0.9778	90
Nerale	1.0000	0.9839	0.9919	62
Nooni	0.9861	0.9861	0.9861	72
Onion	1.0000	0.9783	0.9890	92
Padri	1.0000	1.0000	1.0000	73
Palak(Spinach)	0.9673	0.9933	0.9801	149
Papaya	1.0000	0.9926	0.9963	135
Parijatha	0.9851	1.0000	0.9925	66
Pea	1.0000	1.0000	1.0000	47
Pepper	1.0000	1.0000	1.0000	8
Pomoegranate	0.9868	1.0000	0.9934	75
Pumpkin	1.0000	1.0000	1.0000	92
Raddish	1.0000	1.0000	1.0000	40
Rose	0.9813	0.9906	0.9859	106
Sampige	0.9683	1.0000	0.9839	61
Sapota	0.9767	0.9545	0.9655	44
Seethaashoka	1.0000	0.9362	0.9670	47
Seethapala	1.0000	1.0000	1.0000	114
Spinach1	1.0000	0.9851	0.9925	67
Tamarind	1.0000	0.9943	0.9972	176
Taro	1.0000	1.0000	1.0000	69
Tecoma	0.9851	0.9565	0.9706	69
Thumbe	1.0000	1.0000	1.0000	74
Tomato	1.0000	1.0000	1.0000	62
Tulsi	0.9665	0.9774	0.9719	177
Turmeric	1.0000	1.0000	1.0000	39
ashoka	1.0000	1.0000	1.0000	81
camphor	1.0000	1.0000	1.0000	66
kamakasturi	0.9848	0.9701	0.9774	67
kepala	1.0000	1.0000	1.0000	76
accuracy			0.9851	6900
macro avg	0.9854	0.9854	0.9853	6900
weighted avg	0.9853	0.9851	0.9851	6900

Fig 3: Classification Report from EfficientNet Model

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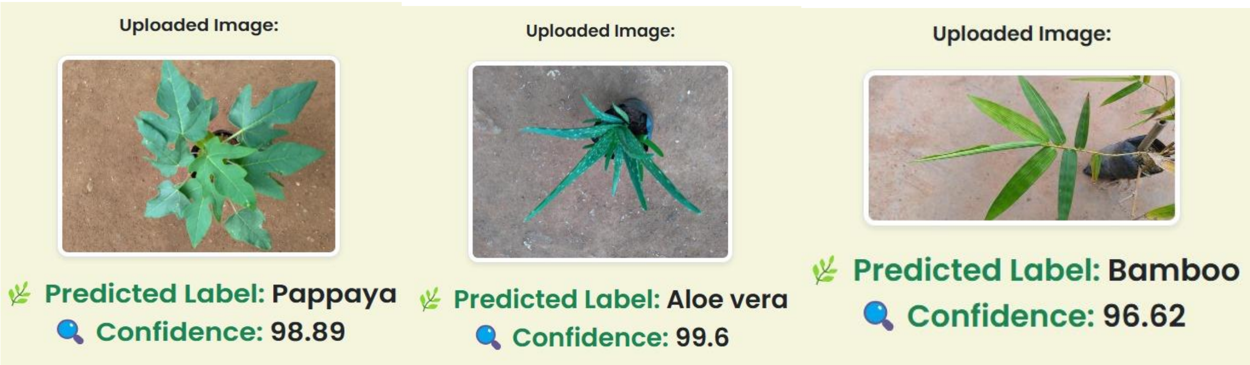
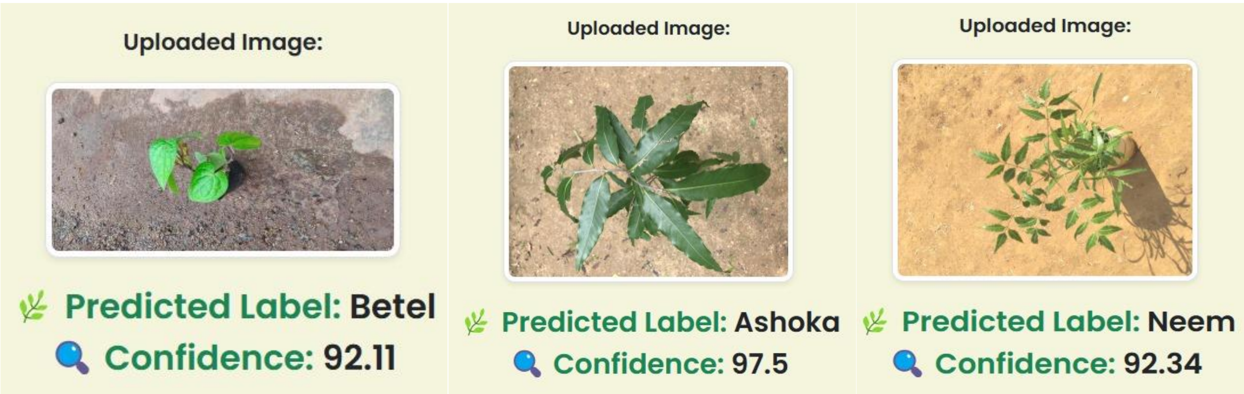
The validation data accuracy measured at 98% when using EfficientNet model while ResNet model achieved 97% accuracy. The model reached above 96% accuracy when classifying members of the Solanaceae and Rubiaceous plant families. Through its exceptional precision the model managed perfect identifications of particular species including Aloe vera and Bamboo. Gardens with their best defences still contain at least one unwanted intruder. The model faced some minor identification issues when encountering Ashoka along with Camphor and other few plants because of limited training on distinctive yet visually similar plant species. The model functioned effectively with basic two-class and complex multiple-class identification responsibilities thus showcasing an impressive range of abilities.

With expanded training data consisting of diverse challenging examples this model is likely to transform into a powerful identification tool for botanists together with conservationists and everyone fascinated by plants. The following are predictions made from test data analysis.

Here are some predictions on test data:



(a) (b) (c)



(d) (e) (d)

Fig 4: Testing Data

V. CONCLUSION

The work introduces two CNN models that include EfficientNet and ResNet. The proposed Plantify relies on EfficientNet model features for identification through an artificial neural network that achieves 98% average accuracy using the Medicinal Plant dataset. The system provides immediate classification features while supporting multiple languages and featuring a simple interface which makes it useful for researchers alongside botanists and healthcare professionals.

The model exhibited excellent capabilities for medical plant classification together with strong ability to generalize across different datasets. The analysis of errors pointed to two main weaknesses identified with images having poor illumination quality and intricate backgrounds. Research will concentrate on collecting more plant data while strengthening image augmentation procedures as well as implementing AI-powered disease identification technology into the system.

With the integration of deep learning models to the system, the correct recognition and classification of medicinal plants is improved, which helps healthcare and scientific research programs.

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The combination of deep learning with informatics transforms the entire sector. If further advanced, this system has the capability of becoming the international standard in recognition and categorization of herbal plants. Feedback functionalities in the system allow continuous accuracy improvement to produce adaptive learning from user feedback. The platform shows versatility in its capabilities which allows its widespread deployment for agricultural production and environmental monitoring purposes. External databases gain access to plant data because of the system's export feature leading to increased applications within research and conservation and pharmaceutical industries. The integration of deep learning technology into botanical informatics through this system improves the capabilities for healthcare-driven plant medicine identification that propels health research progress.

Further development and optimization will make this project suitable for becoming an internationally recognized standard tool for medicinal plant identification and classification.

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