Plantify-Enhanced Medicinal Plant Identification Using Convolutional Neural Networks

Submitted for partial fulfillment of the requirements

for the award of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE ENGINEERING – ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

by

P. Naga Sai Venkata Dakshaini	**-**	**22BQ5A4214**
R. Chandu	**-**	**21BQ1A42F0**
SK. Khadeer	**-**	**21BQ1A42G2**
SK. Ushman Basha	**-**	**21BQ1A42G4**

Under the guidance of

Dr. T. Kameswara Rao, Professor

VASIREDDY VENKATADRI INSTITUTE OF TECHNOLOGY

DEPARTMENT OF COMPUTER SCIENCE ENGINEERING – ARTIFICIAL INTELLIGENCE & MACHINE LEARNING
VASIREDDY VENKATADRI INSTITUTE OF TECHNOLOGY

Permanently Affiliated to JNTU Kakinada, Approved by AICTE
Accredited by NAAC with 'A' Grade, ISO 9001:2008 Certified

NAMBUR (V), PEDAKAKANI (M), GUNTUR – 522 508

Tel no: 0863-2118036, url: www.vvitguntur.com

April 2024

VASIREDDY VENKATADRI INSTITUTE OF TECHNOLOGY
Permanently Affiliated to JNTUK, Kakinada, Approved by AICTE
Accredited by NAAC with 'A' Grade, ISO 9001:20008 Certified
Nambur, Pedakakani (M), Guntur (Gt) -522508

DEPARTMENT OF COMPUTER SCIENCE ENGINEERING - ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

CERTIFICATE

This is to certify that this **Project Report** is the Bonafide work of **Ms. P. Naga Sai Venkata Dakshaini, Mr. R. Chandu, Mr. SK. Khadeer, Mr. SK. Ushman Basha**, bearing Reg. No. **22BQ5A4214, 21BQ1A42F0, 21BQ1A42G2, 21BQ1A42G4** respectively who had carried out the project entitled **"Plantify-Enhanced Medicinal Plant Identification Using Convolutional Neural Networks"** under our supervision.

Project Guide	**Head of the Department**
(Dr. T. Kameswara Rao, Professor)	(Dr. K. Suresh Babu, Professor)

Submitted for Viva voce Examination held on ____________________________

Internal Examiner	**External Examiner**

DECLARATION

We, Ms. P. Naga Sai Venkata Dakshaini, Mr. R. Chandu, Mr. SK. Khadeer, Mr. SK. Ushman Basha hereby declare that the Project Report entitled **Plantify-Enhanced Medicinal Plant Identification Using Convolutional Neural Networks”** done by us under the guidance of Dr.T. Kameswara Rao, Professor, Computer Science Engineering - Artificial Intelligence & Machine Learning at Vasireddy Venkatadri Institute of Technology is submitted for partial fulfillment of the requirements for the award of Bachelor of Technology in Computer Science Engineering - Artificial Intelligence & Machine Learning. The results embodied in this report have not been submitted to any other University for the award of any degree.

DATE :

PLACE : Nambur

SIGNATURE OF THE CANDIDATES

P.N.S.V. Dakshaini

R. Chandu

SK. Khadeer

SK. Ushman Basha

ACKNOWLEDGEMENT

We take this opportunity to express my deepest gratitude and appreciation to all those people who made this project work easier with words of encouragement, motivation, discipline, and faith by offering different places to look to expand my ideas and helped me towards the successful completion of this project work.

First and foremost, we express my deep gratitude to **Mr. Vasireddy Vidya Sagar**, Chairman, Vasireddy Venkatadri Institute of Technology for providing necessary facilities throughout the B.Tech program.

We express my sincere thanks to **Dr. Y. Mallikarjuna Reddy**, Principal, Vasireddy Venkatadri Institute of Technology for his constant support and cooperation throughout the B.Tech program.

We express my sincere gratitude to **Dr. K. Suresh Babu**, Professor & HOD, Computer Science Engineering - Artificial Intelligence & Machine Learning, Vasireddy Venkatadri Institute of Technology for his constant encouragement, motivation and faith by offering different places to look to expand my ideas.

We would like to express my sincere gratefulness to our Guide **Dr. T. Kameswara Rao**, Professor, Computer Science Engineering - Artificial Intelligence & Machine Learning for her insightful advice, motivating suggestions, invaluable guidance, help and support in successful completion of this project.

We would like to express our sincere heartfelt thanks to our Project Coordinator **Mrs. K. Deepika**, Assistant Professor, Computer Science Engineering - Artificial Intelligence & Machine Learning for his valuable advices, motivating suggestions, moral support, help and coordination among us in successful completion of this project.

We would like to take this opportunity to express my thanks to the **Teaching and Non-Teaching** Staff in the Department of Computer Science Engineering - Artificial Intelligence & Machine Learning, VVIT for their invaluable help and support.

P. Naga Sai Venkata Dakshaini
R. Chandu
SK. Khadeer
SK. Ushman Basha

TABLE OF CONTENTS

CH No	Title	Page No
	Contents	i
	List of Figures	iv
	Nomenclature	v
	Abstract	vi
1	**INTRODUCTION**	
	1.1 Background and rationale for the study	1
	1.2 Statement of the problem	2
	1.3 Aims and objectives of the research	2
	1.4 Research questions or hypotheses	
	1.4.1 Research Questions	3
	1.4.2 Hypotheses	4
	1.5 Scope and limitations of the study	4
	1.6 Peculiarity of Project	5
2	**LITERATURE SURVEY**	
	2.1 CNN architecture used in	6
	2.2 Images related to the first activation layer used in	7
	2.3 Flowchart of proposed system used in	8
	2.4 Conclusion	9
3	**PROPOSED SYSTEM**	
	3.1 Existing System	
	3.1.1 Disadvantages	12
	3.2 Proposed System	
	3.2.1 Advantages	13
	3.3 Methodology	
	3.3.1Description of the AI model development process	14

	3.3.2 Data collection for Plant image datasets	15
	3.3.3 Details of the algorithm and software used	16
	3.3.4 User role definitions and interactions	17
	3.3.5 Ethical considerations and data privacy measures	18
	3.4 System Analysis	
	3.4.1 Feasibility Study	19
	3.4.2 Technical Feasibility	19
	3.4.3 Economic Feasibility	20
	3.4.4 Social Feasibility	20
	3.4.5 Operational Feasibility	20
	3.5 Requirement Analysis	
	3.5.1 Functional Requirements	21
	3.5.2 Non-Functional Requirements	22
	3.6 System Requirements	
	3.6.1 Software Requirements	24
	3.6.2 Hardware Requirements	24
4	**System Design and Architecture**	
	4.1 System Architecture	25
	4.2 Input Design	26
	4.3 Output Design	27
	4.4 UML Diagrams	
	4.4.1 Use Case Diagram	28
	4.4.2 Class Diagram	28
	4.4.3 Sequence Diagram	29
	4.4.4 Collaboration Diagram	30
	4.4.5 Component Diagram	31
	4.4.6 DFD Diagram	33
	4.5 Database Design	34

5	**IMPLEMENTATIONS**	
	5.1 Deep Learning Algorithms	
	5.1.1 EfficientNet	37
	5.1.2 ResNet	38
	5.1.3 Code	40
	5.2 Visual Studio Code	44
	5.3 Python Flask Server	44
6	**RESULTS AND TESTING**	
	6.1 Testing Methodologies	
	6.1.1 Unit Testing	45
	6.1.2 Integration Testing	45
	6.1.3 System Testing	45
	6.2 Test case Reports	46
	6.3 Performance Metrics Analysis	47
	6.4 Output Screenshots	48
7	**CONCLUSION AND FUTURE SCOPE**	34
8	**REFERENCES**	36
	APPENDIX	
	Conference Presentation Certificate	37

LIST OF FIGURES

Figure No	Figure Name	Page No
2.1.1	CNN Layers	7
2.2.1	First activation layer of CNN	8
4.1.1	System Architecture	25
4.4.1	Use Case Diagram	28
4.4.2	Class Diagram	29
4.4.3	Sequence Diagram	30
4.4.4	Collaboration Diagram	31
4.4.5	Component Diagram	32
4.4.6	DFD Diagram	33
5.1.1.1	EfficientNet Architecture	37
5.1.2.1	ResNet Architecture	39
6.2	Testing Report	40
6.3	Classification Report	41
6.4.1	Home Page	45
6.4.2	Plantify Green Hub	45
6.4.3	Search and Retrieval	46
6.4.4	Multi Language	46
6.4.5	Image Recognition	47
6.4.6	Remedies	48
6.4.7	Contribute Plant	49

NOMENCLATURE

ML	Machine Learning
DL	Deep Learning
AI	Artificial Intelligence
CNN	Convolution Neural Network
PC	Personal Computer
ER	Entity Relationship
DFD	Data Flow Diagram

ABSTRACT

The identification of medicinal plants and raw materials plays a crucial role in various fields, including healthcare, pharmaceuticals, and environmental conservation. However, manual identification methods are often time-consuming and require expert botanical knowledge. In this project, we propose a novel approach to automate the identification process using image processing and machine learning algorithms.

We present a comprehensive study on the identification of different medicinal plants and raw materials through image processing techniques. Our methodology involves the collection of a diverse dataset containing images of various plant species and raw materials. We preprocess the dataset to standardize the images and remove noise, ensuring the robustness of our models.

We employ state-of-the-art Deep learning models, including Efficient Net, ResNet for plant identification. These models are trained on the dataset to learn features relevant to plant classification. We evaluate the performance of each model using standard metrics such as accuracy, precision, recall, and F1 score.

Our results demonstrate the effectiveness of our approach in accurately identifying medicinal plants and raw materials from images. We compare the performance of individual models and the ensemble model to identify the most effective approach. Additionally, we develop a user-friendly interface for seamless access to the plant identification system.

Overall, our project provides a valuable contribution to the automation of traditional botanical practices, enhancing accessibility to plant identification for users without expert botanical knowledge. Our system has broad applications in healthcare, pharmaceuticals, agriculture, and environmental conservation, paving the way for future advancements in plant recognition technology.

CHAPTER 1
INTRODUCTION

Medicinal plants have been used for centuries as sources of traditional medicine and natural remedies for various ailments. However, identifying these plants accurately can be challenging, especially for those without expert botanical knowledge. In recent years, advancements in image processing and machine learning algorithms have provided new opportunities for automating the identification process.

This project aims to leverage the power of image processing techniques and machine learning algorithms to develop a system capable of accurately identifying different medicinal plants and raw materials from images. By utilizing state-of-the-art models such as EfficientNet and ResNet the project seeks to achieve high accuracy and robustness in plant recognition.

1.1 Background and rationale for the study

Medicinal plants have been used for centuries as sources of traditional medicine and natural remedies for various ailments. However, the identification of these plants is often challenging, particularly for individuals without expert botanical knowledge. Traditional methods of plant identification rely heavily on manual observation and comparison, which can be time-consuming and prone to errors.

With the rapid advancement of technology, particularly in the fields of image processing and machine learning, there is a growing interest in automating the process of plant identification. By leveraging the power of computational techniques, it is possible to develop systems capable of accurately identifying medicinal plants and raw materials from images, thereby streamlining the identification process and making it more accessible to a wider audience.

The rationale for conducting this study lies in the potential benefits it offers to various stakeholders:

Accessibility: By developing an automated system for plant identification, we aim to make this essential task more accessible to a broader range of users, including researchers, healthcare professionals, herbalists, and enthusiasts. This accessibility democratizes botanical knowledge and promotes the sustainable use of medicinal plants.

Efficiency: Manual methods of plant identification are labour-intensive and time-consuming. By automating this process, we can significantly reduce the time and effort required for plant identification, enabling faster decision-making in various applications, such as healthcare, pharmaceuticals, and environmental conservation.

Accuracy: Machine learning algorithms have demonstrated impressive capabilities in image classification tasks. By training models on a diverse dataset of medicinal plants and raw materials, we aim to develop a system capable of accurately identifying plant species with high precision and recall, minimizing the risk of misidentification.

Conservation: The identification of medicinal plants is crucial for their conservation and sustainable use. By facilitating the identification process, our project contributes to efforts aimed at preserving biodiversity and promoting the responsible harvesting and cultivation of medicinal plants.

Innovation: The intersection of image processing, machine learning, and botany presents exciting opportunities for innovation. By pushing the boundaries of technology in plant identification, we pave the way for future advancements in fields such as precision agriculture, personalized medicine, and ecological monitoring.

1.2 Statement of the problem

The identification of medicinal plants and raw materials is a critical task in various fields, including healthcare, pharmaceuticals, and environmental conservation. However, traditional methods of plant identification are often labor-intensive, time-consuming, and require expert botanical knowledge. Manual observation and comparison of plant features can be subjective and prone to errors, leading to potential misidentification.

Furthermore, the increasing demand for medicinal plants, coupled with habitat destruction and overexploitation, poses significant challenges to their conservation and sustainable use. Accurate identification of plant species is essential for ensuring their proper management and conservation.

1.3 Aims and objectives of the research

The primary aim of this research project is to develop a robust system for the automated identification of medicinal plants and raw materials using image processing techniques and machine learning algorithms.

To build a comprehensive dataset containing images of various medicinal plants and raw materials, ensuring diversity in species, morphology, and environmental conditions.

To preprocess the dataset by standardizing images, removing noise, and augmenting data to enhance the robustness of the models.

To investigate and implement state-of-the-art machine learning models, including EfficientNet and ResNet, for plant identification.

To train the selected models on the dataset to learn features relevant to plant classification, optimizing hyperparameters and model architectures for improved performance.

To evaluate the performance of each model using standard metrics such as accuracy, precision, recall, and F1 score, comparing the effectiveness of individual models and the ensemble approach.

To develop a user-friendly interface for the deployment of the trained models, allowing users to upload images and receive real-time predictions on plant identification.

To assess the usability and effectiveness of the developed system through user testing and feedback, iteratively refining the interface and functionality based on user input.

To validate the accuracy and reliability of the system through field testing, comparing automated identifications with expert botanical assessments.

To explore potential applications of the developed system in various fields, including healthcare, pharmaceuticals, agriculture, and environmental conservation.

To contribute to the advancement of knowledge in the intersection of image processing, machine learning, and botany, fostering innovation and collaboration in interdisciplinary research.

1.4 Research questions or hypotheses

The study is guided by the following research questions and hypotheses:

1.4.1 Research Questions

- How effective are state-of-the-art machine learning models, including EfficientNet and ResNet, in accurately identifying medicinal plants and raw materials from images?
- What is the impact of dataset size, diversity, and quality on the performance of machine learning models for plant identification?
- How do preprocessing techniques such as image standardization, noise removal, and data augmentation affect the robustness and accuracy of the identification system?
- What are the key factors influencing the performance differences between individual machine learning models and ensemble approaches in plant identification?
- How does the complexity and variability of plant morphology affect the accuracy and reliability of automated identification systems?

- What is the usability and user satisfaction with the developed interface for plant identification, and how can it be improved to enhance user experience?
- What are the potential applications of the developed system in fields such as healthcare, pharmaceuticals, agriculture, and environmental conservation, and how do they benefit from automated plant identification?
- How does the accuracy of automated plant identification compare to expert botanical assessments, and what are the implications for research, conservation, and practice?

1.4.2 Hypotheses

The accuracy of machine learning models, such as EfficientNet and ResNet, in identifying medicinal plants and raw materials will positively correlate with the size, diversity, and quality of the dataset.

Preprocessing techniques, including image standardization, noise removal, and data augmentation, will enhance the robustness and accuracy of machine learning models for plant identification.

Ensemble approaches combining multiple machine learning models will outperform individual models in terms of accuracy and reliability due to their ability to capture complementary features.

The developed system for automated plant identification will demonstrate high usability and user satisfaction, with potential improvements identified through user feedback and testing.

The accuracy of automated plant identification will be comparable to or exceed that of expert botanical assessments, demonstrating the feasibility and reliability of the developed system for botanical research, conservation, and practice.

1.5 Scope and limitations of the study

This research focuses on automating the identification process of medicinal plants and raw materials using advanced image processing techniques and machine learning algorithms. The study encompasses a diverse range of medicinal plant species and raw materials utilized in traditional medicine and natural remedies. Various image processing techniques will be employed to preprocess the dataset, including standardization, noise removal, and data augmentation, to ensure the quality and robustness of the images used for training machine learning models.

The research will investigate the effectiveness of state-of-the-art machine learning models such as EfficientNet and ResNet for accurately classifying medicinal plants and raw materials from images. It will involve rigorous training, evaluation, and comparison of these models to determine their performance and suitability for automated plant identification tasks.

Despite its scope and objectives, this research faces several limitations that may impact its outcomes. One such limitation is the size and diversity of the dataset used for model training and evaluation. While efforts will be made to collect a comprehensive dataset, it may not capture all possible variations in plant morphology, environmental conditions, and image quality, potentially limiting the generalization of the models.

1.6 Peculiarity of the Project

The project focuses on automating the identification process of medicinal plants and raw materials through image processing and machine learning. It encompasses a wide range of medicinal plant species and raw materials typically used in traditional medicine and natural remedies. Various image processing techniques, such as standardization, noise removal, and data augmentation, will be employed to enhance the quality and robustness of the dataset used for training machine learning models.

The research will assess the effectiveness of advanced machine learning models like Efficient and ResNet\ in accurately classifying medicinal plants and raw materials from images. Rigorous training, evaluation, and comparison of these models will be conducted to determine their performance and suitability for automated plant identification tasks.

CHAPTER 2

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.

2.1 CNN architecture

The comparison of the performance of the ML and DL models can helpdetermine which model is more suitable for this problem. Once a suitable model is selected, a web or mobile application can be developed to allow usersto take pictures of medicinal plants and classify them using the trained model. The system should be validated by testing it on a different dataset or collectingfeedback from experts in traditional medicine [2.1.1].

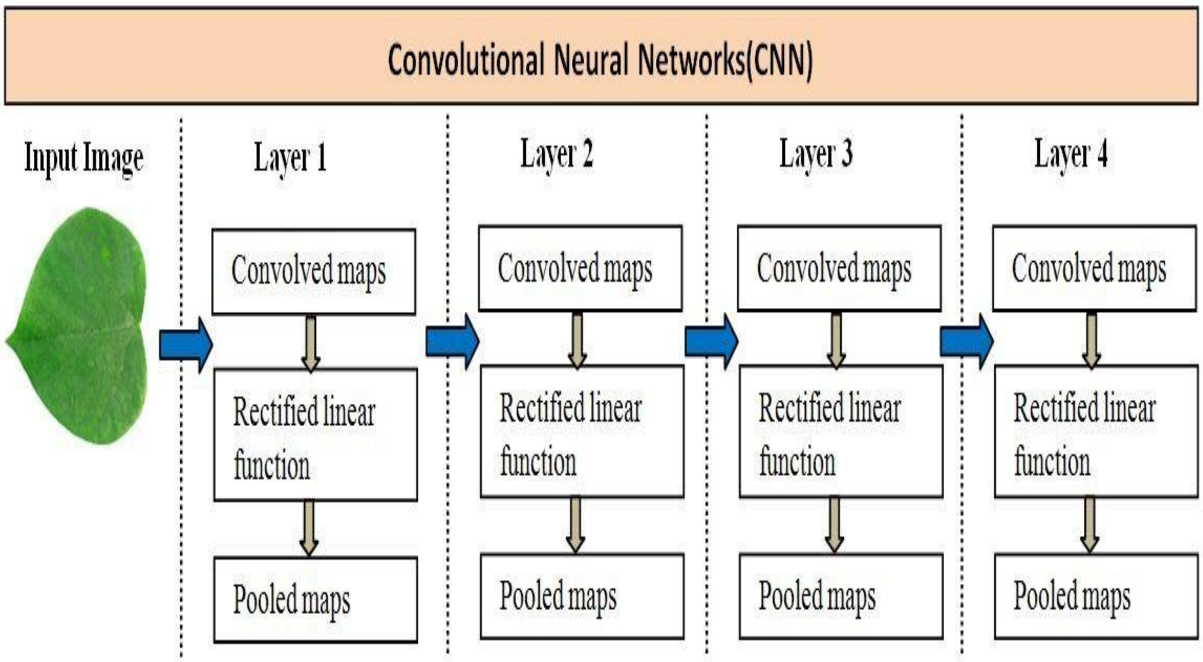


Fig 2.1.1 CNN Layers

2.2 Images related to the first activation layer of CNN

The separation of therapeutic plants from other non-edible plants is crucial in the realms of botany and the food industry. However, conventional techniques for identifying medicinal plants are difficult, time-consuming, and requireskilled specialists. An autonomous real-time vision-based system has been presented to identify commonly used medicinal herbs with similar leaves in order to solve this problem. This system makes use of a convolutional and classifier block-based upgraded convolutional neural network (CNN) network.Global Average Pooling (GAP), dense, dropout, and softmax layers are all present in the classifier. This technique improves the model's speed and accuracy while reducing the number of parameters compared to earlier studies.With overall accuracy rates of 99.66%, 99.32%, and 99.45%, respectively, the proposed CNN model (Fig 2.2.1 shows images related to the first activationlayer of CNN model) can recognize medicinal plant photos at three different levels of image definition, 64 64, 128 128, and 256 256 pixels. As a result, combining image processing with the suggested CNN algorithm is a productive replacement for conventional approaches.

To verify the efficacy of the developed approach, additional work will be doneto enhance the model's performance in the classification of additional species of medicinal plants. A smart smartphone application for the real-time identification of medicinal plants will also be created using the model. This is especially crucial in light of the rising acceptance and demand for both artisanal and commercial uses and applications of medicinal plants. In order to recognize and classify various therapeutic plants distinct from other non-edibleplants, the suggested Deep Learning (DL) algorithm and image processing technique can have a special role in plant research and even industrial markets.

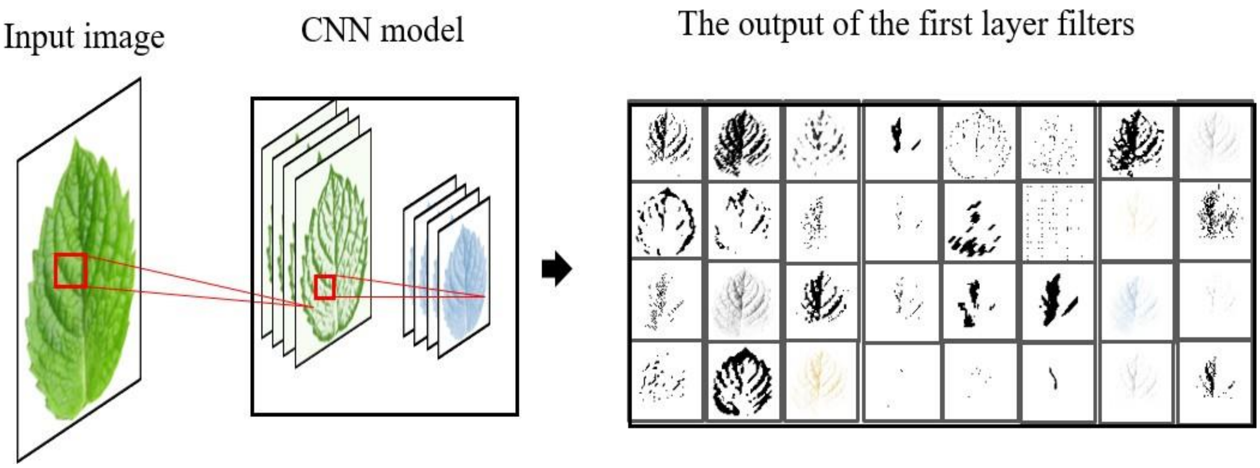


Fig 2.2.1 First activation layer of CNN

2.3 Steps of the proposed method used in Deep Learning Models:

Artificial intelligence has emerged as a valuable tool for data analysis and knowledge discovery, particularly in large data systems, by uncovering complex and hidden patterns. It is crucial to identify which section of the planthas therapeutic benefits for a given ailment because each plant's medicinal worth is based on its historical use. The model 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.

A statistical analysis of leaf characteristics has been conducted to identify the key features that aid in plant identification, and form was found to be a crucial factor. This promising approach has the potential to aid individuals in identifying medicinal plants automatically, as well as in conservation andutilization efforts. The development of an artificial intelligence system for plant recognition is essential to achieving these objectives, as it can process large amounts of data efficiently and accurately. 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.

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.

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.

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.

2.4 Conclusion

In conclusion, the literature survey conducted for the project on automating the identification process of medicinal plants and raw materials through image processing and machine learning has provided valuable insights and guidance. The survey revealed the prevalence of advanced techniques such as convolutional neural networks (CNNs) and transfer learning in the field of plant recognition. Notable models like EfficientNet and ResNet and ensemble approaches have shown promise in accurately classifying plant species from images.

Furthermore, the literature emphasized the critical importance of dataset quality and diversity for training robust and generalizable models. Preprocessing techniques such as standardization, noise removal, and data augmentation were identified as essential steps to enhance dataset quality and model performance. Rigorous model evaluation using standard performance metrics was highlighted as crucial for assessing the effectiveness of different approaches.

Moreover, the literature underscored the significance of developing user-friendly interfaces for seamless interaction with automated plant identification systems. Such interfaces enable users to upload images and receive real-time predictions on plant species, thereby enhancing accessibility and usability.

Overall, the literature survey illuminated the wide-ranging applications of automated plant recognition systems in various fields, including healthcare, pharmaceuticals, agriculture, and environmental conservation. These systems have the potential to streamline processes, accelerate research, and promote sustainability in plant-related endeavors.

CHAPTER 3
PROPOSED SYSTEM

3.1 Existing System

The existing systems for automated plant recognition often utilize a combination of image processing techniques and machine learning algorithms. While there are several systems available, some notable examples include:

Plantes Medicinales:

Plantes Medicinales is a mobile application that employs image recognition technology to identify plant diseases and nutrient deficiencies. Users can upload images of affected plants, and the app provides real-time diagnosis and recommendations for treatment.

The system uses a combination of convolutional neural networks (CNNs) trained on large datasets of plant images to classify and diagnose plant diseases accurately.

Plantees Medicinales also incorporates crowdsourced data and expert knowledge to continuously improve its accuracy and expand its database of plant diseases.

Flora Incognita:

Flora Incognita is a smartphone app developed for automated plant identification in the wild. Users can take pictures of plants, and the app identifies them based on leaf shape, flower colour, and other characteristics.

The system utilizes deep learning algorithms trained on extensive datasets of plant images to achieve high accuracy in plant identification.

Flora Incognita also includes features for species documentation and biodiversity monitoring, making it useful for both casual users and researchers.

MediScan:

MediScan is a web and mobile application that allows users to identify plants by uploading pictures of their leaves.

The system employs image recognition algorithms trained on a small database of plant images contributed by users and experts.

MediScan also provides additional information about identified plants, including their distribution, habitat, and ecological importance.

LeafSnap:

LeafSnap is a mobile app designed for identifying tree species from photographs of their leaves. Users can take pictures of leaves against a white background, and the app matches them to a database of tree species.

The system uses computer vision algorithms to analyze leaf characteristics such as shape, margin, and venation patterns for accurate identification.

LeafSnap also includes educational resources and information about tree species, making it a valuable tool for nature enthusiasts and educators.

3.1.1 Disadvantages

While existing systems for automated plant recognition offer valuable tools for plant identification and analysis, they also come with some disadvantages. Here are some common drawbacks associated with these systems:

1. **Limited Accuracy**: One of the main challenges faced by existing systems is limited accuracy, especially when dealing with complex plant species or variations in environmental conditions. Inaccurate identification results can undermine the reliability of these systems, leading to misdiagnosis or incorrect recommendations.
2. **Dependency on Image Quality**: Many existing systems rely heavily on the quality of input images for accurate identification. Poor lighting conditions, background clutter, or occlusions can negatively impact the system's performance, reducing its effectiveness in real-world scenarios where capturing high-quality images may be challenging.
3. **Limited Coverage**: Existing systems may have limited coverage of plant species or geographic regions. They may be biased towards commonly encountered species or regions with extensive training data, while lacking support for less common or region-specific plants. This limitation restricts the applicability of these systems in diverse botanical contexts.
4. **Resource Intensive**: Some automated plant recognition systems require significant computational resources for image processing and model training, making them inaccessible to users with limited computing capabilities or internet connectivity.

3.2 Proposed System

The proposed system for automating the identification process of medicinal plants and raw materials through image processing and Deep learning aims to address the limitations of existing systems while leveraging cutting-edge technologies to achieve accurate and efficient plant recognition. The system will begin with the compilation of a comprehensive dataset containing images of various medicinal plant species and raw materials, ensuring diversity in morphology, habitat, and geographic location. Preprocessing techniques such as standardization, noise removal, and data augmentation will be applied to enhance the quality and robustness of the dataset. Machine learning models, including state-of-the-art architectures like EfficinetNet and ResNet, will be trained on the pre-processed dataset to learn features relevant to plant classification. Model selection and hyperparameter optimization will be conducted to maximize performance and generalization capabilities. The developed system will include a user-friendly interface that allows users to upload images and receive real-time predictions on plant identification. Continuous monitoring and updates will ensure the system's accuracy, reliability, and adaptability to changes in plant taxonomy, environmental conditions, and user feedback. By integrating advanced image processing techniques with machine learning algorithms, the proposed system aims to provide a valuable tool for researchers, healthcare professionals, and conservationists in accurately identifying medicinal plants and raw materials for various applications, including drug discovery, biodiversity monitoring, and sustainable resource management.

3.2.1 Advantages

1. **Enhanced Accuracy**: By leveraging state-of-the-art machine learning algorithms and preprocessing techniques, the proposed system aims to achieve higher accuracy in plant identification. Advanced models like EfficientNet and ResNet have demonstrated superior performance in image classification tasks, leading to more reliable identification results.
2. **Improved Coverage**: The comprehensive dataset compiled for training the machine learning models ensures a wide coverage of medicinal plant species and raw materials. This diversity enhances the system's ability to accurately identify plants across different morphologies, habitats, and geographic regions, addressing the limitation of limited coverage in existing systems.
3. **User-Friendly Interface**: The development of a user-friendly interface facilitates seamless interaction with the automated identification system. Users, including researchers, healthcare professionals, and enthusiasts, can easily upload images and receive real-time predictions on plant identification without requiring specialized botanical knowledge or technical expertise.
4. **Continuous Updates and Maintenance**: The proposed system incorporates mechanisms for continuous updates and maintenance, ensuring that the system remains up-to-date with changes in plant taxonomy, environmental conditions, and user feedback. Regular updates to the dataset and model retraining help to improve accuracy and reliability over time, addressing the challenge of outdated information in existing systems.

5. **Scalability and Adaptability**: With its scalable architecture and adaptable design, the proposed system can accommodate a growing volume of data and users. It can be easily extended to support additional plant species, features, and functionalities, making it suitable for various applications and research domains.
6. **Potential for Integration:** The proposed system has the potential to be integrated with existing platforms and databases, further enhancing its utility and interoperability. Integration with other systems, such as biodiversity databases or mobile applications, can broaden its reach and impact in botanical research, conservation, and practice.

3.3 Methodology

3.3.1 Description of the AI model development process

The development process of the AI model for the automated identification of medicinal plants and raw materials involves several key steps, as outlined below:

- Data Collection and Preprocessing**:** Gather a diverse dataset containing images of medicinal plants and raw materials from various sources. This dataset should cover a wide range of plant species, morphologies, and environmental conditions. Preprocess the dataset to enhance its quality and suitability for model training. This includes tasks such as image standardization, noise removal, resizing, and data augmentation to increase dataset diversity.

- Model Selection and Architecture Design**:** Choose appropriate deep learning architectures for the task of image classification. Common choices include convolutional neural networks (CNNs) such as EfficientNet and ResNet, known for their effectiveness in image recognition tasks. Design the architecture of the AI model, specifying the number of layers, kernel sizes, activation functions, and other hyperparameters. Fine-tune the model architecture based on the characteristics of the dataset and the complexity of the classification task.

- Training and Validation**:** Split the pre-processed dataset into training, validation, and testing sets. The training set is used to update the model's parameters during training, while the validation set is used to tune hyperparameters and monitor model performance. Train the AI model using the training set and monitor its performance on the validation set. Adjust hyperparameters as needed to optimize model performance, avoiding overfitting or underfitting.

- Model Evaluation**:** Evaluate the trained AI model's performance using the testing set, which contains unseen data not used during training or validation. Measure metrics such as accuracy, precision, recall, and F1 score to assess the model's effectiveness in classifying medicinal plants and raw materials.

- Fine-Tuning and Optimization**:** Fine-tune the AI model based on the evaluation results and feedback from model performance. This may involve adjusting hyperparameters, refining preprocessing techniques, or incorporating additional data to improve model accuracy and generalization.

- Deployment and Integration**:** Deploy the trained AI model into the production environment, integrating it with the user interface or application developed for plant identification. Continuously monitor the model's performance in real-world scenarios, collecting feedback from users and updating the model as needed to ensure ongoing accuracy and effectiveness.

3.3.2 Data collection for plant image datasets

Collecting a comprehensive dataset for plant image datasets involves several steps to ensure diversity, quality, and relevance. Here's a breakdown of the data collection process for the above project:

Identify Plant Species: Begin by compiling a list of medicinal plants and raw materials relevant to the project's scope. Consult botanical databases, literature, and domain experts to identify a wide range of plant species known for their medicinal properties.

- Gather Images: Collect images of the identified plant species from various sources, including:

- Online databases: Access publicly available botanical databases and repositories containing images of medicinal plants. Websites like the USDA Plants Database, Tropics and Flora of North America provide valuable resources for plant images.

- Scientific literature: Extract images from research articles, journals, and botanical studies focusing on medicinal plants and their identification.

- Field surveys: Conduct field surveys to capture high-quality images of medicinal plants in their natural habitats. Ensure proper documentation of plant species, location, and environmental conditions during the surveys.

- Crowdsourcing: Engage citizen scientists, botanical enthusiasts, and researchers to contribute images of medicinal plants to the dataset. Leverage crowdsourcing platforms or citizen science projects to gather diverse image samples.

- Ensure Diversity: Ensure diversity in the dataset by including images of plants from various geographic regions, habitats, growth stages, and environmental conditions. Incorporate images with different resolutions, angles, lighting conditions, and backgrounds to capture the variability in plant appearances.

- Quality Assurance: Perform quality checks on the collected images to ensure they meet the desired standards:

- Image resolution: Ensure images have sufficient resolution and clarity for accurate identification.

- Authenticity: Verify the authenticity and correctness of plant species labels associated with each image.

- Consistency: Maintain consistency in image format, orientation, and aspect ratio to facilitate preprocessing and model training.

- Annotation and Metadata: Annotate the images with relevant metadata, including plant species labels, botanical names, geographic location, date of capture, and any additional information pertinent to the plant's identification and classification.

- Ethical Considerations: Adhere to ethical guidelines and legal regulations governing the collection and use of plant images, especially if images are sourced from protected areas, private properties, or third-party sources.

- Documentation and Versioning: Document the data collection process thoroughly, including sources, annotations, and any preprocessing steps applied to the images. Maintain version control to track changes and updates to the dataset over time.

3.3.3 Details of the algorithm and software used

For the project focused on automating the identification process of medicinal plants and raw materials through image processing and machine learning, several algorithms and software tools are utilized to develop and implement the automated plant recognition system. The primary algorithms employed include convolutional neural networks (CNNs), particularly state-of-the-art architectures such as EfficientNet and ResNet. These CNNs are chosen for their proven effectiveness in image classification tasks, which makes them well-suited for accurately identifying plant species from images. Additionally, preprocessing techniques such as standardization, noise removal, and data augmentation are applied to enhance the quality and diversity of the dataset, ensuring optimal performance of the machine learning models.

The software tools used for implementing the project include Python programming language along with popular libraries and frameworks for deep learning and image processing tasks. Specifically, libraries such as TensorFlow or PyTorch are employed for building and training the CNN models, providing comprehensive support for developing complex neural network architectures and optimizing model performance. Moreover, libraries like OpenCV are utilized for image preprocessing tasks, offering a wide range of functions for manipulating and enhancing images before feeding them into the CNN models.

In addition to the core algorithms and software mentioned above, the project may involve the development of a user-friendly interface for interacting with the automated plant recognition system.

3.3.4 User role definitions and interactions

In the project focused on automating the identification process of medicinal plants and raw materials through image processing and machine learning, various user roles and their interactions with the system can be defined as follows:

Administrators:

Administrators have full control over the system, including user management, data management, and system configuration.

They are responsible for adding and removing users, assigning roles and permissions, and overseeing system operations.

Administrators may also manage the dataset, including uploading new images, updating annotations, and maintaining data integrity.

Researchers:

Researchers are primary users who utilize the system for conducting botanical research, identifying medicinal plants, and analyzing plant species.

They interact with the system to upload images of medicinal plants and raw materials, initiate plant identification tasks, and review identification results.

Researchers may explore additional features of the system, such as accessing detailed plant information, viewing classification metrics, and analyzing trends in plant identification.

Healthcare Professionals:

Healthcare professionals, such as pharmacists, herbalists, or clinicians, utilize the system to identify medicinal plants for therapeutic purposes.

They upload images of plants encountered in clinical practice, receive automated identification results, and access supplementary information on plant properties, uses, and potential therapeutic benefits.

Healthcare professionals may integrate the system into their workflow to assist in prescribing herbal remedies, formulating botanical preparations, or advising patients on plant-based therapies.

Enthusiasts and Citizen Scientists:

Enthusiasts and citizen scientists are casual users who engage with the system out of interest in botany, conservation, or nature photography.

They upload images of plants encountered in their environment, such as during hikes, nature walks, or gardening activities, to learn about plant species and contribute to biodiversity monitoring efforts.

Enthusiasts may use the system to explore plant identification features, learn about plant taxonomy, and participate in citizen science projects focused on plant diversity and distribution.

System Interactions:

Users interact with the system through a user-friendly interface, which allows them to upload images, initiate plant identification tasks, and view identification results.

Upon uploading an image, the system processes the image using machine learning algorithms, classifies the plant species, and provides automated identification results in real-time.

Users may explore additional functionalities of the system, such as accessing plant profiles, viewing diagnostic features, and contributing feedback on identification accuracy.

The system may also incorporate features for collaborative annotation, allowing users to contribute annotations, corrections, or additional information to improve the dataset and model performance over time.

3.3.5 Ethical considerations and data privacy measures

In the project aiming to automate the identification process of medicinal plants and raw materials through image processing and machine learning, a strong emphasis is placed on ethical considerations and data privacy measures to ensure responsible and secure handling of data. To begin with, obtaining informed consent from human participants, if applicable, is paramount, ensuring that individuals fully understand and consent to the use of their images in the project. Additionally, clarifying data ownership and intellectual property rights ensures that contributors retain appropriate ownership rights to their images, fostering transparency and fairness in data usage.

Ethical data handling practices extend to anonymization and de-identification techniques, which safeguard sensitive information by removing personally identifiable details from the dataset. Robust data security measures, such as encryption, access controls, and regular security audits, are implemented to protect the confidentiality and integrity of the collected data, mitigating the risk of unauthorized access or breaches.

3.4 System Analysis

System Analysis is the process of studying a system in detail to understand its components, requirements, and workflow. It involves identifying problems, defining objectives, and designing solutions to improve efficiency and effectiveness.

3.4.1 Feasibility Study

The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

Three key considerations involved in the feasibility analysis are

- ECONOMICAL FEASIBILITY
- TECHNICAL FEASIBILITY
- SOCIAL FEASIBILITY

3.4.2 Economical Feasibility

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus, the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased

3.4.3 Technical Feasibility

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system

3.4.4 Social Feasibility

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

3.4.5 Operational Feasibility

Operational feasibility focuses on whether a system can function effectively within an organization's existing workflows and processes. It evaluates if the system meets business needs, integrates with current operations, and enhances productivity. For instance, an inventory management system in a retail store should streamline stock tracking without disrupting daily operations. If a system is operationally feasible, it ensures smooth implementation and efficient performance.

3.5 Requirement Analysis

Requirement analysis is the process of identifying, gathering, and defining user and stakeholder needs for a system. It ensures the system meets business goals and functions as intended. Techniques like interviews, surveys, and document analysis help collect functional (system behavior) and non-functional (performance, security) requirements. Proper documentation, such as SRS, ensures clear communication, reducing misunderstandings and streamlining development**.**

3.5.1 Functional Requirements

Functional Requirements define what a system should do. They specify system behavior, features, and functionalities

1. **Medicinal Plant Identification**
   - The system must be able to identify medicinal plants accurately based on input images.
2. **Extended CNN-Based Classification**
   - The model should implement an Extended Convolutional Neural Network (CNN) to classify medicinal plants effectively.
3. **Handling Image Variability**
   - The system should account for variations in lighting, angles, and background clutter to improve recognition accuracy.
4. **Training Data Utilization**
   - The model must leverage diverse and extensive training datasets to minimize biases and enhance classification performance.
5. **Integration of Specialized Architectures**
   - The system should incorporate advanced architectures such as ResNet and DenseNet to improve feature extraction and classification accuracy.
6. **Training Data Augmentation**
   - The model should include data augmentation techniques to enhance the diversity of training samples and improve robustness.

7. **Performance Evaluation**
    - The system must compare the accuracy of the Extended CNN model with traditional techniques to validate its effectiveness.
8. **User Input and Image Processing**
    - The system should accept images of medicinal plants as input, preprocess them, and classify them accordingly.
9. **Output Generation**

    The system must provide accurate classification results, including plant names and confidence scores, for practical applications.

3.5.2 Non-Functional Requirements

Non-Functional Requirements define how a system should perform. They focus on system quality, performance, and constraints. These are basically the quality constraints that the system must satisfy according to the project contract. The priority or extent to which these factors are implemented varies from one project to other. They are also called non-behavioral requirements.

- **Performance:**
  The system should ensure high detection speed and accuracy, minimizing false positives and false negatives while processing large datasets efficiently.
- **Scalability:**
  The system must be able to scale and handle increased traffic, ensuring real-time phishing detection for large volumes of websites without performance degradation.
- **Security:**
  The system must ensure secure handling of sensitive user data and prevent tampering with the ML models or detection process to maintain the integrity of the results.
- **Reliability:**
  The system should ensure consistent uptime and availability, especially during high-demand periods, to reliably detect phishing websites at all times.

- **Usability:**
  The system should have an intuitive interface for end-users, providing clear, understandable alerts and explanations for detected phishing sites without requiring deep technical knowledge

3.6 System Requirements

3.6.1 Software Requirements

Software's	:	Python 3.6 or high version
IDE	:	Visual Studio Code
Framework	:	Deep Learning Frame works (TensorFlow)

3.6.2 Hardware Requirements

Operating system	:	Windows 7 or 7+
RAM	:	8 GB or more
Hard disc or SSD	:	More than 500 GB
Processor	:	Intel 3rd generation or high or Ryzen with 8 GB Ram

CHAPTER 4

SYSTEM DESIGN AND ARCHITECTURE

4.1 System Architecture

System architecture is a conceptual model that describes the structure and behavior of multiple components and subsystems.

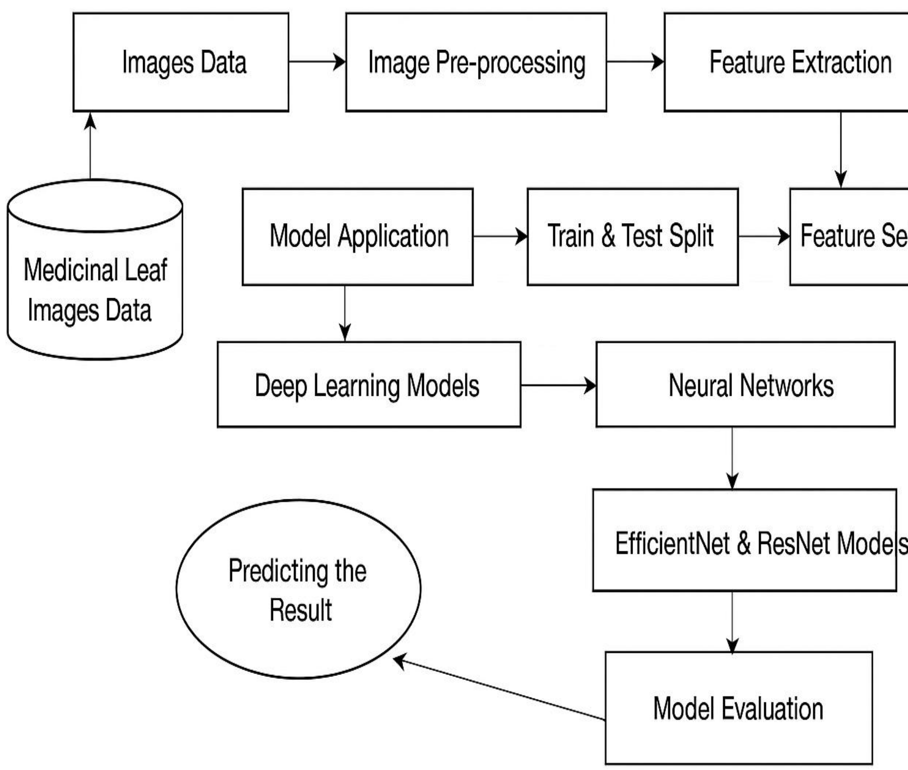


Fig 4.1.1 System Architecture

4.2 Input Design

The design encompasses various aspects related to user inputs and their objectives, as outlined below:

User-Friendly Interface: The primary objective of the system input design is to create a user-friendly interface that enables users to interact with the system effortlessly. This involves designing intuitive user interfaces with clear navigation, well-organized layouts, and user-friendly controls for uploading images and initiating plant identification tasks.

Image Upload: The system allows users to upload images of medicinal plants and raw materials for identification. The input design should support various file formats (e.g., JPEG, PNG) and provide mechanisms for uploading single or multiple images conveniently.

Real-Time Feedback: The system provides real-time feedback to users during the image upload process, indicating the progress of the identification task and any errors or issues encountered. This objective ensures that users are informed about the status of their requests and can take appropriate actions if necessary**.**

Error Handling: Effective error handling mechanisms are integrated into the input design to detect and address common errors or invalid inputs from users. Clear error messages and prompts are displayed to guide users in resolving issues and resubmitting their requests.

Metadata Collection: In addition to image data, the system may collect metadata associated with uploaded images, such as timestamps, geographic location, and user-provided annotations. The input design includes fields or prompts for capturing relevant metadata to enrich the dataset and improve the accuracy of plant identification**.**

Accessibility: The input design considers accessibility requirements to ensure that users with diverse needs and abilities can interact with the system effectively. This may involve providing alternative input methods, such as voice commands or keyboard shortcuts, and adhering to accessibility standards for web-based interfaces.

Security Measures: Security measures are implemented in the input design to protect user data and prevent unauthorized access. This includes mechanisms for securely handling and transmitting images, encrypting sensitive information, and implementing user authentication and authorization controls.

Scalability: The input design is scalable to accommodate varying levels of user demand and system load. This involves optimizing input processing workflows, leveraging asynchronous processing techniques, and provisioning resources dynamically to handle spikes in user activity.

4.3 Output Design

The design encompasses various aspects related to presenting output information and achieving specific objectives, as outlined below:

Identification Results Display: The primary objective of the output system design is to display the identification results to users in a visually appealing and comprehensible format. This involves presenting the identified plant species, confidence scores or probabilities, and any additional information or metadata associated with the identification.

Confidence Levels and Uncertainty: The output design may include confidence levels or uncertainty estimates associated with the identification results to convey the reliability or uncertainty of the classification. This objective helps users interpret the identification results and make informed decisions based on the level of confidence.

User Interaction: The output system design enables user interaction with the identification results, allowing users to explore additional information, provide feedback, or take further actions based on the results. This objective enhances user engagement and satisfaction with the system.

4.4 UML Diagrams

UML stands for Unified Modelling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed and was created by, the Object Management Group.

UML is a very important part of developing object-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS: The Primary goals in the design of the UML are as follows:

1. Provide users with a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.
2. Provide extensibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modeling language.
5. Encourage the growth of the OO tools market.
6. Support higher-level development concepts such as collaborations, frameworks, patterns, and components.
7. Integrate best practices.

4.4.1 Use Case Diagram

A use-case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis.

Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases (4.4.1).

The main purpose of a use case diagram is to show what system functions are performed for which actor. The roles of the actors in the system can be depicted system can be depicted.

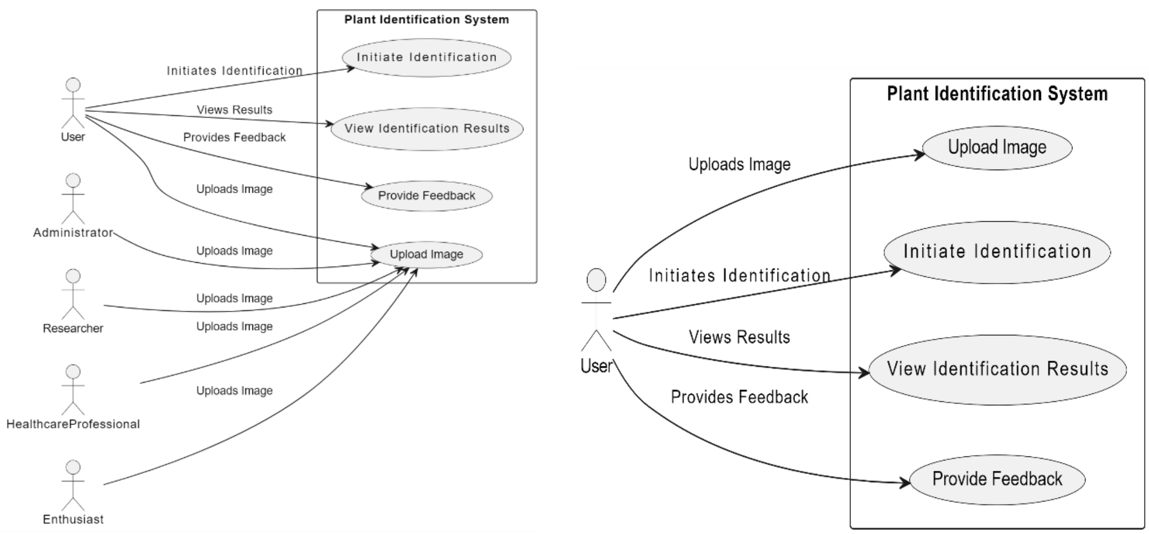


Fig 4.4.1 Use Case Diagram

4.4.2 Class Diagram

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, attributes, operations (or methods), and the relationships among the classes. It explains which class contains information(4.4.2).

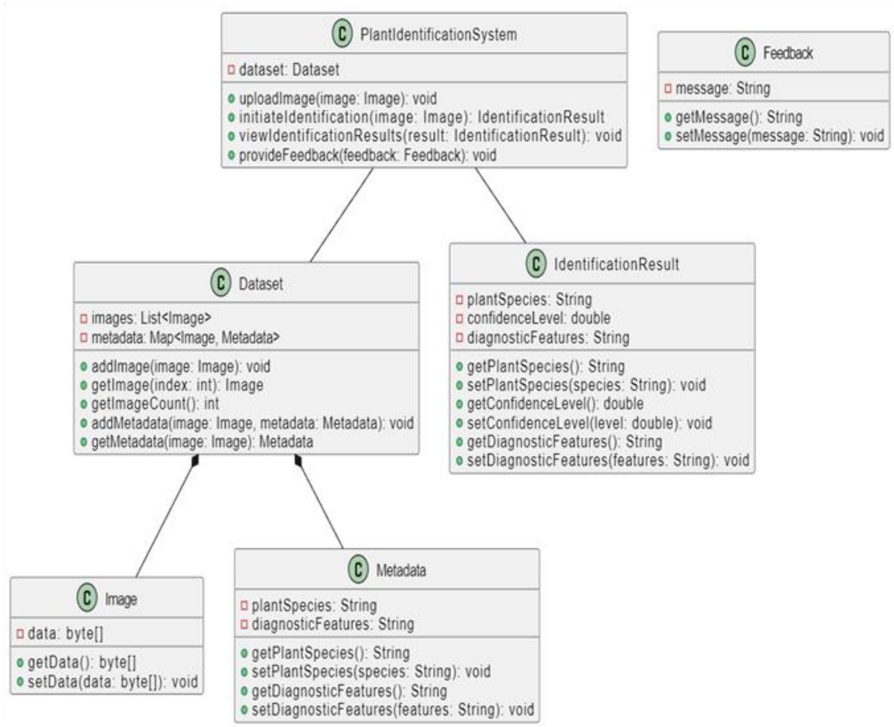


Figure 4.4.2 Class diagram

4.4.3 Sequence Diagram

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams(4.4.3).

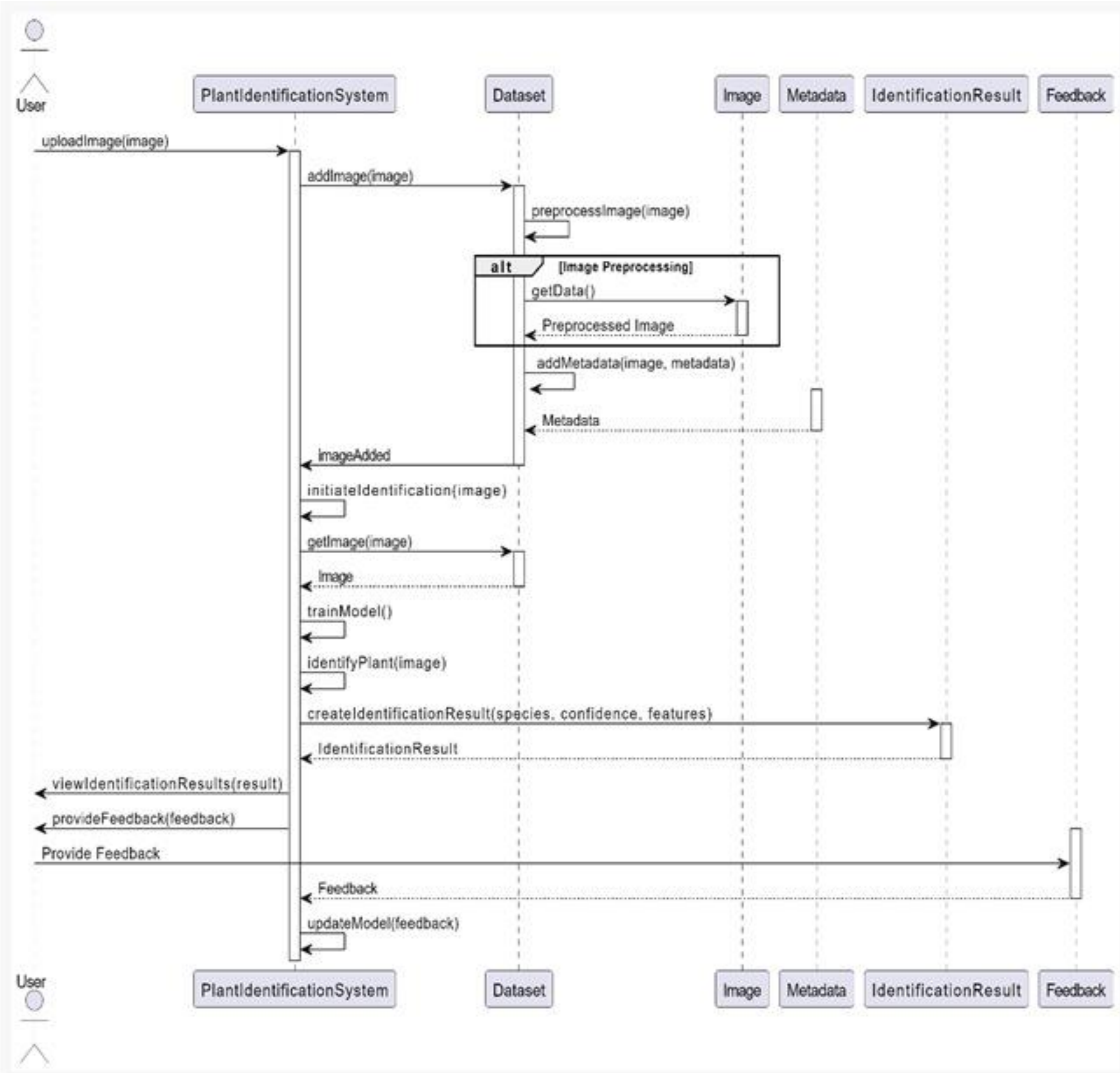


Fig 4.4.3 Sequence Diagram

4.4.4 Collaboration Diagram

In the collaboration diagram, the method call sequence is indicated by some numbering technique as shown below. The number indicates how the methods are called one after another. We have taken the same order management system to describe the collaboration diagram(4.4.4). The method calls are similar to that of a sequence diagram. But the difference is that the sequence diagram does not describe the object organization whereas the collaboration diagram shows the object organization.

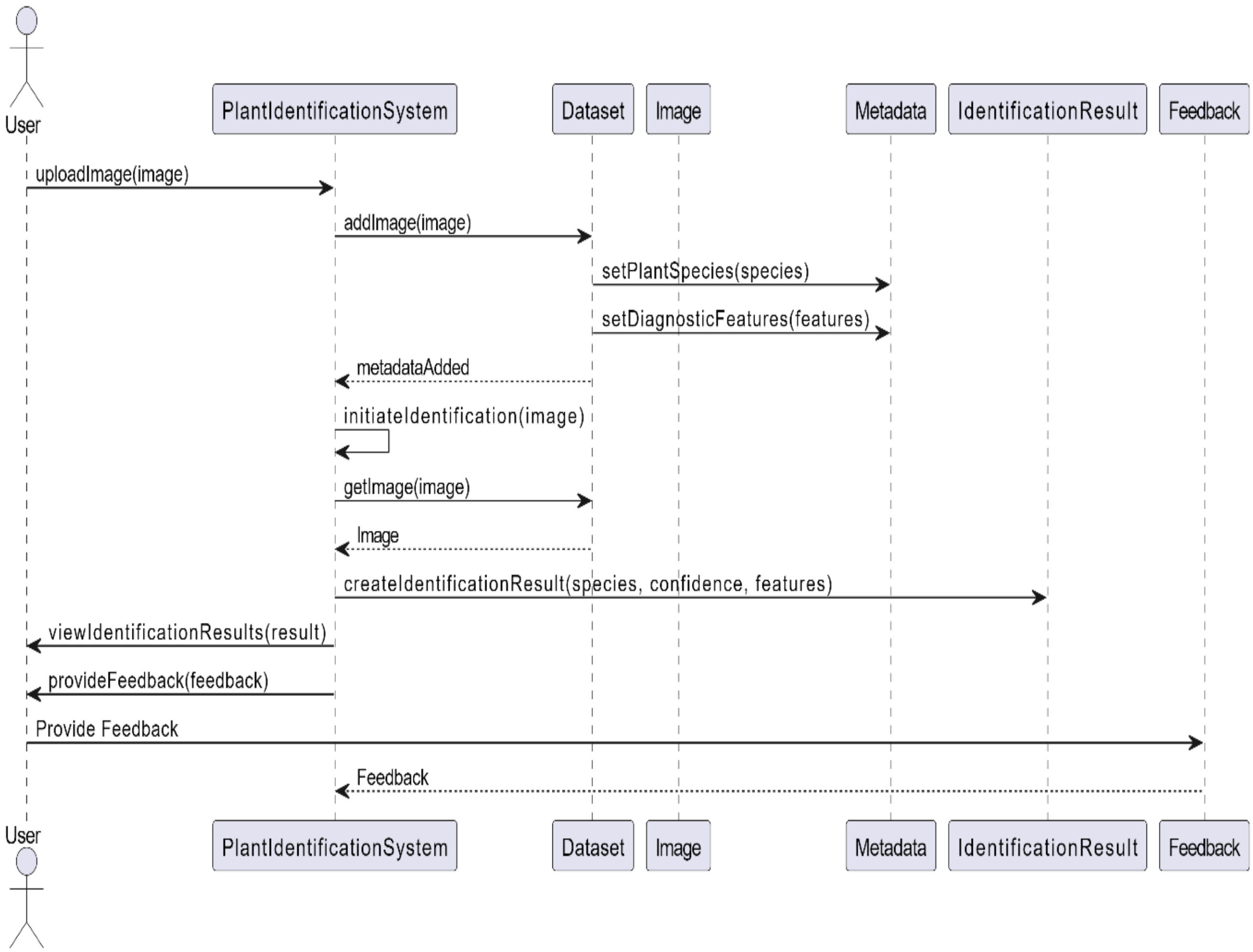


Fig 4.4.4 Collaboration diagram

4.4.5 Component Diagram

A component diagram, also known as a UML component diagram, describes the organization and wiring of the physical **c**omponents in a system. Component diagrams are often drawn to help model implementation details and double-check that every aspect of the system's required function is covered by planned development(4.4.5).

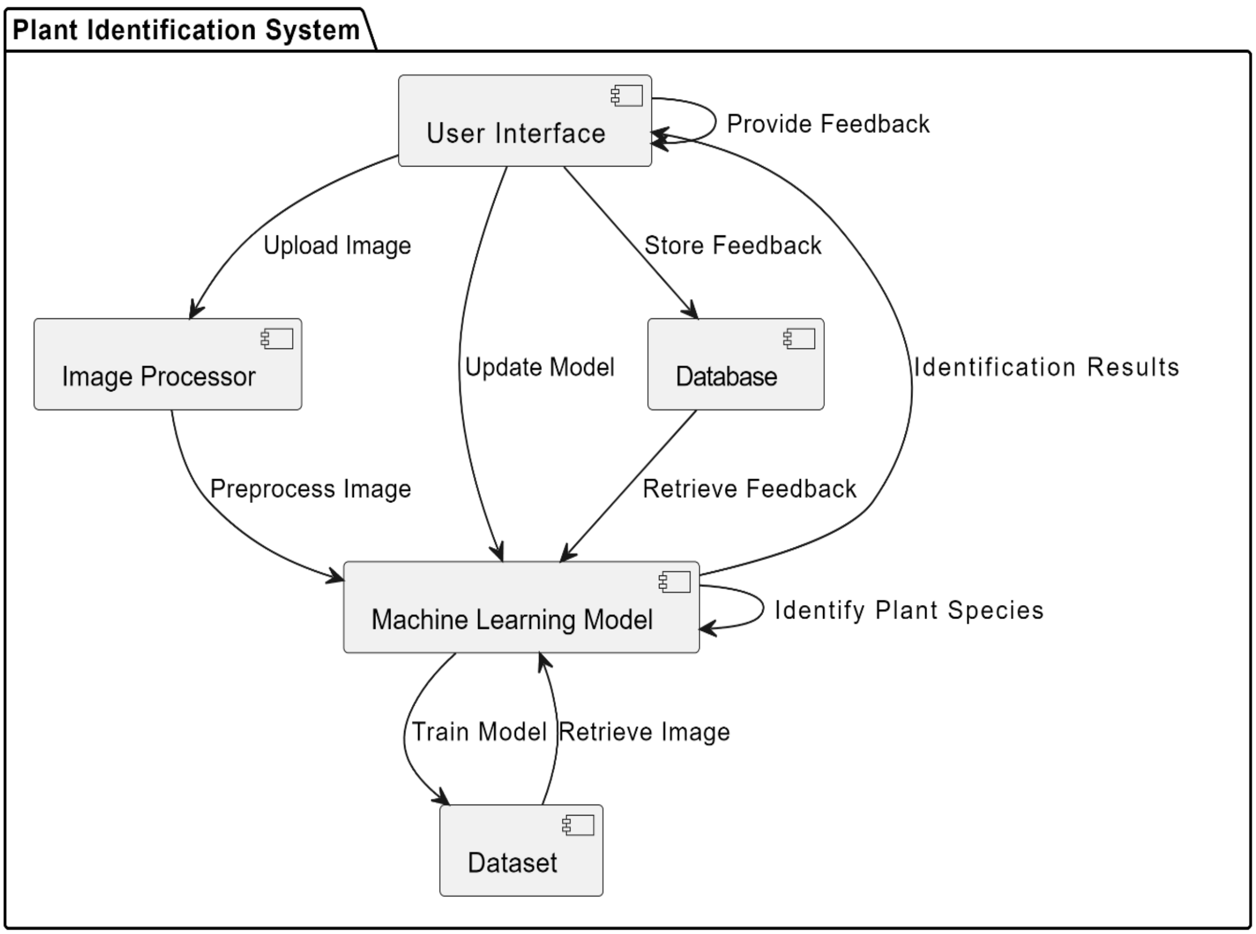


Fig 4.4.5 Component Diagram

4.4.6 DFD Diagram

A Data Flow Diagram (DFD) is a traditional way to visualize the information flows within a system. A neat and clear DFD can depict a good amount of the system requirements graphically. It can be manual, automated, or a combination of both. It shows how information enters and leaves the system, what changes the information and where information is stored. The purpose of a DFD is to show the scope and boundaries of a system as a whole(4.4.6).

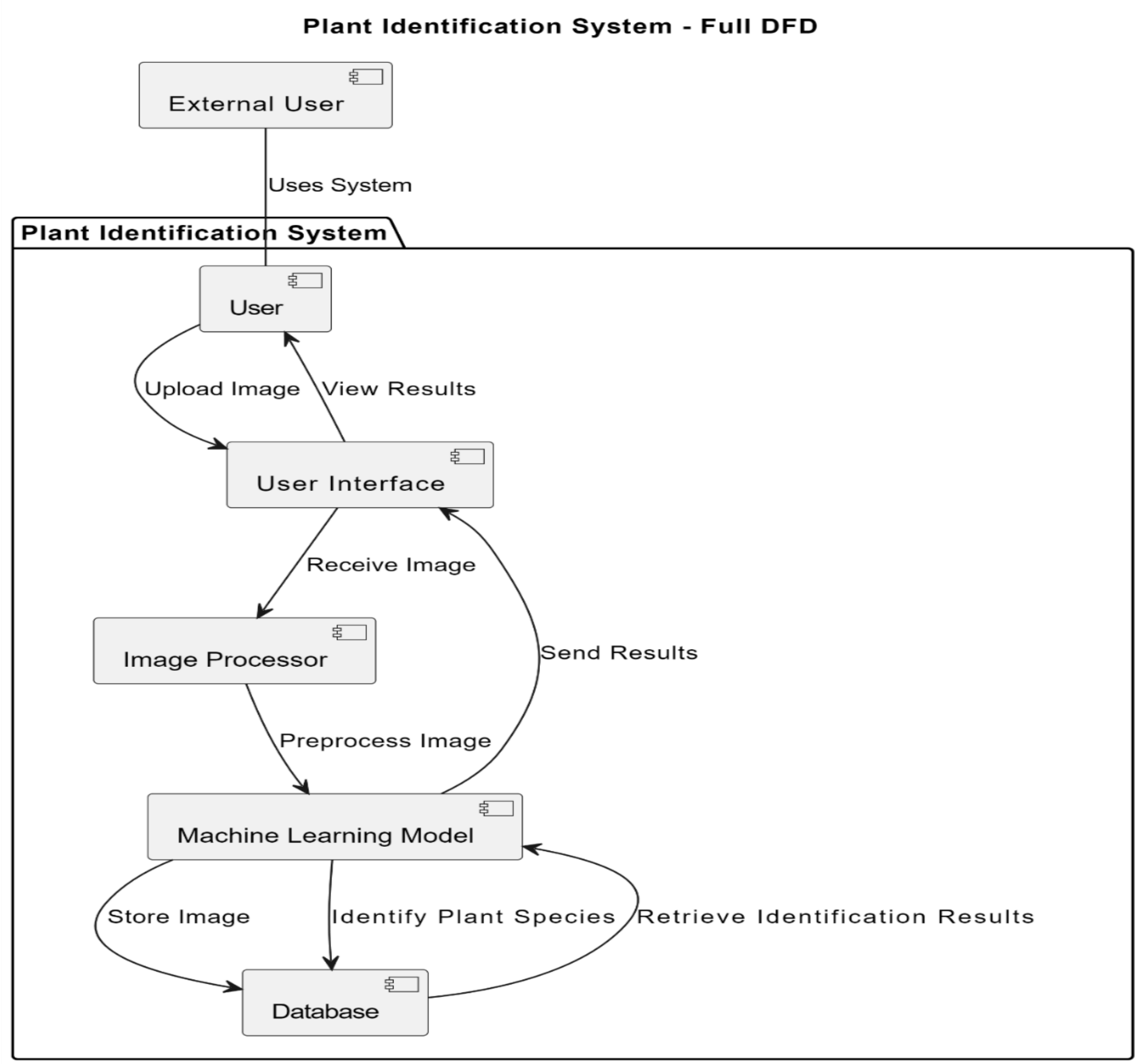


Fig 3.6.6 DFD Diagram

4.5 Database Design

Database design is a crucial step in the development of any software system, ensuring efficient data storage, retrieval, and management. It involves structuring the database to optimize performance, maintain integrity, and support scalability.

Tables Created for Plantify Project:

- User
- Admin
- OTP
- Prediction
- Medicinal_plants
- Medicinal_plants_diseases

```
mysql> DESCRIBE otp;
+------------+--------------+------+-----+---------+----------------+
| Field      | Type         | Null | Key | Default | Extra          |
+------------+--------------+------+-----+---------+----------------+
| id         | int          | NO   | PRI | NULL    | auto_increment |
| email      | varchar(100) | NO   | UNI | NULL    |                |
| otp        | varchar(6)   | NO   |     | NULL    |                |
| created_at | datetime     | YES  |     | NULL    |                |
| expires_at | datetime     | YES  |     | NULL    |                |
+------------+--------------+------+-----+---------+----------------+
5 rows in set (0.00 sec)

mysql> DESCRIBE admin;
+------------+--------------+------+-----+---------+----------------+
| Field      | Type         | Null | Key | Default | Extra          |
+------------+--------------+------+-----+---------+----------------+
| id         | int          | NO   | PRI | NULL    | auto_increment |
| username   | varchar(100) | NO   | UNI | NULL    |                |
| password   | varchar(255) | NO   |     | NULL    |                |
| created_at | datetime     | YES  |     | NULL    |                |
| role       | varchar(50)  | YES  |     | NULL    |                |
+------------+--------------+------+-----+---------+----------------+
5 rows in set (0.00 sec)
```

MySQL 8.0 Command Line Cli

```
mysql> DESCRIBE medicinal_plants;
+-----------------+--------------+------+-----+---------+----------------+
| Field           | Type         | Null | Key | Default | Extra          |
+-----------------+--------------+------+-----+---------+----------------+
| id              | int          | NO   | PRI | NULL    | auto_increment |
| common_name     | varchar(255) | NO   |     | NULL    |                |
| description     | text         | YES  |     | NULL    |                |
| scientific_name | varchar(255) | NO   |     | NULL    |                |
| uses            | text         | YES  |     | NULL    |                |
| origin          | text         | YES  |     | NULL    |                |
| availability    | varchar(255) | YES  |     | NULL    |                |
| related_species | varchar(255) | YES  |     | NULL    |                |
| climate         | varchar(255) | YES  |     | NULL    |                |
| soil            | varchar(255) | YES  |     | NULL    |                |
| image_name      | varchar(255) | NO   |     | NULL    |                |
| status          | varchar(20)  | YES  |     | pending |                |
+-----------------+--------------+------+-----+---------+----------------+
12 rows in set (0.01 sec)

mysql> DESCRIBE medicinal_plants_diseases;
+-------------------------+--------------+------+-----+---------+----------------+
| Field                   | Type         | Null | Key | Default | Extra          |
+-------------------------+--------------+------+-----+---------+----------------+
| id                      | int          | NO   | PRI | NULL    | auto_increment |
| disease_name            | varchar(255) | NO   | UNI | NULL    |                |
| description             | text         | YES  |     | NULL    |                |
| medicinal_plants_used   | text         | YES  |     | NULL    |                |
| comabination            | varchar(255) | YES  |     | NULL    |                |
| combination_description | text         | NO   |     | NULL    |                |
| image_name_one          | varchar(255) | NO   |     | NULL    |                |
| image_name_two          | varchar(255) | NO   |     | NULL    |                |
| image_name_three        | varchar(255) | NO   |     | NULL    |                |
+-------------------------+--------------+------+-----+---------+----------------+
9 rows in set (0.01 sec)
```

```
mysql> DESCRIBE user;
+-------------------+--------------+------+-----+---------+----------------+
| Field             | Type         | Null | Key | Default | Extra          |
+-------------------+--------------+------+-----+---------+----------------+
| id                | int          | NO   | PRI | NULL    | auto_increment |
| name              | varchar(100) | NO   |     | NULL    |                |
| email             | varchar(100) | NO   | UNI | NULL    |                |
| password          | varchar(255) | NO   |     | NULL    |                |
| mobile            | varchar(20)  | NO   |     | NULL    |                |
| dob               | date         | NO   |     | NULL    |                |
| security_question | varchar(255) | NO   |     | NULL    |                |
| security_answer   | varchar(255) | NO   |     | NULL    |                |
| status            | varchar(20)  | YES  |     | NULL    |                |
| created_at        | datetime     | YES  |     | NULL    |                |
+-------------------+--------------+------+-----+---------+----------------+
10 rows in set (0.00 sec)

mysql> DESCRIBE prediction;
+-----------------+-------------+------+-----+---------+----------------+
| Field           | Type        | Null | Key | Default | Extra          |
+-----------------+-------------+------+-----+---------+----------------+
| id              | int         | NO   | PRI | NULL    | auto_increment |
| user_id         | int         | NO   | MUL | NULL    |                |
| prediction_type | varchar(50) | NO   |     | NULL    |                |
| input_data      | text        | NO   |     | NULL    |                |
| result          | text        | NO   |     | NULL    |                |
| created_at      | datetime    | YES  |     | NULL    |                |
| status          | varchar(20) | YES  |     | NULL    |                |
+-----------------+-------------+------+-----+---------+----------------+
7 rows in set (0.00 sec)
```

```
mysql> select * from prediction;
+-----+---------+-----------------+-----------------------------------------------+------------+---------------------+-----------+
| id  | user_id | prediction_type | input_data                                    | result     | created_at          | status    |
+-----+---------+-----------------+-----------------------------------------------+------------+---------------------+-----------+
| 182 |       8 | herbal          | OIP (1).jpeg                                  | Bamboo     | 2025-02-19 05:14:43 | completed |
| 183 |       8 | herbal          | OIP.jpeg                                      | Ashoka     | 2025-02-19 05:16:10 | completed |
| 184 |       8 | herbal          | WhatsApp Image 2025-02-15 at 11.29.22_09fb94bf.jpg | Rose  | 2025-02-19 08:54:17 | completed |
| 185 |       8 | herbal          | download.jpg                                  | Mint       | 2025-02-19 08:54:50 | completed |
| 186 |       8 | herbal          | OIP (3).jpeg                                  | Curry_Leaf | 2025-02-19 08:55:02 | completed |
| 187 |       8 | herbal          | OIP (2).jpeg                                  | Aloevera   | 2025-02-19 08:55:11 | completed |
| 188 |       8 | herbal          | OIP (1).jpg                                   | Bamboo     | 2025-02-19 08:55:26 | completed |
| 189 |       8 | herbal          | Aloevera.jpg                                  | Aloevera   | 2025-02-19 08:55:56 | completed |
| 190 |       8 | herbal          | OIP (12).jpg                                  | Mint       | 2025-02-19 08:56:15 | completed |
| 191 |       8 | herbal          | OIP (5).jpeg                                  | Ashoka     | 2025-02-19 08:57:35 | completed |
```

CHAPTER 5

IMPLEMENTATION

5.1 Deep Learning Algorithms

5.1.1 EfficientNet

EfficientNet is a 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.

Here are some key characteristics and components of the EfficientNet model:

Architecture: EfficientNet 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 a shrewdly methodology.

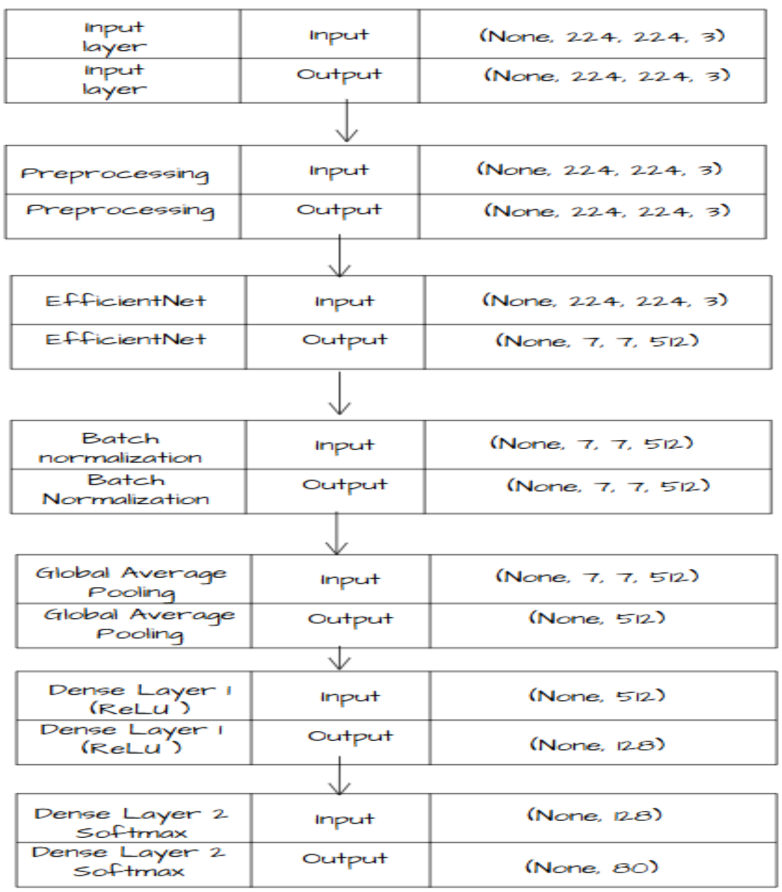


Fig 5.1.1.1: Architecture Image

Compound Scaling: EfficientNet uses a compound scaling method to balance width, depth, and resolution systematically. This allows it to achieve higher accuracy with fewer parameters compared to traditional CNN architectures.

Depth-wise Separable Convolutions: EfficientNet employs depth-wise separable convolutions, reducing the number of parameters and improving efficiency while maintaining feature extraction capability.

Squeeze-and-Excitation (SE) Blocks: EfficientNet integrates SE blocks to enhance feature learning by adaptively recalibrating channel-wise feature responses. This improves model performance without significantly increasing computational cost.

Pretrained Weights: EfficientNet models are pretrained on large datasets like ImageNet, making them highly useful for transfer learning. Fine-tuning with pretrained weights leads to faster convergence and improved accuracy on smaller datasets.

Activation Functions EfficientNet often uses the Swish activation function (shown in Fig 5.1.1.1), which helps in smooth gradient flow and better representation learning the network and facilitate the learning of complex patterns and representations in the input data.

Overall, EfficientNet is a powerful and versatile convolutional neural network architecture that has been widely used for various computer vision tasks, including image classification, object detection, and image segmentation. Its modular design and efficient utilization of computational resources make it well-suited for real-world applications requiring high-performance image recognition capabilities.

5.1.2 ResNet

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.

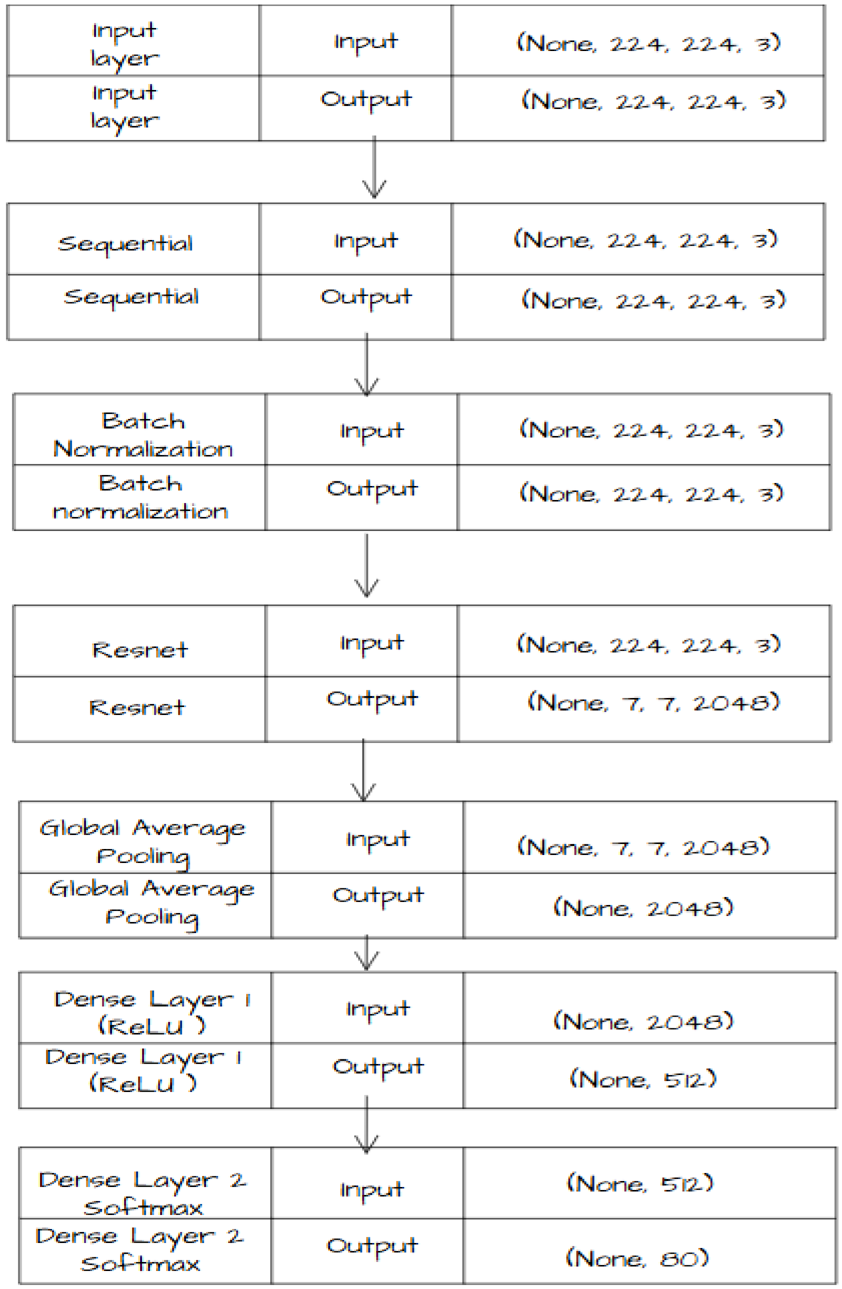


Fig 5.1.2.1: Architecture Image

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 (Fig 5.1.2.1). Highlights are down examined through max pooling and stride-2 convolutional layers which capture vital information whereas diminishing the generally estimate.

5.1.3 Code

```
import tensorflow as tf
from tensorflow.keras.preprocessing import image_dataset_from_directory
from tensorflow.keras.applications import EfficientNetB0
from tensorflow.keras.applications.efficientnet import preprocess_input
from tensorflow.keras.layers import Dense, Flatten, GlobalAveragePooling2D
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import classification_report
import numpy as np

batch_size = 32
img_size = (224, 224)
train_dataset = image_dataset_from_directory(
    root_dir,
    validation_split=0.2,
    subset="training",
    seed=42,
    image_size=img_size,
    batch_size=batch_size
)

val_dataset = image_dataset_from_directory(
  root_dir,
    validation_split=0.2,
    subset="validation",
    seed=42,
```

```
    image_size=img_size,
    batch_size=batch_size
)
```

Class names

```
class_names = train_dataset.class_names
num_classes = len(class_names)
print(f"Classes: {class_names}, Total Classes: {num_classes}")

# Normalize and preprocess images
def preprocess (image, label):
    image = preprocess_input(image)  # Apply EfficientNet preprocessing
    return image, label

train_dataset = train_dataset.map(preprocess).cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
val_dataset = val_dataset.map(preprocess).cache().prefetch(buffer_size=tf.data.AUTOTUNE)
```

Load pre-trained EfficientNet

```
base_model = EfficientNetB0(weights="imagenet", include_top=False, input_shape=(224, 224, 3))

# Freeze the base model
base_model.trainable= False

# Add classification head
x = GlobalAveragePooling2D()(base_model.output)
```

```
x = Dense(128, activation='relu')(x)

x = Dense(num_classes, activation="softmax")(x)  # Multi-class classification

# Create final model

model = Model(inputs=base_model.input, outputs=x)


# Compile model

model.compile(optimizer=Adam(learning_rate=0.001), loss="sparse_categorical_crossentropy",
metrics=["accuracy"])


# Summary

model.summary()
```

Train the model

```
Epochs = 2  # Adjust as needed

history = model.fit(train_dataset, validation_data=val_dataset, epochs=epochs)
```

Load test dataset

```
test_dataset = image_dataset_from_directory(

   root_dir,

   image_size=img_size,

   batch_size=batch_size

)


# Preprocess test dataset

test_dataset = test_dataset.map(preprocess).cache().prefetch(buffer_size=tf.data.AUTOTUNE)
```

Evaluate model

test_loss, test_acc = model.evaluate(test_dataset)

print(f"Test Accuracy: {test_acc:.4f}")

Get true labels and predictions and classification report

```
y_true, y_pred = [], []

for images, labels in test_dataset:
    preds = model.predict(images)
    y_pred.extend(np.argmax(preds, axis=1))
    y_true.extend(labels.numpy())

print(classification_report(y_true, y_pred, target_names=class_names, digits=4))
```

Model saving

```
model.save("../models/EfficientNetModel.h5")
print("Model saved as 'EffcientNetModel.h5'")
```

5.2 Visual Studio Code

Visual Studio Code (VS Code) is a widely used integrated development environment (IDE) known for its lightweight yet powerful features. It provides a user-friendly interface with extensive support for various programming languages, including Python. With features such as syntax highlighting, IntelliSense code completion, and integrated Git control, VS Code streamlines the development process and enhances productivity. Its vast ecosystem of extensions allows developers to customize their workflow according to their preferences and project requirements, making it an ideal choice for developing Python applications.

5.3 Python Flask Server

Python Flask is a lightweight and versatile web framework that simplifies the process of building web applications in Python. With its minimalist design and easy-to-use syntax, Flask offers developers the flexibility to create web services and APIs quickly and efficiently. Flask's modular structure allows for easy integration with other Python libraries and frameworks, making it suitable for a wide range of web development tasks. By leveraging Flask, Plantify can implement robust server-side functionality, handle HTTP requests, and serve dynamic web content with ease, providing a seamless user experience.

CHAPTER 6

TESTING AND RESULTS

6.1 Testing Methodologies

Software testing methodologies define structured approaches to ensure the quality, reliability, and security of an application**.**

6.1.1 Unit Testing

Unit testing focuses on testing individual components or functions of the application in isolation. It ensures that each module works correctly before integration**.**

Example:

1**.**Testing Flask API endpoints (e.g., /upload_plant, /get_plant_details).

2.Validating the image processing function for plant identification.

6.1.2 Integration Testing

Integration testing checks if different modules of the system work together correctly. It ensures seamless interaction between backend, frontend, and database.

Example:

1.Testing interactions between the frontend and Flask API.

2.Verifying image upload, processing, and storage.

6.1.3 System Testing

System testing evaluates the entire application to verify that it meets all functional and non-functional requirements. It tests the system as a whole before deployment.

Example:

1.Ensuring plant identification works correctly for different image inputs.

6.2 Testing Results

	Test Case Description	Expected Output	Actual Output	Pass/Fail
1	**Importing the Libraries**	Libraries should import without any errors	Libraries imported without errors	Pass
2	**Collecting the Image Data**	Collect images from dataset and load into the model	Images collected and loaded successfully	Pass
3	**Data Preprocessing**	Preprocess the images for normalization and resizing	Images preprocessed without errors	Pass
4	**Data Augmentation**	Apply rotation, flipping, and zooming to augment data	Data augmented successfully	Pass
5	**Splitting Data into Train & Test Sets**	Split data into 70% training and 30% testing	Data split successfully	Pass
6	**Loading Pre-trained EfficientNet Model**	Load pre-trained EfficientNet model	EfficientNet model loaded successfully	Pass
7	**Loading Pre-trained ResNet Model**	Load pre-trained ResNet model	ResNet model loaded successfully	Pass
8	**Training the Model**	Train the ResNet and EfficientNet models on the training data	Models trained successfully without errors	Pass
9	**Model Evaluation**	Evaluate model performance using test dataset	Model evaluated successfully with high accuracy	Pass
10	**Predict the Results**	Input an image and predict the class using the trained models	Correct prediction with confidence score displayed	Pass

Fig 6.2 Testing Report

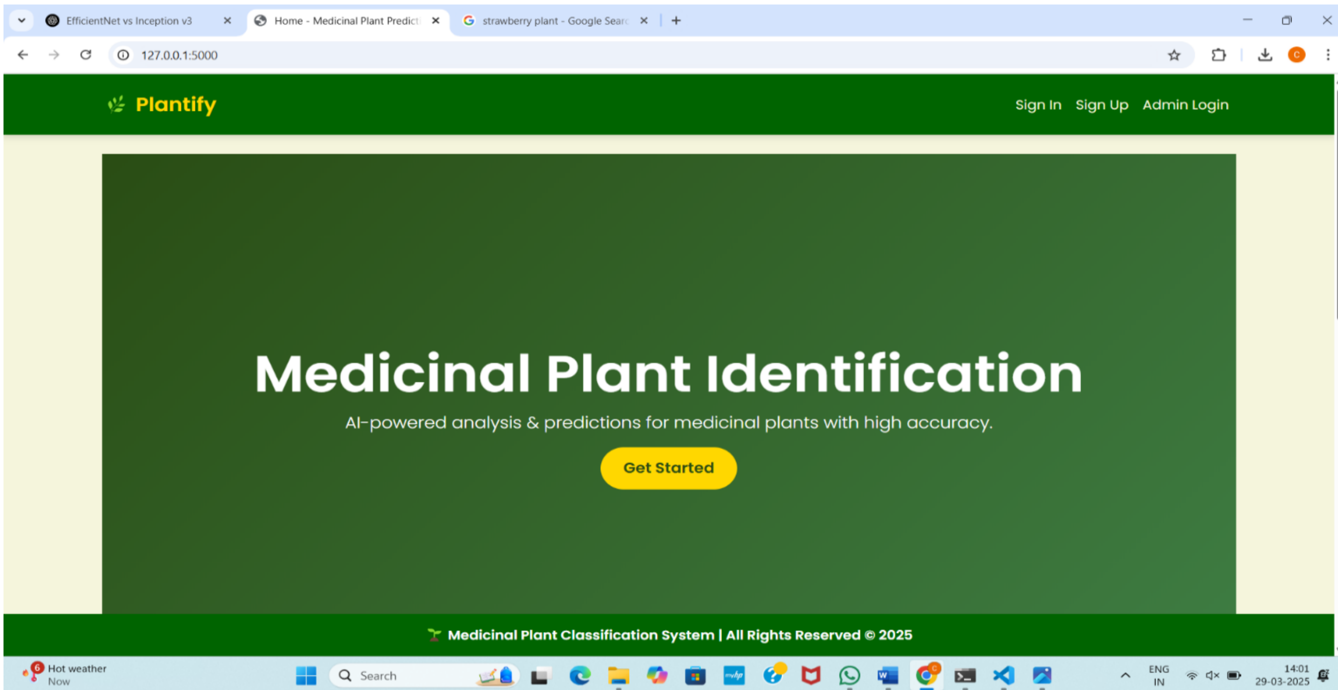
6.3 Performance Metrics

	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

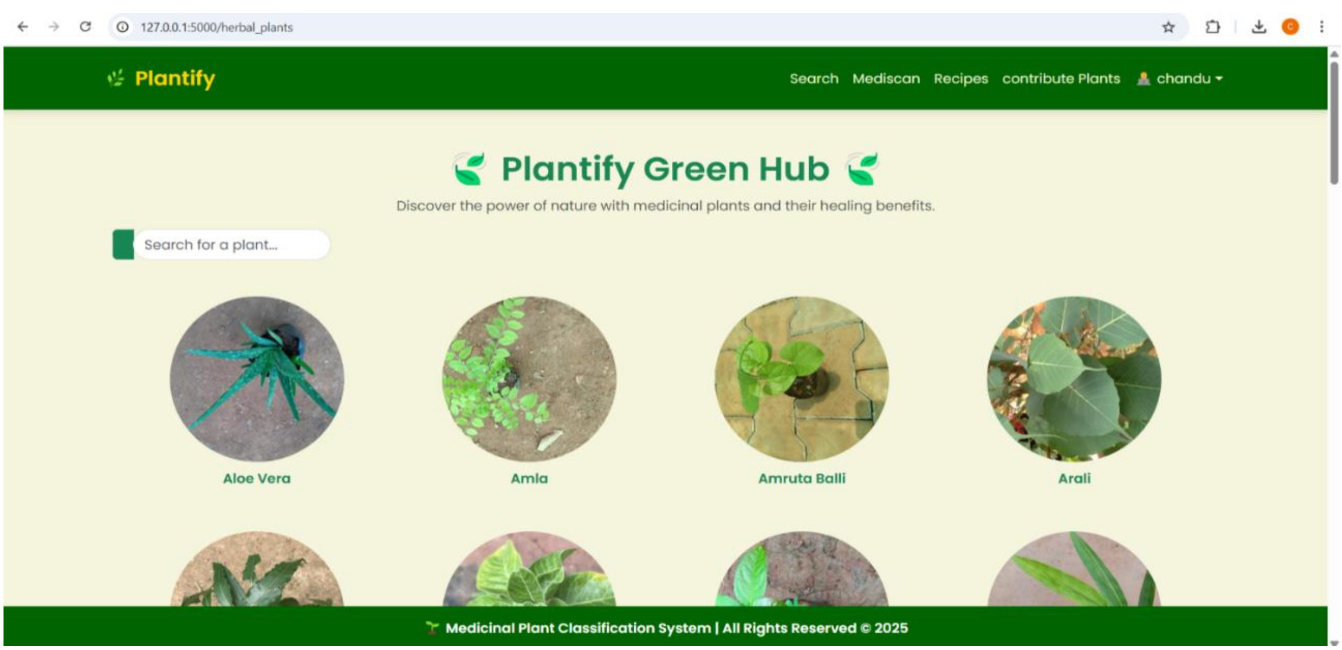
Fig 6.5 Classifcation Report

6.4 **OUTPUT SCREENSHOTS**

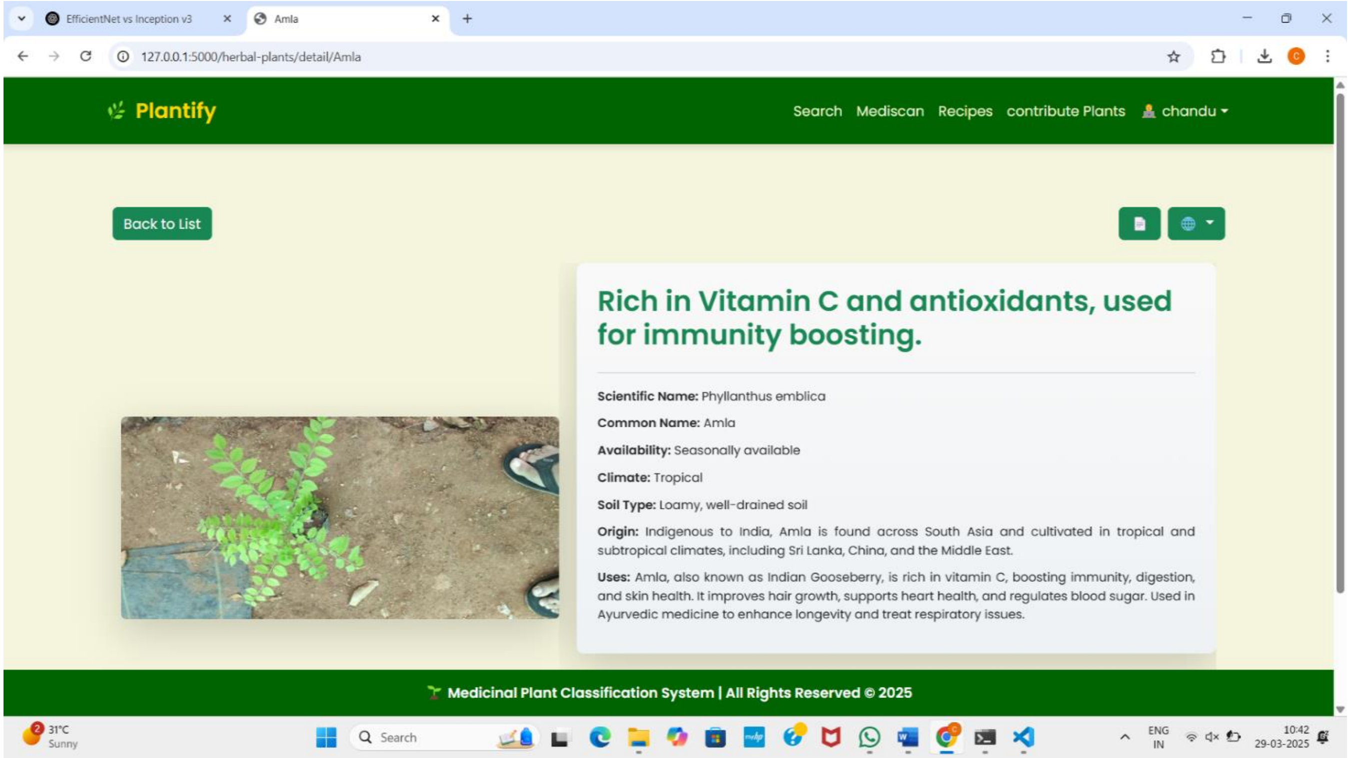
6.4.1 Home Page Design



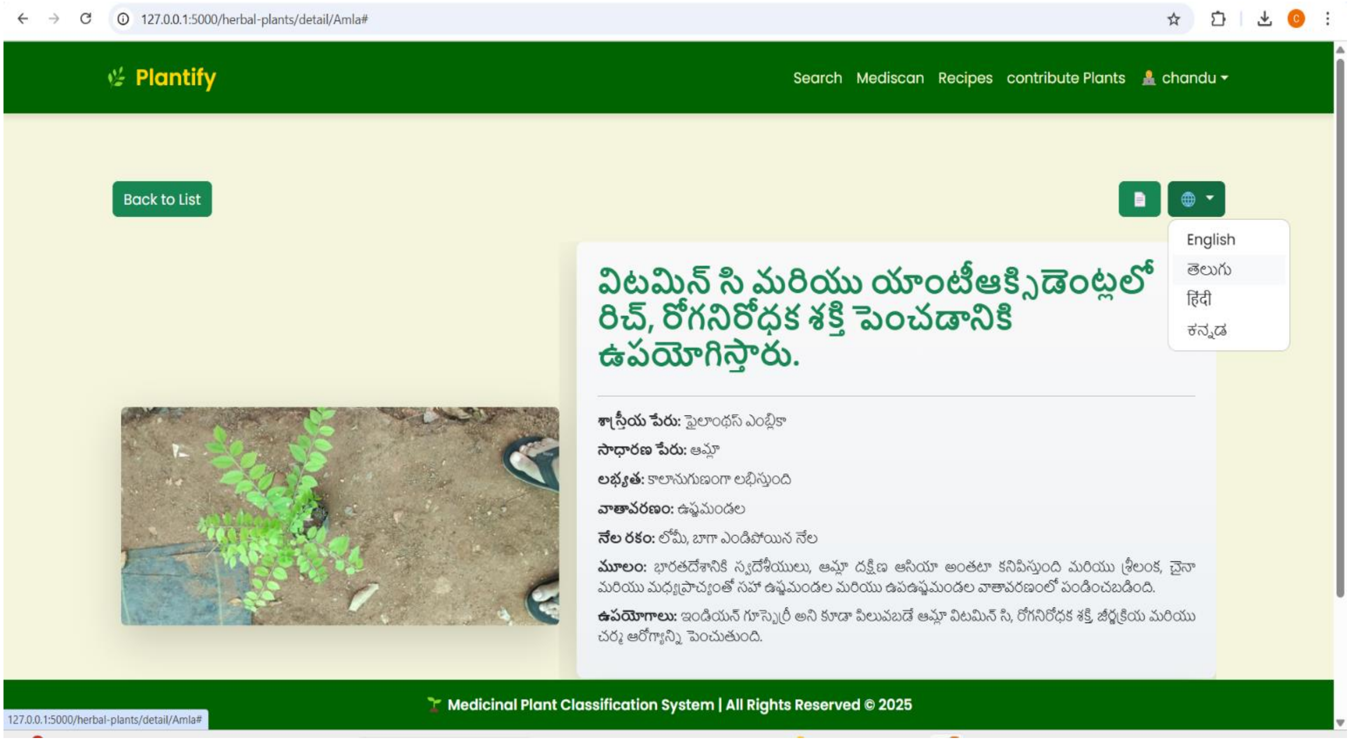
6.4.2 Plantify Green Hub



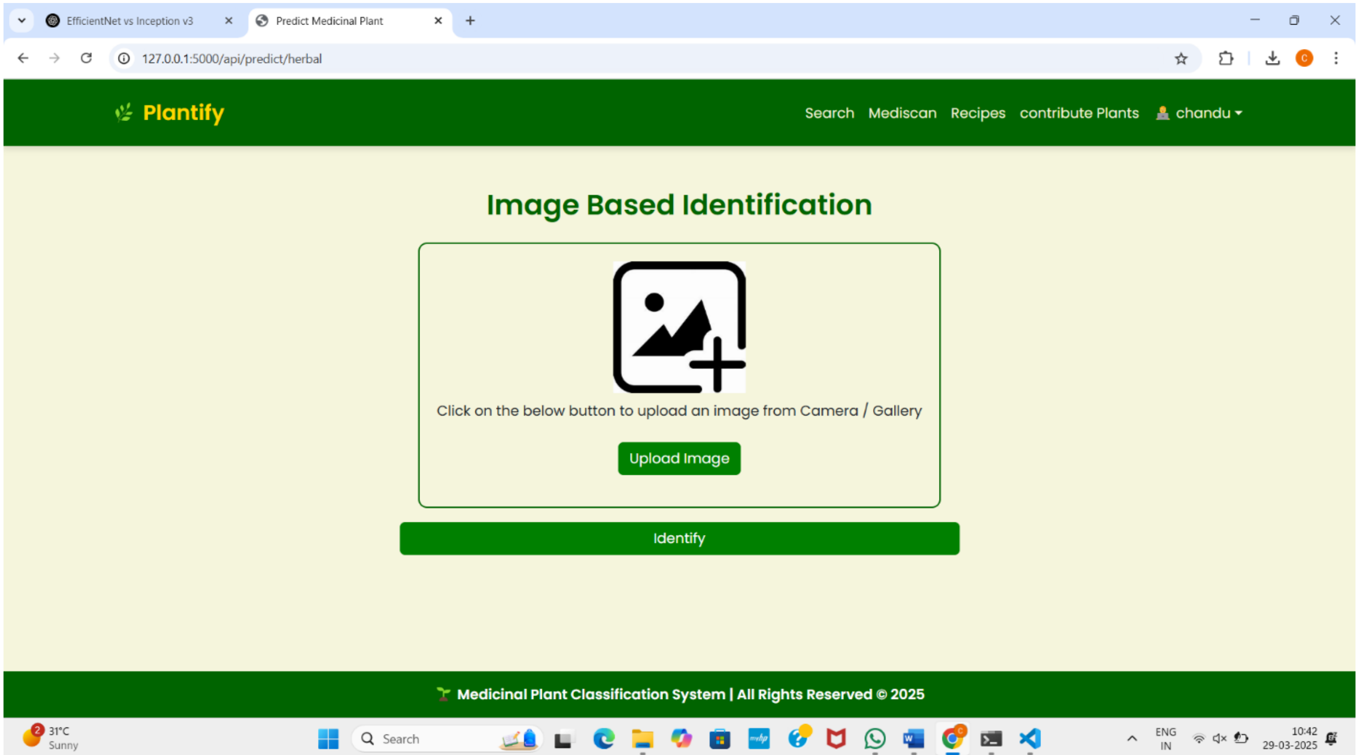
6.4.3 Search and Retrieval

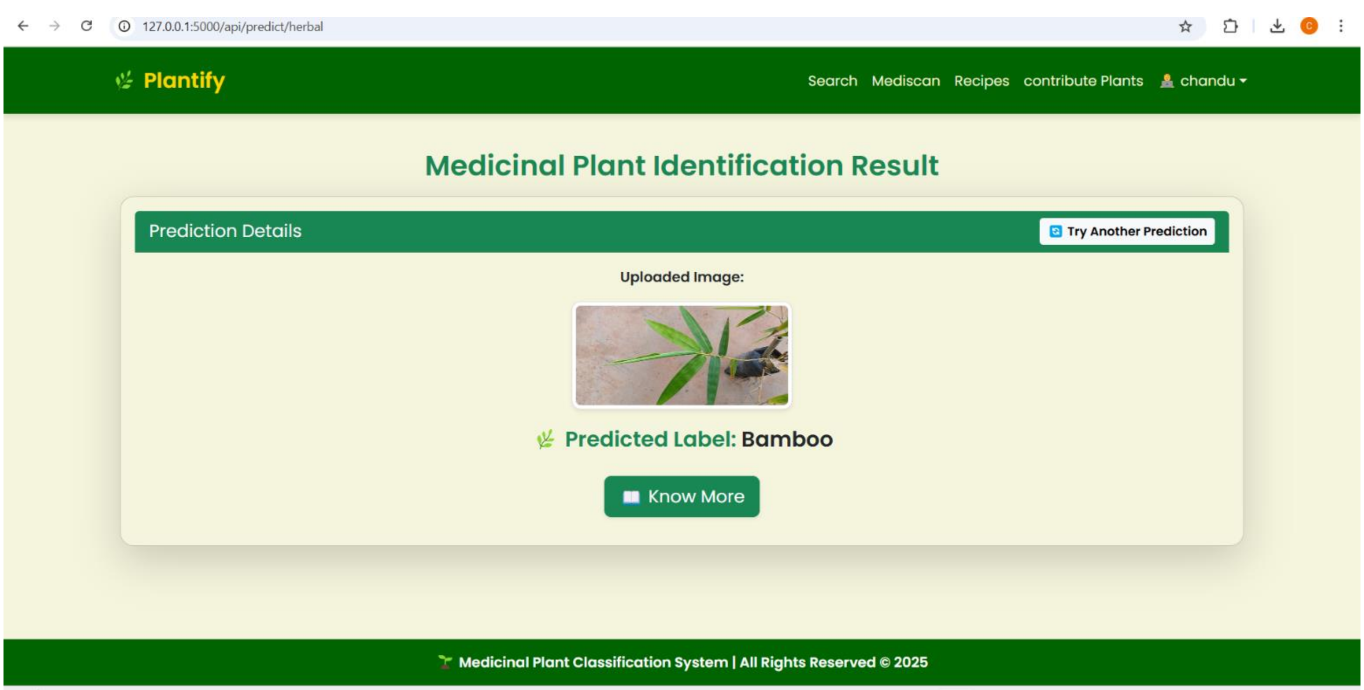


6.4.4Multi-Language

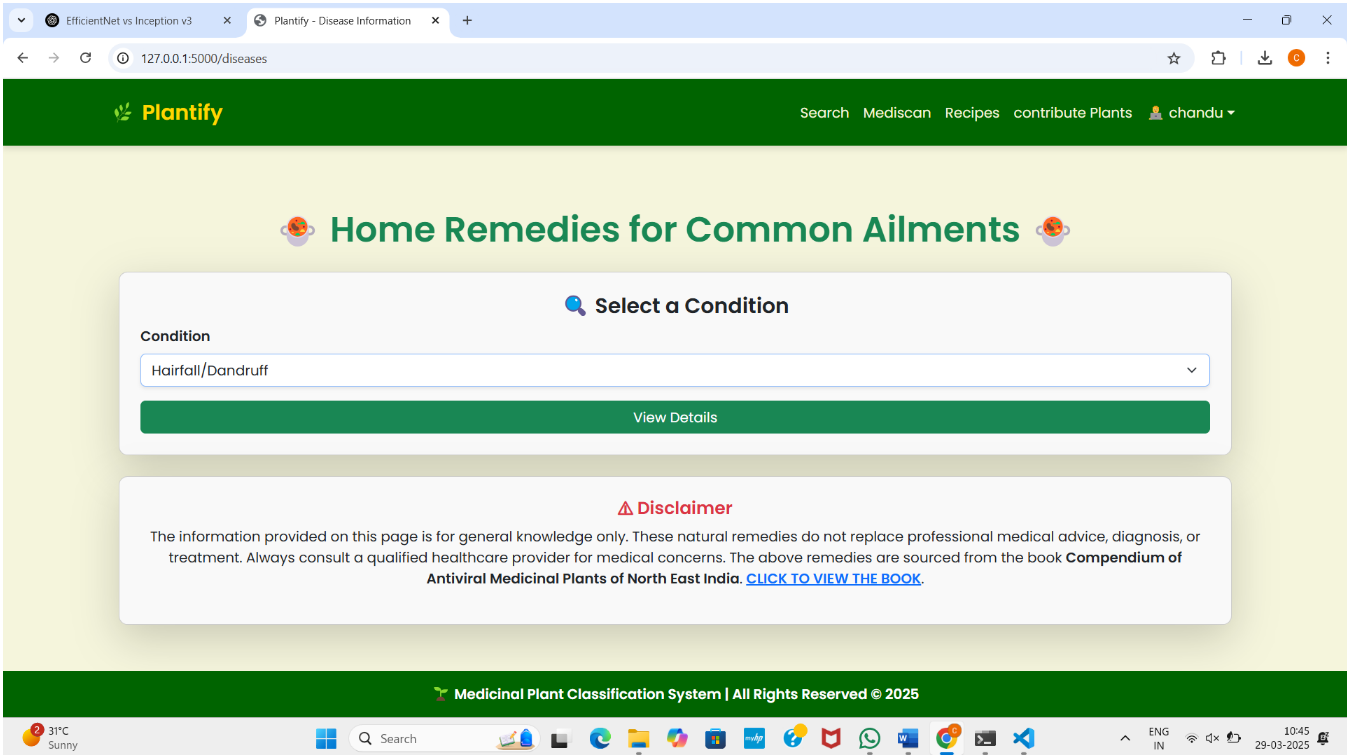


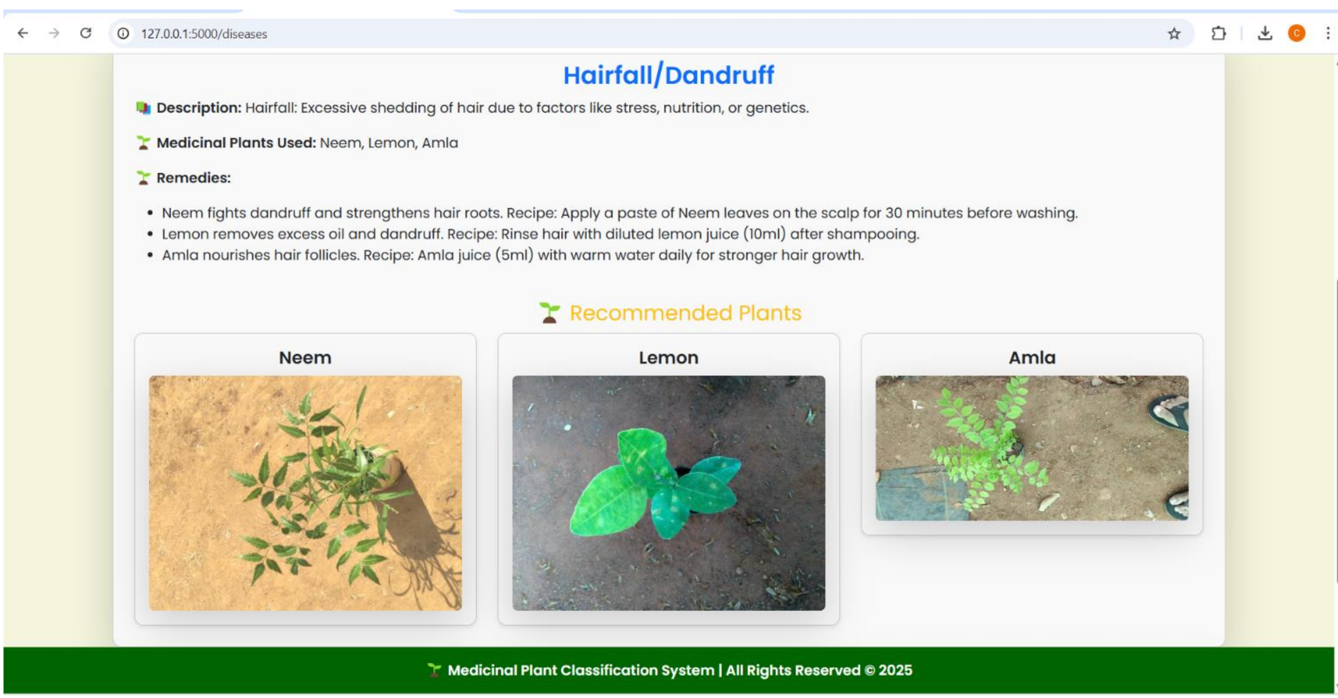
6.4.5 Image Based Identification



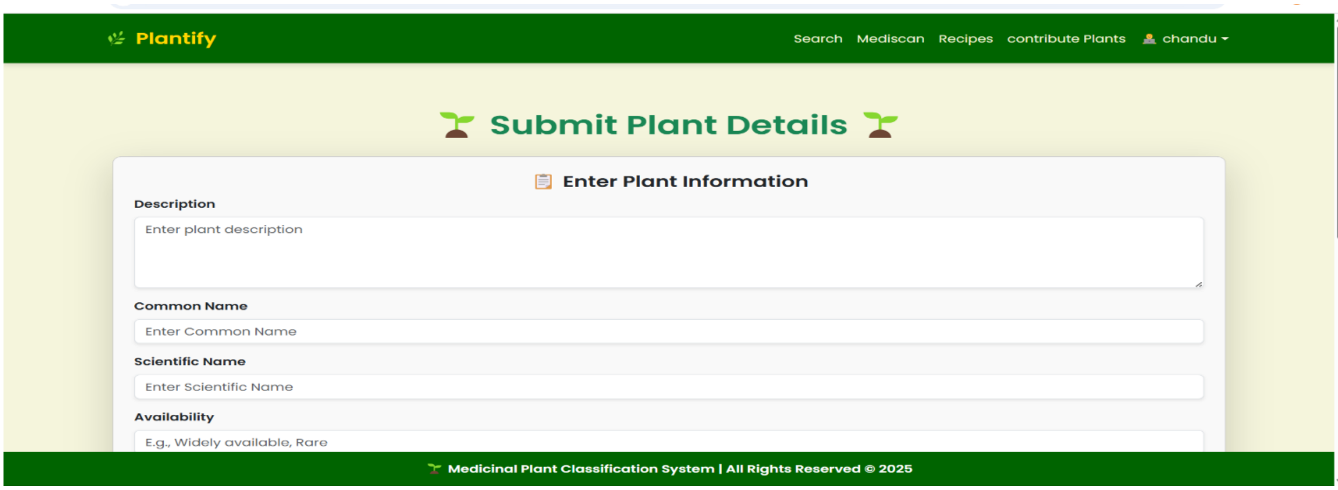


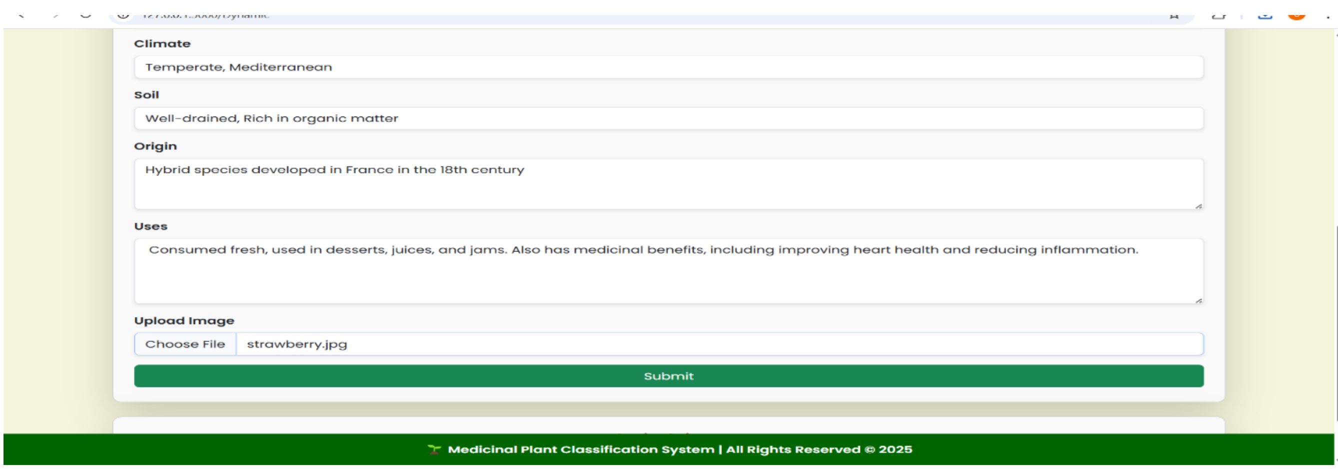
6.4.6 Remedies

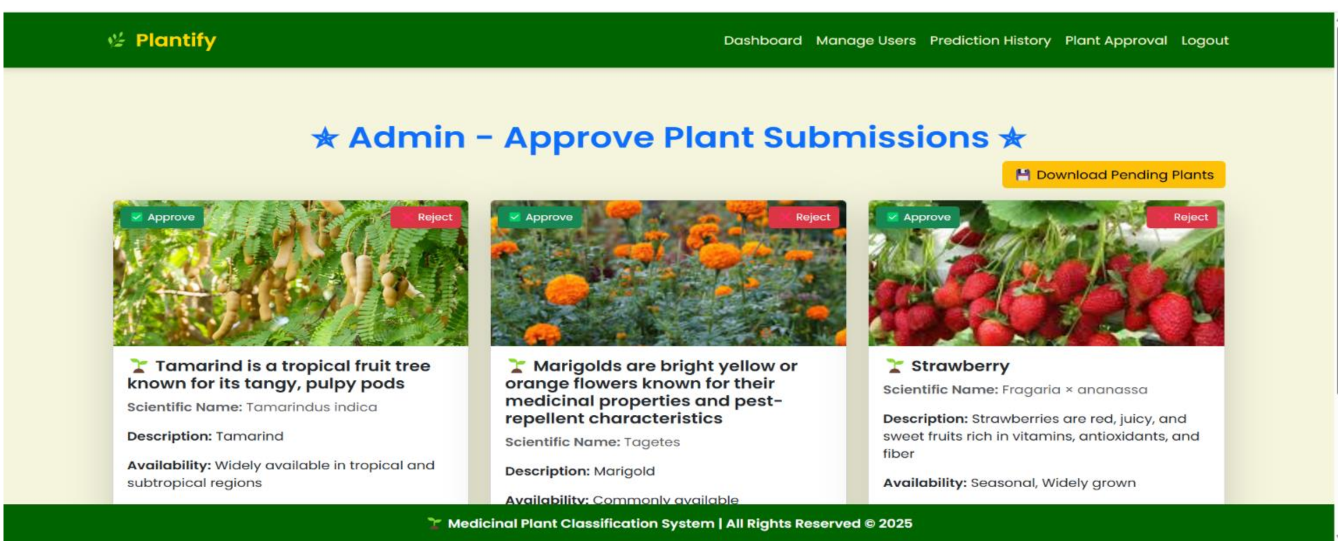




6.4.7 Contribute Plant







CHAPTER 7

CONCLUSION AND FUTURE SCOPE

CONCLUSION

Concluding the project on "Plantify-Enhanced Medicinal Plant Identification Using Convolutional Neural Networks" presents a significant milestone in harnessing technology for botanical and medicinal applications. Throughout this endeavour, we have successfully leveraged machine learning algorithms and image processing techniques to automate the identification process, offering an efficient and accurate solution for classifying various medicinal plants and raw materials.

Our exploration began with the selection and preprocessing of a diverse dataset comprising images of medicinal plants and raw materials. We meticulously curated and standardized the dataset to ensure robustness and reliability in model training. Subsequently, we delved into the implementation of state-of-the-art machine learning models, including EfficientNet and ResNet, to extract meaningful features from the input images.

Through rigorous experimentation and evaluation, we observed the effectiveness of these models in accurately classifying the botanical specimens. The ensemble approach, combining the strengths of Efficient and ResNet architectures, exhibited promising results, showcasing improved classification accuracy and robustness. This highlights the significance of leveraging ensemble techniques to harness the complementary capabilities of multiple models.

Furthermore, the deployment of the trained models into a practical application demonstrates the real-world utility of our solution. Users can now conveniently identify various medicinal plants and raw materials by simply uploading images, thereby streamlining the identification process and promoting accessibility to botanical knowledge.

FUTURE SCOPE

The project on " Plantify -Enhanced Medicinal Plant Identification Using Convolutional Neural Networks " presents a promising avenue for future advancements and extensions. As we conclude this endeavour, it's essential to highlight the potential future scopes that can further elevate the project's impact and relevance in the field of botanical science and healthcare.

Firstly, one of the primary areas of focus for future enhancements lies in the refinement of the machine learning models utilized in the project. By continuously refining model architectures, optimizing hyperparameters, and exploring novel regularization techniques, we can enhance the performance of the classification models in terms of accuracy, speed, and generalization capabilities.

Expanding the dataset to encompass a broader spectrum of medicinal plants and raw materials from various geographical regions and ecosystems represents another crucial aspect of future development. By incorporating more annotated images and comprehensive metadata, we can enrich the dataset, enabling the models to adapt and generalize better to diverse botanical specimens.

Furthermore, there is immense potential in extending the project's scope beyond binary classification to more fine-grained classification tasks. This could involve species-level identification, classification based on specific medicinal properties or chemical constituents, or even identifying plants at different stages of growth or maturity.

Developing a user-friendly mobile application based on the trained models opens up new avenues for practical applications and widespread dissemination of botanical knowledge. Integration with smartphone cameras, cloud-based inference engines, and crowdsourced data collection can empower users to identify medicinal plants and raw materials conveniently and access relevant information on-the-go.

CHAPTER 8
REFERENCES

[1] S. Prasad and P. P. Singh, ‘‘Vision system for medicinal plant leaf acquisition and analysis,’’ in Applications of Cognitive Computing Systems and IBM Watson. Singapore: Springer, 2017, pp. 37–45.

[2] Santhi Daggubati (2024) “Mediscan: Real-Time Identification of Medicinal Plants Species Using Deep Learning Models.”

[3] S. U. Habiba, M. K. Islam, and S. M. M. Ahsan, ‘‘Bangladeshi plant recognition using deep-learning based leaf classification,’’ in Proc. Int. Conf. Comput., Commun., Chem., Mater. Electron. Eng. (IC ME 4), Jul. 2019, pp. 1–4.

[4] Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., & Adam, H. (2017). "MobileNets: Efficient convolutional neural networks for mobile vision applications." arXiv preprint arXiv:1704.04861.

[5] Lekshmi Kalinathan, Ruba Soundar Kathavarayan & Jagadish Kumar K J, “Real-Time Identification of Medicinal Plants using Machine Learning Techniques”.

CHAPTER 8

APPENDIX - Conference Presentation Certificate


IJARCCE

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH IN COMPUTER AND COMMUNICATION ENGINEERING

A monthly Peer-reviewed & Refereed journal

Impact Factor 8.102

Indexed by Google Scholar, Mendeley, Crossref, Scilit,

SCIENCEOPEN, SCIENCEGATE, DORA, KOAR

Certificate of Publication

DR. T. KAMESWARA RAO

Professor, Dept.of.CSE Artificial Intelligence and Machine Learning, VVIT, GUNTUR, AP, INDIA

Published a paper entitled

Plantify-Enhanced Medicinal Plant Identification

Using Convolutional Neural Networks

Volume 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14265

Certificate# IJARCCE/2025/1

ISSN (Online) 2278–1021
ISSN (Print) 2319–5940

IJARCCE
DOI 10.17148/IJARCCE

Editor-in-Chief
IJARCCE

www.ijarcce.com

IJARCCE

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH IN COMPUTER AND COMMUNICATION ENGINEERING

A monthly Peer-reviewed & Refereed journal

Impact Factor 8.102

Indexed by Google Scholar, Mendeley, Crossref, Scilit,

SCIENCEOPEN, SCIENCEGATE, DORA, KOAR

SERTIFIKAAT 証明書 Sertifikat CERTYFIKAT CERTIFICADO 증명서 СЕРТИФИКАТ 证书 POTVRDA SERTIFIKA

Certificate of Publication

P DAKSHAINI

Student, Dept.of.CSE Artificial Intelligence and Machine Learning, VVIT, GUNTUR, AP, INDIA

Published a paper entitled

Plantify-Enhanced Medicinal Plant Identification Using Convolutional Neural Networks

Volume 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14265

Certificate# IJARCCE/2025/1

ISSN (Online) 2278–1021
ISSN (Print) 2319–5940

IJARCCE
DOI 10.17148/IJARCCE

Editor-in-Chief
IJARCCE

www.ijarcce.com

IJARCCE

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH IN COMPUTER AND COMMUNICATION ENGINEERING

A monthly Peer-reviewed & Refereed journal

Impact Factor 8.102

Indexed by Google Scholar, Mendeley, Crossref, Scilit,

SCIENCEOPEN, SCIENCEGATE, DORA, KOAR

DORA Google Scholar doi Crossref MENDELEY

Certificate of Publication

R CHANDU

Student, Dept.of.CSE Artificial Intelligence and Machine Learning, VVIT, GUNTUR, AP, INDIA

Published a paper entitled

Plantify-Enhanced Medicinal Plant Identification Using Convolutional Neural Networks

Volume 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14265

Certificate# IJARCCE/2025/1

SERTIFIKAAT 証明書 شهادة Sertifikat CERTYFIKAT CERTIFICADO 증명서 СЕРТИФИКАТ 证书 POTVRDA SERTIFIKA

ISSN (Online) 2278–1021
ISSN (Print) 2319–5940

IJARCCE
DOI 10.17148/IJARCCE

Editor-in-Chief
IJARCCE

www.ijarcce.com

IJARCCE

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH IN COMPUTER AND COMMUNICATION ENGINEERING

A monthly Peer-reviewed & Refereed journal

Impact Factor 8.102

Indexed by Google Scholar, Mendeley, Crossref, Scilit,

SCIENCEOPEN, SCIENCEGATE, DORA, KOAR

Certificate of Publication

SK KHADEER

Student, Dept.of.CSE Artificial Intelligence and Machine Learning, VVIT, GUNTUR, AP, INDIA

Published a paper entitled

Plantify-Enhanced Medicinal Plant Identification Using Convolutional Neural Networks

Volume 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14265

Certificate# IJARCCE/2025/1

ISSN (Online) 2278–1021
ISSN (Print) 2319–5940

IJARCCE
DOI 10.17148/IJARCCE

Editor-in-Chief
IJARCCE

www.ijarcce.com

IJARCCE

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH IN COMPUTER AND COMMUNICATION ENGINEERING

A monthly Peer-reviewed & Refereed journal

Impact Factor 8.102

Indexed by Google Scholar, Mendeley, Crossref, Scilit,

SCIENCEOPEN, SCIENCEGATE, DORA, KOAR

DORA Google Scholar doi Crossref MENDELEY

Certificate of Publication

SK USHMAN BASHA

Student, Dept.of.CSE Artificial Intelligence and Machine Learning, VVIT, GUNTUR, AP, INDIA

Published a paper entitled

Plantify-Enhanced Medicinal Plant Identification Using Convolutional Neural Networks

Volume 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14265

Certificate# IJARCCE/2025/1

ISSN (Online) 2278–1021
ISSN (Print) 2319–5940

IJARCCE
DOI 10.17148/IJARCCE

Editor-in-Chief
IJARCCE

SERTIFIKAAT 証明書 شهادة Sertifikat CERTYFIKAT CERTIFICADO 증명서 СЕРТИФИКАТ 证书 POTVRDA SERTİFİKA

www.ijarcce.com