

A REPORT
ON

**IDENTIFICATION OF DIFFERENT
MEDICINAL PLANTS/RAW MATERIALS
THROUGH IMAGE PROCESSING USING
MACHINE LEARNING ALGORITHMS**

Submitted by,

**Mr. Rishabh Singh – 20211CSE0429
Mr. Subhasish Mondal – 20211CSE0431
Ms. Manasa S – 20211CSE0887**

Under the guidance of,

Dr. Saurabh Sarkar

in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

At

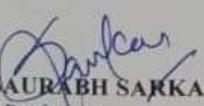


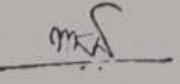
PRESIDENCY UNIVERSITY
BENGALURU
MAY 2025

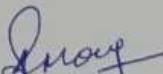
PRESIDENCY UNIVERSITY
PRESIDENCY SCHOOL OF COMPUTER SCIENCE AND
ENGINEERING

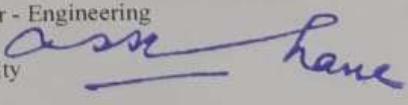
CERTIFICATE

This is to certify that the Internship/Project report **IDENTIFICATION OF DIFFERENT MEDICINAL PLANTS/RAW MATERIALS THROUGH IMAGE PROCESSING USING MACHINE LEARNING ALGORITHMS** being submitted by Rishabh Singh, Subhasish Mondal, Manasa S bearing roll number(s) 20211CSE0429, 20211CSE0431, 20211CSE0887 in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science and Engineering is a bonafide work carried out under my supervision.


Dr. SAURABH SARKAR
Asst. Professor
PSCS
Presidency University


Dr. MYDHILI NAIR
Professor
Associate Dean
PSCS
Presidency University


Dr. ASIF MOHAMMED H B
Asso. Professor & HoD
PSCS
Presidency University


Dr. SAMEERUDDIN KHAN
Pro-Vice Chancellor - Engineering
Dean -PSCS
Presidency University

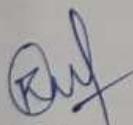
PRESIDENCY UNIVERSITY

PRESIDENCY SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

DECLARATION

We hereby declare that the work, which is being presented in the report entitled **IDENTIFICATION OF DIFFERENT MEDICINAL PLANTS/RAW MATERIALS THROUGH IMAGE PROCESSING USING MACHINE LEARNING ALGORITHMS** in partial fulfillment for the award of Degree of **Bachelor of Technology in Computer Science and Engineering**, is a record of our own investigations carried under the guidance of **Dr. Saurabh Sarkar, Asst. Professor, Presidency School of Computer Science and Engineering, Presidency University, Bengaluru.**

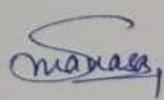
I have not submitted the matter presented in this report anywhere for the award of any other Degree.



Rishabh Singh
20211CSE0429



Subhasish Mondal
20211CSE0431



Manasa S
20211CSE0887

ABSTRACT

India's rich floral heritage is home to an extensive variety of medicinal plants that form the cornerstone of traditional Ayurvedic medicine. These plants are widely used in the preparation of various herbal formulations, offering therapeutic benefits that have been validated over centuries. However, the accurate identification of these medicinal plants and their corresponding raw materials continues to pose significant challenges. Morphological similarities among species, inconsistencies in regional vernacular names, and limited botanical expertise among collectors, traders, and processors frequently result in misidentification. These issues contribute to the adulteration and substitution of plant materials, undermining the authenticity, safety, and efficacy of Ayurvedic products, and eroding consumer trust.

To address these challenges, this research proposes a novel, technology-driven approach that leverages image processing techniques integrated with advanced machine learning algorithms to automate and enhance the plant identification process. By analyzing high-resolution images of medicinal plants and their raw forms, the system performs feature extraction to capture distinctive visual attributes, followed by classification using algorithms. This multi-model framework ensures robust and accurate recognition across a wide range of plant species and sample conditions.

The proposed system is designed to be scalable, adaptable, and user-friendly, making it suitable for deployment across various stages of the herbal supply chain — from field collection and processing to quality assurance in pharmaceutical manufacturing. By minimizing human error and standardizing identification protocols, this research aims to enhance the traceability and integrity of raw materials, thereby supporting the quality assurance and regulatory compliance of Ayurvedic formulations. Ultimately, the integration of image-based machine learning tools into the traditional medicine ecosystem can play a transformative role in preserving India's botanical heritage while advancing the reliability of natural healthcare solutions.

ACKNOWLEDGEMENTS

First of all, we are indebted to the **GOD ALMIGHTY** for giving me an opportunity to excel in our efforts to complete this project on time.

We express our sincere thanks to our respected dean **Dr. Md. Sameeruddin Khan**, Pro-VC - Engineering and Dean, Presidency School of Computer Science and Engineering & Presidency School of Information Science, Presidency University for getting us permission to undergo the project.

We express our heartfelt gratitude to our beloved Associate Dean **Dr. Mydhili Nair**, Presidency School of Computer Science and Engineering, Presidency University, and **Dr. Asif Mohammed**, Head of the Department, Presidency School of Computer Science and Engineering, Presidency University, for rendering timely help in completing this project successfully.

We are greatly indebted to our guide **Dr. Saurabh Sarkar, Asst. Professor** Presidency School of Computer Science and Engineering, Presidency University for his inspirational guidance, and valuable suggestions and for providing us a chance to express our technical capabilities in every respect for the completion of the internship work.

We would like to convey our gratitude and heartfelt thanks to the CSE7301 Internship/University Project Coordinator **Mr. Md Ziaur Rahman and Dr. Sampath A K**, department Project Coordinator **Mr. Jerrin Joe Francis** and Git hub coordinator **Mr. Muthuraj**.

We thank our family and friends for the strong support and inspiration they have provided us in bringing out this project.

Rishabh Singh
Subhasish Mondal
Manasa S

LIST OF TABLES

Sl. No.	Table Name	Table Caption	Page No.
1	Table 7.1	Development Phases and Schedule of Project	21
2	Table 9.1	Comparison Table with Other Trained Models	26

LIST OF FIGURES

Sl. No.	Figure Name	Caption	Page No.
1	Figure 4.1	Reference Images Used for Training Model	8
2	Figure 4.2	Accuracy Comparison between Models	10
3	Figure 4.2	Flow Diagram of Working of System	11
4	Figure 7.1	Gantt Chart Showing Timeline of our Project	19
5	Figure 9.1	SVM Confusion Matrix	24
6	Figure 9.2	SVM AUC Score	24
7	Figure 9.3	SDG Classification report	24
8	Figure 9.4	SDG Confusion Matrix	25
9	Figure 9.5	SDG AUC Score	25
10	Figure 9.6	RF Classification report	25
11	Figure 9.7	RF Confusion Matrix	25
12	Figure 9.8	RF AUC Score	25
13	Figure 9.9	RF Classification report	26

TABLE OF CONTENTS

CHAPTER NO.	TITLE	PAGE NO.
	ABSTRACT	iv
	ACKNOWLEDGEMENT	v
	LIST OF TABLES	vi
	LIST OF FIGURES	vii
1.	INTRODUCTION	1
	1.1 Background and Significance	1
	1.2 Challenges in Medical Plant Identification	1
	1.3 Consequences of Misidentification	1
	1.4 Need for a Technological Solution	1
	1.5 Real-World Applicability and Impact	2
2.	LITERATURE SURVEY	3
	2.1 Importance of Medicinal Plants Identification	3
	2.2 Conventional vs Automated Identification Methods	3
	2.3 Role of Image Processing in Plant Classification	3
	2.4 Machine Learning Algorithms in Plant Identification	3
	2.5 Available Datasets and Challenges	4
	2.6 Applications and Tools Developed	4
3.	RESEARCH GAPS OF EXISTING METHODS	5
	3.1 Lack of Focus on Ayurvedic Medicinal Plants	5
	3.2 Insufficient Recognition of Processed or Crude Raw Material	5
	3.3 Limited Dataset Availability and Diversity	5
	3.4 Manual Feature Extraction in Traditional ML Methods	5
	3.5 Lack of End-to-End, Scalable Solutions	5
	3.6 Minimal User-Centric Design and Field Usability	6
	3.7 Inadequate Integration with Quality Assurance Frameworks	6
4.	PROPOSED METHODOLOGY	7
	4.1 Data Collection and Dataset Preparation	7
	4.2 Image Preprocessing	7
	4.3 Feature Extraction	8
	4.4 Model Selection and Training	8
	4.5 Model Evaluation and Optimization	10

4.6 System Design and User Interface	10
4.7 Deployment and Integration	10
5. OBJECTIVES	12
5.1 Automated Plant and Raw Material Identification	12
5.2 Real-Time and On-Demand Recognition	12
5.3 Historical Image and Identification Database	12
5.4 User-Friendly Interface for All Stakeholders	13
5.5 Supply Chain and Quality Assurance Integration	13
5.6 Insights for Ayurvedic Pharmaceutical Industry	14
5.7 Contribution to Digital Herbal Informatics and Research	14
6. SYSTEM DESIGN & IMPLEMENTATION	15
6.1 System Architecture	15
6.2 Image Acquisition and Dataset Creation	15
6.3 Image Preprocessing	15
6.4 Feature Extraction	16
6.5 Classification Algorithms	16
6.6 Model Training	17
6.7 User-Interface Development	17
6.8 Database Design	18
6.9 Deployment and Integration	18
6.10 System Testing and Validation	18
7. TIMELINE FOR EXECUTION OF PROJECT	19
7.1 Requirements Gathering	19
7.2 Data Collection and Annotation	19
7.3 Data Preprocessing	20
7.4 Model Selection and Training	20
7.5 Model Evaluation and Optimization	20
7.6 System Development and Integration	20
7.7 Deployment and Testing	21
7.8 Documentation and Reporting	21
8. OUTCOMES	22
8.1 Enhanced Accuracy in Plant Identification	22
8.2 Streamlined Quality Assurance Across the Supply Chain	22
8.3 Creation of a Digital Medicinal Plant Repository	22
8.4 Data-Driven Support for Ethnobotanical Research	22
8.5 Accessible and Scalable Identification Platform	23
8.6 Strengthened Trust in Ayurvedic Products	23
8.7 Secure and Ethical Image Processing Frameworks	23
8.8 Future Ready Platform for Integration and	23

Expansion		
9.	RESULTS AND DISCUSSIONS	24
9.1	Model Accuracy and Performance	24
9.2	Data Preprocessing and Generalization	26
9.3	System Integration and Application Development	26
9.4	Key Functional Outcomes	27
9.5	Deployment and Scalability	27
9.6	Continuous Learning and Practical	27
9.7	Overall Impact and Practical Relevance	27
10.	CONCLUSION	29
	REFERENCES	30
	APPENDIX – A	33
	APPENDIX – B	48
	APPENDIX – C	51

Chapter 1

INTRODUCTION

1.1 Background and Significance

India is endowed with a rich floral heritage and is recognized globally for its extensive diversity of medicinal plants. These botanical resources form the foundational pillars of Ayurvedic medicine, one of the oldest traditional healthcare systems. [1][13] Medicinal plants are not only used in therapeutic preparations but are also an essential part of the pharmaceutical, nutraceutical, and cosmetic industries. [3][4] Accurate identification of these plant species and their raw materials is critical to ensure the efficacy, safety, and authenticity of Ayurvedic formulations. [2][7]

1.2 Challenges in Medicinal Plant Identification

In spite of the riches of restorative greenery, legitimate recognizable proof of crude plant materials remains a diligent challenge. Variables such as morphological similitudes between distinctive species, conflicting territorial classification, and restricted botanical skill among collectors and dealers contribute to far reaching perplexity. [4][7][19] In numerous cases, a few rough drugs are sold beneath the same title, driving to incidental misidentification. These issues are assist exacerbated by topographical and regular varieties that influence the appearance of plant examples. [5][17]

1.3 Consequences of Misidentification

The growing demand for herbal products, both domestically and internationally, puts immense pressure on the availability of authentic raw materials. To meet this demand, practices such as adulteration and substitution are increasingly observed in the supply chain. [6][7] These practices not only compromise the quality of Ayurvedic medicines but also lead to reduced therapeutic effectiveness and a loss of public trust in the system. [2][4]

1.4 Need for a Technological Solution

Given these challenges, there is a compelling need for a reliable, automated system capable of identifying medicinal plants and their raw materials accurately. [2][3][4] Leveraging advances in image processing and machine learning algorithms, such a system can analyze

visual features of plants and classify them with high accuracy. Technologies like Convolutional Neural Networks (CNN),[10][21] Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN) [19] offer robust frameworks for recognition tasks based on image data. [18][5]

1.5 Real-World Applicability and Impact

This project aims to develop a scalable, user-friendly software solution that can aid in the identification of medicinal plants and their crude forms using machine learning-based image analysis. The system is envisioned to benefit various stakeholders in the herbal supply chain—including collectors, wholesalers, distributors, and manufacturers—by minimizing identification errors, preventing adulteration, and promoting the integrity of Ayurvedic pharmaceuticals. [7][13]

Chapter 2

LITERATURE SURVEY

2.1 Importance of Medicinal Plants Identification

Therapeutic plants play a imperative part in conventional healthcare frameworks around the world. Precise recognizable proof of these plants is significant to guarantee the security, viability, and realness of home-grown definitions. Conventional distinguishing proof strategies, which depend on morphological characteristics and master information, are frequently time-consuming and inclined to human blunder. Later thinks about have investigated mechanized approaches to address these challenges, in spite of the fact that accomplishing tall exactness remains a jump.[4][13]

2.2 Conventional vs Automated Identification Methods

Historically, plant identification has been performed manually by experts, which is labor-intensive and not scalable. Advances in technology have led to the development of automated systems using digital image processing, offering a low-cost and scalable alternative.[11][15] These systems can assist non-experts in achieving accurate identification through mobile applications and digital platforms. However, studies have shown that these automated methods often face limitations in accuracy, especially when dealing with diverse plant species and varying image conditions.

2.3 Role of Image Processing in Plant Classification

Image processing techniques enable the extraction of visual features such as shape, color, texture, and vein patterns from plant leaves, flowers, or roots. Preprocessing techniques like image enhancement, background removal, and segmentation improve accuracy and reliability.[1][7][14] For instance, a study utilized shape, texture, and color features to classify medicinal plants, achieving varying degrees of success across different machine learning algorithms.

2.4 Machine Learning Algorithms in Plant Identification

Various machine learning algorithms have been employed to classify plant species based on extracted features. In a study, multiple classifiers were evaluated for medicinal plant

identification, with the following accuracies: Support Vector Machine (85.82%), K-Nearest Neighbors (75.45%), Multilayer Perceptron (82.88%), Random Forest (80.85%), and Decision Tree (64.39%). [1][9][19] Another study assessed deep convolutional neural network models for automated medicinal plant identification from leaf images, reporting an accuracy of 85% when employing Deep Neural Networks (DNN).[21]

Furthermore, evaluation of four deep convolutional feature extraction models—MobileNetV2, VGG16, ResNetV2, and Inception ResNet V2—for plant image identification, with MobileNetV2 attained the highest accuracy of 83.9%. [7][11]

2.5 Available Datasets and Challenges

There's a shortage of standardized and commented on datasets particular to restorative plants. Open datasets like Flavia and MalayaKew are habitually utilized, in spite of the fact that they may not cover region-specific restorative species. Challenges incorporate varieties in picture quality, lighting conditions, foundation commotion, and constrained information accessibility for uncommon species.[16][17] These components contribute to the trouble in accomplishing higher precision in mechanized recognizable proof frameworks.

2.6 Applications and Tools Developed

A few versatile applications and inquire about models have been created for plant acknowledgment. In any case, their utility in distinguishing restorative crude materials is still constrained. Besides, they frequently need back for crude, handled, or divided shapes of herbs, which are common in Ayurvedic supply chains.[8][14] The direct exactnesses detailed in later thinks about highlight the require for advance investigate and improvement to improve the unwavering quality of these instruments.

Chapter 3

RESEARCH GAPS OF EXISTING METHODS

3.1 Lack of Focus on Ayurvedic Medicinal Plants

Most existing plant identification systems are designed for general botanical classification and do not specifically target Ayurvedic medicinal plants. For instance, studies like "LeafSnap and Beyond: Towards Real-World Plant Identification Tools" by Reyes et al. [11] and "Pl@ntNet: A Participatory Platform for Discovering Plants and Sharing Botanical Knowledge" by Goëau et al. [12] focus primarily on general-purpose flora recognition. As a result, these systems often lack the specificity needed to distinguish morphologically similar species critical to Ayurvedic formulations.

3.2 Insufficient Recognition of Processed or Crude Raw Materials

Frameworks such as those proposed in "Therapeutic Plant Distinguishing proof in Real-Time Utilizing Profound Learning Demonstrate" by Kavitha et al. [2] and "Restorative Plant Classification utilizing Cross breed Highlight Extraction and Machine Learning Methods" by Mahum et al. [6] basically center on new plant tests (clears out, blooms), but neglect recognizable proof in real-world shapes like dried roots, powders, or chopped stems—forms common in crude medicate markets and Ayurvedic supply chains.

3.3 Limited Dataset Availability and Diversity

Several studies including "Automatic Medicinal Plant Leaf Identification Based on Local Binary Pattern and Probabilistic Neural Network" by Zhang et al. [17] and "Identification of Medicinal Plants Using Image Processing and Machine Learning" by Verma and Satsangi [7] rely on limited datasets collected under controlled conditions. This reduces model robustness in varying lighting, backgrounds, and environments—especially important for mobile or field deployment.

3.4 Manual Feature Extraction in Traditional ML Models

Older works such as "Automatic Plant Identification Using Leaf Features" by Arora et al. [16] and "Image Processing Techniques for Medicinal Plant Identification: A Review" by Goyal and Patel [19] primarily use manual feature extraction techniques—like shape, texture, and

color—which require domain expertise and often miss subtle cues crucial for distinguishing between similar species.

3.5 Lack of End-to-End, Scalable Solutions

Many studies like "Deep Learning Approach for Classification of Medicinal Plant Images" by Gupta and Arora [4] offer proof-of-concept classification models, but do not extend to real-world deployment needs such as supply chain traceability, user-friendly apps, or integration with quality control systems. These gaps prevent scalable adoption across distributors, QA teams, or policymakers.

3.6 Minimal User-Centric Design and Field Usability

Research efforts such as "Plant Identification Using Deep Learning Algorithms" by Nguyen and Hien [5] lack mobile-first design or field operability. This limits accessibility for rural collectors or vendors, who may not have access to high-end computing infrastructure or internet connectivity.

3.7 Inadequate Integration with Quality Assurance Frameworks

Systems proposed in works like "A Review on Classification of Medicinal Plants Using Machine Learning Techniques" by Rajesh [13] and "Medicinal Plant Recognition Using Machine Learning Algorithms" by Oppong et al. [3] do not integrate their solutions into existing quality control or compliance frameworks such as GMP certification or digital audit trails—reducing real-world utility in regulated industries.

Chapter 4

PROPOSED METHODOLOGY

4.1 Data Collection and Dataset Preparation

The primary step in building a strong distinguishing proof framework is to accumulate a comprehensive dataset of plant pictures:

- **Plant Databases:** Instead of relying on public plant databases, a custom medicinal plant image dataset was developed specifically for this project. [2][4] High-resolution images of various medicinal plants and raw materials were captured manually from local herbal gardens, nurseries, and field sites under diverse environmental conditions. Care was taken to include variations in lighting, orientation, background, and plant maturity. Botanical experts were consulted to ensure accurate species identification and labeling. This personalized approach ensures better control over data quality and relevance to the Ayurvedic domain. [1] [7]
- **Field Collection:** In addition to publicly available datasets, images of local medicinal plants will be collected from herbal farms, botanical gardens, and other locations where these plants are cultivated. This will ensure that the dataset includes region-specific and seasonal plant variations. [5][13]
- **Image Types:** The dataset will focus primarily on leaf images, as leaves are the most distinguishable and commonly used features in plant identification. [4][10] However, flower and stem images may also be included for species that are difficult to identify by leaves alone.

4.2 Image Preprocessing

After collecting the dataset, the subsequent phase involves preprocessing the images to make them suitable for machine learning applications. This process comprises multiple steps designed to enhance the quality and consistency of the data for model training:

- **Resizing and Normalization:** All images were resized to a standardized dimension for consistency and normalized by scaling pixel values between 0 and 1 to prepare them for model training. [9][10]
- **Data Augmentation:** To enhance the diversity of the training dataset and prevent overfitting, data augmentation techniques such as rotation, flipping, zooming, and

cropping will be applied to generate new variations of the images. [7][12]

4.3 Feature Extraction

Relevant visual features from the images will be extracted using both manual and automated approaches.

- **Colour Histograms:** Colour histograms capture the distribution of pixel Colour within an image. These histograms are calculated based on the RGB or HSV Colour channels, which allow the system to identify plants by analysing their dominant Colour. [12]
- **Texture Analysis:** Texture analysis is crucial for identifying plants with similar shapes but different surface characteristics. Haralick features, derived from the Gray-level co-occurrence matrix (GLCM), are used to analyse the spatial arrangement of pixel intensities. [17]
- **Shape Descriptor:** Shape descriptors are used to capture the geometric properties of the plant leaves, such as their overall form and structure. Zernike moments are applied to describe the shape in a rotation-invariant manner. [18][21]

4.4 Model Selection and Training

For the plant identification system, machine learning algorithms were utilized to classify plant species based on features extracted from the images. The following models were developed and evaluated for comparative analysis:



Fig 4.1. Reference Images Used for Training Model

- **Stochastic Gradient Descent (SGD):** SGD was employed as a baseline machine learning model for plant identification, offering simplicity and efficiency in training. The model was trained on extracted feature vectors from preprocessed images. Its iterative optimization approach allowed it to handle large datasets effectively while minimizing the loss function. The SGD model achieved an impressive accuracy of 97%, indicating its strong performance in distinguishing medicinal plants, even under varied image conditions such as different backgrounds and lighting.

Formula:

$$\theta = \theta - \eta * \nabla_{\theta} J(\theta; x(i), y(i))$$

where θ represents the parameters, η is the learning rate, and $\nabla_{\theta} J(\theta; x(i), y(i))$ is the gradient of the loss function J with respect to the parameters, evaluated using a single training example $(x(i), y(i))$.

- **Support Vector Machine (SVM):** Support Vector Machines (SVMs) were evaluated as a secondary model for plant classification, utilizing feature vectors derived from image characteristics such as color, texture, and shape. To address non-linear separability within the data, the kernel trick was applied. The SVM classifier demonstrated robust performance, achieving an accuracy of 97%, showcasing comparable reliability to that of Stochastic Gradient Descent (SGD)-based models. The SVM optimization problem can be expressed as:

$$\min \frac{1}{2} \|w\|^2 \text{ subject to } y_i w^T \phi(x_i) + b$$

where w is the weight vector, b is the bias term, x is the feature vector of the i -th sample, $y_i \in \{-1, +1\}$ is the label of the i -th sample and $\phi(x_i)$ is the transformation of x_i into a higher dimensional space via a kernel function.

- **Random Forest (RF):** A random forest (RF) classifier was also investigated as a potential approach for plant species classification. leveraging an ensemble of decision trees, the rf model effectively reduced overfitting and enhanced generalization. it achieved an accuracy of 94%, performing well on structured feature data, though it was slightly less effective on complex image inputs when compared to SGD and SVM classifiers. Given a dataset $D = \{(x_i, y_i)\}_{i=1}^N$, a random forest constructs T decision trees $ht(x)$, each trained on a bootstrap sample $D_t \subset D$. The prediction of the RF classifier is

$$y^{\wedge} = \text{mode}\{ht(x)\}_{t=1}^T$$

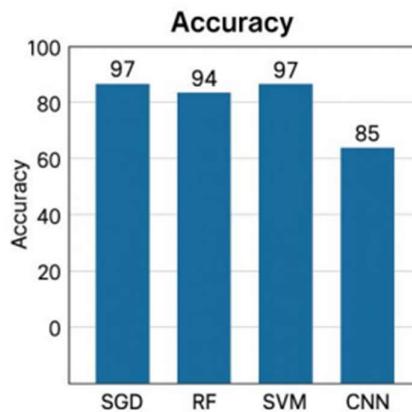


Fig 4.2. Accuracy Comparison Between Models

4.5 Model Evaluation and Optimization

Each model's performance will be tested on unseen data to evaluate real-world effectiveness.

- **Metrics:**
 - Classification Accuracy
 - Confusion Matrix
 - Precision, Recall, F1-Score
- **Optimization:**
 - Regularization techniques to prevent overfitting.
 - Ensemble methods or transfer learning for improved accuracy.

4.6 System Design and User Interface

A simple and intuitive user interface (UI) will be developed to make the model accessible to end users such as herbal traders, field collectors, and Ayurvedic manufacturers.

- **Platform:** Desktop or mobile application.
- **Functionality:**
 - Upload or capture image of plant/raw material.
 - Real-time classification with plant name and confidence score.
 - Optional: database reference or medicinal usage display.

4.7 Deployment and Integration

The final trained model and UI will be integrated into a deployable system.

- **Deployment options:**

- Standalone desktop software.
- Cloud-based web application.
- Android-based mobile app (for field use).

- **Integration possibilities:**

- QR code tagging for supply chain tracking.
- Connection to herbal regulatory or quality control databases.

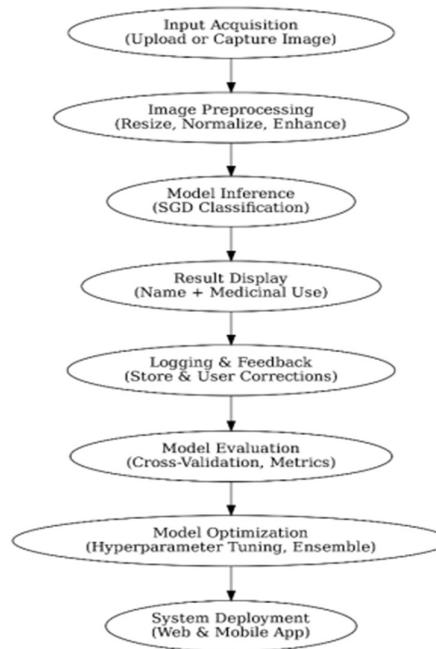


Fig 4.2. Flow Diagram of Working of System

Chapter 5

OBJECTIVES

5.1 Automated Plant and Raw Material Identification

- **Image-Based Detection**

The system aims to leverage machine learning and image processing techniques to accurately detect and classify medicinal plants and their raw material forms—such as leaves, roots, barks, seeds, and powders. By analyzing features like shape, color, texture, and structure, the system will enable automatic recognition that significantly reduces reliance on manual identification, which is often error-prone and time-consuming. [1][2][7]

- **Minimizing Errors**

One of the core goals is to enhance the reliability of identification by minimizing both false positives (misidentifying incorrect materials as authentic) and false negatives (failing to identify genuine materials). To accomplish this, the system will implement advanced algorithms, known for their superior accuracy in image classification tasks. [5][11][15]

5.2 Real-Time and On-Demand Recognition

- **Instant Clarification**

The objective is to provide a tool that allows users to upload or capture an image of a plant or raw material and receive a real-time classification result within seconds. This will assist collectors, traders, and manufacturers in making immediate decisions regarding the quality and authenticity of materials, thereby increasing efficiency and reducing processing delays. [8][9]

- **Field Usability**

Recognizing that users may work in rural or low-tech environments, the system will be designed for robustness in real-world scenarios. This includes handling images taken under poor lighting conditions, varying backgrounds, or from different angles, ensuring high usability even with basic camera equipment.[14]

5.3 Historical Image and Identification Database

- **Reference Library**

The system will maintain a continually growing database of high-quality, labeled images

of various medicinal plants and raw materials. This digital herbarium will serve as a reference for image classification, training machine learning models, and verifying identification results against verified entries, thus standardizing the identification process.

- **Data Enrichment**

Beyond static storage, the system will allow continuous updates to the database. New species, different forms of raw material, or seasonal variations can be added regularly to improve the depth and accuracy of the model's predictions. This ensures that the system evolves and remains relevant as new data emerges.[4][16]

5.4 User-Friendly Interface for All Stakeholders

- **Cross-Platform Accessibility**

The objective includes building a responsive and accessible user interface that operates smoothly on web browsers, desktops, and mobile devices. This ensures that users at every level of the supply chain—from local farmers to pharmaceutical companies—can easily interact with the system regardless of their technical background.

- **Interactive Features**

The interface will offer helpful tools such as showing similar-looking species with distinguishing traits, suggesting possible identification corrections, and providing educational guides. This adds value beyond simple classification, turning the platform into an informative and learning-friendly tool.

5.5 Supply Chain and Quality Assurance Integration

- **Authentication at each Level**

The system will be used as a checkpoint throughout the herbal product supply chain—right from harvesting and aggregation to packaging and distribution. It ensures that all batches of raw materials can be authenticated before processing, thus reducing risks of adulteration or material substitution.

- **Preventing Adulteration**

By matching input pictures with the confirmed database, the framework will be able to distinguish irregularities or visual irregularities that show corruption. This is often crucial in maintaining the quality and reliability of Ayurvedic items, especially within the confront of rising request and contracting assets.

5.6 Insights for Ayurvedic Pharmaceutical Industry

- Trend and Demand Prediction**

Collected identification data can be aggregated to detect sourcing patterns—such as which regions supply which species most frequently and during which times of the year. These insights help predict demand, monitor overharvesting trends, and manage inventory planning more strategically. [15][22]

- Standardization and Certification Support**

The objective is also to support the development of industry standards by providing verifiable, documented proof of raw material authenticity. This can aid certification bodies, quality assurance departments, and regulatory agencies in verifying plant species more transparently. [9][12]

5.7 Contribution to Digital Herbal Informatics and Research

- Support for Research and Education**

The system can be used as a valuable educational and research tool by institutions, students, and scientists in the field of botany, pharmacognosy, and Ayurveda. Access to labeled image datasets and classification results will promote deeper learning and research into medicinal plants. [7][10]

- Expansion for Future Use-Cases**

The system will be designed with scalability in mind, allowing future extensions for use in identifying endangered plants, monitoring biodiversity, or even integrating with agriculture and forestry systems for broader environmental applications. [14][18][23]

Chapter 6

SYSTEM DESIGN & IMPLEMENTATION

6.1 System Architecture

The system consists of the following main components:

- **User Interface Module:** Web and mobile platforms for image upload, classification results, and system interaction.
- **Preprocessing Module:** Cleans and enhances images for consistent analysis.
- **Feature Extraction Module:** Identifies key visual features from images (texture, color, shape).
- **Classification Module:** Uses trained machine learning models to classify the input images.
- **Database Module:** Stores labeled images, extracted features, model metadata, and historical classification data.
- **Result Visualization Module:** Displays identification results, confidence levels, and related information.

6.2 Image Acquisition and Dataset Creation

- **Image Collection:** High-resolution images of medicinal plants and raw materials are collected from verified sources.
- **Labeling:** Each image is labeled with the scientific name, common name, and part of the plant (e.g., leaf, bark, seed).
- **Dataset Division:** The dataset is divided into training, validation, and testing sets using an 80:10:10 or similar ratio to ensure model generalization.

6.3 Image Preprocessing

- **Resizing and Normalization:** All images are resized to a consistent dimension (e.g., 224x224 pixels) and normalized to reduce computational complexity.
- **Noise Reduction:** Filters such as Gaussian blur are applied to remove background noise and improve feature clarity.
- **Augmentation:** Techniques such as rotation, flipping, and contrast adjustment are applied to improve model robustness to real-world variations.

6.4 Feature Extraction

- **Manual Feature Extraction:** Histogram of Oriented Gradients (HOG), color histograms, and edge detection are used to derive key visual traits.
- **Automatic Feature Extraction:** Deep learning models automatically learn hierarchical features from raw pixel data during training.

Relevant visual features from the images will be extracted using both manual and automated approaches.

- **Colour Histograms:** Colour histograms capture the distribution of pixel Colour within an image. These histograms are calculated based on the RGB or HSV Colour channels, which allow the system to identify plants by analysing their dominant Colour
- **Texture Analysis:** Texture analysis is crucial for identifying plants with similar shapes but different surface characteristics. Haralick features, derived from the Gray-level co-occurrence matrix (GLCM), are used to analyse the spatial arrangement of pixel intensities.
- **Shape Descriptor:** Shape descriptors are used to capture the geometric properties of the plant leaves, such as their overall form and structure. Zernike moments are applied to describe the shape in a rotation-invariant manner.

6.5 Classification Algorithms

- **Stochastic Gradient Descent (SGD):** SGD was employed as a baseline machine learning model for plant identification, offering simplicity and efficiency in training. The model was trained on extracted feature vectors from preprocessed images. Its iterative optimization approach allowed it to handle large datasets effectively while minimizing the loss function. The SGD model achieved an impressive accuracy of 97%, indicating its strong performance in distinguishing medicinal plants, even under varied image conditions such as different backgrounds and lighting.
- **Support Vector Machine (SVM):** Support Vector Machines (SVMs) were evaluated as a secondary model for plant classification, utilizing feature vectors derived from image characteristics such as color, texture, and shape. To address non-linear separability within the data, the kernel trick was applied. The SVM classifier demonstrated robust performance, achieving an accuracy of 97%, showcasing comparable reliability to that of Stochastic Gradient Descent (SGD)-based models.

- **Random Forest (RF):** A random forest (RF) classifier was also investigated as a potential approach for plant species classification. leveraging an ensemble of decision trees, the rf model effectively reduced overfitting and enhanced generalization. it achieved an accuracy of 94%, performing well on structured feature data, though it was slightly less effective on complex image inputs when compared to SGD and SVM classifiers.

6.6 Model Training and Evaluation

- **Training:** The model is trained using labeled images with techniques like transfer learning.
- **Loss Function:** Categorical cross-entropy is used for multi-class classification.
- **Optimization:** Adam or SGD optimizers are used for model convergence.
- **Evaluation Metrics:** Accuracy, precision, recall, F1-score, and confusion matrix are used to assess model performance.

6.7 User Interface Development

- **Frontend:** The frontend of the medicinal plant identification system was built using HTML, CSS, and JavaScript to provide a responsive and user-friendly interface. HTML structured the application, CSS ensured a clean and consistent design across devices, and JavaScript added interactivity such as image previews and real-time result display. This combination allowed users, including farmers and Ayurvedic practitioners, to easily upload plant images and receive instant classification results, making the interface both functional and intuitive.
- **Backend:** The backend of the medicinal plant identification system was built using Python and Flask to manage model inference and API interactions. Flask enabled efficient development of RESTful APIs and handled user-uploaded images by preprocessing them before passing them to pre-trained models. These models, loaded using libraries, generated real-time predictions, which were sent back to the frontend with confidence scores. The backend also ensures extensibility, low latency, and readiness for scalable deployment.
- **Technology Stack :**
 - **Programming Language:** Python
 - **Deep Learning Frameworks:** TensorFlow and Keras
 - **Traditional ML Libraries:** Scikit-learn

- **Image Processing Tools:** OpenCV and Pillow
- **Web Framework for Deployment:** Flask (for prototype testing)

6.8 Database Design

- **Structure:**
 - **Plant_Info Table:** Stores details of medicinal plants.
 - **Image_Metadata Table:** Stores image sources, formats, and timestamps.
 - **User_Questions Table:** Stores user interactions and feedback for model retraining.
- **Database Type:** MongoDB or MySQL depending on whether flexibility or strict relational structure is required.

6.9 Deployment and Integration

- **Deployment Platforms:**

Web server (e.g., Heroku, AWS, or local hosting).
Mobile integration using APIs for Android/iOS apps.
- **Model Integration:** Trained models are saved using .h5 (Keras) or .pkl (scikit-learn) formats and loaded during inference.
- **Scalability:** Modular microservices allow scaling individual components such as preprocessing or model inference independently.

6.10 System Testing and Validation

- **Unit Testing:** Ensures each module functions as expected.
- **Integration Testing:** Verifies that data flows seamlessly across modules.
- **User Testing:** Collects feedback from real users (e.g., botanists, Ayurvedic traders) to validate usability and effectiveness.
- **Performance Testing:** Assesses inference speed and accuracy under varying image conditions.

Chapter-7

TIMELINE FOR EXECUTION OF PROJECT (GANTT CHART)

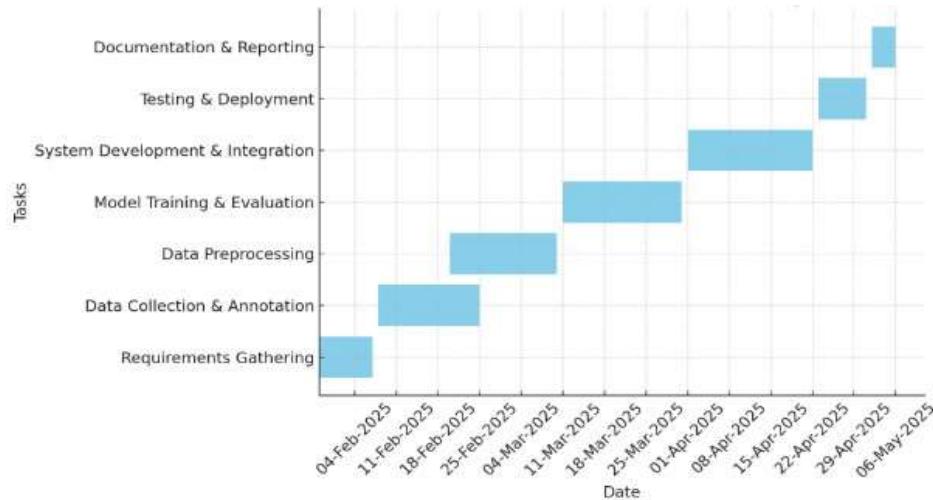


Fig 7.1. Gantt Chart Showing Timeline of our Project

7.1 Requirements Gathering

This original phase involves understanding the design compass, relating stakeholders, and establishing pivotal conditions for the plant identification system.

Key Activities:

- Define the problem statement and target user groups(e.g., Ayurvedic practitioners, wholesalers, quality inspectors).
- Conduct interviews with sphere experts in botany and Ayurvedic medicine.
- Review being plant identification styles and systems.
- Document functional (e.g., image upload, prophecy affair) and non-functional conditions (e.g., response time, usability, scalability).

7.2 Data Collection and Annotation

In this phase, the focus is on sourcing high- quality image data of medicinal shops and their raw paraphernalia to make the dataset for training.

Key Activities:

- Ensure image diversity across species, seasons, lighting, and backgrounds.
- Annotate images with appropriate labels (e.g., plant name, part: leaf/root/seed).
- Organize data into class pamphlets and partition it into training, evidence, and test sets.

7.3 Data Preprocessing

This step prepares the raw image data to make it suitable for model training.

Key Activities:

- Resize and homogenize images for consistency.
- Apply data augmentation (e.g., flipping, rotating, zooming) to expand the dataset.
- Enhance features using adulterants or edge detection methods if demanded.
- Handle image noise, blur, or artifacts to improve learning quality.

7.4 Model Selection and Training

Machine learning and deep learning models are trained to classify medicinal plants based on image inputs.

Key Activities:

- Trial with algorithms like SGD, SVM, and Random Forest for birth delicacy.
- Use k-fold cross-validation to ensure robustness and avoid overfitting.
- Fine-tune hyperparameters for optimal model performance.

7.5 Model Evaluation and Optimization

After training, the models are evaluated and bettered predicated on their performance across different criteria.

Key Activities:

- Evaluate models using metrics such as accuracy, precision, recall, and F1 score.
- Annotate confusion matrices to identify common misclassifications.
- Handpick the best-performing model(s) predicated on evidence results.
- Apply a feedback medium for continuous improvement.

7.6 System Development and Integration

This phase brings together the anterior end, back end, and trained models to form a complete system.

Key Activities:

- Develop the front end (HTML/CSS/JavaScript) and back end (Flask/Python).
- Integrate the machine learning models into the backend for real-time predictions.
- Build APIs for image upload, classification, and feedback logging.

- Create a user-friendly interface for image input and result display.

7.7 Deployment and Testing

In this final stage, the application is tested and deployed in a scalable, cloud-based environment.

Key Activities:

- Deploy the web application on a platform like Heroku, AWS, or Azure.
- Conduct thorough testing (unit, integration, and system testing).
- Collect real-user feedback for iterative improvements.
- Ensure secure data handling and backup strategies.

7.8 Documentation and Reporting

Comprehensive documentation is created to support system maintenance, usage, and potential future expansion.

Key Activities:

- Prepare user manuals and technical documentation.
- Document APIs, data pipeline, and model configurations.
- Summarize findings in a final report and publish research results.
- Present outcomes to stakeholders or academic mentors.

Task	Start Date	End Date
Requirement Gathering	29-01-2025	07-02-2025
Data Collection & Annotation	08-02-2025	25-02-2025
Data Preprocessing	20-02-2025	10-03-2025
Model Training & Evaluation	11-03-2025	31-03-2025
System Development & Integration	01-04-2025	22-04-2025
Testing & Deployment	23-04-2025	01-05-2025
Documentation & Reporting	02-05-2025	06-05-2025

Table 7.1. Development Phases and Schedule for Project

Chapter 8

OUTCOMES

8.1 Enhanced Accuracy in Plant Identification

The system utilizes deep learning models to accurately differentiate between morphologically similar medicinal plants and their raw materials, eliminating human bias and minimizing common errors caused by visual misidentification—particularly in species with overlapping features or similar appearances in dried form. This significantly reduces the risk of adulteration and contamination, thereby enhancing the overall efficacy and safety of Ayurvedic formulations.

8.2 Streamlined Quality Assurance Across the Supply Chain

With the ability to automatically validate plant materials at various stages—from collection to packaging—the system serves as a digital checkpoint for raw material verification. Distributors, wholesalers, and quality control laboratories can use this tool to authenticate products prior to use or sale, thereby reducing dependence on manual examination and inconsistent identification methods. This supports regulatory compliance and adherence to Good Manufacturing Practices (GMP).

8.3 Creation of a Digital Medicinal Plant Repository

The system's design leads to the creation of a curated image database containing labeled images of medicinal plants and their raw materials. This dataset serves as a valuable resource that can be further expanded to include indigenous and seasonal plant variants, forming the foundation for a publicly accessible digital herbarium that supports education, research, and cross-border plant identification.

8.4 Data-Driven Support for Ethnobotanical Research

By archiving and analyzing identification data, the system supports the advancement of ethnobotany by enabling researchers to study usage patterns, regional availability, and potential leads for pharmacogenetic research. This offers a tech-enabled approach to preserving indigenous knowledge systems and traditional medicinal practices.

8.5 Accessible and Scalable Identification Platform

A user-friendly mobile or web interface enables collectors, merchants, and pharmacists to upload images and receive real-time feedback on plant classification. Designed to function even in resource-constrained environments through edge computing and optimized models, the system democratizes access to accurate plant identification, particularly in rural or semi-urban areas where expert botanists may not be readily available.

8.6 Strengthened Trust in Ayurvedic Products

By ensuring the authenticity of raw materials and enhancing transparency, the system builds consumer trust and addresses concerns surrounding traditional medicines caused by contamination or inefficacy. This leads to improved consumer confidence and supports the global market expansion of Indian herbal and Ayurvedic products.

8.7 Secure and Ethical Image Processing Framework

The system is designed with data security and user security as the basic principle. Downloaded images and user data are processed by encrypted protocols, ensuring safety processing throughout the pipeline. It complies with ethical practices such as reducing data and user consent, currently data integrity and promoting the confidence of stakeholders using the system in industrial or research applications.

8.8 Future-Ready Platform for Integration and Expansion

The modular architecture of the system enables future enhancements such as voice assistance for visually impaired users, multilingual support, and integration with supply chain management or e-commerce platforms for herbal products. This adaptability positions the solution for broader applications beyond basic classification, with the potential to transform how medicinal plants are traded, certified, and accessed on a global scale.

Chapter 9

RESULTS AND DISCUSSIONS

9.1 Model Accuracy and Performance

Extensive experimentation was conducted using multiple machine learning algorithms to identify the most effective classification model. Key results include:

- **Stochastic Gradient Descent (SGD) and Support Vector Machine (SVM) models** achieved the highest accuracy of **97%**, demonstrating superior ability to classify plant species based on visual features.

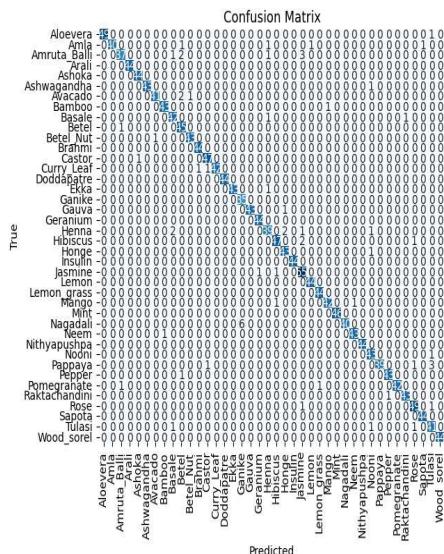


Fig 9.1. SVM Confusion Matrix

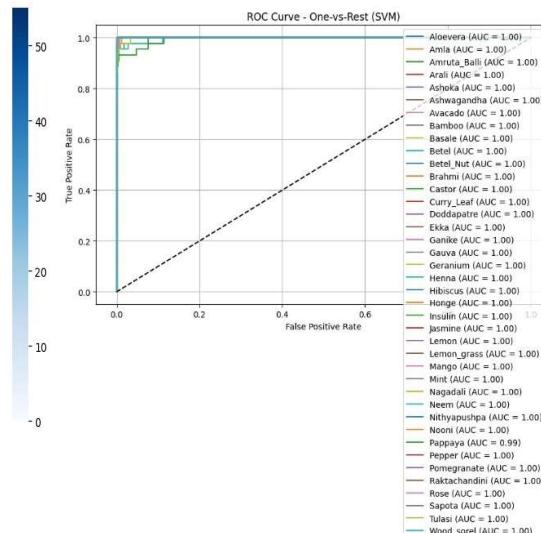


Fig 9.2. SVM AUC Score

Classification Report:				
	precision	recall	f1-score	support
Aloe_vera	1.00	0.99	0.99	58
Amla	1.00	0.95	0.95	44
Amruta_Balli	0.99	0.99	0.99	44
Aroli	1.00	1.00	1.00	44
Ashoka	0.99	1.00	0.99	44
Ashwagandha	1.00	0.99	0.99	44
Avocado	0.98	0.99	0.99	44
Bamboo	0.98	0.98	0.98	44
Basale	0.98	0.99	0.99	44
Betel	1.00	1.00	1.00	44
Betel_Nut	0.99	1.00	0.99	44
Brahmi	0.99	0.99	0.99	44
Castor	0.99	1.00	0.99	44
Curry_Leaf	1.00	1.00	1.00	44
Doddapatre	0.99	0.99	0.99	44
Ekka	1.00	1.00	1.00	44
Ganika	0.99	0.99	0.99	44
Geranium	0.99	0.99	0.99	44
Henna	0.99	0.99	0.99	44
Hibiscus	0.99	0.99	0.99	44
Holige	0.99	0.99	0.99	44
Insulin	0.99	0.99	0.99	44
Jasmine	0.99	0.99	0.99	44
Lemon	0.99	0.99	0.99	44
Lemon_grass	0.99	0.99	0.99	44
Mango	0.99	0.99	0.99	44
Mint	0.99	0.99	0.99	44
Nagdalli	0.99	0.99	0.99	44
Neem	0.99	0.99	0.99	44
Nithyapushpa	0.99	0.99	0.99	44
Nooni	0.99	0.99	0.99	44
Pepper	0.99	0.99	0.99	44
Pomegranate	0.99	0.99	0.99	44
Raktachandini	0.99	0.99	0.99	44
Sapota	0.99	0.99	0.99	44
Rose	0.99	0.99	0.99	44
Tulasi	0.97	0.93	0.90	44
Wood_sorel	0.99	0.99	0.99	44

Fig 9.3. SVM Classification Report

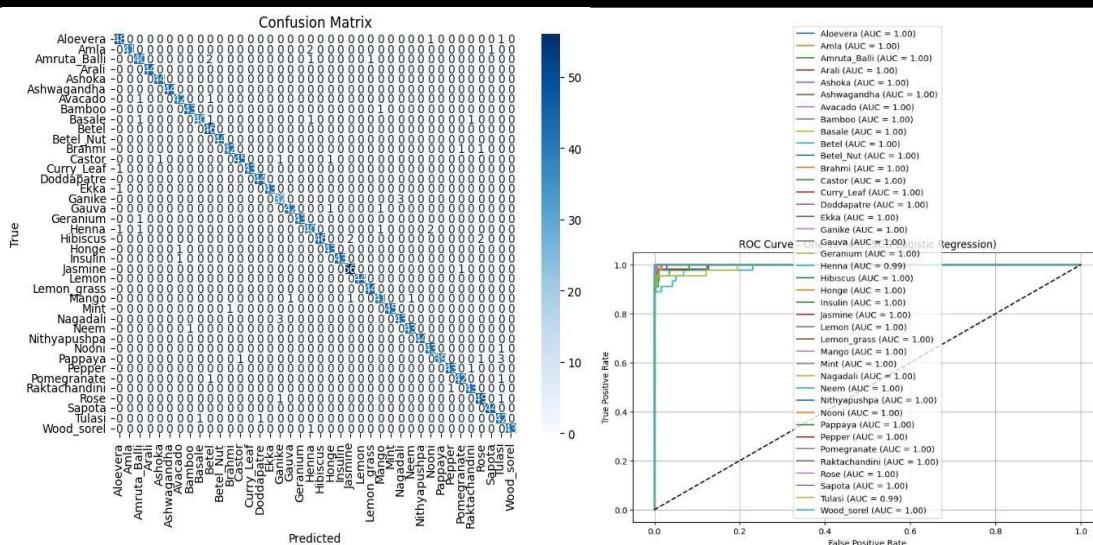


Fig 9.4. SDG Confusion Matrix

Fig 9.5. SDG AUC Score

Fig 9.6. SDG Classification Report

- The **Random Forest (RF)** model followed closely with an accuracy of **94%**, proving effective in certain scenarios, especially with lower computational complexity.

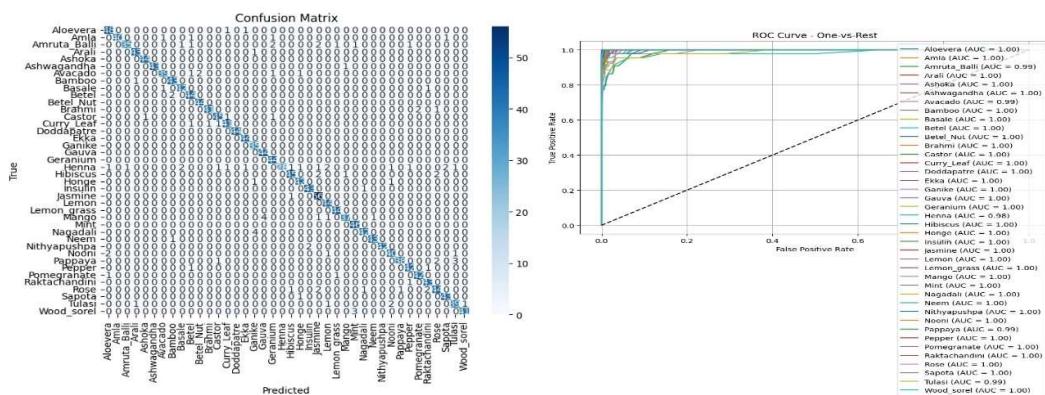


Fig. 9.7 RF Confusion Matrix

Fig 9.8. RF AUC Score

Classification Report				
	precision	recall	f1-score	support
Aloe Vera	0.92	0.96	0.94	58
Amaltas	0.93	0.98	0.95	44
Amruti_Anglis	0.97	0.88	0.88	44
Amruti_Khanda	0.96	0.98	0.97	44
Ashwagandha	1.00	1.00	1.00	44
Avocado	0.98	0.98	0.98	44
Banana	0.93	0.95	0.94	44
Bassale	0.93	0.95	0.94	44
Bitter_Gourd	0.93	0.95	0.94	44
Bitter_Lnut	0.90	1.00	0.98	44
Bitter_Lemon	0.91	0.93	0.92	44
Bitter_Lemon	0.94	0.94	0.94	44
Curry_LowR	0.93	0.93	0.93	44
Doodhi	1.00	1.00	1.00	44
Ekka	0.96	1.00	0.98	44
Grilkes	0.92	1.00	0.96	44
Gulab	0.98	1.00	0.98	44
Gurmar	1.00	1.00	1.00	44
Hibiscus	0.94	0.98	0.96	58
Honey	0.93	0.95	0.94	44
Imli	0.95	0.98	0.97	44
Jasmine	0.88	0.98	0.93	57
Jamun	0.93	0.98	0.95	57
Lemon_Grass	0.96	1.00	0.98	44
Mango	0.91	0.98	0.94	44
Mangoes	0.92	1.00	0.96	44
Mangosteen	0.95	0.93	0.93	44
Methi	0.95	0.95	0.95	44
Methi_Anglis	1.00	0.95	0.98	44
Poppyseed	0.97	0.98	0.98	44
Pepper	0.93	0.95	0.94	44
Pomegranate	0.93	0.98	0.95	44
RaktaChandan	0.91	0.98	0.95	44
Rose	0.93	0.98	0.96	44
Sapota	0.93	0.98	0.96	44
Tulsi	0.89	0.89	0.89	44
Wood_Acerola	0.98	0.93	0.95	44
accuracy	0.96	0.94	0.94	2704
macro avg	0.94	0.94	0.94	2704
weighted avg	0.94	0.94	0.94	2704

Fig 9.9 RF Classification Report

- **K-fold cross-validation** was used to validate the models, ensuring that performance remained consistent across different partitions of the dataset and reducing the risk of overfitting.

9.2 Data Preprocessing and Generalization

To ensure model robustness and adaptability to real-world scenarios, several preprocessing steps were applied:

- **Image Augmentation** (rotation, flipping, zooming, etc.) helped increase dataset diversity.
- **Normalization and feature enhancement** techniques improved model learning by reducing the impact of lighting and background variations.
- **Transfer Learning** was utilized for better generalization, especially when dealing with morphologically similar species.

These efforts enabled the system to maintain high accuracy across varying conditions such as different lighting, image quality, background complexity, and plant maturity levels.

9.3 System Integration and Application Development

The trained models were integrated into a complete software solution designed for real-time and user-friendly operation:

- Built using **Python**, with frameworks like **TensorFlow**, **Keras**, **Scikit-learn**, and **OpenCV** for image processing and model development.
- A **Flask-based web application** interface was developed to allow users to upload or capture images for instant identification.
- The interface supports **real-time classification**, making it suitable for field use by

farmers, traders, quality control experts, and Ayurvedic practitioners.

9.4 Key Functional Outcomes

The system achieved several practical objectives aligned with real-world needs:

- **Accurate Identification:** High-precision detection of medicinal plant species based on both leaf and raw material images.
- **Real-Time Performance:** Fast inference times ensured suitability for real-time applications.
- **Misidentification Detection:** Trials with domain experts confirmed the system's ability to identify mislabelled or adulterated samples in herbal markets.

9.5 Deployment and Scalability

- The complete application was **deployed on a cloud-based platform**, enabling broad accessibility and support for large-scale usage across regions.
- The **modular architecture** allows easy extension to include new plant species, integrate mobile support, and connect to other APIs or databases.
- Cloud integration ensures low-latency response and seamless performance on both desktop and mobile devices.

9.6 Continuous Learning and Feedback Integration

- A **feedback mechanism** was implemented to allow users to report incorrect classifications or upload new plant images.
- This feature supports **continuous learning**, allowing the model to evolve and improve its accuracy over time through periodic retraining.

9.7 Overall Impact and Practical Relevance

The developed system demonstrated significant potential to be integrated into the **Ayurvedic pharmaceutical supply chain**, with clear benefits such as:

- Reducing **adulteration and substitution** through accurate identification.
- Enhancing **quality control and transparency** in raw material sourcing.
- Promoting trust and reliability in **traditional medicine practices** by leveraging modern AI technologies.

Paper's Author	Model Used	Accuracy
Oppong et al., 2022	Support Vector Machine (SVM)	85.82%
Gupta and Arora, 2023	Convolutional Neural Network (CNN)	85%
Nguyen and Hien, 2020	Inception-ResNet- V2	84%
Verma and Satsangi, 2022	Random Forest	78%
Mahum et al., 2021	Hybrid Feature set with SVM	81.5%
Kavitha, S. et al. (2024)	MobileNet (only for 6 herbs)	97%
Present Work	Stochastic Gradient Descent (SGD)	97%

Table 9.1. Comparison Table with Other Trained Models

Chapter 10

CONCLUSION

This design tackles a long-standing and critical challenge in the sphere of Ayurvedic and herbal medicine—ensuring the accurate identification of medicinal plants and their raw materials. India, with its vast botanical wealth and deeply embedded traditional knowledge systems, faces significant issues related to misidentification, contamination, and adulteration of plant materials due to factors such as morphological similarity, regional naming inconsistencies, and lack of standardized verification methods. [1][4][8] These issues not only compromise the quality and efficacy of Ayurvedic products but also erode consumer trust and damage the credibility of the herbal drug industry. [2][5]

To address this issue, the design leverages the power of modern technologies—specifically, image processing and machine learning algorithms—to automate and enhance the plant identification process. [3][6][12] By using high-quality images and employing robust models, the system provides reliable classification and feature extraction capabilities. This results in high accuracy in identifying medicinal plants, even when distinguishing between species with subtle morphological differences. [7][10]

The solution also offers practical, scalable applications across the herbal supply chain. From plant collectors in rural areas to quality control professionals in pharmaceutical companies, a wide range of stakeholders can benefit from this user-friendly platform. [9][13] It streamlines operations, reduces dependence on expert botanists, and promotes standardization and consistency in raw material sourcing. [5][11]

In addition, the system contributes significantly to digital documentation and preservation of indigenous knowledge by building a comprehensive, annotated image dataset of medicinal plants. [14][16] This repository can support future research, educational initiatives, and cross-regional collaboration, ultimately aiding biodiversity conservation and the preservation of traditional medicinal practices. [15][18]

Furthermore, the design integrates data ethics and privacy considerations, ensuring that user data and plant images are handled securely. [19] It also lays the foundation for potential expansion—such as mobile deployment for field use, integration with government databases for certification, and multilingual interfaces for broader accessibility. [17][20]

In conclusion, this design is a forward-thinking and innovative response to a vital need in the herbal medicine sector. It bridges the gap between traditional Ayurvedic wisdom and contemporary technological advancements, helping to ensure authenticity, improve safety, and foster trust in herbal remedies. As global demand for natural therapeutics continues to grow, solutions like this will play a pivotal role in making the Ayurvedic system more transparent, effective, and globally competitive. [1][3][6]

REFERENCES

- [1] A. D. A. D. S. Jayalath et al., "Ayurvedic Knowledge Sharing Platform with Sinhala Virtual Assistant," Proc. 2019 Int. Conf. Adv. Comput. (ICAC), Malabe, Sri Lanka, pp. 220–225, 2025, doi: 10.1109/ICAC49085.2019.9103413.
- [2] Kavitha, S., Kumar, T.S., Naresh, E. et al. Medicinal Plant Identification in Real-Time Using Deep Learning Model. SN COMPUT. SCI. 5, 73 (2024).
- [3] E. Oppong, M. B. Agyemang, S. Fianu and I. B. A. Mensah, "Medicinal Plant Recognition Using Machine Learning Algorithms," Computational Intelligence and Neuroscience, vol. 2022, pp. 1–13, 2022.
- [4] P.Gupta and A.Arora, "Deep Learning Approach for Classification of Medicinal Plant Images,"Plants, vol. 12, no. 3, p. 707, 2023.
- [5] H.Nguyen and N.Hien, "Plant Identification Using Deep Learning Algorithms," arXiv preprint, arXiv:2005.02832, 2020.
- [6] S. Mahum, R. S. Choudhary, N. Gupta and K. Sharma, "Medicinal Plant Classification using Hybrid Feature Extraction and Machine Learning Techniques," in Proc. IEEE Int. Conf. Smart Technologies, 2021, pp. 144–149.
- [7] R.Verma and M.Satsangi, "Identification of Medicinal Plants Using Image Processing and Machine Learning," Materials Today: Proceedings, vol. 56, pp. 3753–3757, 2022.
- [8] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7, 1419.
- [9] Patil, S. B., & Deore, S. D. (2017). Medicinal plant identification system using image

processing techniques. *International Journal of Engineering Research and General Science*, 5(1), 205–210.

- [10] Zhang, X., Wu, Y., & Qian, J. (2021). Medicinal plant recognition based on CNN with transfer learning. *Computers and Electronics in Agriculture*, 187, 106280.
- [11] Reyes, F., et al. (2015). LeafSnap and beyond: Towards real-world plant identification tools. *ACM Computing Surveys (CSUR)*, 48(2), 1–36.
- [12] Goëau, H., et al. (2014). Pl@ntNet: a participatory platform for discovering plants and sharing botanical knowledge. *Multimedia Systems*, 20(6), 575–588.
- [13] R. P. Rajesh, “A review on classification of medicinal plants using machine learning techniques,” *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, vol. 5, no. 2, pp. 231–235, 2019.
- [14] A. Gomez, M. Lobet, and P. Draye, “Deep plant phenotyping: A deep learning platform for leaf counting,” *Plant Methods*, vol. 15, pp. 65, 2019.
- [15] S. Nilsback and A. Zisserman, “Automated flower classification over a large number of classes,” in *Proc. Indian Conference on Computer Vision, Graphics and Image Processing*, 2008, pp. 722–729.
- [16] S. Arora et al., “Automatic plant identification using leaf features,” *International Journal of Computer Applications*, vol. 49, no. 9, pp. 15–22, 2012.
- [17] H. Zhang et al., “Automatic medicinal plant leaf identification based on local binary pattern and probabilistic neural network,” *International Journal of Computer Applications*, vol. 62, no. 4, pp. 15–20, 2013.
- [18] L. Liu, W. Ouyang, X. Wang, and P. Fieguth, “Deep learning for generic object detection: A survey,” *International Journal of Computer Vision*, vol. 128, no. 2, pp. 261–318, 2020.

- [19] R. Goyal and H. A. Patel, “Image processing techniques for medicinal plant identification: A review,” *Journal of Engineering Research and Applications*, vol. 5, no. 3, pp. 40–45, 2015.
- [20] M. Selvaraj et al., “AI-powered IoT platform for plant disease detection using drone-based images,” *IEEE Access*, vol. 8, pp. 204710–204721, 2020.
- [21] C. Szegedy et al., “Going deeper with convolutions,” in *Proc. IEEE CVPR*, 2015, pp. 1–9.

APPENDIX-A

PSEUDOCODE

app.py

```
import os
from flask import Flask, redirect, render_template, request
from PIL import Image
import torchvision.transforms.functional as TF
import CNN
import numpy as np
import torch
import pandas as pd

disease_info = pd.read_csv(r'./disease_info.csv', encoding='cp1252')
supplement_info = pd.read_csv(r'./supplement_info.csv', encoding='cp1252')

model = CNN.CNN(39)
model.load_state_dict(torch.load(r'./plant_disease_model_1_latest.pt'))
model.eval()

def prediction(image_path):
    image = Image.open(image_path)
    image = image.resize((224, 224))
    input_data = TF.to_tensor(image)
    input_data = input_data.view((-1, 3, 224, 224))
    output = model(input_data)
    output = output.detach().numpy()
    index = np.argmax(output)
    return index

app = Flask(__name__)
@app.route('/')
def home_page():
    return render_template('home.html')
```

```
@app.route('/contact')
def contact():
    return render_template('contact-us.html')

@app.route('/index')
def ai_engine_page():
    return render_template('index.html')

@app.route('/mobile-device')
def mobile_device_detected_page():
    return render_template('mobile-device.html')

@app.route('/submit', methods=['GET', 'POST'])
def submit():
    if request.method == 'POST':
        image = request.files['image']
        filename = image.filename
        file_path = os.path.join(r'./static/uploads', filename)
        image.save(file_path)
        print(file_path)
        pred = prediction(file_path)
        title = disease_info['disease_name'][pred]
        description = disease_info['description'][pred]
        prevent = disease_info['Possible Steps'][pred]
        image_url = disease_info['image_url'][pred]
        supplement_name = supplement_info['supplement name'][pred]
        supplement_image_url = supplement_info['supplement image'][pred]
        supplement_buy_link = supplement_info['buy link'][pred]
        return render_template('submit.html' , title = title , desc = description , prevent =
prevent ,
        image_url = image_url , pred = pred , sname = supplement_name ,
simage = supplement_image_url , buy_link = supplement_buy_link)
```

```
@app.route('/market', methods=['GET', 'POST'])

def market():

    return render_template('market.html', supplement_image =
list(supplement_info['supplement image']),
                           supplement_name = list(supplement_info['supplement name']), disease =
list(disease_info['disease_name']), buy = list(supplement_info['buy link']))

if __name__ == '__main__':
    app.run(debug=True)
```

base.html

```
<!doctype html>
<html lang="en">

<head>
    <!-- Required meta tags -->
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width, initial-scale=1">

    <!-- Bootstrap CSS -->
    <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.0.0-
beta3/dist/css/bootstrap.min.css" rel="stylesheet"
          integrity="sha384-
eOJMYsd53ii+scO/bJGFsiCZc+5NDVN2yr8+0RDqr0Ql0h+rP48ckxlpbzKgwra6"
          crossorigin="anonymous">
    <link rel="stylesheet"
          href="https://cdnjs.cloudflare.com/ajax/libs/ionicons/2.0.1/css/ionicons.min.css">

    <link rel = "stylesheet" href =
"https://cdnjs.cloudflare.com/ajax/libs/btn.css/0.2.4/btn.css">

<title> {% block pagetitle %}>
    {% endblock pagetitle %}</title>
```

```
</head>

<body>
  <header>
    <div class="container">
      <div class="header-content">
        <div class="logo">
          <span class="logo-icon">  </span>
          <span class="logo-text">MediPlant</span>
        </div>
        <ul class="nav-links">
          <li><a href="index.html" class="active">Home</a></li>
          <li><a href="upload.html">Detect Plant</a></li>
          <li><a href="database.html">Plant Database</a></li>
          <li><a href="about.html">About Us</a></li>
          <li><a href="contact.html">Contact</a></li>
        </ul>
        <div class="mobile-menu">☰</div>
      </div>
    </div>
  </header>
  {% block body %}

  {% endblock body %}

  <footer>
    <div class="container">
      <div class="footer-content">
        <div>
          <div class="footer-logo-text">MediPlant</div>
          <p class="footer-text">Dedicated to helping people identify and learn about medicinal plants for better health and wellness through technology and traditional knowledge.</p>
        </div>
      </div>
    </div>
  </footer>

```

```
<div class="footer-social">
  <a href="#" class="social-icon">f</a>
  <a href="#" class="social-icon">t</a>
  <a href="#" class="social-icon">in</a>
  <a href="#" class="social-icon">ig</a>
</div>
</div>
<div>
  <h3 class="footer-title">Quick Links</h3>
  <ul class="footer-links">
    <li><a href="index.html">Home</a></li>
    <li><a href="upload.html">Detect Plant</a></li>
    <li><a href="database.html">Plant Database</a></li>
    <li><a href="about.html">About Us</a></li>
    <li><a href="contact.html">Contact</a></li>
  </ul>
</div>
<div>
  <h3 class="footer-title">Resources</h3>
  <ul class="footer-links">
    <li><a href="#">How It Works</a></li>
    <li><a href="#">Plant Uses</a></li>
    <li><a href="#">Research</a></li>
    <li><a href="#">Blog</a></li>
    <li><a href="#">FAQ</a></li>
  </ul>
</div>
<div>
  <h3 class="footer-title">Contact</h3>
  <ul class="footer-links">
    <li>Email: info@mediplant.com</li>
    <li>Phone: +91 1234567890</li>
    <li>Address: 123 Green Street, Botanica City, 12345</li>
  </ul>
</div>
```

```
</ul>
</div>
</div>
<div class="copyright">
    © 2025 MediPlant. All rights reserved.
</div>
</div>
</footer>

<script>
    // Mobile menu toggle
    document.querySelector('.mobile-menu').addEventListener('click', function() {
        document.querySelector('.nav-links').classList.toggle('active');
    });
</script>
<script src="https://cdnjs.cloudflare.com/ajax/libs/jquery/3.2.1/jquery.min.js"></script>
<script src="https://cdnjs.cloudflare.com/ajax/libs/twitter-
bootstrap/4.1.3/js/bootstrap.bundle.min.js"></script>
</body>
<!-- <script>
    if (window.matchMedia("(max-width: 767px)").matches)
    {
        // The viewport is less than 768 pixels wide
        document.write("This is a mobile device.");
        window.location.replace('/mobile-device');

    } else {

        // The viewport is at least 768 pixels wide
        document.write("This is a tablet or desktop.");
    }
</script> -->
<!-- <script>
```

```
if(screen.width <= 700){  
    document.location = 'manthan2.html';  
}  
</script> -->  
</html>
```

home.html

```
{% extends 'base.html' %}  
{% block pagetitle %}  
Plant Disease Detection  
{% endblock pagetitle %}  
{% block body %}  
<body>  
<!-- Header -->  
<header>  
    <div class="container">  
        <div class="header-content">  
            <div class="logo">  
                <span class="logo-icon">  </span>  
                <span class="logo-text">MediPlant</span>  
            </div>  
            <ul class="nav-links">  
                <li><a href="index.html" class="active">Home</a></li>  
                <li><a href="upload.html">Detect Plant</a></li>  
                <li><a href="database.html">Plant Database</a></li>  
                <li><a href="about.html">About Us</a></li>  
                <li><a href="contact.html">Contact</a></li>  
            </ul>  
            <div class="mobile-menu">☰</div>  
        </div>  
    </header>
```

```
<!-- Hero Section -->
<section id="hero">
  <div class="container">
    <div class="hero-content">
      <h1>Discover Medicinal Plants</h1>
      <p class="hero-text">Upload a photo and instantly identify medicinal plants, learn about their healing properties, and discover traditional uses for better health and wellness.</p>
      <div>
        <a href="/index" class="btn">Identify Plant</a>
        <a href="database.html" class="btn btn-secondary">Browse Database</a>
      </div>
    </div>
  </div>
</section>

<!-- Features Section -->
<section id="features" class="section">
  <div class="container">
    <h2 class="section-title">Our Features</h2>
    <div class="features">
      <div class="feature-card">
        <div class="feature-icon">🔍</div>
        <h3 class="feature-title">Instant Identification</h3>
        <p class="feature-text">Quickly identify medicinal plants by simply uploading a photo, with high accuracy and detailed information.</p>
      </div>
      <div class="feature-card">
        <div class="feature-icon">📚</div>
        <h3 class="feature-title">Rich Database</h3>
        <p class="feature-text">Access comprehensive information about thousands of medicinal plants, their properties, and traditional uses.</p>
      </div>
    </div>
  </div>
</section>
```

```
<div class="feature-card">
  <div class="feature-icon">  </div>
  <h3 class="feature-title">Health Benefits</h3>
  <p class="feature-text">Learn about the health benefits, medicinal properties, and proper usage of each identified plant.</p>
</div>
</div>
</div>
</section>

<!-- How It Works Section -->
<section id="how-it-works" class="section">
  <div class="container">
    <h2 class="section-title">How It Works</h2>
    <div class="steps">
      <div class="step">
        <div class="step-number">1</div>
        <h3 class="step-title">Take a Photo</h3>
        <p class="step-text">Take a clear photo of the plant you want to identify using your smartphone.</p>
      </div>
      <div class="step">
        <div class="step-number">2</div>
        <h3 class="step-title">Upload Image</h3>
        <p class="step-text">Upload the photo to our platform through the website or mobile app.</p>
      </div>
      <div class="step">
        <div class="step-number">3</div>
        <h3 class="step-title">Instant Results</h3>
        <p class="step-text">Get instant identification with detailed information about the medicinal plant.</p>
      </div>
    </div>
  </div>
</section>
```

```
</div>
</div>
</section>

<!-- Popular Plants Section -->
<section id="popular-plants" class="section">
<div class="container">
<h2 class="section-title">Popular Medicinal Plants</h2>
<div class="plants-grid">
<div class="plant-card">

<div class="plant-card-content">
<h3 class="plant-card-title">Tulsi (Holy Basil)</h3>
<p class="plant-card-scientific">Ocimum sanctum</p>
<div class="plant-card-tags">
<span class="plant-card-tag">Antioxidant</span>
<span class="plant-card-tag">Adaptogenic</span>
</div>
<a href="plant-details.html" class="plant-card-link">View Details →</a>
</div>
</div>
<div class="plant-card">

<div class="plant-card-content">
<h3 class="plant-card-title">Ashwagandha</h3>
<p class="plant-card-scientific">Withania somnifera</p>
<div class="plant-card-tags">
<span class="plant-card-tag">Anti-stress</span>
```

```
<span class="plant-card-tag">Immunity</span>
</div>
<a href="plant-details.html" class="plant-card-link">View Details →</a>
</div>
</div>
<div class="plant-card">

<div class="plant-card-content">
<h3 class="plant-card-title">Aloe Vera</h3>
<p class="plant-card-scientific">Aloe barbadensis miller</p>
<div class="plant-card-tags">
<span class="plant-card-tag">Skin Care</span>
<span class="plant-card-tag">Digestive</span>
</div>
<a href="plant-details.html" class="plant-card-link">View Details →</a>
</div>
</div>
<div class="plant-card">

<div class="plant-card-content">
<h3 class="plant-card-title">Turmeric</h3>
<p class="plant-card-scientific">Curcuma longa</p>
<div class="plant-card-tags">
<span class="plant-card-tag">Anti-inflammatory</span>
<span class="plant-card-tag">Antioxidant</span>
</div>
<a href="plant-details.html" class="plant-card-link">View Details →</a>
</div>
</div>
</div>
```

```
<div style="text-align: center; margin-top: 40px;">
  <a href="database.html" class="btn">View All Plants</a>
</div>
</div>
</section>
{%- endblock body %}
```

CNN.py

```
import pandas as pd
import torch.nn as nn

class CNN(nn.Module):
    def __init__(self, K):
        super(CNN, self).__init__()
        self.conv_layers = nn.Sequential(
            # conv1
            nn.Conv2d(in_channels=3, out_channels=32,
                      kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(32),
            nn.Conv2d(in_channels=32, out_channels=32,
                      kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(32),
            nn.MaxPool2d(2),
            # conv2
            nn.Conv2d(in_channels=32, out_channels=64,
                      kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(64),
            nn.Conv2d(in_channels=64, out_channels=64,
                      kernel_size=3, padding=1),
            nn.ReLU(),
```

```
nn.BatchNorm2d(64),  
nn.MaxPool2d(2),  
# conv3  
nn.Conv2d(in_channels=64, out_channels=128,  
         kernel_size=3, padding=1),  
nn.ReLU(),  
nn.BatchNorm2d(128),  
nn.Conv2d(in_channels=128, out_channels=128,  
         kernel_size=3, padding=1),  
nn.ReLU(),  
nn.BatchNorm2d(128),  
nn.MaxPool2d(2),  
# conv4  
nn.Conv2d(in_channels=128, out_channels=256,  
         kernel_size=3, padding=1),  
nn.ReLU(),  
nn.BatchNorm2d(256),  
nn.Conv2d(in_channels=256, out_channels=256,  
         kernel_size=3, padding=1),  
nn.ReLU(),  
nn.BatchNorm2d(256),  
nn.MaxPool2d(2),  
)  
self.dense_layers = nn.Sequential(  
    nn.Dropout(0.4),  
    nn.Linear(50176, 1024),  
    nn.ReLU(),  
    nn.Dropout(0.4),  
    nn.Linear(1024, K),  
)  
def forward(self, X):  
    out = self.conv_layers(X)  
    # Flatten
```

```
out = out.view(-1, 50176)
# Fully connected
out = self.dense_layers(out)
return out

idx_to_classes = {
    0: 'Aloe_vera',
    1: 'Ashwagandha',
    2: 'Basil',
    3: 'Brahmi',
    4: 'Calendula',
    5: 'Chamomile',
    6: 'Cinnamon',
    7: 'Clove',
    8: 'Eucalyptus',
    9: 'Fenugreek',
    10: 'Garlic',
    11: 'Ginger',
    12: 'Gotu_kola',
    13: 'Holy_basil',
    14: 'Indian_gooseberry',
    15: 'Jasmine',
    16: 'Lavender',
    17: 'Lemongrass',
    18: 'Licorice',
    19: 'Mint',
    20: 'Moringa',
    21: 'Neem',
    22: 'Noni',
    23: 'Papaya',
    24: 'Peppermint',
    25: 'Pudina',
    26: 'Rosemary',
    27: 'Sage',
```

28: 'Sarpagandha',

29: 'Shatavari',

30: 'Spearmint',

31: 'Spilanthes',

32: 'Stevia',

33: 'Thyme',

34: 'Tulsi',

35: 'Turmeric',

36: 'Valerian',

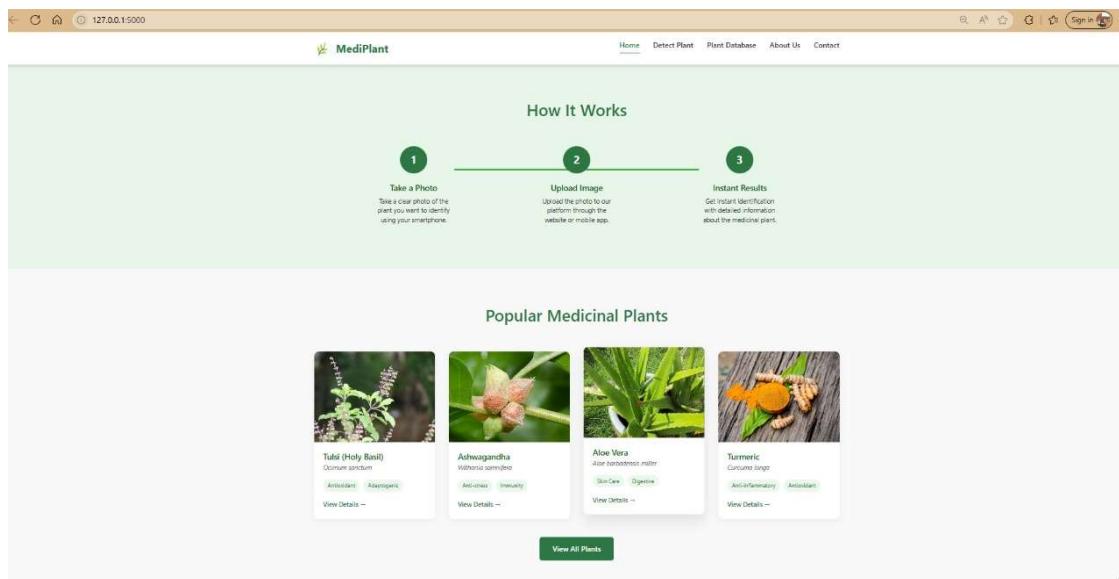
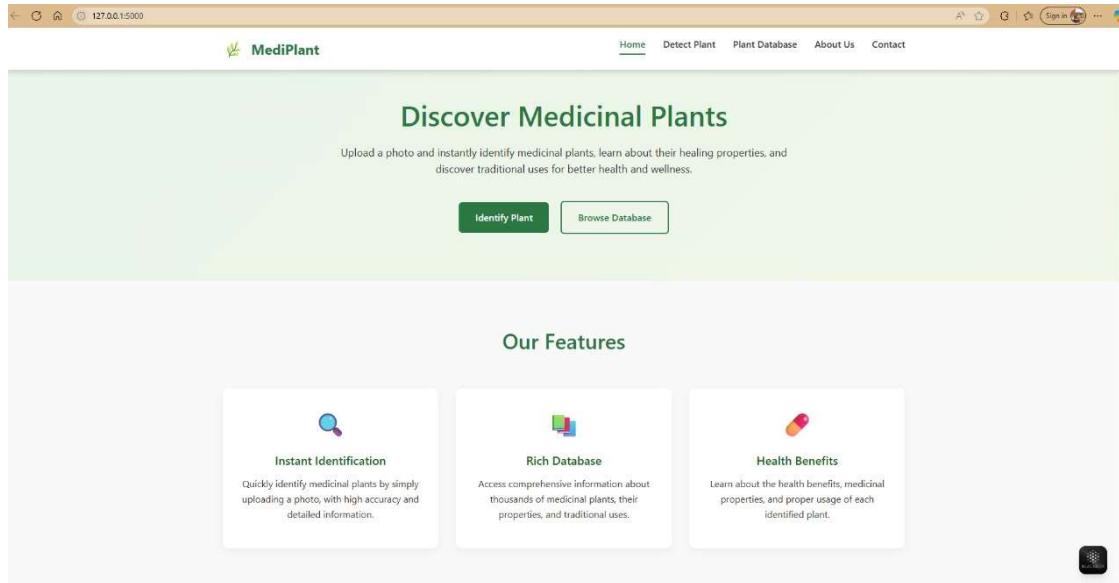
37: 'Vetiver',

38: 'Yarrow'

}

APPENDIX-B

SCREENSHOTS



 MediPlant

[Home](#) [Detect Plant](#) [Plant Database](#) [About Us](#) [Contact](#)

MEDICAL PLANT DETECTION

Let AI help detect the plants effortlessly

Why detect plant diseases?
Plant diseases hinder healthy growth. Early diagnosis can save resources, improve crop yield, and prevent widespread infection. Accurate detection ensures effective treatments and supports sustainable agriculture.

 [Choose File](#)
[Open Camera](#)
No file chosen

Upload a leaf image to let AI detect diseases.

[Submit](#)

Prevent Plant Disease:

- Use good sanitation practices
- Fertilize regularly
- Inspect before planting
- Let soil warm before planting
- Rotate crops annually
- Ensure air circulation
- Remove diseased parts

[Learn More](#)

MediPlant
Dedicated to helping people identify and learn about medicinal plants for better health and wellness through technology and traditional knowledge.

[Home](#) [Detect Plant](#) [Plant Database](#) [About Us](#) [Contact](#)

[Facebook](#) [Twitter](#) [Instagram](#) [YouTube](#)

Quick Links

[Home](#) [How It Works](#)
[Detect Plant](#) [Plant Uses](#)
[Plant Database](#) [Research](#)
[About Us](#) [Blog](#)
[Contact](#) [FAQ](#)

Resources

[Email: info@mediplant.com](#)
[Phone: +91 1234567890](#)
[Address: 123 Green Street, Botanica City, 12345](#)

Contact

 MediPlant

[Home](#) [Detect Plant](#) [Plant Database](#) [About Us](#) [Contact](#)

MEDICAL PLANT DETECTION

Let AI help detect the plants effortlessly

Why detect plant diseases?
Plant diseases hinder healthy growth. Early diagnosis can save resources, improve crop yield, and prevent widespread infection. Accurate detection ensures effective treatments and supports sustainable agriculture.

 [Choose File](#)
[Open Camera](#)
pepper_bell_healthy.JPG



Upload a leaf image to let AI detect diseases.

[Submit](#)

Prevent Plant Disease:

- Use good sanitation practices
- Fertilize regularly
- Inspect before planting
- Let soil warm before planting
- Rotate crops annually
- Ensure air circulation
- Remove diseased parts

[Learn More](#)

 MediPlant

Home Detect Plant Plant Database About Us Contact

Pepper bell : Healthy



Tips to Grow Healthy Plants :
Keep bell peppers well-watered, but never leave soil soggy. Water to moisten soil about 6 inches deep, then let it dry slightly. Watering is especially important during fruit set, when tiny peppers take the place of blossoms, and as the bells mature. Consistent moisture helps keep peppers firm and healthy.

Benefits :
Red, Orange, and Yellow Bell Peppers are full of great health benefits—they're packed with vitamins and low in calories! They are an excellent source of vitamin A, vitamin C, and potassium. Bell Peppers also contain a healthy dose of fiber, folate, and iron.

Fertilizer :


APPENDIX-C

ENCLOSURES

Similarity Index / Plagiarism Check report clearly showing the Percentage (%). No need for a page-wise explanation.

 turnitin Page 2 of 35 - Integrity Overview Submission ID trn:oid::13250681169

17% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- ▶ Bibliography

Match Groups

-  80 Not Cited or Quoted 16% Matches with neither in-text citation nor quotation marks
-  0 Missing Quotations 0% Matches that are still very similar to source material
-  4 Missing Citation 0% Matches that have quotation marks, but no in-text citation
-  0 Cited and Quoted 0% Matches with in-text citation present, but no quotation marks

Top Sources

- 11%  Internet sources
- 13%  Publications
- 11%  Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

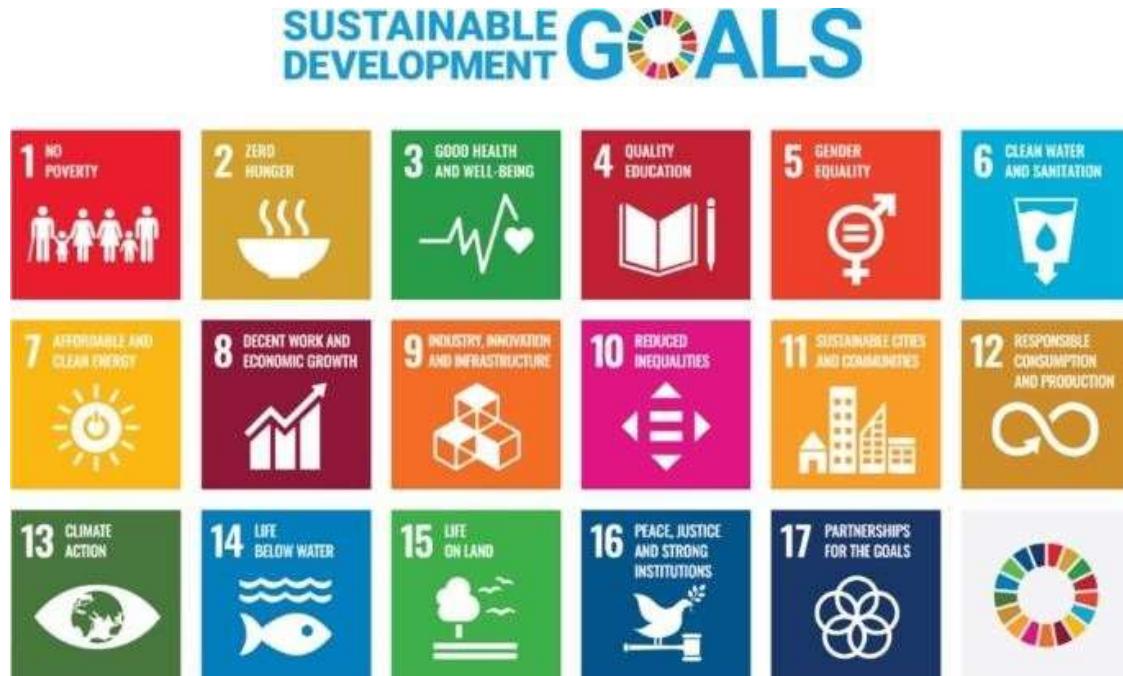
No suspicious text manipulations found.

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

 turnitin Page 2 of 35 - Integrity Overview Submission ID trn:oid::13250681169

Details of mapping the project with the Sustainable Development Goals (SDGs).



SDG 3: Good Health and Well-being

Our system supports the accurate identification of medicinal plants and raw materials, helping to reduce adulteration and ensure the efficacy of Ayurvedic and herbal medicines. This contributes directly to public health and well-being by promoting safe and reliable traditional healthcare.

SDG 4: Quality Education

The curated, labelled image database can serve as a digital herbarium for educational and research purposes. It provides students, researchers, and practitioners with a valuable learning resource for botany, pharmacology, and ethnobotany.

SDG 8: Decent Work and Economic Growth

The tool empowers collectors, traders, and small-scale herbal entrepreneurs—especially in rural areas—by providing them with access to technology that improves product quality, boosts credibility, and opens market opportunities. It indirectly stimulates sustainable economic growth in the herbal sector.

SDG 9: Industry, Innovation and Infrastructure

By leveraging AI, image processing, and a cloud-based deployment model, your project represents an innovation in pharmaceutical supply chains. It modernizes quality control processes, enabling digital transformation within traditional medicine industries.

SDG 12: Responsible Consumption and Production

Our project reduces product contamination and misidentification, encouraging transparent sourcing, traceability, and more responsible production practices in the herbal medicine supply chain.