Automated Identification of Medicinal Plants Through Image Processing and Transfer Learning

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FINAL YEAR DESIGN PROJECT REPORT

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APPROVAL

This Project titled "Automated Identification of Medicinal Plants Through Image Processing and Transfer Learning", submitted by Tanver Hassan Tanver & Mehdi Hasan Parvez, ID No: 211-15-4076 & 211-15-4075 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 12 January, 2025.

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We hereby declare that this project has been done by us under the supervision of **Mr. Rahmatul Kabir Rasel Sarker,Lecturer,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

This study presents an automated system for medicinal plant identification using deep learning techniques, addressing the need for accurate classification to support traditional healthcare, biodiversity conservation, and sustainable practices. Five advanced CNN models—VGG19, MobileNetV2, ResNet50v2, DenseNet201, and Inceptionv3—were evaluated on a dataset of 6,890 images, divided into training (70%), validation (15%), and testing (15%) sets. The models were trained using standardized parameters, including a 224×224 image resolution, batch size of 128, 50 epochs, and the Adam optimizer with a learning rate of 1e-4. DenseNet201 achieved the highest performance, with a testing accuracy of 95.19% and an average AUC score of 0.998, demonstrating exceptional generalization and class discrimination, followed closely by ResNet50v2. A mobile application was developed to integrate the classification tool, enabling real-time plant identification in field settings. The mobile app was optimized for efficiency, ensuring compatibility with low-resource environments and offline functionality. While DenseNet201's robustness made it the most suitable model for deployment, Inceptionv3 struggled with stability and precision, highlighting areas for potential refinement. This integrated mobile application offers a scalable and accessible solution for researchers, practitioners, and communities, facilitating the accurate identification of medicinal plants in diverse ecological settings. Future work will expand datasets, incorporate additional plant features, and further optimize the tool for real-world applications, ensuring its utility in both healthcare and conservation initiatives.

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Chapter 1

Introduction

1.1 Introduction

Medicinal plants have been a cornerstone of traditional healthcare systems and modern pharmacology for centuries, serving as the basis for numerous natural and synthetic drugs. Across the globe, systems such as Ayurveda in India and Traditional Chinese Medicine (TCM) continue to rely heavily on these plants, highlighting their significance in both cultural heritage and modern healthcare [2-3]. In countries like Vietnam, medicinal plants are deeply integrated into healthcare practices, underscoring the importance of accurate identification methods [1].

Traditionally, identifying medicinal plants has relied on the expertise of trained practitioners, who analyze morphological features such as leaf shape, texture, and color. However, this approach is time-consuming, subjective, and often unavailable in rural or resource-limited areas [4-5]. Advances in technology have opened new possibilities for automated identification systems that promise greater accuracy, efficiency, and accessibility, thereby supporting sustainable plant conservation and enhancing the safety and efficacy of plant-based medicinal products [6-7].

In recent years, significant progress has been made in this field through the application of image processing and machine learning techniques. From early models such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) to advanced deep learning architectures like Convolutional Neural Networks (CNNs) and Vision Transformers (ViT), these methods have demonstrated remarkable potential in accurately classifying medicinal plants [8-10]. These advancements pave the way for scalable, real-time solutions that can be deployed on mobile or embedded devices, offering promising applications in both research and field settings [11-12].

1.2 Motivation

The accurate identification of medicinal plants is crucial for ensuring their safe and sustainable use in healthcare and pharmaceutical industries. Traditional knowledge, while invaluable, is gradually diminishing due to urbanization and generational shifts, leaving a pressing need for automated systems to fill this gap [1], [5]. The limitations of manual methods, combined with the growing demand for reliable plant classification tools, have driven research into leveraging advanced technologies to address these challenges.

While traditional machine learning models like SVM and ANN provided an initial foundation, their reliance on handcrafted features and controlled datasets limited their scalability and generalizability [3], [8]. This constraint is particularly significant in real-world, resource-limited settings where diverse plant species are harvested and utilized [6]. With the introduction of CNNs and transfer learning, substantial improvements have been achieved in feature extraction and classification accuracy, as demonstrated by studies such as TS [2] and Oppong [9].

However, despite these advances, challenges remain. Existing models often struggle to balance computational efficiency with accuracy, a critical factor for real-time applications on mobile devices. Moreover, the lack of cross-dataset generalizability restricts their applicability across diverse ecological regions and plant species, leaving a gap in achieving universally reliable systems [11-13]. Addressing these challenges through the development of adaptable, robust, and scalable models not only supports sustainable medicinal plant use but also ensures these technologies are accessible to communities where they are needed most [15].

1.3 Objectives

The primary objective of this research is to develop an automated, reliable, and scalable system for identifying and classifying medicinal plants that address the limitations of current models. Specifically, the research aims to:

- Develop an accurate classification model which utilises advanced machine learning and deep learning techniques, including CNNs and transformer-based architectures, to achieve high classification accuracy in identifying medicinal plants based on leaf, texture, and shape features.

- Create a robust and generalisable system that enhances model robustness by incorporating diverse datasets to ensure adaptability across various ecological regions and plant species. This objective aims to overcome the dataset-specific limitations seen in prior studies by exploring cross-dataset validation and fine-tuning [10-11].
- Ensure real-time accessibility for designing the model to function efficiently on mobile and embedded systems, allowing real-time identification in field applications. By optimising the model for computational efficiency, this objective addresses the need for accessible identification tools in remote or resource-limited settings.
- By integrating traditional knowledge with technological advances, traditional plant identification knowledge, particularly in medicinal plant-rich regions, improves model relevance and utility. This objective aims to preserve and enhance traditional botanical knowledge through technology.
- Support conservation and sustainable use to contribute to the conservation of medicinal plant species by creating an identification tool that supports sustainable harvesting and aids practitioners in identifying endangered species. This objective underlines the broader conservation goals tied to accurate medicinal plant identification.

These objectives collectively aim to bridge the gap between traditional medicinal knowledge and modern technological capabilities, supporting the global healthcare system and biodiversity conservation efforts.

1.4 Methodology

The methodology for this study involves designing a system to accurately classify medicinal plant leaves using convolutional neural networks (CNNs). The process begins with the collection and preparation of a dataset consisting of medicinal plant leaf images. Preprocessing steps, including normalization, resizing, DPI adjustment, and augmentation, are applied to standardize the images and enhance their quality. Multiple CNN architectures, such as VGG19, InceptionV3, MobileNetV2, ResNet50V2, and DenseNet201, are implemented and compared to identify the most effective model based on performance metrics like accuracy, precision, and recall. The best-performing model is then optimized and converted into a lightweight format (`.tflite`) suitable for deployment on mobile and embedded devices. A user-friendly application, developed using the Flutter framework, integrates this optimized model to allow real-time classification of medicinal plant leaves. The application provides users with classification results and disease reports, offering a practical and accessible tool for field use while promoting sustainable and accurate medicinal plant identification.

1.5 Project Outcome

The outcome of this project is a robust, user-friendly system for identifying medicinal plant leaves with high accuracy and efficiency. By leveraging advanced convolutional neural network (CNN) architectures, the system provides a reliable automated classification mechanism. The preprocessing pipeline ensures consistent image quality through normalization, resizing, DPI adjustments, and augmentation, enabling the model to generalize well across diverse plant datasets. The comparative analysis of CNN models, including VGG19, InceptionV3, MobileNetV2, ResNet50V2, and DenseNet201, identifies the best-performing model, which is optimized and converted into a lightweight `.tflite` format for seamless deployment on mobile devices. The final application, developed using the Flutter framework, integrates this optimized model, offering real-time classification capabilities. Users can upload leaf images and receive instant results, including classification and disease reports, through an intuitive interface. This outcome provides an accessible and scalable solution for medicinal plant identification, supporting fieldwork, research, and conservation efforts.

1.6 Organization of the Report

This report is systematically organized into six chapters, each addressing critical aspects of the research on medicinal plant leaf classification using Convolutional Neural Networks (CNNs) and mobile deployment with Flutter. The structure and content of the report are as follows:

- Chapter 1(Introduction):

This chapter provides an overview of the research topic, articulating the motivation, objectives, and methodology of the study. It establishes the context, significance, and expected outcomes of the research, laying the foundation for subsequent chapters.

- Chapter 2 (Background):

This chapter offers a comprehensive review of existing literature, exploring related research on medicinal plant classification, traditional and automated methods, and the application of machine learning models in plant identification. It identifies key gaps in the field, highlighting the need for advanced solutions like CNN-based models.

- Chapter 3 (Research Methodology):

This chapter details the methodology adopted in the study, including dataset collection and preprocessing steps such as normalization, resizing, DPI adjustments, and augmentation. It outlines the comparative analysis of CNN architectures (VGG19, InceptionV3, MobileNetV2, ResNet50V2, and DenseNet201) and describes the optimization and deployment of the best-performing model using the Flutter framework. Diagrams illustrating the system design and workflow are included to provide a clear understanding of the approach.

- Chapter 4 (Implementation and Results)

This chapter focuses on the technical implementation of the proposed system, describing the experimental setup, model training, and evaluation procedures. It presents the results of the study, including performance metrics of the compared models, and discusses the effectiveness and limitations of the selected model.

- Chapter 5 (Engineering Standards and Design Challenges):

This chapter examines the compliance of the research with relevant standards in software and mobile application development. It also discusses ethical considerations, sustainability implications, and the challenges faced during the implementation and optimization of the classification system.

- Chapter 6 (Conclusion):

The final chapter synthesizes the key findings of the research, reflecting on its contributions to the field of medicinal plant identification. It highlights the limitations of the study and proposes future research directions to extend the applicability and scalability of the system.

This organization ensures a logical progression of ideas, guiding readers from the foundational aspects of the research to the technical implementation, results, and broader implications. It provides a comprehensive understanding of the study and its significance in the field of automated medicinal plant classification.

Chapter 2

Background

2.1 Introduction

This literature review examines recent advancements in medicinal plant identification, focusing on the integration of image processing, machine learning, and deep learning techniques. Early research utilized traditional machine learning models like SVM and ANN to classify plant species based on handcrafted features, yielding moderate accuracy. With the emergence of CNNs and transfer learning, models such as ResNet, DenseNet, and MobileNet have significantly improved classification accuracy and computational efficiency. Recent works also leverage transformer-based architectures and hybrid approaches, incorporating both deep and handcrafted features for enhanced robustness. However, despite these advancements, several limitations persist, including restricted datasets, limited real-time applications, and challenges in cross-dataset validation, highlighting ongoing gaps in developing universally applicable models.

2.2 Literature Review

The integration of image processing and transfer learning techniques for medicinal plant identification has seen substantial advancements. Duong [1] emphasized the importance of automated classification for traditional medicinal systems, especially in regions like Vietnam, where medicinal plant knowledge forms an essential part of cultural heritage. Utilizing transfer learning on pre-trained deep networks, the authors achieved a high classification accuracy of 98.7%, thus highlighting the potential for technological interventions in regions with limited resources.

In another significant study, TS [2] explored the application of CNN-based models for identifying Indian medicinal plants, aiming to preserve biodiversity and prevent extinction. The authors compared ResNet101, InceptionV3, and VGG16 architectures, finding that InceptionV3, combined with Canny edge detection preprocessing, achieved superior accuracy on the Ayur Bharat dataset.

Azeez [5] contributed to the field by developing a recognition system specifically tailored for Sri Lankan herbal plants, thereby aiding local practitioners in plant identification. Their model, which employed deep CNNs like Inception-v3 and ResNet, achieved 95.5% accuracy and demonstrated that transfer learning could bridge the knowledge gap between traditional practices and modern AI technologies. The study notably involved the use of traditional medical experts for dataset validation, reinforcing the model's practical relevance in the context of local medicinal knowledge.

Focusing on scalability and public accessibility, Kukreja [14] proposed a web-based system for identifying medicinal plants within Ayurvedic practices using DenseNet121. Despite dataset limitations, this model achieved a classification accuracy of 77.2%. The study offers a unique contribution by emphasizing the need for real-time, accessible solutions in plant identification and suggests future work to expand datasets, integrate environmental data, and improve model optimization. The integration of a web application demonstrates the potential for the practical deployment of AI in traditional medicine.

Lakshmanarao [13] investigated the combination of traditional feature extraction methods with deep learning to enhance medicinal plant classification. Using VGG16 to extract deep learning features and combining these with shape, texture, and color features, the authors achieved an impressive accuracy of 98.3% with a Random Forest classifier. Their hybrid approach emphasizes the value of fusing traditional and modern techniques, thereby providing more robust models for accurate plant classification, which can benefit applications in botanical research and healthcare.

A progressive approach to transfer learning was explored by Joshi [18] who optimized the ResNet50 architecture by applying differential learning rates and progressively increasing image sizes during training. Their fine-tuned model demonstrated superior accuracy across several benchmark datasets, achieving 100% top-1 accuracy on the Flavia dataset. This study highlights the adaptability of progressive learning techniques for leaf image classification, ensuring high accuracy across various datasets and image conditions.

The use of MobileNetV3 for efficient medicinal plant classification was examined by Valdez [19] Their low-cost, reliable model achieved 97.43% accuracy, further emphasizing the role of transfer learning in making complex models accessible for practical use, especially in resource-constrained environments. Their work reveals the feasibility of using lightweight architectures for real-world applications, providing a balanced approach between computational efficiency and classification accuracy.

Dahigaonkar [4] proposed a unique system for Ayurvedic plant identification by focusing on leaf features such as shape, color, and texture. Using Support Vector

Machines (SVM) for classification, they achieved 96.66% accuracy, showcasing the potential of leaf characteristics in building reliable plant identification models. This approach, grounded in traditional Ayurvedic practices, highlights the intersection of AI and traditional knowledge, potentially aiding practitioners in accurate plant selection.

Expanding on the traditional approach, Kumar [20] investigated front and back leaf features, using morphological characteristics to achieve a classification rate of up to 99% with various classifiers. This study extended the scope of identification to include dried leaves, enhancing the model's adaptability and reliability. Their work highlights the effectiveness of combining multiple features, offering a robust solution for Ayurvedic plant identification and ensuring a higher degree of accuracy in plant selection.

Azadnia and Kheiralipour [17] developed a robust algorithm for identifying medicinal plants like Falcaria vulgaris and Pelargonium sidoides, among others. By applying a smartphone-based vision system and artificial neural networks, they achieved a flawless 100% accuracy, demonstrating the potential for accessible, mobile-friendly solutions in medicinal plant classification. Their model's ease of use and accuracy under controlled conditions makes it a valuable contribution to the field, offering a practical solution for on-the-go plant identification.

Gokhale [16] proposed an automated identification system using image processing techniques to classify medicinal plants by leaf features, contributing valuable insights for pharmaceutical applications. Their system used attributes such as leaf length, width, and shape, with a view to developing web-based applications to assist taxonomists and the general public in medicinal plant identification.

In the context of Traditional Chinese Medicine, Kan [3] focused on the classification of medicinal plants by extracting multi-features from leaf images, achieving a 93.3% recognition rate using SVM. Their findings provided a theoretical foundation for enhancing medicinal plant classification systems within Chinese medicine, bridging traditional knowledge with computational methodologies.

Janani [8] presented an ANN-based approach for medicinal plant leaf classification, focusing on color, shape, and texture features to achieve 94.4% accuracy on 63 leaf images. Their study highlighted the potential of ANN in building leaf-based plant identification systems with low computational demands, offering a promising avenue for resource-constrained applications.

Oppong [9] contributed a novel model (OTAMNet) incorporating Log-Gabor filters and DenseNet201 for high-accuracy classification, achieving 98% on MyDataset and up to 100% on benchmark datasets. Their approach demonstrated that the combination of Log-Gabor filters with CNNs effectively enhances feature extraction for medicinal plant classification, paving the way for more precise automated identification methods.

Naeem [6] achieved 99.01% accuracy using a multi-layer perceptron classifier on multispectral and texture features. This work underscored the utility of integrating multispectral image processing with machine learning, especially for classifying multiple plant species, and highlighted the importance of feature optimization in achieving high classification accuracy.

Loganathan [21] explored SVM-based disease prediction in medicinal plant leaves, positioning SVM as a highly efficient, cost-effective alternative to traditional methods. Their image-processing approach allowed for affordable plant leaf disease classification, offering potential applications in sectors reliant on labour-intensive sorting and grading.

Nhut [10] employed Vision Transformer (ViT) and BEiT for medicinal plant recognition, finding that BEiT achieved the highest accuracy of 99.14% on the VNPlant-200 dataset. Their findings underscore the superiority of Transformer-based architectures over traditional CNNs in complex natural settings, establishing a new standard for medicinal plant recognition accuracy.

Pukhrambam [7] examined recent advancements in image processing for plant classification, noting the potential of automated systems to address the expertise shortage in plant taxonomy. They discussed the role of image processing in enhancing accuracy in medicinal plant identification, underscoring the potential for practical applications in traditional medicine.

Islam [11] introduced a PSO-optimized ResNet50-SVM cascaded network for smartphone-based medicinal plant classification, achieving an accuracy of 99.6%. Their system emphasised the need for efficient, portable solutions capable of identifying medicinal plants with high accuracy and rapid processing times, advocating for widespread adoption in field applications.

Das [12] presented a standalone device using GLCM features and LGBM for real-time identification of Ayurvedic plants, achieving 95.5% accuracy. Their work highlighted the potential of embedded systems for on-the-go medicinal plant identification, contributing to conservation efforts and public education on plant-based medicine.

Jerin [15] utilised the VGG-19 model for medicinal plant classification, focusing on distinct plant features like branches, flowers, and leaves. Their work demonstrated the effectiveness of CNNs for accessible medicinal plant identification, promoting natural remedy awareness among rural populations and aiding conservation efforts.

Lastly, Koli [22] addressed the detection of plant leaf diseases in Ayurvedic plants, using computer vision techniques to identify infections that impact yield. Their work emphasises the role of disease detection in maintaining the quality and availability of Ayurvedic plants, suggesting advancements for improving plant health monitoring in agricultural settings.

Table 2.1: Summary of Literature Reviewed.

Author (s)	**Year**	**Title**	**Methodology**	**Key Findings**
Duong-Trung et al.	2019	A combination of transfer learning and deep learning for medicinal plant classification.	Transfer Learning with Deep Networks	Custom dataset of medicinal plants from Vietnam, Accuracy(98.7%)
TS and Prabalakshmi	2021	Identification of indian medicinal plants from leaves using transfer learning approach.	ResNet101, InceptionV3, VGG16	Ayur Bharat dataset, 10 classes, 10,000 images, Accuracy(97.32%)
Azeez and Rajapakse	2019	An application of transfer learning techniques in identifying herbal plants in sri lanka.	Inception-v3, ResNet, MobileNet	Sri Lankan herbal plants, 5 classes, validated by practitioners, Accuracy(95.5%)
Kukreja et al.	2024	Web-Based Application for Medicinal Plant Identification Using Transfer Learning Approach.	DenseNet121	Kaggle dataset, 40 classes, web application focused, Accuracy(72.2%)
Lakshmana rao et al.	2024	Medicinal Plant Classification Using Transfer Learning Through Hybrid Machine Learning and Image Processing Techniques.	VGG16 with SVM, RF, DT, KNN	Kaggle dataset with additional shape, texture, color features, Accuracy(98.3%)

Joshi et al.	2021	Progressive transfer learning approach for identifying the leaf type by optimizing network parameters	ResNet50 with Progressive Transfer Learning	Flavia, LeafSnap, and MalayaKew datasets, Accuracy(99.89%)
Valdez et al.	2022	Medicinal plant classification using convolutional neural network and transfer learning.	MobileNetV3	New medicinal plant dataset, 10 classes, Accuracy(97.43%)
Dahigaonkar and Kalyane	2018	Identification of ayurvedic medicinal plants by image processing of leaf samples.	SVM with Shape, Color, Texture features	Self-collected Ayurvedic plant dataset, Accuracy(96.66%)
Kumar et al.	2017	Identification of ayurvedic medicinal plants by image processing of leaf samples.	Various Classifiers with Morphological Features	Scanned images of Ayurvedic medicinal plants, Accuracy(99%)
Azadnia and Kheiralipour	2021	Recognition of leaves of different medicinal plant species using a robust image processing algorithm and artificial neural networks classifier.	ANN with Texture, Color, Shape features	Smartphone-acquired images, 5 plant species, Accuracy(100%)
Gokhale et al.	2020	Identification of medicinal plant using image processing and machine learning.	Image Processing with ML techniques	Self-collected medicinal plant leaf images, Accuracy(Not specified)
Kan et al.	2017	Classification of medicinal plant leaf image based on multi-feature extraction.	SVM with Shape, Texture features	Dataset of 12 medicinal plant species, Accuracy(93.3%)
Janani and Gopal	2013	Identification of selected medicinal plant leaves using	ANN with Shape, Color, Texture features	Self-collected dataset, 63 leaf images, Accuracy(94.4%)

		image features and ANN.		
Oppong et al.	2022	A Novel Computer Vision Model for Medicinal Plant Identification Using Log-Gabor Filters and Deep Learning Algorithms.	OTAMNet (DenseNet201 + Log-Gabor)	MyDataset and benchmark datasets (Flavia, Swedish Leaf), Accuracy(98%)
Naeem et al.	2021	The classification of medicinal plant leaves based on multispectral and texture feature using machine learning approach.	MLP with Texture, Multispectral Features	Pakistani medicinal plants, 6 classes, Accuracy(99.01%)
Loganathan and Muthukumaravel	2023	Image Processing-Based Disease Prediction in Medical Plant Leaf.	SVM	Medicinal plant disease dataset, MATLAB-based, Accuracy(Not specified)
Nhut et al.	2024	Medicinal plant recognition based on Vision Transformer and BEiT.	BEiT, ViT, EfficientNetB0, EfficientNetV2-S	VNPlant-200 dataset, natural setting, Accuracy(99.14%)
Pukhrambam and Rathna (2021)	2021	A smart study on medicinal plants identification and classification using image processing techniques.	General Image Processing Techniques	Literature review, general medicinal plant images, Accuracy(Not specified)
Islam et al.	2024	Medicinal Plant Classification Using Particle Swarm Optimized Cascaded Network.	ResNet50-PSO-SVM	Smartphone-captured images of 7 medicinal plants, Accuracy(99.6%)
Das et al.	2023	Ayurvedic Medicinal Plant Identification System Using Embedded	LGBM with GLCM, Gabor filter	Embedded system dataset for Ayurvedic plants, Accuracy(95.5%)

		Image Processing Techniques.		
Jerin and Jeciyazhini	2024	Medicinal Plant Classification Using VGG-19.	VGG-19	Dataset of medicinal plant features (branches, leaves, flowers), Accuracy(Not specified)
Koli et al.	2024	Fostering ayurvedic plant wellness: Innovative leaf disease detection using computer vision and machine learning.	Image Processing, ML Techniques	Ayurvedic plant leaf disease detection dataset, Accuracy(Not specified)

2.2.1 Similar Applications

Several studies have explored automated systems for medicinal plant classification, demonstrating the potential of AI and machine learning in bridging the gap between traditional knowledge and modern technology. Duong [1] developed a high-accuracy model using transfer learning for Vietnamese medicinal plants, achieving 98.7% accuracy. Kukreja [14] proposed a web-based solution leveraging DenseNet121 for Ayurvedic plants, achieving 77.2% accuracy, emphasizing the need for real-time identification despite dataset limitations. Azeez [5] developed a recognition system for Sri Lankan herbal plants, achieving 95.5% accuracy, with datasets validated by traditional practitioners, ensuring practical relevance. Similarly, Azadnia [17] introduced a smartphone-based system for plant classification, achieving 100% accuracy, providing a scalable, mobile-friendly solution for on-the-go identification. These efforts highlight the potential of integrating AI into accessible applications for preserving and enhancing traditional medicinal practices.

2.2.2 Related Research

A comprehensive investigation into related studies reveals a variety of methodologies and advancements in medicinal plant identification. TS [2] demonstrated that InceptionV3, when combined with Canny edge detection, outperformed other CNN architectures on the Ayur Bharat dataset. Joshi [18] explored progressive transfer learning techniques with ResNet50, achieving near-perfect accuracy on diverse datasets. Kumar [20] extended the scope by incorporating morphological features, including dried leaves, to achieve a 99% classification rate. Valdez [19] utilized MobileNetV3 for efficient classification in resource-constrained settings, balancing accuracy (97.43%) with computational efficiency. Traditional feature extraction combined with deep learning, as shown by Lakshmanarao [13], achieved 98.3% accuracy, highlighting the robustness of hybrid approaches. Dahigaonkar [4] used SVMs with leaf features like shape, texture, and color to achieve 96.66% accuracy, reinforcing the relevance of combining traditional and modern techniques. These studies collectively underscore the efficacy of leveraging AI, transfer learning, and feature engineering for accurate and accessible medicinal plant classification systems.

2.3 Gap Analysis

Existing research on medicinal plant identification has demonstrated advancements through traditional machine learning, CNNs, and recent transformer-based architectures. However, certain limitations and research gaps remain:

- Dataset Limitations: While many studies, like those by Naeem [6] and Gokhale [16], have focused on specific regional datasets, there is limited work on comprehensive, global datasets that cover diverse plant species across ecosystems. Furthermore, many studies rely on limited classes of plants or low-resolution images, impacting the models generalizability and robustness in diverse real-world conditions.
- Feature Extraction Methods: Traditional feature extraction methods (e.g., shape, colour, texture) used by Janani [8] and Kan [3] continue to play a role in model performance. However, models leveraging deeper features extracted through CNNs, such as Oppong [9] and Islam [11], have shown the need for hybrid approaches that combine these handcrafted and deep features, as individual methods alone have limitations in handling complex patterns.
- Real-Time Application and Accessibility: Although Islam [11] developed a smartphone-based solution with a rapid identification time, many studies do not consider the computational constraints of real-time applications or the potential for mobile deployment.
- Model Optimization and Generalization: Several works, like Joshi [18] and Oppong [9], utilise advanced architectures like ResNet and DenseNet with progressive transfer learning or hybrid methods. Yet, achieving a balance between model complexity and computational efficiency remains a challenge, particularly for applications in low-resource environments. This gap emphasises the need for lightweight models that maintain high accuracy while minimising computational demands.

- Lack of Cross-Validation Across Regions: Despite the impressive accuracies achieved by studies on specific datasets, there is a noticeable lack of cross-validation across different regional datasets to evaluate model robustness. For instance, models tested solely on datasets like VNPlant-200 or Ayur Bharat have limited insight into how they would perform in diverse ecological settings, necessitating future research to explore model transferability across datasets.

2.4 Summary

This chapter provided a comprehensive review of studies on automated medicinal plant identification, examining traditional and modern methodologies. It detailed how the field has evolved from feature-based classification with machine learning to advanced CNN and transformer-based models utilizing transfer learning. High accuracy and computational efficiency have been achieved, yet challenges such as dataset limitations, lack of real-time applicability, and model generalization persist. The review underscores a need for future research to develop robust, scalable solutions that support real-world applications, contributing to enhanced accessibility in medicinal plant identification and conservation.

Chapter 3

Research Methodology

3.1 Methodology/Requirement Analysis & Design Specification

3.1.1 Overview

This study develops an automated medicinal plant identification system using image processing and transfer learning. The methodology begins with the collection of a diverse medicinal plant dataset, followed by preprocessing steps including normalization, image resizing, DPI adjustments, and data augmentation to enhance model training. Five CNN models—VGG19, InceptionV3, DenseNet201, MobileNetV2, and ResNet50V2—are fine-tuned and compared for performance. The best-performing model is saved as an .h5 file, converted to TensorFlow Lite format, and integrated into a user-friendly mobile application developed with Flutter. This application allows real-time medicinal plant identification by analyzing leaf images, making it practical for end-user deployment.

3.1.2 Proposed Methodology/ System Design

The diagram outlines a methodology for a medicinal plant identification system integrating machine learning, image preprocessing, and mobile application deployment. Below is a breakdown of the process:

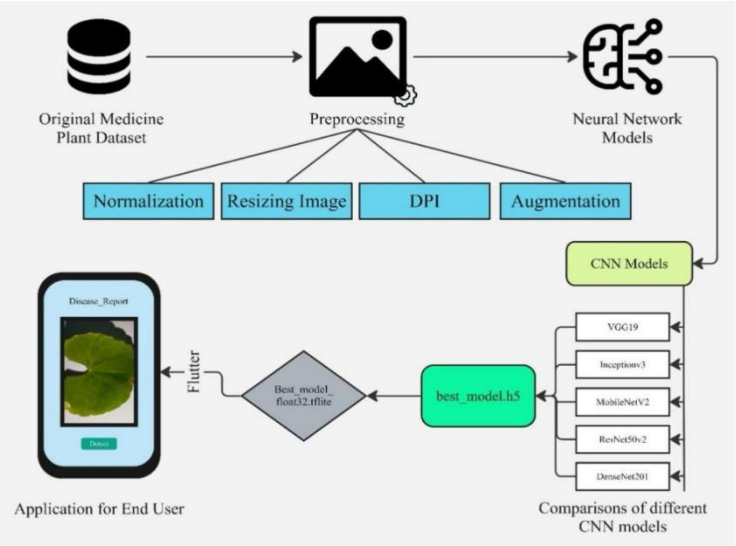

Figure 3.1: The Methodological Flowchart

Original Medicinal Plant Dataset:

The images in the original dataset were captured at a resolution of 3024 × 4032 pixels using a high-quality smartphone camera, ensuring clear and detailed visuals. To optimize storage and processing requirements, these images were resized to 240 × 240 pixels and converted to JPEG format. The initial dataset comprised 1,378 images, which were expanded to 6,890 images through data augmentation techniques to address the challenge of training a deep learning model with limited data.

Augmentation techniques included flipping, rotation, scaling, and adjustments to brightness and contrast, introducing diverse variations while preserving the core characteristics of each class. This process not only enriched the dataset but also improved the model's ability to generalize by simulating real-world variations in leaf appearances. The augmented dataset provided a diverse and representative input for model training, helping to reduce overfitting and enhancing the model's adaptability to unseen data.

Class Labels:

The dataset is organized into five distinct classes, each representing a specific medicinal plant species:

- Aristolochia_indica: Images in this class feature leaves from Aristolochia_indica, known for its unique leaf shape and medicinal properties.

- Centella_asiatica: This class includes images of Centella_asiatica, a plant widely used in traditional medicine for its therapeutic benefits.

- Giant_calotrope: Images in this category showcase leaves of the Giant_Calotrope(Calotropis_gigantea),recognized for its medicinal applications.

- Green_chiretta: This class consists of images of Andrographis_ paniculata, valued for its anti-inflammatory and antimicrobial properties.

- Terminalia_bellirica: Images in this category depict leaves of Terminalia_bellirica, a plant known for its significant role in herbal remedies.

Aristolochia_indica

Centella_asiatica

Giant_calotrope

Green_chiretta

Terminalia_bellirica

Figure 3.2 The Sample Image of each Class

Unlike many conventional datasets, this dataset was not pre-divided into training, testing, and validation subsets. Instead, this splitting process was integrated into the model training pipeline. This automated approach ensures a fair and systematic distribution of images, minimizing the risk of data leakage and ensuring that each subset accurately represents the overall dataset. This methodology strengthens the reliability of the results, as it provides a consistent framework for evaluating model performance.

Table 3.1: Dataset Specifications

Properties	Values
Image Resolution (Original)	3024 x 4032 pixels
Image Resolution	240 × 240 pixels
Format	.jpg
Total Images (Original)	1378
Total Images (Augmented)	6890
Classes	5

The process begins with a dataset of medicinal plant images, which forms the foundation for training and evaluation.

Preprocessing:

The dataset undergoes preprocessing steps, which include:

- Normalization: Adjusting pixel values to a consistent scale to improve model performance.
- Resizing Image: Standardizing image dimensions to fit the neural network input requirements.
- DPI Adjustment: Optimizing image resolution to balance quality and computational efficiency.
- Augmentation: Generating additional training data by applying transformations such as rotations, flips, or zooms, improving model generalization.

Neural Network Models:

Preprocessed images are fed into various CNN (Convolutional Neural Network) architectures for training and evaluation. The diagram highlights a comparison between models, including:

- VGG19
- InceptionV3
- MobileNetV2
- ResNet50
- DenseNet201

The best-performing model is selected for deployment.

Model Selection and Conversion:

The optimal model (stored as best_model.h5) is converted into a lightweight format (best_model_float32.tflite) suitable for mobile deployment using Flutter, a cross-platform app development framework.

Mobile Application for End Users:

The lightweight model is integrated into a mobile application that allows users to upload an image of a plant leaf and receive a **Disease Report** or identification results. This app is designed to make the technology accessible for practical, real-world use.

This methodology combines robust preprocessing, advanced CNN architectures, and user-friendly deployment, creating a scalable solution for medicinal plant identification and disease diagnosis.

3.1.3 Functional and Nonfunctional Requirements

Functional Requirements:

The functional requirements outline the essential features and operations of the proposed system for medicinal plant identification:

- Image Input and Preprocessing:

The system must allow users to upload images of medicinal plant leaves through a mobile application or desktop interface.The input images should be automatically resized to the standard dimensions (224×224 pixels) for consistent preprocessing.

- Plant Identification:

The system must classify the uploaded images into one of the predefined plant categories using the DenseNet201 model as the primary classifier.
The classification results must include the plant's name, scientific details, and potential medicinal uses.

- Real-Time Functionality:

The mobile application must provide real-time identification, delivering results within seconds after an image is uploaded.The app must support offline functionality, allowing plant identification without continuous internet access.

- Feedback Mechanism:

Users must be able to report incorrect classifications or provide feedback to improve model performance.A system for updating the model with new user-provided data should be in place.

- Database Integration:

The system must maintain a database of medicinal plant species, including their images, descriptions, and medicinal properties.

Nonfunctional Requirements:

The nonfunctional requirements address the system's quality attributes, ensuring reliability, usability, and performance:

- Performance:

The system should classify an image with an accuracy of at least 95% (as achieved by the DenseNet201 model).The processing time for classification must not exceed 2 seconds for a single image.

- Scalability:

The system must support an increasing number of plant species as new data becomes available.The mobile application should function smoothly on devices with limited processing power and memory.

- Reliability:

The system must be highly reliable, minimizing crashes or errors during image processing and classification tasks.

- Usability:

The interface must be intuitive and user-friendly, requiring minimal effort from users to upload images and view results.Instructions for capturing clear and accurate plant images should be provided within the app.

- Security:

User data, including uploaded images, must be securely stored and handled in compliance with data protection regulations.The system should ensure no unauthorized access to the classification results or the underlying database.

- Maintainability:

The system architecture must allow for easy updates to the database and model to improve accuracy or incorporate additional features.Regular performance audits should be conducted to identify and address any inefficiencies.

This section ensures the system is functional, user-focused, and scalable while addressing technical and quality-related constraints.

3.1.4 Data Flow Diagram Level 1

This data flow diagram illustrates the workflow of a this project, for leaf-based medicinal plant identification. Here's a detailed description:

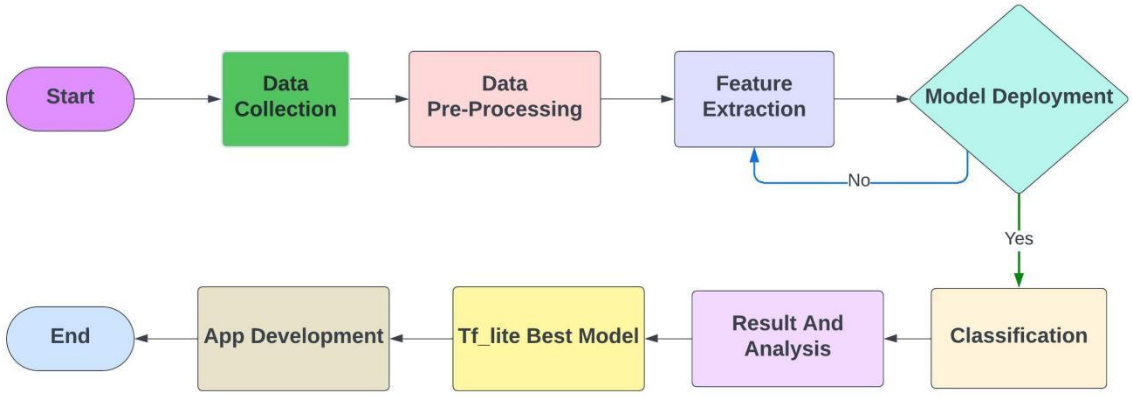

Figure 3.3: The Data Flow Diagram Level 1

Start: The process begins here.

Data Collection: The first step involves gathering data, which could include images of medicinal plant leaves.

Data Pre-Processing: The collected data is pre-processed. This might include cleaning, resizing images, normalization, and augmentation to ensure consistency and improve model performance.

Feature Extraction: Key features from the pre-processed data are extracted. These features are used as inputs to the machine learning model. If this step isn't satisfactory, the process may loop back for improvement.

Model Deployment Decision: A decision point checks if the model is ready for deployment.

- If "No," it loops back to refine the process.
- If "Yes," it proceeds to classification.

Classification: The model classifies the input data, likely identifying plant species based on leaf patterns.

Result and Analysis: The classification results are analyzed for accuracy, precision, and other performance metrics.

Tflite Best Model: The best-performing model is converted into TensorFlow Lite (Tflite) format for deployment on edge devices or mobile applications.

App Development: The Tflite model is integrated into an application for end-user interaction.

End: The project concludes here.

This workflow is systematic and designed to ensure a robust model for practical application.

3.1.5 UI Design

The application is designed to provide real-time identification of medicinal plants directly to end-users, such as botanists, researchers, or herbal medicine practitioners, through a mobile interface. This setup leverages a lightweight deep learning model, optimized and deployed on mobile devices, allowing users to upload or capture images of medicinal plant leaves and receive instant classification results. The best-performing CNN model, saved as a TensorFlow Lite (TFLite) file for mobile compatibility, is integrated into the application. The app is developed using Flutter, a cross-platform UI toolkit, which allows seamless deployment across both Android and iOS devices.

The application setup includes several components:

- User Interface (UI): The application features a simple and intuitive interface, providing options to capture or upload images, initiate plant identification, and display results. The UI is designed for ease of use, with clear buttons and prompts guiding the user through the identification process.

- Backend Model Inference: The TFLite model embedded within the app performs on-device inference, classifying the uploaded or captured images in real-time. On-device processing ensures rapid response times without relying on an internet connection, making it ideal for remote field applications.

- Output Display: Once the model completes inference, the app displays the result, indicating the predicted medicinal plant species along with the confidence score. Additional details, such as the plant's scientific name and common uses, can be included to enhance usability.

This setup enables users to identify medicinal plants on the spot, providing a tool for quick and accurate identification, promoting field research and practical application in herbal medicine.

Two-Tier Architecture:

The application follows a **Two-Tier Architecture**, comprising the Client Tier and the Application Tier. This architecture separates the user interface from the underlying model processing, ensuring a clean and efficient structure suitable for mobile deployment.

Client Tier (Presentation Layer):

The Client Tier, or Presentation Layer, represents the interface that the end-user interacts with. Built using Flutter, this layer manages all user interactions and handles the display of information. Its main components include:

- Image Capture/Upload: Users can capture a photo using their device's camera or upload an existing image from their gallery. The image is then passed to the Application Tier for processing.
- Result Display: After processing, the results from the model inference are displayed on this tier, showing the predicted plant species and its confidence score. Additional botanical details or related information can also be presented.

Application Tier (Model Processing Layer):

The Application Tier, or Model Processing Layer, is responsible for executing the machine learning model and handling data preprocessing. Embedded within the mobile device, this tier ensures offline functionality and includes the following components:

- TFLite Model Inference: This component loads the pre-trained TFLite model and processes the input image to classify it. The lightweight TFLite format ensures the model runs efficiently, even on devices with limited computational resources.
- Image Preprocessing: Before passing the image to the model, this layer performs necessary preprocessing steps, such as resizing the image to 240×240 pixels and normalizing pixel values to the range [0, 1]. These steps ensure the inference is accurate and consistent with the training process.

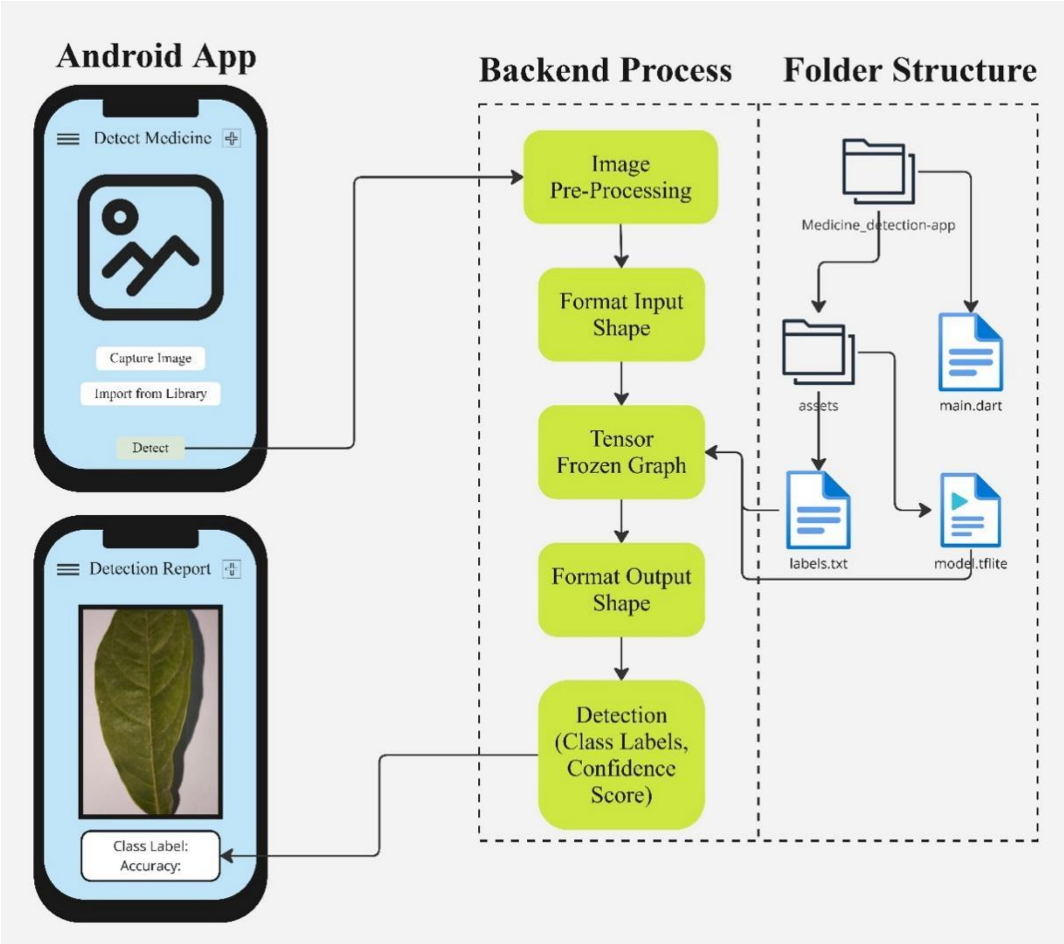

Figure 3.4: Two-Tier Architecture for Proposed Application

3.2 Detailed Methodology and Design

- Convolutional Neural Network (CNN) Algorithm:

A Convolutional Neural Network (CNN) is a deep learning architecture widely used for image classification and other computer vision tasks due to its ability to automatically learn and extract relevant features from images. In this study, CNNs serve as the foundation for detecting and classifying medicinal leaves. Below is a step-by-step breakdown of the CNN algorithm, including key mathematical procedures.

- Input Representation:

The input to the CNN is an image represented as a 3D array with dimensions H×W×C, where: H is the height of the image, W is the width of the image, C is the number of channels (e.g., 3 for RGB images).Each pixel of the image has an intensity value:

$$I(x,y,c), \quad x \in [1,H],\ y \in [1,W],\ c \in [1,C].$$

- Convolution Layer:

The convolution layer applies a set of learnable filters (kernels) to the input image. These filters slide across the image to detect features like edges, textures, or patterns. The mathematical operation for a convolution is:

$$F(x, y) = \sum_{i=1}^{k} \sum_{j=1}^{k} K(i, j) \cdot I(x + i, y + j) + b,$$

where:

- K(i,j): Kernel (filter) weights of size k×k,
- I(x+i,y+j): Input pixel values in the receptive field of the filter,
- b: Bias term,
- F(x,y): Output feature map at position (x,y).

- Activation Function:

To introduce non-linearity into the network, an activation function is applied to the output of the convolution operation. A commonly used activation function is the Rectified Linear Unit (ReLU), defined as:

$$A(x, y) = \max(0, F(x, y)).$$

- Pooling Layer:

Pooling reduces the spatial dimensions of the feature map while retaining its most important information. This helps in reducing computational complexity and prevents overfitting.The most used pooling method is Max Pooling, which selects the maximum value in a window of size p× p.

- Flattening:

After several convolutional and pooling layers, the feature maps are flattened into a one-dimensional vector. Flattening transforms the multi-dimensional output into a format suitable for the fully connected layer.

Mathematically, the flattened vector is:

$$x_{\text{flattened}} = [f_1, f_2, \ldots, f_n],$$

- Fully Connected Layer:

The fully connected layer combines all extracted features to make predictions. This layer performs a linear transformation on the input vector:

$$y = W \cdot x + b,$$

where: W is the weight matrix, x is the input vector, b is the bias vector, y is the output vector (logits).These logits represent the raw predictions for each class.

- Softmax Function:

For multi-class classification, the softmax function is applied to the logits to convert them into probabilities. The softmax function is defined as:

$$P(c) = \frac{e^{z_c}}{\sum_{i=1}^{n} e^{z_i}},$$

where: z_c is the Logit for class c, n is the Total number of classes.The output probabilities P(c) sum to 1, and the class with the highest probability is selected as the prediction.

- Loss Function:

The network is trained to minimize a loss function, such as Categorical Cross-Entropy Loss for multi-class classification:

$$L = -\sum_{c=1}^{n} y_c \log(P(c)),$$

where: y_c is the True label (1 for the correct class, 0 otherwise), P(c) is the Predicted probability for class ccc.This loss quantifies the difference between the predicted probabilities and the true labels.

- Backpropagation:

The network adjusts its weight and biases using backpropagation. Gradients of the loss function with respect to weights and biases are computed using the chain rule:

$$\frac{\partial L}{\partial W}, \quad \frac{\partial L}{\partial b}.$$

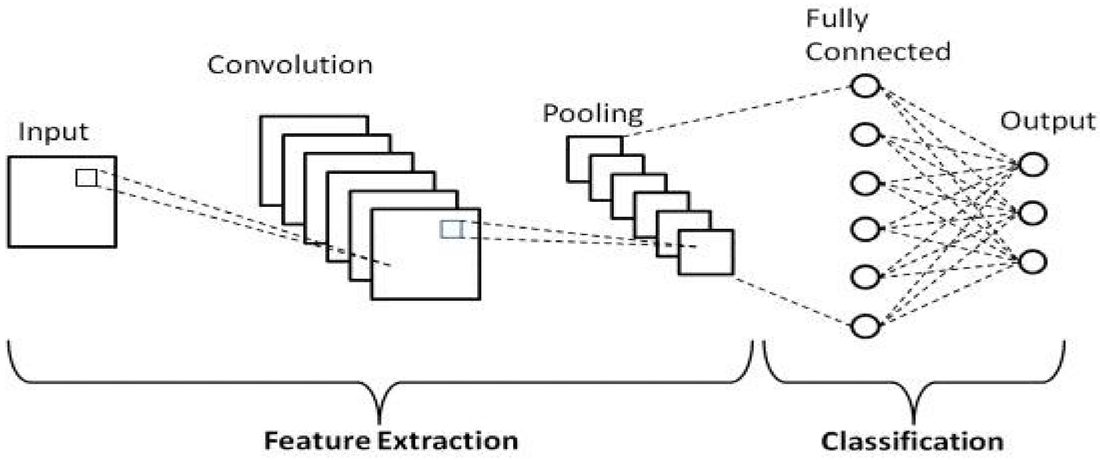

Figure 3.5: The Architecture of Convolutional Neural Network [1]

- Comparison between CNN Models:

A detailed comparison of the five CNN architectures—VGG19, InceptionV3, DenseNet201, MobileNetV2, and ResNet50V2—to highlight their strengths, limitations, and specific characteristics in the context of training for medicinal plant identification.

VGG19:

VGG19 is a deep, sequential architecture with 19 layers, including 16 convolutional and 3 fully connected layers. It employs small 3×33 \times 33×3 filters and max pooling with 2×22 \times 22×2 windows, focusing on straightforward and uniform design. This simplicity makes VGG19 effective for datasets requiring detailed feature extraction, such as fine-grained leaf patterns. However, its large number of parameters (~143M) increases computational costs and memory requirements, which may lead to overfitting on smaller datasets without sufficient data augmentation or regularization techniques.

InceptionV3:

InceptionV3 introduces a modular architecture with 48 layers, employing "Inception modules" that combine 1×1, 3×3, and 5×5 convolutions in parallel. This enables the network to capture multi-scale features efficiently. It also uses auxiliary classifiers to reduce vanishing gradient issues during training. InceptionV3 is computationally efficient compared to VGG19 due to its lower parameter count (~23M). However, its complex architecture requires more careful tuning and is less interpretable compared to simpler models.

DenseNet201:

DenseNet201 connects each layer to every other layer in a dense block, allowing feature reuse and mitigating the vanishing gradient problem. With fewer parameters (~20M), it achieves high computational efficiency and avoids redundancy in feature learning. DenseNet201 excels in extracting intricate patterns from datasets with limited samples, such as medicinal plant images. However, its dense connections increase memory requirements during training, making it slower compared to other architectures.

MobileNetV2:

MobileNetV2 is a lightweight architecture designed for mobile and embedded applications. It employs depthwise separable convolutions, drastically reducing parameters (~3.4M) and computational costs while maintaining performance. The inclusion of inverted residuals and linear bottlenecks enhances feature extraction in a low-resource setting. While it performs well on resource-constrained systems, its lightweight design may compromise accuracy when compared to deeper architecture like DenseNet201 or InceptionV3 on complex datasets.

ResNet50V2:

ResNet50V2 employs residual learning with skip connections, allowing deeper networks to avoid vanishing gradients and improving feature extraction. With 50 layers and a parameter count of ~25M, it strikes a balance between depth and efficiency. ResNet50V2 is particularly effective for complex datasets where hierarchical features (e.g., textures and structures) are critical. However, its deeper architecture may lead to higher training time and computational overhead compared to MobileNetV2.

Table 3.2: Summary Table of Key Metrics

Model	Depth	Parameters (M)	Primary Strength	Primary Limitation
VGG19	19	143	Excellent for detailed feature extraction	High computational cost, prone to overfitting
InceptionV3	48	23	Captures multi-scale features efficiently	Complex architecture requires careful tuning
DenseNet201	201	20	Efficient feature reuse, avoids vanishing gradients	High memory requirements, slower training
MobileNetV2	53	3.4	Lightweight, ideal for mobile applications	Lower accuracy on highly complex datasets
ResNet50V2	50	25	Balances depth and efficiency, avoids vanishing gradients	Higher training time compared to lightweight models

3.3 Project Plan

The project followed an iterative methodology, progressing through distinct phases to ensure the systematic development and deployment of the medicinal plant identification system. The initial phase focused on collecting medicinal plant leaf images from field observations and performing preprocessing steps, including resizing, normalization, and augmentation, to expand the dataset. Next, state-of-the-art CNN architectures (e.g., VGG19, InceptionV3, DenseNet201, MobileNetV2, ResNet50V2) were trained and fine-tuned using Google Colab, with evaluation metrics like accuracy and F1-score guiding the selection of the best-performing model. The selected model was converted to TensorFlow Lite for mobile deployment and integrated into a Flutter-based application. Subsequent phases involved testing and validating the application in real-world scenarios, followed by iterative debugging and performance optimization. The project concluded with the successful launch of the mobile application, ensuring cross-platform compatibility and user accessibility on both Android and iOS devices.

Table 3.3: GANTT Chart of Estimated Project Timeline

Process	**May'24**	**June'24**	**July'24**	**Aug'24**	**Sep'24**	**Oct'24**	**Nov'24**	**Dec'24**
Working Plan								
Theoretical Study								
Literature Review								
Data Collection								
Data Preprocessing								
Model Design								
Methodology Writing								
Report Writing								
Review and Finalization								

3.4 Task Allocation

This table is based on our work contribution of this project

Table 3.4: Task allocation of team.

Task	Team Mate	
Choose leaf	Tanver Hassan Tanver	Mehdi Hasan Parvez
	Both	Both
Data Collection	Both	Both
Data preprocessing	No	Yes
Model Run	Yes	No
Model Selection	Both	Both
Report Writing	Both	Both

3.5 Summary

This study outlines a systematic methodology for developing a medicinal plant identification system using transfer learning and image processing. The dataset, expanded from 1,378 to 6,890 images through augmentation, was used to train five CNN architectures—VGG19, InceptionV3, DenseNet201, MobileNetV2, and ResNet50V2—on Google Colab. The best model was converted into TensorFlow Lite and integrated into a Flutter-based mobile application with a two-tier architecture, combining a user-friendly Client Tier for interaction and an Application Tier for offline model processing. Risk management strategies ensured robust performance by addressing overfitting, input variability, and platform compatibility. The project, completed at an estimated cost of 10,000 BDT, offers a cost-effective and practical tool for researchers, botanists, and herbal medicine practitioners.

Chapter 4

Implementation and Results

4.1 Environment Setup

The experimented models' training utilized several key parameters to optimize performance. Each input image was resized to a standard dimension of 224 × 224 pixels, ensuring consistency and efficient processing across the neural network. A batch size of 128 was employed, allowing the model to process 128 images simultaneously before updating the model's parameters, which contributes to more stable gradient estimates and accelerates convergence. The training was conducted over 50 epochs for all the models, meaning the model iterated 50 times through the entire dataset, progressively refining its predictions with each cycle. The Adam optimizer (Adaptive Moment Estimation) was selected to update the model's weights, combining the advantages of RMSprop and momentum by adjusting the learning rate for each parameter individually. The learning rate of the VGG19, MobileNetv2, ResNet50v2, DenseNet201, and Inceptionv3 models was set to 1e-4. This choice typically enhances training efficiency and accelerates convergence, improving model performance. Together, these parameters facilitated an effective and streamlined training process.

Table 4.1. Common parameter table for all experimented models.

Parameter Name	**Parameter Value**
Image Size	224 × 224
Batch Size	128
Epoch	50
Optimizer	**Adam**
Learning Rate	1e - 4

The dataset for this project is divided into three parts: training, validation, and testing. This split is designed to ensure that the model can be properly trained, fine-tuned, and evaluated, all while avoiding data overlap between phases. In this case, the training set consists of 70% of the total data, which equals 4,820 images. This set is crucial for allowing the model to learn the underlying patterns within the data, as it serves as the main source for the model's training. The large proportion of images in the training set helps the model to generalize well by providing diverse examples.

The validation set, comprising 15% of the dataset or 1,030 images, is used to tune hyperparameters and monitor the model's performance on data it hasn't seen during training. By observing the model's accuracy and loss on the validation set, you can adjust settings like the learning rate or the number of layers to optimize the model before finalizing it. The validation set provides a snapshot of how well the model generalizes beyond the training set without overfitting or underfitting.

Finally, the test set, which includes 15% of the dataset or 1040 images, is reserved solely for evaluating the model after the complete training. This set remains completely unseen by the model during both training and validation. Its purpose is to give an unbiased evaluation of how the model would perform on new, real-world data. This three-way split across all three models ensures that the performance comparison is fair and consistent. By keeping the dataset split the same, any performance differences between the models can be attributed to the model architectures and training configurations rather than variations in the data used for each phase.

Table 4.2. Common data split for all experimented models.

Dataset	In Percentage	Number of Images
Train set	70%	4820
Validation Set	15%	1030
Test Set	15%	1040

In evaluating the effectiveness of machine learning models for the study, appropriate performance metrics must be used to provide insights into model accuracy, reliability, and generalization capabilities. The following metrics are commonly used in classification tasks, especially in the context of agricultural disease detection:

- Accuracy:

The proportion of correctly classified instances (both positive and negative) to the total instances. Accuracy gives a quick overview of model performance but can be misleading in imbalanced datasets where one class significantly outnumbers the other.

- Recall:

The ratio of correctly predicted positive observations to all actual positives. Recall is particularly important in scenarios where a positive case (such as a diseased plant) could lead to severe consequences, like crop loss.

- Precision:

The ratio of correctly predicted positive observations to the total predicted positives. Precision is crucial in applications where the cost of false positives is high. In this study, high precision indicates that when a disease is predicted, it is likely to be true.

- F1-Score:

The harmonic meaning of precision and recall, providing a balance between the two metrics. The F1 score is especially useful when dealing with imbalanced classes, as it considers both false positives and false negatives, offering a more comprehensive view of model performance.

- Confusion Matrix:

A table used to describe the performance of a classification model, showing the true vs. predicted classifications. The confusion matrix provides insights into the types of errors made by the model, allowing for more targeted improvements.

- Receiver Operating Characteristic (ROC) Curve:

A graphical representation of a classifier's performance across various threshold settings, plotting the true positive rate (recall) against the false positive rate. It illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. It plots the True Positive Rate (TPR), also known as recall or sensitivity, against the False Positive Rate (FPR) at various threshold settings.

- Area Under Curve (AUC):

The area under the ROC curve, which provides a single metric to assess model performance; a value closer to 1 indicates a better model.

In this study, the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) are crucial for evaluating classification models. They allow for visual comparisons of model performance across various thresholds, facilitating optimal threshold selection by balancing sensitivity and specificity. Additionally, the ROC curve is robust against class imbalances, providing reliable assessments where accuracy may mislead.

4.2 Testing and Evaluation/Performance/ Comparative Analysis

The experimental result of subsection 4.2 states that, ResNet50v2 and DenseNet201 emerge as the top performers across all metrics, with high stability in learning, accurate classification, and excellent discriminative ability, making them highly reliable for robust classification tasks. VGG19 also performs well but with minor fluctuations that suggest it may not be as consistently reliable as the top models. MobileNetV2 shows moderate performance with occasional misclassifications, indicating that its lightweight architecture may limit its ability to capture fine details in complex datasets. Inceptionv3 demonstrates the least stability and accuracy, particularly in distinguishing between similar classes, suggesting it may not be as suitable for tasks requiring high precision in multi-class classification. This analysis indicates that ResNet50v2 and DenseNet201 are the most suitable choices for accurate and robust classification, while Inceptionv3 may benefit from further refinement to achieve comparable results.

In this study, DenseNet201 emerged as the best-performing model, achieving the highest testing accuracy of 95.19% and an impressive average AUC score of 0.998, indicating excellent class discrimination and generalization on unseen data. It reached optimal performance early, with training stopping at epoch 15, highlighting its efficiency in learning complex patterns without overfitting. In contrast, Inceptionv3 was the lowest performer, with a testing accuracy of 88.95% and an AUC score of 0.988. Despite also stopping early at epoch 15, Inceptionv3 fell short in capturing subtle distinctions between classes, suggesting limitations in its architecture or feature extraction capabilities for this dataset. This comparison underscores DenseNet201 as the most reliable model for high-accuracy classification tasks, while Inceptionv3 may be less suitable due to its lower precision and sensitivity.

Table 4.3. Comparison analysis of five models based on early stopping, testing accuracy and AUC score.

Model Name	Early stop epoch	Testing accuracy	Average AUC score
VGG19	15	94.13%	0.998
MovileNetv2	22	92.06%	0.992
ResNet50v2	17	94.52%	0.996
DenseNet201	15	95.19%	0.998
Inceptionv3	15	88.95%	0.988

While competing for all aspects of measurement (epoch, AUC score, confusion matrix, classification report, loss and accuracy curve, and testing accuracy) it is a verdict that the DenseNet201 is the best performer model outperforming all the existing and experimented deep CNN models. This model is best suited for automated identification of medicinal plants.

4.3 Results and Discussion

The loss and accuracy curves provide valuable insight into each model's learning behavior and generalization capability. ResNet50v2 and DenseNet201 demonstrate consistent and smooth learning patterns, with training and validation loss decreasing steadily as epochs progress. The corresponding accuracy curves for these models show a stable upward trajectory, eventually reaching close to 100% accuracy, which suggests strong learning and minimal overfitting. This smooth convergence in both loss and accuracy curves highlights these models' robustness in learning from the data without excessively fitting to the training data alone. VGG19 also shows a stable learning curve, although with slight fluctuations in validation loss, indicating some variability in its generalization performance. However, it still achieves high validation accuracy, making it a reliable performer overall. MobileNetV2 shows more pronounced fluctuations in both loss and accuracy, suggesting that while it can learn effectively, it occasionally struggles with generalization, likely due to challenges in fully capturing complex patterns in the data. Inceptionv3 exhibits the most unstable loss and accuracy curves, with sharp spikes in validation loss and corresponding drops in accuracy. This instability suggests that Inceptionv3 might be more sensitive to variations in the data and may face challenges in consistently capturing the underlying patterns, potentially leading to poorer generalization on unseen data.

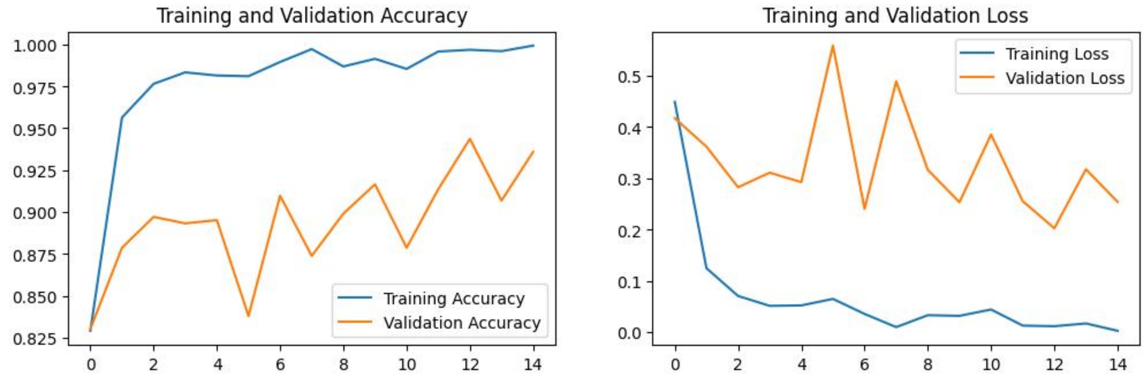

Figure 4.1. The loss and accuracy curve on training and validation set over 50 epochs for VGG19 models.

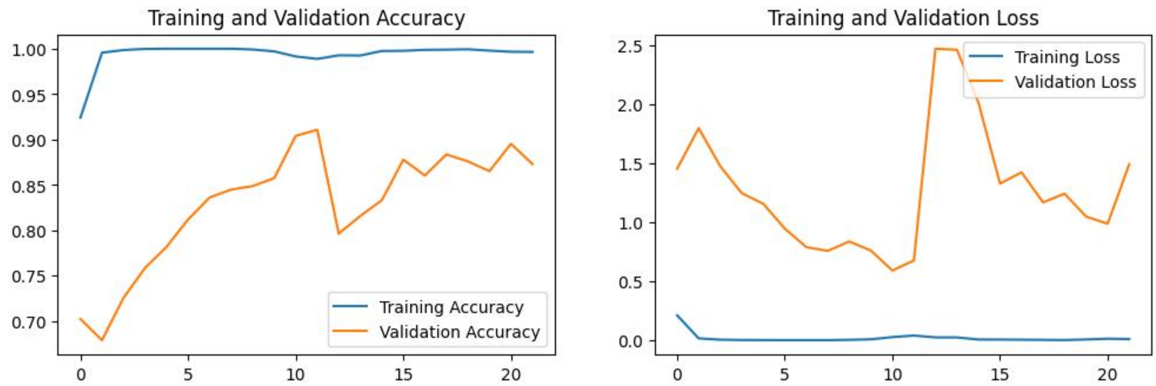

Figure 4.2. The loss and accuracy curve on training and validation set over 50 epochs for MobileNetv2 models.

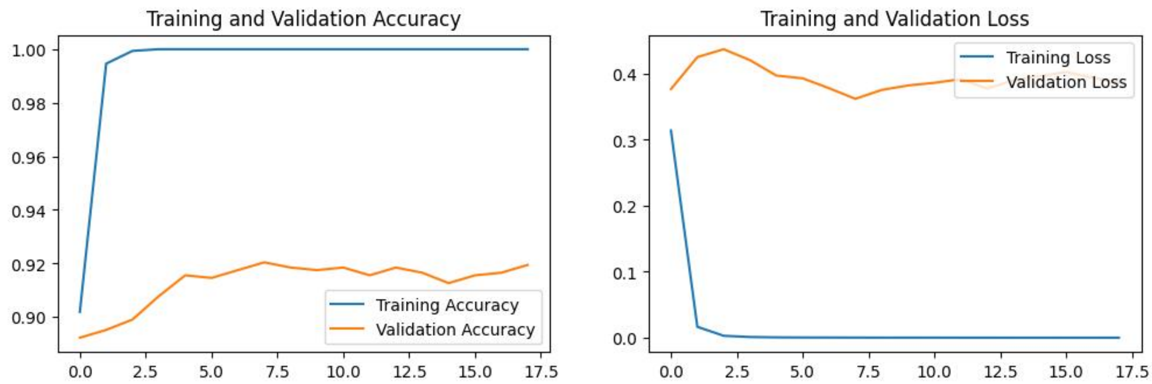

Figure 4.3. The loss and accuracy curve on training and validation set over 50 epochs for ResNet50v2 models.

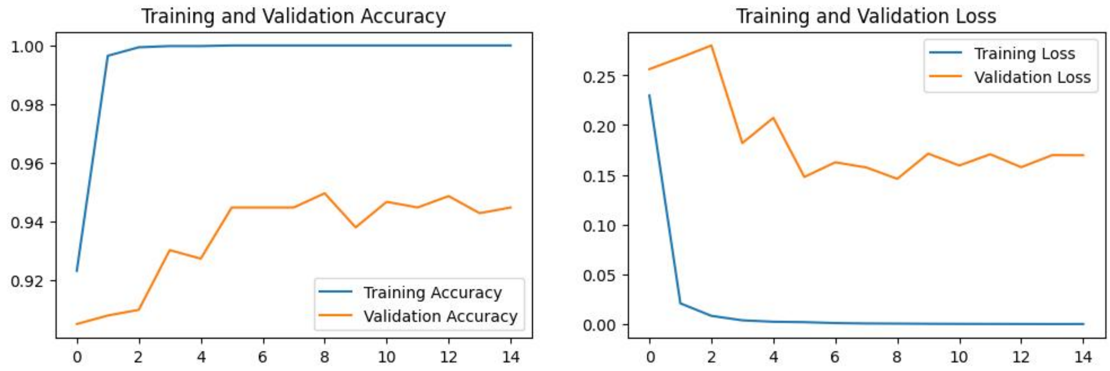

Figure 4.4. The loss and accuracy curve on training and validation set over 50 epochs for DenseNet201 models.

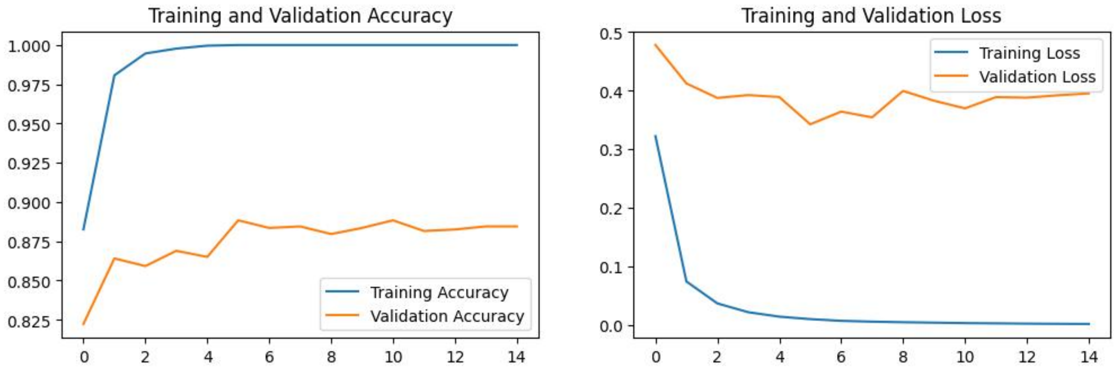

Figure 4.5. The loss and accuracy curve on training and validation set over 50 epochs for Inceptionv3 models.

The confusion matrices for each model reveal their performance in correctly classifying individual classes. ResNet50v2 and DenseNet201 show high correct classification rates across all classes, with minimal misclassifications. For instance, they demonstrate near-perfect classification for "Centella_asiatica" and "Green_chiretta," indicating that these models effectively distinguish these classes from others. This accurate classification reflects their capability to handle complex features within these categories. VGG19 also performs well in classifying most classes but shows slight misclassifications for "Giant_calotrope," suggesting it occasionally struggles to distinguish between classes with similar characteristics. MobileNetV2 shows more misclassifications, particularly in classes like "Giant_calotrope" and "Terminalia_bellirica," indicating that capturing subtle differences between similar classes may be challenging. Inceptionv3 has the highest misclassification rate, particularly noticeable in the "Giant_calotrope" and "Terminalia_bellirica" classes. This suggests that Inceptionv3 is less reliable in differentiating certain classes, possibly due to its complex architecture not aligning well with the feature representations in these specific classes.

0 = Aristolochia_indica, 1 = Centella_asiatica, 2 = Giant_calotrope , 3 = Green_chiretta, 4 = Terminalia_bellirica

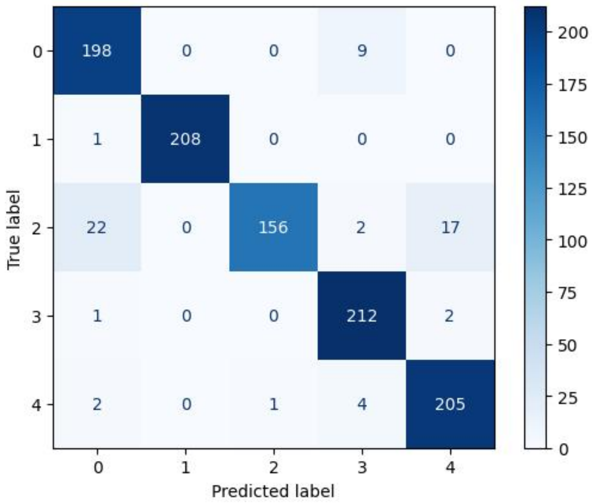

Figure 4.6. Confusion matrix on the test dataset for VGG19 models.

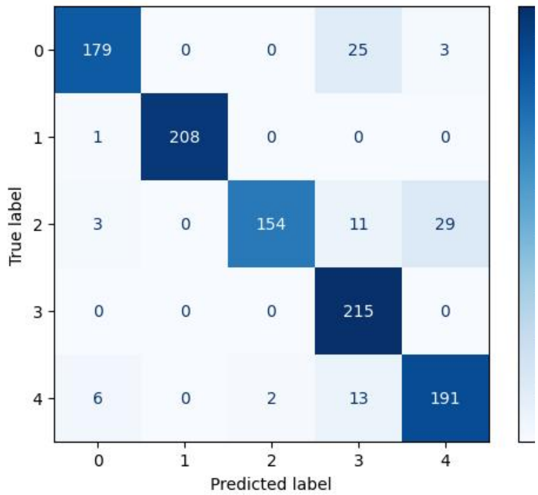

Figure 4.7. Confusion matrix on the test dataset for MobileNetv2 models.

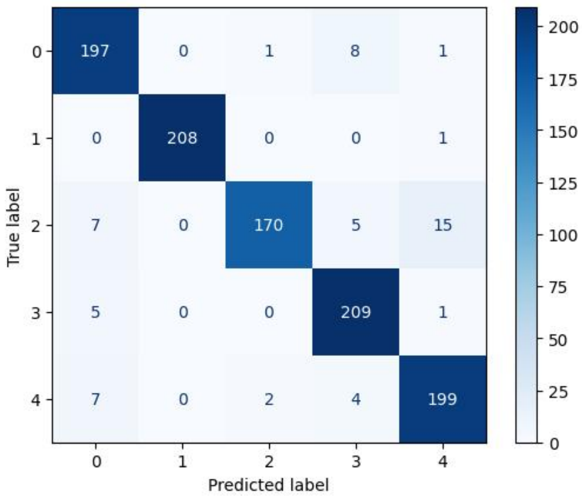

Figure 4.8. Confusion matrix on the test dataset for ResNet50v2 models.

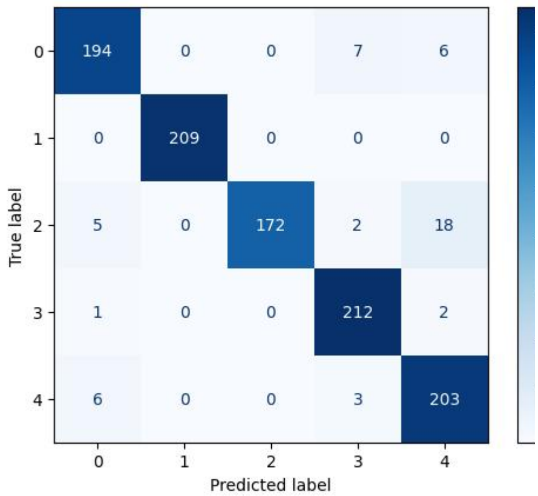

Figure 4.9. Confusion matrix on the test dataset for DenseNet201 models.

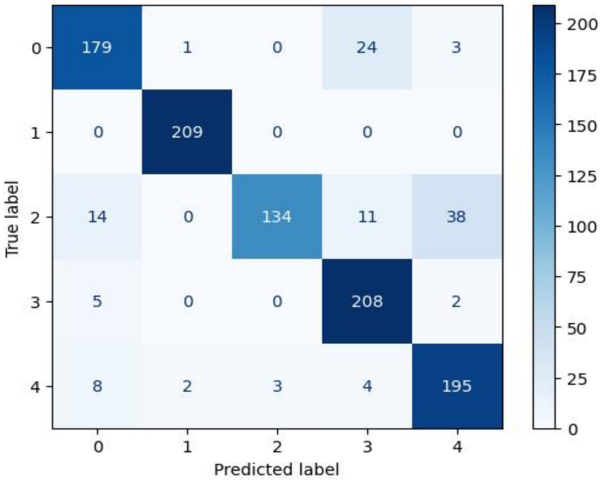

Figure 4.10. Confusion matrix on the test dataset for Inceptionv3 models.

The classification reports further highlight each model's performance in terms of precision, recall, and F1-score, providing a detailed view of their ability to correctly identify each class. ResNet50v2 and DenseNet201 demonstrate balanced performance, with consistently high precision, recall, and F1-scores across most classes. For example, both models achieve F1-scores around 0.93 to 0.97 across classes, indicating they minimize both false positives and false negatives effectively. This balanced performance implies that these models are highly reliable in accurately classifying each class without bias towards particular ones. VGG19 also shows high F1-scores, particularly for "Centella asiatica" (1.00) and "Green chiretta" (0.96), demonstrating its strong capability in handling these classes. However, it has slightly lower scores for classes with more complex or overlapping features, like "Giant calotrope." MobileNetV2 performs moderately, with lower F1-scores for "Giant calotrope" (0.87) and "Terminalia bellirica" (0.88), which suggests it may struggle with distinguishing these classes due to its lightweight architecture that might not capture detailed features as effectively. Inceptionv3 has the lowest F1-scores overall, particularly for "Giant calotrope" (0.80) and "Terminalia bellirica" (0.87), confirming its relatively lower classification accuracy and higher misclassification rate in these challenging classes.

Table 4.4. Classification report of the five deep CNN models.

Classes	Precision	Recall	F1-score	Support
VGG19				
Aristolochia_indica	0.88	0.96	0.92	207
Centella_asiatica	1.00	1.00	1.00	209
Giant_calotrope	0.99	0.79	0.88	197
Green_chiretta	0.93	0.99	0.96	215
Terminalia_bellirica	0.92	0.97	0.94	212
accuracy			0.94	1040
macro avg	0.95	0.94	0.94	1040
weighted avg	0.94	0.94	0.94	1040
MobileNetv2				
Aristolochia_indica	0.95	0.86	0.90	207
Centella_asiatica	1.00	1.00	1.00	209
Giant_calotrope	0.99	0.78	0.87	197
Green_chiretta	0.81	1.00	0.90	215
Terminalia_bellirica	0.86	0.90	0.88	212
accuracy			0.91	1040
macro avg	0.92	0.91	0.91	1040
weighted avg	0.92	0.91	0.91	1040
ResNet50v2				
Aristolochia_indica	0.91	0.95	0.93	207
Centella_asiatica	1.00	1.00	1.00	209
Giant_calotrope	0.98	0.86	0.92	197
Green_chiretta	0.92	0.97	0.95	215
Terminalia_bellirica	0.92	0.94	0.93	212
accuracy			0.95	1040
macro avg	0.95	0.94	0.94	1040
weighted avg	0.95	0.95	0.95	1040
DenseNet201				
Aristolochia_indica	0.94	0.94	0.94	207
Centella_asiatica	1.00	1.00	1.00	209
Giant_calotrope	1.00	0.87	0.93	197
Green_chiretta	0.95	0.99	0.97	215

Terminalia_bellirica	0.89	0.96	0.92	212
accuracy			0.95	1040
macro avg	0.95	0.95	0.95	1040
weighted avg	0.95	0.95	0.95	1040
Inceptionv3				
Aristolochia_indica	0.87	0.86	0.87	207
Centella_asiatica	0.99	1.00	0.99	209
Giant_calotrope	0.98	0.68	0.80	197
Green_chiretta	0.84	0.97	0.90	215
Terminalia_bellirica	0.82	0.92	0.87	212
accuracy			0.89	1040
macro avg	0.90	0.89	0.89	1040
weighted avg	0.90	0.89	0.89	1040

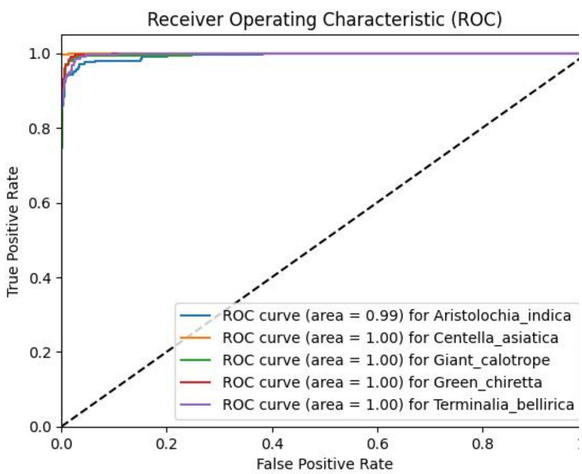

Figure 4.11. ROC curve and AUC score of the VGG19 models.

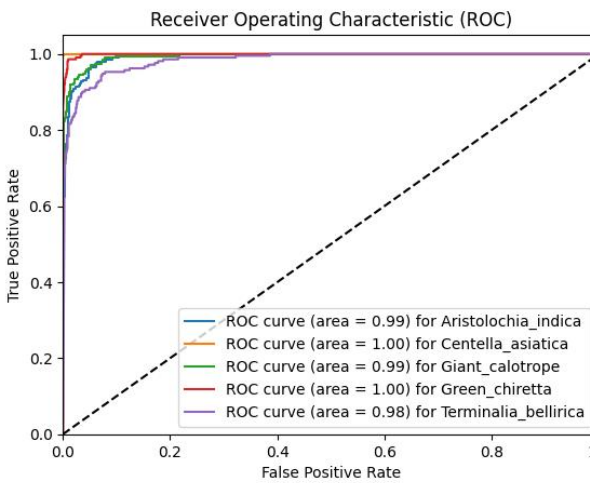

Figure 4.12. ROC curve and AUC score of the MobileNetv2 models.

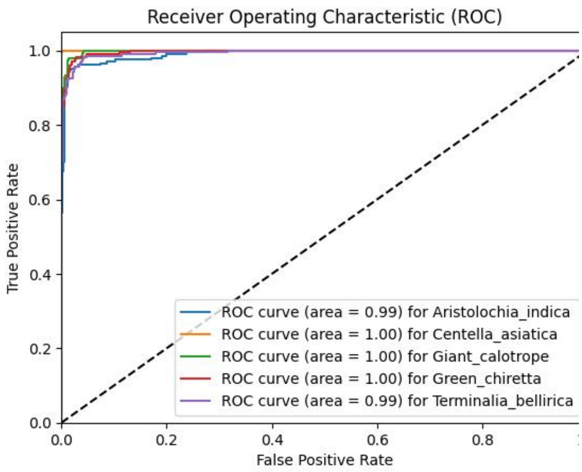

Figure 4.13. ROC curve and AUC score of the ResNet50v2 models.

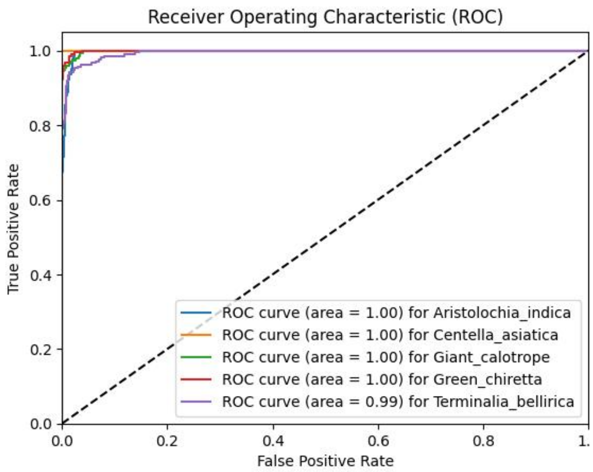

Figure 4.14. ROC curve and AUC score of the DenseNet201 models.

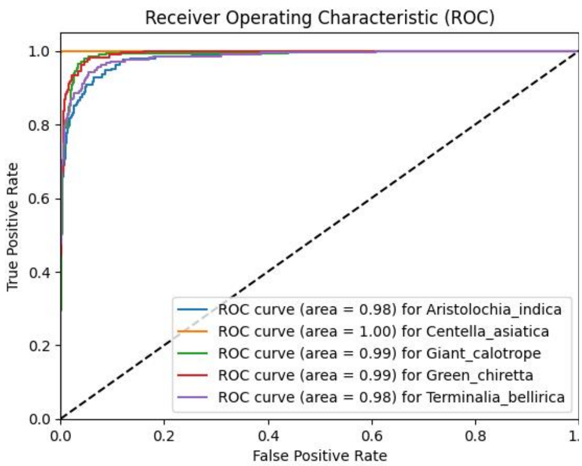

Figure 4.15. ROC curve and AUC score of the Inceptionv3 models.

The ROC curves and AUC scores further illustrate each model's discriminative capability across classes. ResNet50v2 and DenseNet201 achieve nearly perfect AUC scores, close to 1.0, across all classes. This indicates excellent model performance in distinguishing positive and negative cases for each class, showing that these models have a strong ability to identify relevant features that separate one class from another. VGG19 also achieves high AUC scores, with only minor reductions for challenging classes, reflecting its high but slightly variable discriminative performance. MobileNetV2 shows moderately high AUC values, although with slight inconsistencies, suggesting it may not be as effective as ResNet50v2 or DenseNet201 in distinguishing certain classes with high confidence. Inceptionv3 has the lowest overall AUC scores, particularly for classes like "Giant_calotrope" and "Terminalia_bellirica," which aligns with its higher misclassification rate. This lower discriminative ability is consistent with its lower F1-scores and suggests that Inceptionv3 may require further tuning or adjustments to effectively handle fine-grained distinctions between certain classes.

4.4 Summary

This chapter evaluated the performance of five CNN models using multiple metrics, including accuracy, recall, precision, F1-score, confusion matrices, and ROC-AUC scores. DenseNet201 outperformed the other models in all aspects, showing strong generalization and reliability in classifying medicinal plant species. In contrast, Inceptionv3 demonstrated limitations in handling complex classifications, suggesting the need for further refinement. The findings highlight DenseNet201 as the most suitable model for automated medicinal plant identification, achieving optimal accuracy and generalization, and validating its efficacy for real-world applications.

Chapter 5

Engineering Standards and DesignChallenges

5.1 Compliance with the Standards

5.1.1 Software Standards

The software standards for this project are centered around tools and technologies that support efficient and scalable development of cross-platform mobile applications. These include:

- Flutter (for cross-platform mobile application development)
- Dart (programming language for Flutter)
- Android Studio or Visual Studio Code (for IDEs)
- Xcode (for iOS testing, if using macOS)

5.1.2 Hardware Standards

The hardware requirements for the model training and application development phases are designed to ensure optimal performance and reliability:

Hardware: Google Colab (Free Tier)

- GPU: NVIDIA Tesla T4 (provided by Google Colab)
- RAM: 12 GB (Approx.)
- Disk Space: 100 GB (cloud storage for temporary data)

5.1.3 Communication Standards

For the application development process, the hardware requirements include a processor with at least an Intel i5 or AMD Ryzen 3 or a higher configuration to ensure smooth operation and efficiency during development tasks. The system should have a minimum of 8 GB of RAM, though 16 GB is recommended for optimal performance, especially when handling resource-intensive operations like debugging and emulation. Additionally, a storage capacity of at least 20 GB is required to accommodate

TensorFlow Lite models, application development files, and other necessary resources. This setup ensures a seamless workflow for mobile application development and deployment.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The development of an AI-based tool for medicinal plant identification has substantial implications for individual health and well-being. By providing an accessible method for accurately identifying medicinal plants, this tool empowers individuals to make informed choices regarding plant-based health treatments, reducing the risk of misidentification that can lead to ineffective or even harmful outcomes. Furthermore, as traditional knowledge of medicinal plants diminishes in many regions, this tool serves as a bridge, preserving essential knowledge for future generations while making it available to a broader audience.

For individuals in rural or remote areas, where access to conventional healthcare may be limited, an accurate, user-friendly plant identification system offers an alternative by promoting safe, traditional medicinal practices. It also enhances the autonomy of individuals and practitioners who rely on plant-based medicines, ensuring they have reliable information at hand. This tool further supports sustainable healthcare by encouraging the use of locally available plants, potentially reducing dependence on costly pharmaceuticals and emphasizing the value of native flora.

5.2.2 Impact on Society & Environment

On a societal level, the integration of AI in medicinal plant identification fosters a renewed appreciation for traditional medicinal knowledge, encouraging communities to preserve and utilize their local plant resources responsibly. By providing a scientifically validated means to identify medicinal plants, the tool also supports local practitioners, traditional healers, and small-scale farmers, helping them maintain sustainable practices and better serve their communities.

Environmentally, this tool plays a critical role in biodiversity conservation. Accurate plant identification helps avoid the overharvesting of endangered plant species, as communities and harvesters can discern sustainable sources for plant-based products. By guiding users toward correct plant identification and harvesting techniques, the tool indirectly promotes ecosystem health and helps maintain local biodiversity.

Additionally, as the tool encourages the use of native plant species, it minimizes the need for invasive species that might otherwise harm local ecosystems.
This technology also reduces the environmental impact associated with modern healthcare systems by promoting the sustainable use of plant-based medicines. By encouraging local, natural resources for health treatments, the tool reduces reliance on pharmaceutical manufacturing, which is often resource-intensive and environmentally damaging. In sum, this tool aligns with global efforts to achieve sustainability in healthcare by advocating for responsible, nature-based practices that preserve biodiversity and support traditional cultural practices.

5.2.3 Ethical Aspects

The development and deployment of an AI-based tool for medicinal plant identification must address several ethical considerations. First, the tool's reliance on traditional plant knowledge raises issues of intellectual property and cultural sensitivity. Many indigenous communities have safeguarded medicinal plant knowledge for generations, and ethical use of this knowledge requires acknowledgment and respect for its origins. Engaging with these communities and ensuring that they have a voice in the development and use of the technology is essential to prevent cultural exploitation and ensure respectful integration of traditional knowledge.
Additionally, the ethical responsibility of ensuring accurate information in medicinal plant identification is paramount. Misidentification of plants can lead to health risks for
users who rely on the tool for self-medication or home remedies. Rigorous testing and validation of the model are required to minimize error rates and ensure that the tool provides safe and reliable guidance, particularly since some plant species have toxic look-alikes. Clear disclaimers and guidance on responsible usage should accompany the tool to remind users that the tool is an aid rather than a substitute for professional medical advice.
Finally, privacy concerns related to data usage, especially when the tool is accessible via mobile applications, must be considered. User data, if collected, should be protected under strict data security protocols and used transparently. Ensuring compliance with data protection regulations, such as GDPR, is essential to maintain users' trust and safeguard their privacy.

5.2.4 Sustainability Plan

The sustainability plan for this AI-based medicinal plant identification tool is integral to its long-term impact and usability. First, continued model refinement through regular updates and retraining on new datasets will be prioritized to ensure that the tool remains relevant and accurate. Partnerships with local institutions and researchers can provide access to more diverse datasets, making the tool applicable across different ecological regions and expanding its scope to include more plant species.

Another aspect of the sustainability plan involves making the tool widely accessible, particularly in rural and low-resource areas where it is most needed. By optimizing the tool for mobile devices and reducing its computational demands, the tool can be used offline or with minimal data connectivity, ensuring it serves those who may have limited digital resources.

To encourage adoption, the tool will be distributed as an open-access resource, with possible funding from environmental and healthcare NGOs interested in supporting biodiversity conservation and sustainable healthcare practices. A dedicated feedback system will be implemented to gather user insights, enabling ongoing improvement and fostering community engagement.

5.3 Project Management and Financial Analysis

Project Management:

The project followed an iterative methodology, progressing through distinct phases to ensure the systematic development and deployment of the medicinal plant identification system. The initial phase focused on collecting medicinal plant leaf images from field observations and performing preprocessing steps, including resizing, normalization, and augmentation, to expand the dataset. Next, state-of-the-art CNN architectures (e.g., VGG19, InceptionV3, DenseNet201, MobileNetV2, ResNet50V2) were trained and fine-tuned using Google Colab, with evaluation metrics like accuracy and F1-score guiding the selection of the best-performing model. The selected model was converted to TensorFlow Lite for mobile deployment and integrated into a Flutter-based application. Subsequent phases involved testing and validating the application in real-world scenarios, followed by iterative debugging and performance optimization. The project concluded with the successful launch of the mobile application, ensuring cross-platform compatibility and user accessibility on both Android and iOS devices.

Table 5.1: GANTT Chart of Project Timeline

Process	May’24	June’24	July’24	Aug’24	Sep’24	Oct’24	Nov’24	Dec’24
Working Plan								
Theoretical Study								
Literature Review								
Data Collection								
Data Preprocessing								
Model Design								
Methodology Writing								
Report Writing								
Review and Finalization								

Risk Management:

Several risks were identified and mitigated throughout the project lifecycle to ensure successful delivery of the system. These risks were categorized as technical, operational, and deployment related.

Key Risks and Mitigation Strategies:

- Technical Risks: Overfitting during model training due to limited dataset size. Applied extensive data augmentation to enhance model robustness. Sometimes, compatibility issues during model conversion to TFLite. Tested the model iteratively during conversion and ensured alignment with TFLite input-output specifications.

- Operational Risks: Variability in user-captured images (e.g., poor lighting, different backgrounds). Trained the model on augmented datasets simulating real-world conditions. There were also limited computational resources on user devices. Selected lightweight architectures like MobileNetV2 and optimized them for mobile inference.

- Deployment Risks: Platform-specific compatibility issues (e.g., Android vs. iOS). Used Flutter for cross-platform development to maintain consistency across devices. User adoption and usability concerns. Designed a simple and intuitive user interface with clear instructions and visual feedback.

Financial Analysis:

The financial aspects of the project were evaluated to ensure cost-effectiveness, with costs distributed across dataset preparation, model training, application development, and deployment. Dataset preparation involved field collection costs for acquiring medicinal plant leaf images and expenses for data labeling and preprocessing. Model training was performed on Google Colab's free tier, minimizing computational costs, with optional investment in cloud storage for managing datasets. Application development utilized open-source tools like Flutter, Android Studio, and Visual Studio Code, reducing software expenses, while testing was conducted on Android and iOS devices.

Table 5.2: Financial Analysis Chart

Category	Expense Description	Estimated Cost (BDT)
Dataset Preparation	Field collection and labeling	000
Model Training	Google Colab (Free Tier)	0
Application Development	Open-source tools (Flutter, IDEs)	0
Deployment	Apple Developer Account subscription	1000
Miscellaneous	App promotion and testing devices	1000
Total Estimated Cost		9000

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.3 provides a detailed mapping of the research problem to the problem-solving categories. It demonstrates how the project addresses key aspects such as depth of knowledge, conflicting requirements, and stakeholder involvement.

Table 5.3: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
Deep understanding of different CNN models(VGG19, InceptionV3, DenseNet201, MobileNetV2, ResNet50V2) for disease detection	Balancing accuracy, computational efficiency, and dataset quality	Evaluating models using accuracy, F1-score, and recall metrics	Addressing dataset limitations and scalability issues	Following best practices in TensorFlow and PyTorch usage	Farmers and agricultural experts as primary beneficiaries	Integration of preprocessing, training, and evaluation workflows

Mapping with Knowledge Profile for EP1

Table 5.4 maps the Depth of Knowledge (EP1) to the Knowledge Profile categories. It illustrates the application of engineering fundamentals, advanced techniques, and research literature in the project.

Table 5.4: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
Application of machine learning and computer vision principles	Advanced techniques like CNN models	Workflow design from data preprocessing to evaluation	Implementation using cloud-based Google Colab platform	Building the foundation through an extensive literature review

5.4.2 Engineering Activities

This section provides a mapping with engineering activities. Each mapping highlights the activities undertaken as part of the research and provides a rationale for their inclusion.

Table 5.3 highlights the complex engineering activities involved in the research, such as utilizing cloud resources, fostering collaboration, introducing innovative hybrid models, and addressing societal and environmental impacts. It emphasizes the familiarity with cutting-edge frameworks.

Table 5.5: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
Utilization of Google Colab's cloud-based GPU resources for efficient model training.	Collaboration with agricultural experts for real-world validation.	Integration of CNN models for innovative solutions.	Reduction in pesticide overuse and environmental harm.	Familiarity with TensorFlow and PyTorch frameworks.

5.5 Summary

This chapter has explored the broader impacts of the AI-based medicinal plant identification tool, examining how it affects individual lives, society, and the environment. The ethical considerations underscore the importance of respecting traditional knowledge, ensuring data privacy, and prioritizing user safety. A sustainability plan has been proposed to maintain the tool's accuracy and accessibility over time, ensuring it remains a valuable resource for medicinal plant identification across diverse communities and regions. This chapter highlights the potential of the tool to positively contribute to healthcare, environmental conservation, and cultural preservation.

Chapter 6

Conclusion

6.1 Summary

This study has aimed to develop an AI-based tool for the identification and classification of medicinal plants, combining traditional botanical knowledge with state-of-the-art machine learning and image processing techniques. By exploring CNN and transformer-based architectures, the research demonstrated the potential for achieving high classification **accuracy** in identifying diverse plant species, with a focus on practical applications in real-world settings.

The tool's successful implementation offers a promising approach to overcoming the challenges of manual plant identification, especially in areas with limited access to expert knowledge. Through its accessible and efficient design, the tool contributes to the conservation of medicinal plants, supports traditional healthcare practices, and helps mitigate the risks of plant misidentification. Furthermore, this study underscores the importance of adapting AI technology to be user-friendly and resource-efficient, making it an asset in rural and low-resource areas where medicinal plants play a crucial role in healthcare.

In conclusion, this work highlights the potential for AI-driven tools to bridge gaps between technology and traditional knowledge, providing an effective solution for medicinal plant identification that aligns with both healthcare and conservation efforts.

6.2 Limitation

Despite its contributions, this research encountered certain limitations. The primary limitation was the dependence on existing datasets, which may restrict the tool's **accuracy** and reliability in identifying plant species not included in the dataset. This limitation underscores the importance of continuous data expansion to improve model performance across diverse plant species and environments.

Furthermore, while the study aimed to optimize the model for mobile and low-resource settings, achieving a balance between computational efficiency and **accuracy** remains challenging. Optimizing complex models for mobile devices without compromising **accuracy** is an area that requires further research.

In terms of potential conflicts of interest, it is crucial to acknowledge that the integration of traditional medicinal knowledge into a technological tool must be handled sensitively. Collaboration with indigenous communities and traditional practitioners should be conducted with transparency and respect, recognizing their intellectual property rights and addressing any ethical concerns.

In summary, this study contributes valuable insights and practical solutions for medicinal plant identification while recognizing the need for continued research to refine and expand the tool's scope and reliability.

6.3 Future Work

Although this research has demonstrated significant potential, several avenues for future work could expand its impact and applicability:

- Expanded Dataset Collection: Future studies could incorporate larger, more diverse datasets from various ecological regions to enhance the model's accuracy and generalizability across plant species globally. Collaborations with botanical institutions and conservation organizations may facilitate the development of more comprehensive datasets.

- Incorporation of Additional Plant Features: Integrating non-leaf features, such as flower, seed, and bark characteristics, may improve the tool's accuracy and robustness. This expansion would require advanced multi-feature learning algorithms capable of handling more complex data structures and patterns.

- Real-Time Mobile and Offline Functionality: To maximize accessibility in field applications, future work could focus on optimizing the tool for mobile deployment and offline use, ensuring it remains reliable in remote or low-infrastructure areas.

- Integration of Additional Languages and Cultural Knowledge: Adding multilingual support and culturally specific medicinal information could enhance the tool's utility for diverse user bases, especially indigenous communities, ensuring the tool remains inclusive and respectful of local knowledge traditions.

- Development of a Feedback Loop for Continuous Learning: Incorporating a feedback mechanism where users can submit images or report inaccuracies could allow the model to continuously improve and adapt to user needs over time. This system could enhance the tool's accuracy and effectiveness by allowing real-world validation.

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