# IMPLEMENTING AN EFFICIENT IMAGE PROCESSING TECHNIQUE WITH DEEP NEURAL NETWORKS FOR THE CLASSIFICATION OF MEDICINAL HERBS

**BY**

**Md. Mahmudul Hasan**
**ID: 201-15-13888**
**AND**

**Nasif Ur Rahman**
**ID: 201-15-13613**

## FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

## Supervised By

**Ms. Tanzina Afroz Rimi**
Lecturer
Department of Computer Science and Engineering
Daffodil International University

## Co-Supervised By

**Ms. Sharun Akter Khushbu**
Senior Lecturer
Department of Computer Science and Engineering
Daffodil International University

**DAFFODIL INTERNATIONAL UNIVERSITY**

**DHAKA, BANGLADESH**

**July 2024**

# APPROVAL

This Project titled "Implementing an Efficient Image Processing Technique With Deep Neural Networks for the Classification of Medicinal Herbs", submitted by **Md. Mahmudul Hasan** and **Nasif Ur Rahman** 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 13-07-2024.

## BOARD OF EXAMINERS

13.07.2024

**Dr. Sheak Rashed Haider Noori (SRH)** — **Board Chairman**
**Professor & Head**
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

**Dr. Md. Zahid Hasan (ZH)** — **Internal Examiner 1**
**Associate Professor**
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

**Mr. Md Mohammad Masum Bakaul (MB)** — **Internal Examiner 2**
**Sr. Lecturer**
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

**Dr. Md. Zulfiker Mahmud (ZM)** — **Eternal Examiner**
**Professor**
Department of CSE
Jagannath University

# DECLARATION

We hereby declare that this project has been done by us under the supervision of **Ms. Tanzina Afroz Rimi, 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.

**Supervised by:**

11/07/24

**Ms. Tanzina Afroz Rimi**
**Lecturer**
Department of CSE
Daffodil International University

**Co-Supervised by:**

13/07/24

**Ms. Sharun Akter Khushbu**
**Senior Lecturer**
Department of CSE
Daffodil International University

**Submitted by:**

Mahmudul
**Md. Mahmudul Hasan**
**ID: 201-15-13888**
Department of CSE
Daffodil International University

Nasif
**Nasif Ur Rahman**
**ID: 201-15-13613**
Department of CSE
Daffodil International University

## ACKNOWLEDGEMENT

First, we express our deepest thanks and gratitude to the Almighty for His divine blessings, which made it possible for us to successfully complete our final year thesis.

We are deeply grateful and profoundly indebted to **Ms. Tanzina Afroz Rimi, Lecturer** in the Department of CSE at Daffodil International University, Dhaka. Her extensive knowledge and keen interest in AI and Machine Learning have been instrumental in carrying out this project. Her endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, and meticulous review of numerous drafts have made it possible to complete this thesis successfully.

We would like to express our deepest gratitude to **Dr. Sheak Rashed Haider Noori** for his invaluable assistance in completing our thesis. We also extend our thanks to the other faculty members and staff of the Department of CSE at Daffodil International University.

We would like to thank all our course mates at Daffodil International University who participated in the discussions during our coursework.

Finally, we must express our sincere appreciation for the unwavering support and patience of our parents.

# ABSTRACT

Plants, in all their diversity, represent a valuable contribution from the environment. When illness strikes, whether physical or mental, medicine becomes our primary recourse. Many pharmaceuticals are derived from natural plants, which serve as vital sources of medicinal compounds. In Bangladesh, these medicinal plants are also known by the names Homeopathy, Unani, and Ayurveda. Experts suggest that the COVID-19 pandemic can be effectively addressed with the aid of medicinal plants. Strengthening our immune system is paramount, as it directly influences overall health. A robust immune system can combat bacteria, viruses, and other pathogens. Conversely, inactive individuals are more susceptible to viral infections and diseases. Certain medicinal plants have been shown to enhance immunity. Therefore, accurately classifying these plants is crucial.

We proposed using four well-known algorithms—DenseNet201, VGG19, and ResNet152—to classify medicinal plants based on leaf images. Our approach achieved accuracies of 96.08% with DenseNet201, 97% with VGG19, 98% with ResNet152, and an impressive 99.12% with a hybrid model combining VGG19 and ResNet50. These results highlight the potential of advanced deep learning techniques in enhancing the identification and utilization of medicinal plants. Our research will help people understand their immune systems better and the medicinal plants that can boost immunity, thereby enabling them to combat diseases and viruses more effectively in the future. As we look ahead, it is important to acknowledge that dangerous infectious viruses may continue to emerge. Our study not only contributes to the field of medicinal plant classification but also underscores the importance of integrating traditional medicinal knowledge with modern technological advancements to improve public health outcomes.

# TABLE OF CONTENTS

## LIST OF FIGURES

## LIST OF TABLES

# CHAPTER 1
# Introduction

## 1.1 Overview

Plants, with their astonishing diversity and inherent biological complexity, have been indispensable to human civilization since time immemorial. Beyond their roles in ecological balance and ecosystem services, plants have served as vital reservoirs of medicinal compounds, offering humanity a treasure trove of remedies for various ailments. Throughout history, diverse cultures around the world have developed sophisticated systems of traditional medicine, rooted in the profound wisdom of botanical knowledge. In Bangladesh, where traditions such as Homeopathy, Unani, and Ayurveda flourish, the therapeutic potential of indigenous plants is deeply woven into the fabric of society.

The onset of the COVID-19 pandemic has propelled the exploration of alternative modalities in healthcare, prompting a reevaluation of the relationship between humans and nature. As conventional medical systems grapple with the challenges posed by emerging pathogens, there has been a resurgence of interest in the medicinal properties of plants as a complementary approach to disease prevention and management. Central to this paradigm shift is the recognition of the pivotal role played by the immune system in safeguarding human health. A robust immune response not only confers resistance to infectious agents but also plays a crucial role in maintaining overall well-being.

Against this backdrop, our research endeavors to harness the potential of deep learning algorithms to bridge the gap between traditional wisdom and modern technology in the realm of plant-based medicine. Drawing on the rich botanical heritage of Bangladesh, we propose a novel approach to medicinal plant classification based on leaf images. Leveraging the capabilities of renowned deep learning architectures- DenseNet201, VGG19, and ResNet152 and a hybrid model combination of VGG19 and ResNet50—we seek to develop a robust framework for accurately identifying and classifying medicinal plants with high precision.

By achieving notable accuracies in plant recognition, our study aims to empower individuals, including those lacking expertise in botanical identification, to harness the therapeutic properties of medicinal plants for enhancing immunity and combating diseases. Furthermore, our research endeavors to elucidate the intricate interplay between medicinal plants and the immune system, shedding light on the mechanisms underlying their immunomodulatory effects.

In this paper, we present the findings of our study, which not only contribute to the burgeoning field of plant-based medicine but also hold promise for informing future strategies in healthcare and disease prevention. Through interdisciplinary collaboration and innovation, we aspire to pave the way for a holistic approach to health and wellness that embraces the invaluable contributions of medicinal plants to human flourishing.

### 1.2 Background and Present State

The classification of medicinal herbs using image processing techniques has gained substantial attention in recent years, driven by the increasing demand for accurate and efficient identification methods in the pharmaceutical, agricultural, and botanical sectors. Traditional methods of herb identification, which rely on expert knowledge and manual analysis, are often time-consuming, subjective, and prone to errors. Consequently, there is a significant interest in developing automated systems that leverage the capabilities of deep neural networks (DNNs) to enhance the accuracy and speed of herb classification. Deep learning, a subset of machine learning, has revolutionized the field of image processing. Convolutional Neural Networks (CNNs), a popular architecture within DNNs, are particularly effective for image recognition tasks due to their ability to automatically extract and learn hierarchical features from raw image data. CNNs have demonstrated remarkable success in various applications, from facial recognition to medical imaging, making them well-suited for the classification of medicinal herbs.

The present state of research in this area involves the development and optimization of CNN-based models to classify different species of medicinal herbs with high accuracy. Researchers are focusing on creating large and diverse datasets of herb images, which are essential for training robust models. Additionally, advanced techniques such as data augmentation, transfer learning, and fine-tuning pre-trained models are being employed to enhance model performance and generalization capabilities.

Recent studies have shown promising results, with CNNs achieving high classification accuracies, often surpassing traditional machine learning methods. These advancements hold potential for practical applications, including automated herb recognition systems for use in the field, quality control in herbal product manufacturing, and preserving endangered species by aiding in their identification and documentation. Despite these advancements, challenges such as the need for extensive labeled datasets and the computational intensity of training deep networks remain active research and development areas.

### 1.3 Problem Statement

The problem statement for implementing an efficient image processing technique with deep neural networks for the classification of medicinal herbs can be articulated as follows:
Traditional methods for the classification and identification of medicinal herbs are often laborintensive, time-consuming, and prone to human error, leading to inefficiencies and inaccuracies in herb recognition. This poses significant challenges in various sectors, including pharmaceuticals, agriculture, and botany, where precise and rapid identification of medicinal herbs is crucial for quality control, research, and conservation efforts. Despite the potential of deep neural networks (DNNs), particularly Convolutional Neural Networks (CNNs), to automate and enhance image classification tasks, there is a need for more effective and efficient image-processing techniques tailored specifically for medicinal herbs. This includes addressing challenges such as the creation of comprehensive and diverse datasets, the development of robust models capable of handling variations in herbs appearance, and the reduction of computational demands associated with training and deploying deep learning models. The objective is to develop a reliable and efficient deep learning-based image processing system that can accurately classify medicinal herbs, thereby improving the accuracy, speed, and scalability of herb identification processes.

### 1.4 Objectives

The objectives of implementing an efficient image processing technique with deep neural networks for the classification of medicinal herbs can be outlined as follows:

- **Develop a Comprehensive Dataset:** Create a large and diverse dataset of high-quality images of various medicinal herbs to train and test the deep learning models.
- **Design and Optimize CNN Architectures:** Develop and optimize Convolutional Neural Network (CNN) architectures tailored for the classification of medicinal herbs to achieve high accuracy and robustness.

- **Implement Data Augmentation Techniques:** Employ data augmentation methods to enhance the diversity and quantity of training data, improving the model's ability to generalize across different conditions and variations.
- **Utilize Transfer Learning:** Apply transfer learning techniques to leverage pre-trained models, reducing the computational resources and time required for training while maintaining high performance.
- **Fine-Tune Models:** Fine-tune pre-trained models on the specific dataset of medicinal herbs to improve classification accuracy and adapt to the specific characteristics of herb images.
- **Evaluate Model Performance:** Conduct thorough evaluations of the developed models using standard metrics such as accuracy, precision, recall, and F1-score to ensure reliability and effectiveness.
- **Reduce Computational Demands**: Optimize the models and training processes to minimize computational requirements, making the system more accessible and practical for real-world applications.

### 1.5 Scope and Limitations

The classification of medicinal herbs using deep neural networks represents a significant advancement in the fields of pharmaceuticals, agriculture, and botanical sciences. Leveraging the power of Convolutional Neural Networks (CNNs) for image processing, this approach aims to automate and enhance the accuracy of herb identification. While promising, the implementation of such a system comes with its own set of opportunities and challenges. Below are the scope and limitations of this technology: **Scope**

- **Wide Range of Herb Species:** The system aims to classify a broad variety of medicinal herbs, making it useful for applications in pharmaceuticals, agriculture, and botanical research.
- **Automated Identification:** The primary focus is on automating the identification process, reducing the need for expert intervention and minimizing human error.
- **Educational Tool:** The system could serve as an educational tool for students and researchers in botany and related fields, providing a hands-on method to learn about different medicinal herbs.

- **Conservation Efforts:** By aiding in the accurate identification of endangered species, the system can support conservation efforts and biodiversity studies.
- **Model Building:** Find out the suitable model for medical herbs detection. **Limitations**
- **Dataset Dependence:** The accuracy of the system is highly dependent on the quality and comprehensiveness of the training dataset. Limited or biased datasets can lead to poor model performance.
- **Variability in Images:** Variations in lighting, angles, and backgrounds in the images can affect the accuracy of the classification, requiring sophisticated preprocessing and augmentation techniques.
- **Computational Resources:** Training deep neural networks, especially with large datasets, requires significant computational resources, which might not be available in all settings.
- **Generalization:** While the system can be highly accurate on the training dataset, it might struggle to generalize to new, unseen data, especially if the new data varies significantly from the training set.
- **Limited by Herb Characteristics:** Herbs that have very similar visual characteristics might be difficult to distinguish, leading to misclassification.

## 1.6 Report Organization

The planned report is structured with a comprehensive framework designed to guide readers through each stage of the research, presenting findings and their implications distinctly in every chapter. This organization aims to ensure coherence and thoroughness across the document.

**Chapter 1:** Introduces the project on medicinal herb classification using deep neural networks, highlighting its importance and the limitations of traditional methods. It outlines the problem statement, scope and limitations, objectives and the overall structure of the report.

**Chapter 2:** Delves into the literature on medicinal herb classification, reviewing existing works and methodologies using deep neural networks. It compares various approaches and discusses their strengths and limitations, highlighting unresolved issues in current research.

The chapter concludes with a summary that emphasizes the gaps in knowledge and the need for further advancements in the field.

**Chapter 3:** Provides an overview of the proposed methodology and system design for classifying medicinal herbs using deep neural networks. It details the hardware and software requirements essential for system implementation. Additionally, the chapter outlines project management strategies and offers a financial analysis, ensuring feasibility and resource allocation. A summary concludes, highlighting the structured approach to be undertaken in subsequent chapters.

**Chapter 4**: This chapter focuses on the practical implementation of the proposed system for medicinal herb classification. It begins with an overview of the implementation process, detailing the training of deep neural network models and the design of prototypes. System testing and model evaluation methods are then discussed to assess performance metrics. The chapter concludes with a summary of key findings and outcomes from the implementation phase.

**Chapter 5**: It presents the results and analysis of the implemented system for medicinal herb classification. It provides an overview of the experimental or simulation results obtained, including metrics such as accuracy and efficiency. The chapter conducts a comprehensive performance and comparative analysis against existing methods, highlighting strengths and areas for improvement. A summary concludes, synthesizing the findings and their implications for future research and application.

**Chapter 6:** Examines the broader impacts of the developed medicinal herb classification system. It discusses its effects on human life, societal benefits, and environmental implications. Ethical considerations related to the system's implementation and use are addressed, ensuring responsible technological deployment.

**Chapter 7:** Provides a comprehensive conclusion to the study on medicinal herb classification using deep neural networks. It summarizes the key findings and implications drawn from the research, highlighting achievements and areas of improvement. Further suggested works outline potential future research directions to enhance the system's capabilities and address existing limitations. The chapter also discusses any identified conflicts of interest or limitations encountered during the study, offering transparency and insights for future endeavors.

**1.7 Summary**

The introduction to the project on medicinal herb classification using deep neural networks emphasizes the significance of automating and improving upon traditional classification methods. It identifies key challenges in current practices, such as labor-intensiveness and potential inaccuracies. The introduction clearly defines the project's problem statement, outlines its scope and limitations, and sets specific objectives to address these challenges. Lastly, it provides a structured overview of the report, guiding the reader through the upcoming chapters and the comprehensive approach taken to achieve the project's goals.

# CHAPTER 2
# Literature Review

## 2.1 Overview

The background chapter delves deeply into pertinent literature and previous research, providing a comprehensive examination of the theoretical underpinnings, methodologies, and technological advancements in medical herbs detection, transfer learning, and deep CNNs. This section establishes the context for the current study and identifies areas where existing knowledge is lacking.

## 2.2 Related Works

The identification and classification of medicinal plants represent a critical aspect of Botanical research with profound implications for various sectors, including healthcare, Conservation, and agriculture. Over the years, numerous studies have delved into the Development of innovative methodologies and technologies aimed at enhancing the Accuracy, efficiency, and reliability of medicinal plant identification. Here, we provide an In-depth exploration of key studies conducted in this domain, highlighting the Methodologies, findings, and contributions of each work:

Raisa et al. introduced an automated system tailored for classifying medicina plants, facilitating rapid identification of useful plant species. Central to their approach was the utilization of CNN to extract key features or high-level features from plant images, resulting in an impressive accuracy rate of 71.3%. The study's findings underscored the efficacy of CNN-based methodologies in streamlining the classification process, thereby enhancing efficiency in medicinal plant identification tasks.[1]

Nayana et al implemented a technique for medicinal plant identification utilizing the random forest algorithm. By incorporating color, texture, and geometrical features, the researchers achieved a remarkable leaf identification accuracy 94.54%. The study's integration of multiple feature extraction techniques underscored the importance of comprehensive data analysis approaches in achieving high accuracy rates in medicinal plant classification tasks.[2]

Md. Ariful Hassan et al addressed the challenge of automated medicinal plant recognition through a machinevision approach based on deep learning. Leveraging a dataset comprising 1,250 images of medicinal plant leaves, the researchers employed three benchmark deep convolutional neural networks (CNNs) – InceptionV3, MobileNet, and Xception. By utilizing state-ofthe-art deep learning architectures, the study showcased the potential of machine-vision approaches in accurately identifying medicinal plants, thus contributing to the advancement of automated recognition systems.[3]

D Venkataraman et al proposed an automated system based on a vision approach for identifying medicinal plants, with a focus on leaf texture classification using the GLCM method. By utilizing texture-based features, the researchers aimed to enhance the accuracy and efficiency of plant identification processes. The study's emphasis on texture-based classification techniques highlighted the importance of incorporating diverse feature extraction methods in automated recognition systems. [4]

Prabhakar Poudel et al. introduced an automation system for leaf detection in medicinal plants, leveraging optical methods and feature extraction techniques such as Support Vector Machine (SVM) and Scale Invariant Feature Transformation (SIFT). By combining optical imaging with advanced feature extraction methodologies, the study aimed to streamline the process of leaf detection and classification, thereby facilitating efficient plant identification. [5]

MM Ghazi et al. utilized Deep Convolutional Networks for plant species identification, leveraging popular deep learning architectures such as GoogLeNet, AlexNet, and VGGNet. By training the models on the LifeCLEF 2015 dataset, the combined system achieved an overall accuracy of 80% on the validation set. The study's incorporation of deep learning techniques highlighted the efficacy of neural network-based approaches in accurately classifying medicinal plant species. [6]

Ananth et al proposed an automation system for plant identification using MATLAB, focusing on mitigating human error associated with manual classification processes. By integrating models such assegmentation and thresholding into a neural network framework, the researchers aimed to streamline the process of plant identification. The study's emphasis on automation highlighted the importance of leveraging computational techniques to enhance the accuracy and efficiency of medicinal plant identification. [7]

P. Chitra et al. utilized digital image processing techniques for the identification of medicinal plants, leveraging Speeded Up Robust Feature Transform (SURF), Scale Invariant Feature Transform (SIFT), and Support Vector Machine (SVM) classifier. By employing advanced feature extraction methodologies, the researchers aimed to accurately distinguish between different plant species based on leaf characteristics. The study's incorporation of digital image processing techniques underscored the importance of leveraging computational algorithms for precise plant identification and classification.[8]

Rajani S et al proposed an automatic identification and classification system for medicinal plants, aiming to raise awareness and encourage learning about these plants. By integrating images of plant leaves, flowers, fruits, and seeds into the classification framework, the researchers aimed to provide a comprehensive approach to plant identification. The study's emphasis on holistic classification approaches highlighted the importance of considering multiple plant characteristics in automated recognition systems. [9]

These seminal studies collectively underscore the breadth and depth of research conducted in the field of medicinal plant identification. By leveraging advanced methodologies and technologies, researchers continue to push the boundaries of knowledge, facilitating advancements in healthcare, conservation, and botanical research. As the field evolves, it is evident that interdisciplinary collaborations and innovative approaches will play a crucial role in addressing the complex challenges associated with medicinal plant identification and classification.

**2.3 Comparison Between Existing Works**

This comparative analysis of medicinal herbs detection encompasses a range of Methodologies and techniques utilized by various researchers. The comparison of prior studies is outlined in the following Table 2.3.1

TABLE 2.3.1: Comparative Analysis Table

| SL No | Author Name | Used Algorithm | Best Accuracy with Algorithm |
|---|---|---|---|
| 1 | Sharrab et al.[10] | Convolutional Neural Networks (CNNs) | 71.3% achieved |
| 2 | Bhuiyan et al.[11] | Random Forest | 94.54% achieved |
| 3 | Aakif et al.[12] | Artificial Neural Network (ANN) | 96% achieved |
| 4 | Begue et al. [13] | Random Forest algorithm | Researchers achieved 90.1% accuracy in automated medicinal plant classification based on leaf characteristics using Random Forest algorithm. |
| 5 | Janani et al. [14] | Artificial Neural Network (ANN) | 94.4% achieved |

## 2.4 Open Issues

Implementing efficient image processing techniques with deep neural networks for the classification of medicinal herbs presents several open issues for researchers to address:

- Dataset Diversity and Quality: Lack of diverse and comprehensive datasets containing high-quality images of medicinal herbs poses a challenge. Researchers need to focus on creating and curating datasets that cover a wide range of herb species with varying visual characteristics.
- Robustness to Environmental Variations: Herbs can exhibit variations in appearance due to factors like lighting conditions, background clutter, and variations in growth stages. Developing models that are robust to such environmental variations is crucial for realworld applications.
- Interpretable Models: Deep neural networks often act as black boxes, making it challenging to interpret how they arrive at their classification decisions. Developing

methods to make these models more interpretable and transparent is essential for gaining trust in automated classification systems.

- Transferability: Ensuring that models trained on one dataset can generalize well to unseen datasets or new herb species is another significant challenge. Techniques for domain adaptation and transfer learning need to be explored to improve the transferability of models.
- Computational Efficiency: Deep learning models for image processing can be computationally expensive and require substantial resources. Optimizing these models for efficiency, both in terms of inference time and resource utilization, is critical for practical deployment, especially in resource-constrained environments.
- Integration with Existing Systems: Integrating automated herb classification systems into existing workflows, such as pharmaceutical manufacturing or botanical research, requires seamless compatibility and minimal disruption. Research is needed to address integration challenges and ensure user acceptance.
- Ethical and Legal Considerations: As with any AI-based system, ethical considerations regarding data privacy, bias in datasets, and the societal impact of automated classification systems need careful attention. Researchers must navigate these considerations to ensure responsible development and deployment.

Addressing these open issues will pave the way for more effective and reliable applications of deep neural networks in the classification of medicinal herbs, benefiting fields such as healthcare, agriculture, and biodiversity conservation.

## 2.4 Summary

The literature review on medicinal herb classification using deep neural networks thoroughly examines existing research and methodologies. It provides a critical analysis by comparing different approaches, assessing their strengths and limitations in accurately classifying herbs based on visual characteristics. The review identifies unresolved issues within current research, such as challenges in dataset diversity, model interpretability, and generalizability across different herb species. Emphasizing gaps in knowledge, the chapter concludes by advocating for further advancements and innovative solutions to enhance the effectiveness and applicability of deep learning techniques in this important domain.

# CHAPTER 3

# Methodology Requirement Analysis & Design Specification

## 3.1 Overview

The proposed methodology for implementing efficient image processing techniques with deep neural networks in medicinal herb classification outlines a structured approach. It details CNN models tailored for accurate classification, ensuring robust performance. Hardware and software requirements are specified to support the implementation, emphasizing scalability and computational efficiency. Project management strategies and financial analysis are integral to ensuring feasibility and effective resource allocation throughout the development and deployment phases.

## 3.2 Proposed Methodology

### A. Data Collection

Data was collected from different nurseries in Savar along with that we will collect data from different websites to enrich our dataset, Bangladesh. Images of various medicinal plants will be captured using a digital camera or smartphone. Care was taken to select diverse plant species and capture multiple images per species to ensure dataset richness. Both of us took extra care to photographed plants. Permission obtained from nursery owners before data collection to adhere to ethical guidelines. Data was labeled according to defined classes, categorizing images based on their identified features or characteristics relevant to the classification task.

Figure 3.2.1: Some Raw Image of Datasets

TABLE 3.2.1: Images Based on Classes

| Classes | Number of Images |
|---|---|
| Tulsi | 730 |
| Mango | 580 |
| Neem | 584 |
| Lemon | 584 |
| Amla | 584 |
| Guava | 584 |
| Rose | 672 |
| Papaya | 657 |
| Aloe vera | 656 |
| Mint | 612 |

**B. Data Pre-processing**

The initial phase of the proposed framework involves gathering information from images of medicinal plants. Given that deep neural networks require ample data for training and optimal performance, researchers sometimes employ data augmentation techniques to address the challenge of limited data availability. Here is an overview of the experimental pre-processing of data.

**Data Cleaning:**

The initial step involved identifying and removing corrupt images that could not be read or were damaged, ensuring a clean dataset free from unreadable data. Duplicate images were systematically detected and removed to streamline the dataset, preventing redundancy and optimizing storage and processing efficiency.

**Background Removal**

Extra portion was executed to enhance image clarity and focus on the relevant features, improving the dataset's suitability for classification tasks.

Image sharpening techniques were applied to enhance image detail and definition, ensuring clarity in feature extraction and analysis.

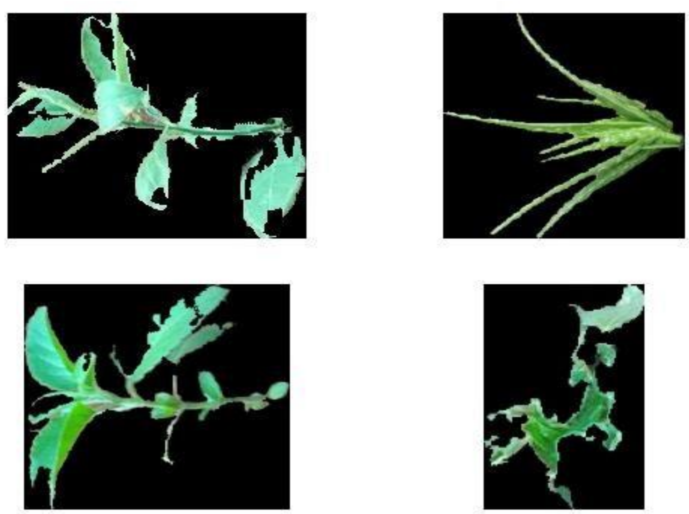

Figure 3.2.2: Images of Background Remove

Adjustments to increase image tone were made to standardize color intensity and enhance visual features, aiding in better classification model training and performance.

**Resizing:**

Image resizing was performed to standardize dimensions across the dataset, facilitating uniform processing and analysis and resizing image width and height are (256,256)

Figure 3.2.3: Resizing Images

**Sharpen the Image and Structured layout**

By utilizing Matplotlib to plot four images in a 2x2 grid. displaying each image within its respective subplot while removes axis labels for cleaner visualization. Finally, `it` ensures optimal spacing between subplots, enhancing overall presentation and structured layout.

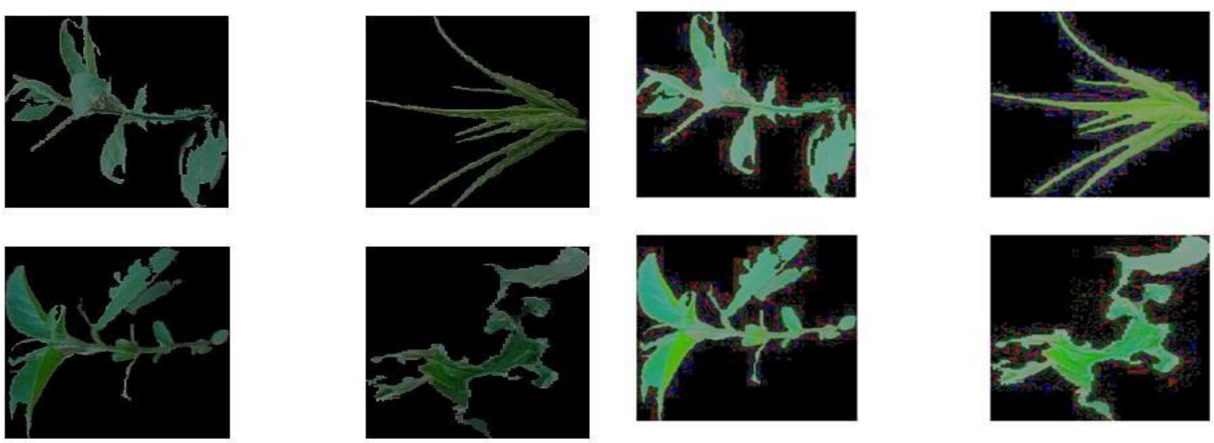

Figure 3.2.4: Sharp and Structured Images

**Exploratory Data Analysis:**

Label distribution was visually represented using pie charts and bar graphs to analyze and understand the distribution of classes within the dataset, providing insights into dataset balance and potential biases.

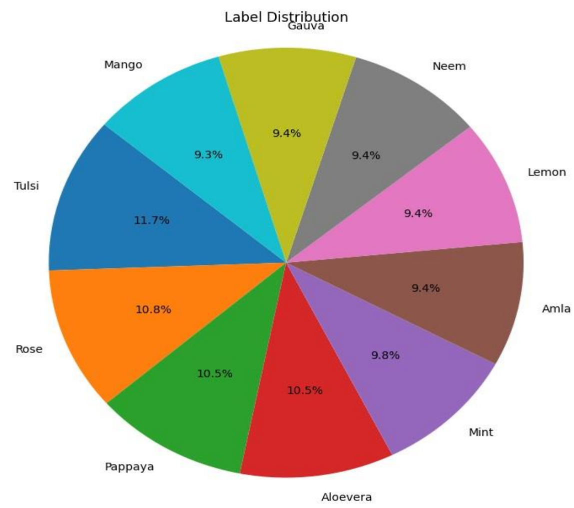


Figure 3.2.5: Image Label Distribution

**Splitting Dataset:**

To ensure robust model training and evaluation, the dataset is partitioned into three distinct subsets: training, validation, and testing. The training set comprises 70% of the total dataset and serves as the foundation for training deep learning models. This subset is crucial for optimizing model parameters and improving predictive performance through iterative learning. The validation set, constituting 20% of the dataset, is used to fine-tune model hyperparameters and assess generalization capabilities, helping to prevent overfitting. Finally, the testing set, comprising 10% of the dataset, remains unseen during training and validation phases and is solely used to objectively evaluate the final model's performance on new, unseen data. This systematic partitioning ensures that the model's accuracy, robustness, and ability to generalize to new data are rigorously evaluated, thereby enhancing the reliability and applicability of the proposed framework for medicinal plant classification.

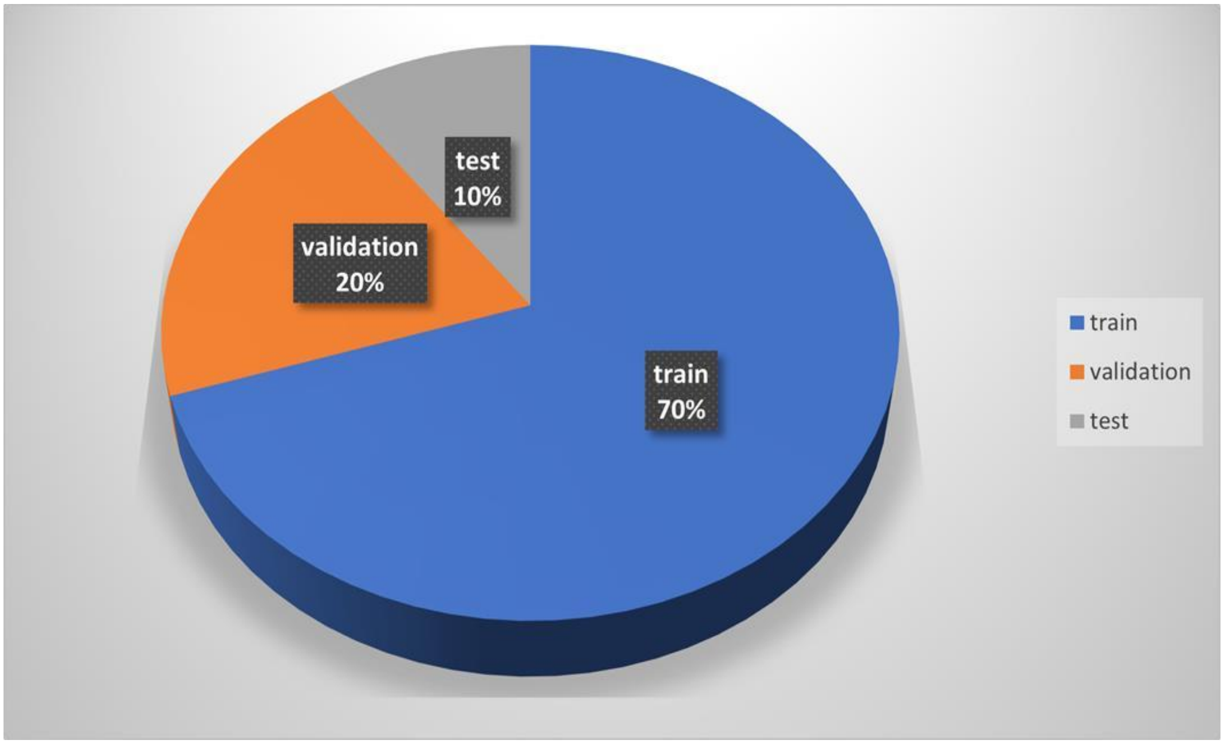


Figure 3.2.6: Splitting Ratio of the dataset

**Applied Mechanism**

In this approach, we employ transfer learning to develop a classification model for detecting medical herbs using various architectures. Initially, we utilize pretrained models known for their efficiency in mobile and embedded applications. By setting the trainable attribute to False, we freeze the base model's layers to retain learned features during training. An input layer is defined to accept images sized at (256, 256, 3), aligning with typical input requirements for pretrained CNNs.

The frozen base model is used for feature extraction, leveraging its pre-learned hierarchical features. Following feature extraction, a Global Average Pooling 2D layer is applied to reduce spatial dimensions while retaining essential information. The model is structured with an output layer containing dense units equal to the number of classes in the dataset of medical herbs, utilizing softmax activation.

During model instantiation, compilation involves defining appropriate optimization, loss, and metric parameters. The training phase fits the model to the dataset, with potential fine-tuning strategies tailored to dataset characteristics and task requirements. This methodology integrates the efficiency of transfer learning with the adaptability of various architectures, making it wellsuited for medical herb classification tasks.

In the model evaluation phase, metrics such as confusion matrix, accuracy, precision, recall, and F1-score are used to comprehensively assess the model's performance in detecting medical herbs.

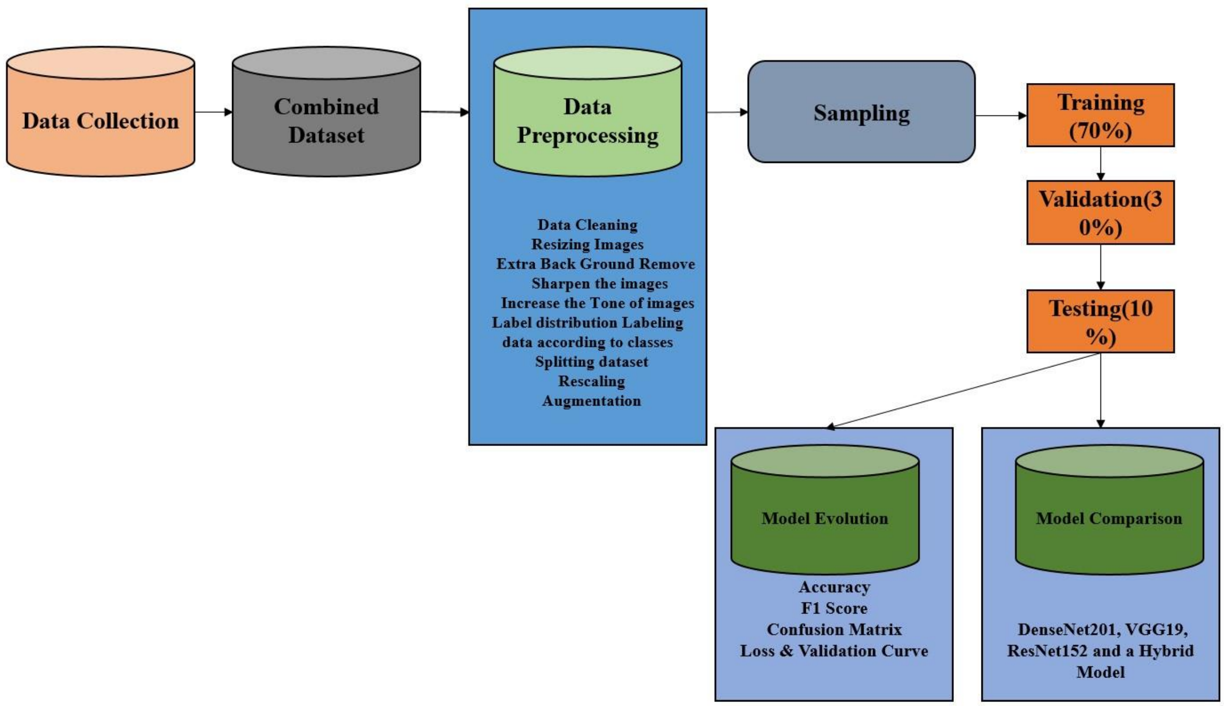


Figure 3.2.7: Process of Experiments

**Hybrid Model:**

The hybrid model architecture combines the feature extraction capabilities of VGG16 and ResNet50, two widely recognized convolutional neural networks (CNNs) pretrained on ImageNet. With an input shape of (256, 256, 3), both models are initialized with weights from ImageNet and configured to exclude their respective top classification layers, ensuring that only the feature extraction parts are utilized. By freezing all layers of VGG16 and ResNet50, the model preserves the hierarchical features learned from extensive training on large-scale image datasets. Features extracted from these models are flattened and concatenated to form a unified feature representation. This concatenated feature vector is then fed through dense layers with 1024 and 512 units, employing rectified linear unit (ReLU) activation functions to capture higher-level abstractions within the data.

Following the feature processing layers, the model culminates in an output layer configured with a softmax activation function, tailored for a classification task with 10 output classes. During compilation, the model is optimized using the Adam optimizer and trained with sparse categorical cross-entropy loss, a suitable choice for multi-class classification problems. Throughout training, accuracy serves as the primary evaluation metric to gauge the model's performance on both training and validation data. This architecture leverages the combined strengths of VGG16 and ResNet50, aiming to enhance classification accuracy by harnessing their diverse feature extraction capabilities.

In practical application, the hybrid model's design flexibility allows for adjustments in trainable parameters or additional layers to accommodate specific dataset characteristics and classification requirements. Fine-tuning strategies can be employed selectively, depending on the dataset size and complexity, to further optimize performance. By integrating features from two powerful CNN architectures, the hybrid model offers a robust framework for tackling various image classification tasks, demonstrating adaptability and potential improvements over single-model approaches in diverse real-world applications.

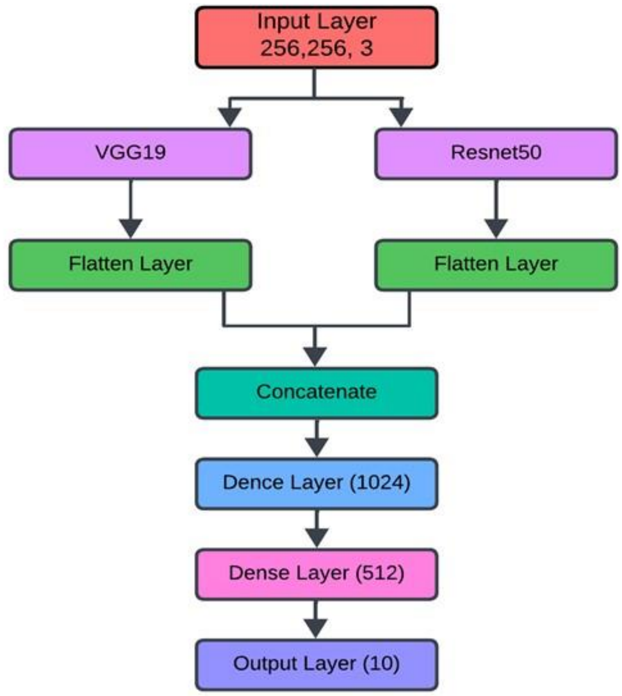


Figure 3.2.8: Hybrid Model

**3.3 Hardware and Software Requirement**

The successful execution of the study on "Implementing an Efficient Image Processing Technique With Deep Neural Networks for the Classification of Medicinal Herbs " involves several key implementation requirements. These requirements span hardware, software, data collection, model training and evaluation, ethical considerations, and documentation to ensure the research is thorough and reliable

.To successfully execute the study on "Implementing an Efficient Image Processing Technique With Deep Neural Networks for the Classification of Medicinal Herbs," several key implementation requirements and tools are necessary:

1. Operating System: Windows 10 provides the foundational environment for software development and execution.
2. Programming Language: Python serves as the primary language for implementing algorithms and interacting with various libraries.
3. Cloud Computing Platform: Utilizing Colab offers scalable computing resources and facilitates collaborative development in a cloud-based environment.

4. Image Processing Libraries: OpenCV (Open Source Computer Vision Library) is essential for image preprocessing, manipulation, and feature extraction.
5. Data Handling: Pandas is used for data manipulation and analysis, facilitating efficient handling of datasets.
6. Numerical Computing: NumPy provides essential numerical operations and array processing capabilities, foundational for mathematical operations in deep learning.
7. Visualization: Matplotlib is employed for data visualization, enabling the graphical representation of results and model performance metrics.
8. Machine Learning Libraries: Sklearn (Scikit-learn) offers a wide range of machine learning algorithms and tools for data preprocessing, model selection, and evaluation.
9. Label Encoding: LabelBinarizer converts categorical data into a numerical format suitable for model training and evaluation.
10. Deep Learning Frameworks: TensorFlow and Keras provide comprehensive tools for building, training, and deploying deep neural networks, including pre-built models like DenseNet121, ResNet50 and many more for efficient model architecture implementation.

These are some important tools collectively support the development, training, evaluation, and deployment of advanced deep learning models tailored for the classification of medicinal herbs based on image data.

### 3.4 Project Management and Financial Analysis

Effective project management and financial oversight play crucial roles in ensuring the success and sustainability of any undertaking, especially in the proposed research on "Implementing an Efficient Image Processing Technique with Deep Neural Networks for the Classification of Medicinal Herbs." Project management involves detailed planning, coordination, and execution of tasks, from data collection to model training and evaluation. A comprehensive project plan will be developed to delineate key milestones, allocate resources efficiently, and establish timelines, promoting a structured and streamlined workflow. Similarly, sound financial management is essential for the project's viability, encompassing budget allocations for equipment, computational resources, and potential research partnerships. A transparent and prudent financial strategy was implemented to optimize resource utilization while upholding fiscal responsibility. These integrated approaches to project management and finance are critical foundations that will enable the research team to navigate the complexities of the study effectively, ensuring that resources are aligned with research objectives and facilitating smooth project progression towards its objectives

### 3.5 Summary

This research project focuses on implementing advanced image processing techniques using deep neural networks for the classification of medicinal herbs. Data collection involved gathering diverse plant images from nurseries in Savar and various online sources, ensuring a rich and varied dataset. The dataset was meticulously cleaned, with corrupt and duplicate images removed, and backgrounds were refined to enhance clarity. Images were standardized through resizing and tone adjustments, optimizing them for deep learning model training. Exploratory data analysis provided insights into class distributions, guiding the dataset partitioning into training, validation, and testing subsets. Transfer learning techniques, including the use of pretrained models like DenseNet121 and a hybrid VGG16-ResNet50 architecture, were employed to enhance classification accuracy. The project also emphasized effective project management and financial oversight to ensure smooth execution and resource utilization.

# CHAPTER 4 Implementation

### 4.1 Overview

The experimental setup for the study on "Implementing an Efficient Image Processing Technique with Deep Neural Networks for the Classification of Medicinal Herbs" involves a meticulously planned arrangement of hardware, software, and data resources to facilitate comprehensive investigations. The computational infrastructure includes high-performance hardware, such as a robust central processing unit (CPU) and a powerful graphics processing unit (GPU), which form the core for computational tasks. Deep learning frameworks like TensorFlow or PyTorch are utilized within a Python programming environment to implement transfer learning models effectively. The experimental dataset, collected from various sources of medical images, undergoes thorough preprocessing, standardization, and normalization procedures to ensure consistent and representative inputs for model training and evaluation. The utilization of pre-trained deep Convolutional Neural Network (CNN) architectures, with fine-tuning tailored for the specific task of medicinal herb classification, is a pivotal component of the model setup. Ethical considerations, including protocols for data privacy and informed consent, are integrated into the setup to uphold ethical standards throughout the research process. Detailed documentation encompassing code specifics, model architecture details, hyper parameters, and experimental results is maintained meticulously to promote transparency, reproducibility, and future collaboration in advancing the field of advanced image processing techniques for medicinal herb classification.

## 4.2 Train Model

This section explores specialized convolutional neural network (CNN) architectures optimized for precise classification of medical herbs. DenseNet121, VGG19, ResNet152, and a hybrid model combining VGG16 and ResNet50 are analyzed for their ability to capture intricate leaf patterns and achieve high accuracy in identifying diverse types of medical herbs. Each architecture leverages unique features such as dense connectivity, deep layering, robust skip connections, and combined strengths for comprehensive feature extraction and effective

### DenseNet121

DenseNet121 is a Convolutional Neural Network (CNN) structure optimized for detecting medical herbs. This architecture excels at capturing intricate details and patterns within medical herbs images, which is crucial for accurately identifying and classifying. The hallmark of DenseNet121 lies in its dense connectivity, where each layer receives input from all preceding layers. This design significantly enhances information flow throughout the network, facilitating thorough and effective feature extraction across different scales and complexities of medical herbs images.

### VGG19

VGG19 tailored for the detection of medical herbs, extends the VGG16 architecture by incorporating 19 layers. Known for its depth, VGG19 excels in capturing intricate patterns present in medical herb images, enhancing its suitability for accurate classification tasks. With its sequential arrangement of convolutional and pooling layers, VGG19 effectively extracts hierarchical features essential for distinguishing various herb patterns. Its deep structure significantly boosts its capability to discern complex variations and patterns within leaf images. Specifically adapted for medical herbs detection, VGG19 demonstrates robust performance, providing a dependable method for identifying and categorizing medical herbs based on their leaf characteristics.

**ResNet152**

It is designed specifically for detecting medical herbs, stands out as an advanced convolutional neural network architecture known for its depth and robust skip connections. Tailored for image classification tasks, particularly in identifying various medical herbs, ResNet152 excels at capturing intricate features within the dataset. The integration of residual connections effectively addresses the vanishing gradient issue, which can hinder the training of deep networks. With its extensive 152-layer structure, ResNet152 achieves high accuracy in distinguishing different types of medical herbs. Its architectural complexity enhances its ability to tackle challenging image recognition tasks, establishing it as a valuable and dependable choice for precise detection of medical herbs.

**Hybrid Model**

Combining VGG16 and ResNet50 in a hybrid model for medical herbs detection offers a powerful approach leveraging the strengths of both architectures. VGG16, renowned for its simplicity and effectiveness, uses smaller convolutional filters repeatedly stacked to capture detailed features in herb images. In contrast, ResNet50 introduces residual connections that help alleviate training difficulties encountered in very deep networks, enhancing its ability to extract and learn intricate herb features. By integrating these models, the hybrid architecture benefits from comprehensive feature extraction capabilities across different scales and complexities of herb images, potentially leading to improved accuracy and robustness in classification tasks. This hybrid approach thus merges VGG16's detailed feature capturing with ResNet50's deep learning capabilities, offering a balanced solution for precise medical herbs detection. classification tasks in herb imagery.

## 4.3 Model Evaluation

Once the data has been preprocessed and the sequential model constructed, the next step involves partitioning the dataset into training, validation, and test sets. The training set is utilized for the machine learning process to learn patterns from the data. The validation set assists in fine-tuning the model's parameters and evaluating its performance during training. Finally, the test set provides an independent dataset to assess the model's generalization ability and accuracy on unseen data, ensuring a reliable evaluation of the trained model's performance on the preprocessed dataset.

A confusion matrix is a tool used to evaluate the accuracy of a classifier's predictions. It assesses the effectiveness of a classification model by detailing the counts of correct and incorrect predictions across different classes. From the confusion matrix, various performance metrics such as accuracy, precision, recall, and F1-score can be derived to measure how well the classification model performs.

### 4.4 Summary

This section outlines the practical implementation of a medicinal herb classification system, detailing the deployment steps from training deep neural networks with architectures like DenseNet121, VGG19, ResNet152, and hybrid models combining VGG16 and ResNet50. It emphasizes thorough system testing, model evaluation using partitioned datasets, and the use of confusion matrices to assess classification accuracy and performance metrics such as precision, recall, and F1-score. The summary encapsulates the systematic approach to developing and evaluating robust models for precise medical herb identification and classification.

# CHAPTER 5 Result and Analysis

### 5.1 Overview

The experimental setup for the study on "Implementing an Efficient Image Processing Technique with Deep Neural Networks for the Classification of Medicinal Herbs" involves a meticulously planned arrangement of hardware, software, and data resources to facilitate comprehensive investigations. The computational infrastructure includes high-performance hardware, such as a robust central processing unit (CPU) and a powerful graphics processing unit (GPU), which form the core for computational tasks. Deep learning frameworks like TensorFlow or PyTorch are utilized within a Python programming environment to implement transfer learning models effectively. The experimental dataset, collected from various sources of medical images, undergoes thorough preprocessing, standardization, and normalization procedures to ensure consistent and representative inputs for model training and evaluation. The utilization of pre-trained deep Convolutional Neural Network (CNN) architectures, with fine-tuning tailored for the specific task of medicinal herb classification, is a pivotal component of the model setup.

Ethical considerations, including protocols for data privacy and informed consent, are integrated into the setup to uphold ethical standards throughout the research process. Detailed documentation encompassing code specifics, model architecture details, hyper parameters, and experimental results is maintained meticulously to promote transparency, reproducibility, and future collaboration in advancing the field of advanced image processing techniques for medicinal herb classification.

### 5.2 Experimental Result

In this section, we discuss the performance metrics, including Precision, Recall, F1Score, and Support, for DenseNet201, VGG19, ResNet152, and a hybrid model combining VGG19 and ResNet50. These are crucial for understanding the effectiveness and accuracy of each model in predicting and identifying positive instances in a dataset.

**Precision:** This measures the accuracy of the positive predictions. It is the ratio of correctly predicted positive observations to the total predicted positives. High precision indicates a low false positive rate. Precision is crucial when the cost of false positives is high.

**Recall:** Also known as sensitivity or true positive rate, recall measures the ability to identify all relevant instances. It is the ratio of correctly predicted positive observations to all observations in the actual class. High recall indicates a low false negative rate. Recall is important when missing a positive case is costly.

**F1-Score:** The F1-Score is the harmonic mean of precision and recall. It balances the two metrics, providing a single measure of a test's accuracy that considers both false positives and false negatives. The F1-Score is useful when the class distribution is uneven.

**Support:** Support refers to the number of actual occurrences of each class in the dataset. It is the count of true instances for each label. High support indicates a well-represented class in the dataset. Support helps in understanding the distribution of classes.

.

TABLE 5.2.1: Precision, Recall, F1-Score, and Support (n) for VGG19 Model

| **VGG19** | | | | |
|---|---|---|---|---|
| | **Precision** | **Recall** | **F1-Score** | **Support** |

| | | | | |
|---|---|---|---|---|
| Aloe Vera | 0.98 | 0.98 | 0.98 | 132 |
| Amla | 0.99 | 0.96 | 0.97 | 117 |
| Gauva | 1.00 | 0.99 | 0.97 | 117 |
| Lemon | 0.99 | 1.00 | 1.00 | 117 |
| Mango | 1.00 | 0.97 | 0.98 | 116 |
| Mint | 1.00 | 1.00 | 1.00 | 123 |
| Neem | 0.99 | 0.98 | 0.96 | 117 |
| Papaya | 0.98 | 1.00 | 0.99 | 132 |
| Rose | 0.99 | 0.96 | 0.97 | 135 |
| Tulsi | 0.96 | 1.00 | 0.98 | 146 |
| Macro Avg | 0.99 | 0.98 | 0.97 | 1252 |
| Weighted Avg | 0.99 | 0.98 | 0.97 | 1252 |

TABLE 5.2.2: Precision, Recall, F1-Score, and Support (n) for Densener201 Model

| Densenet201 | | | | |
|---|---|---|---|---|
| | Precision | Recall | F1-Score | Support |
| Aloe Vera | 0.95 | 0.99 | 0.97 | 132 |
| Amla | 0.98 | 0.97 | 0.98 | 117 |
| Gauva | 1.00 | 0.96 | 0.97 | 117 |
| Lemon | 0.92 | 0.91 | 0.96 | 117 |
| Mango | 0.98 | 0.95 | 0.94 | 116 |
| Mint | 0.98 | 1.00 | 0.99 | 123 |
| Neem | 0.98 | 0.93 | 0.96 | 117 |
| Papaya | 0.91 | 1.00 | 0.95 | 132 |
| Rose | 0.97 | 0.92 | 0.94 | 135 |
| Tulsi | 0.95 | 0.97 | 0.96 | 146 |
| Macro Avg | 0.96 | 0.96 | 0.96 | 1252 |
| Weighted Avg | 0.96 | 0.96 | 0.96 | 1252 |

TABLE 5.2.3: Precision, Recall, F1-Score, and Support (n) for ResNet152 Model

| Resnet152 | | | | |
|---|---|---|---|---|
| | **Precision** | **Recall** | **F1-Score** | **Support** |
| Aloe Vera | 0.98 | 0.98 | 0.98 | 132 |
| Amla | 0.98 | 0.96 | 0.97 | 117 |
| Gauva | 0.96 | 0.99 | 0.97 | 117 |
| Lemon | 01.00 | 1.00 | 1.00 | 117 |
| Mango | 0.97 | 0.96 | 0.97 | 116 |
| Mint | 1.00 | 0.99 | 1.00 | 123 |
| Neem | 0.95 | 0.98 | 0.97 | 117 |
| Papaya | 1.00 | 1.00 | 1.00 | 132 |
| Rose | 0.97 | 0.96 | 0.98 | 135 |
| Tulsi | 0.99 | 1.00 | 0.99 | 146 |
| Macro Avg | 0.98 | 0.98 | 0.98 | 1252 |
| Weighted Avg | 0.98 | 0.98 | 0.98 | 1252 |

TABLE 5.2.4: Precision, Recall, F1-Score, and Support (n) for Hybrid Model

| Hybrid Model | | | | |
|---|---|---|---|---|
| | **Precision** | **Recall** | **F1-Score** | **Support** |
| Aloe Vera | 0.99 | 0.98 | 0.99 | 132 |
| Amla | 0.99 | 0.97 | 0.97 | 117 |
| Gauva | 0.96 | 0.99 | 0.97 | 117 |
| Lemon | 01.00 | 1.00 | 1.00 | 117 |
| Mango | 1.00 | 0.96 | 0.97 | 116 |

| | | | | |
|---|---|---|---|---|
| Mint | 1.00 | 1.00 | 1.00 | 123 |
| Neem | 0.95 | 0.98 | 0.97 | 117 |
| Papaya | 1.00 | 1.00 | 1.00 | 132 |
| Rose | 0.97 | 0.96 | 0.99 | 135 |
| Tulsi | 0.99 | 1.00 | 0.99 | 146 |
| Macro Avg | 0.99 | 0.99 | 0.99 | 1252 |
| Weighted Avg | 0.99 | 0.99 | 0.99 | 1252 |

All the tables above provide a comprehensive overview of the training percentages and model accuracies achieved by three distinct original Convolutional Neural Network (CNN) architectures—VGG19, ResNet152, and DenseNet201—and a hybrid model. It also includes precision, recall, F1-score, and support values for each class. All architectures demonstrate remarkable performance, especially in terms of precision when applied to the test dataset, with the hybrid model outperforming the others. Specifically, these three models consistently exhibit superior precision, recall, and F1-score across various classes, underscoring their effectiveness in accurately detecting medicinal herbs.

## 5.3 Performance Analysis

For performance analysis, we use training and validation loss curves, training and validation accuracy curves, and the confusion matrix. The loss curves help us understand how well the model is learning and whether it is overfitting or under fitting, with decreasing training loss indicating better learning and the validation loss indicating generalization to new data. The accuracy curves show the proportion of correct predictions, with training accuracy reflecting the model's performance on known data and validation accuracy indicating performance on unseen data. By examining these curves, we can identify overfitting if the training accuracy continues to improve while the validation accuracy plateaus or declines. The confusion matrix provides a detailed breakdown of true positives, true negatives, false positives, and false negatives, offering insights into specific areas where the model might be making errors, thus helping to fine-tune and improve the model's performance.

**Training and Validation Accuracy and loss of CNN and Hybrid Networks:**

The figure illustrates the training and classification accuracy of the initial model, with the number of epochs on the x-axis and the accuracy and loss percentages on the y-axis. The data for training and validation are properly separated, and the results show no signs of overfitting.

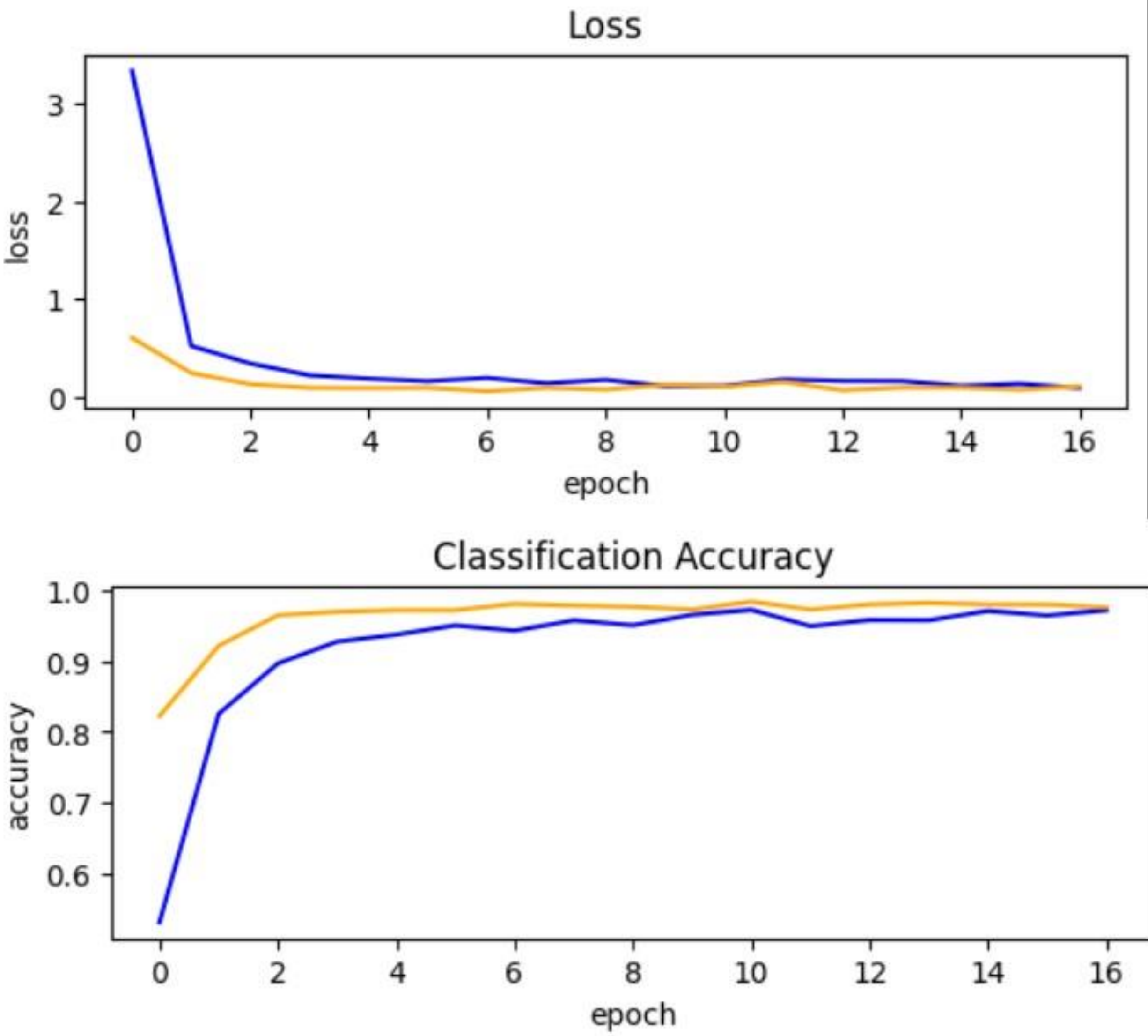


Figure 5.3.1: Training and Classification accuracy and loss over the epochs (VGG19).

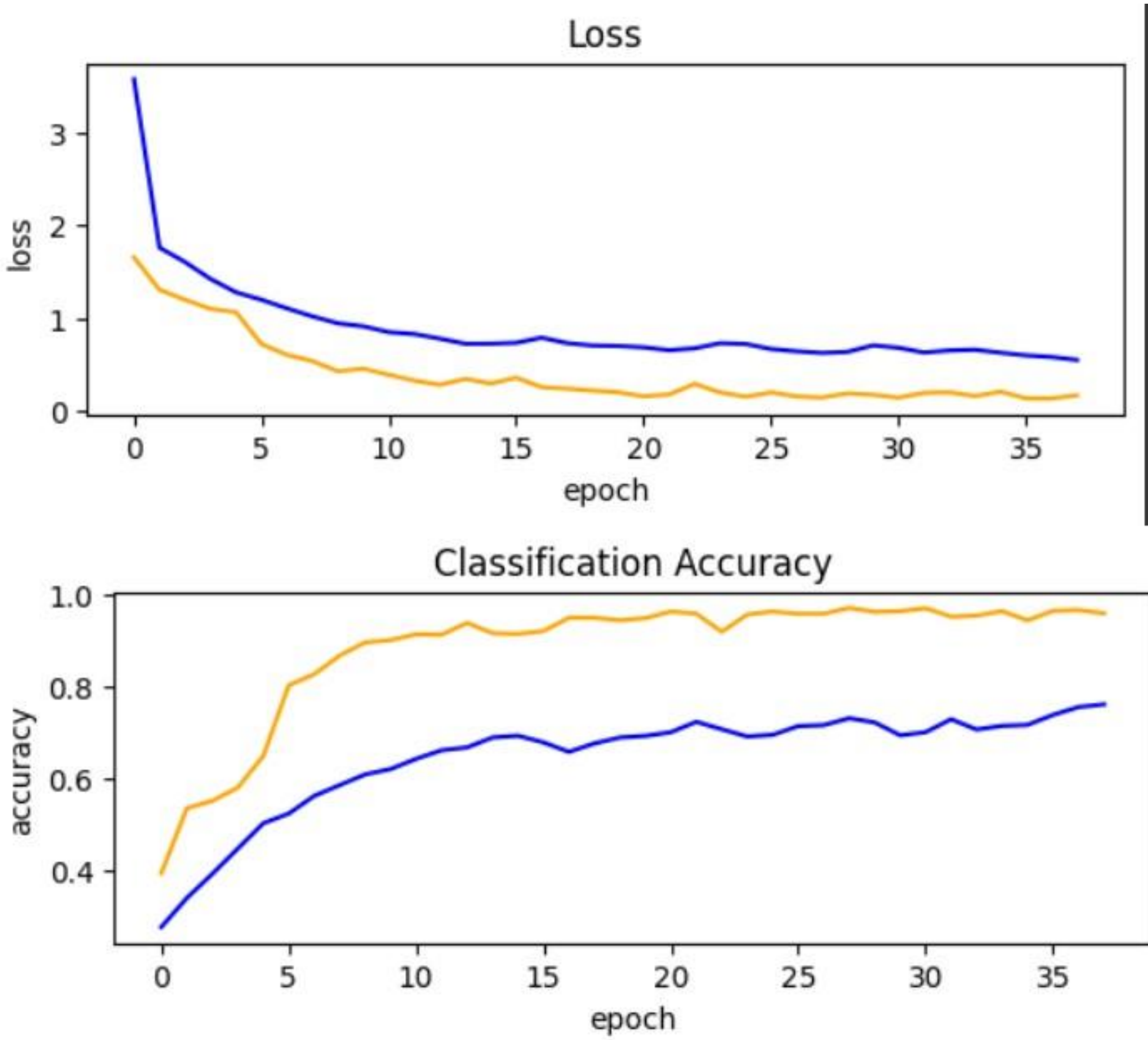


Figure 5.3.2: Training and Classification accuracy and loss over the epochs (Densenet201)

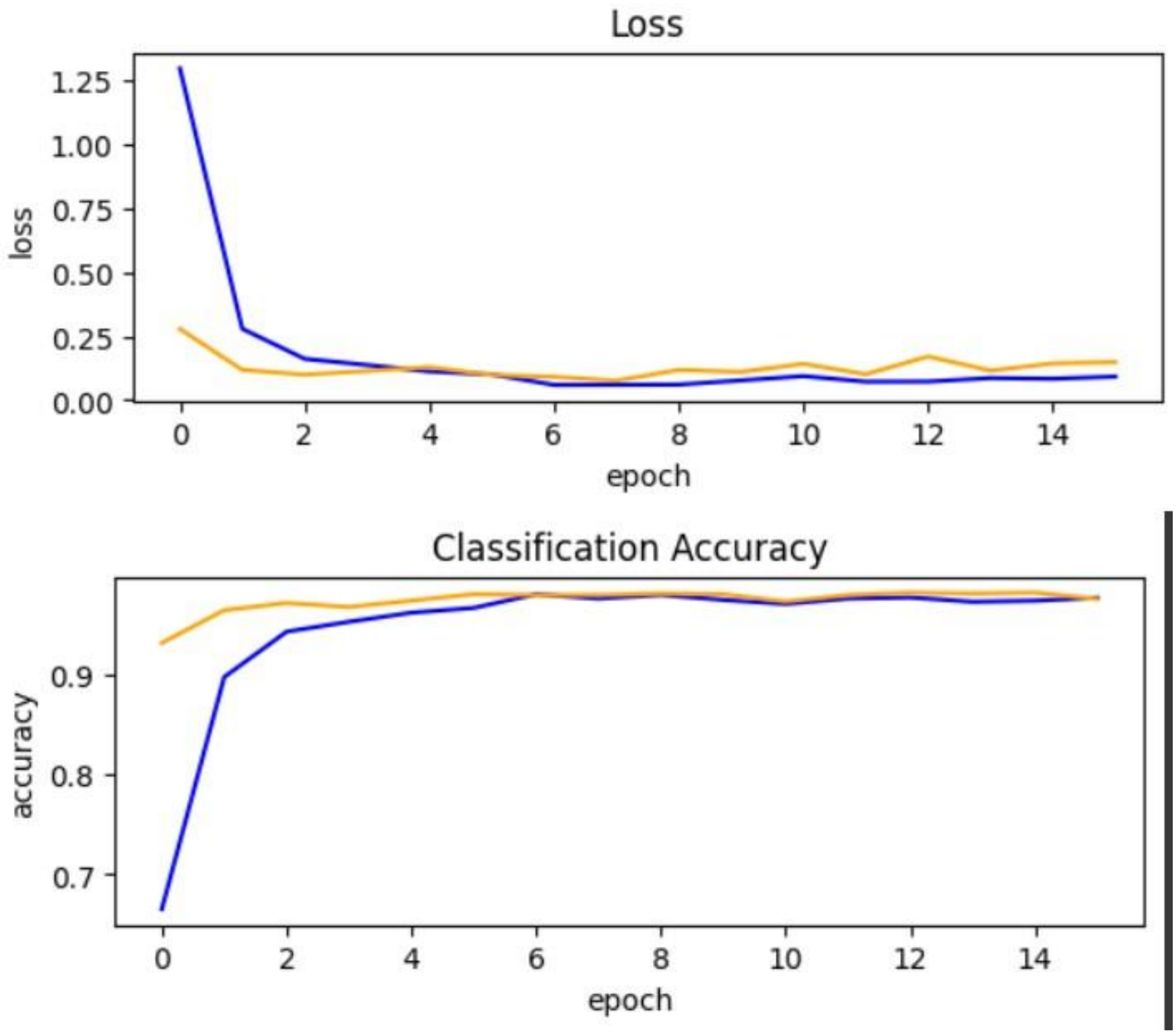


Figure 5.3.3: Training and Classification accuracy and loss over the epochs (Resnet152)

.

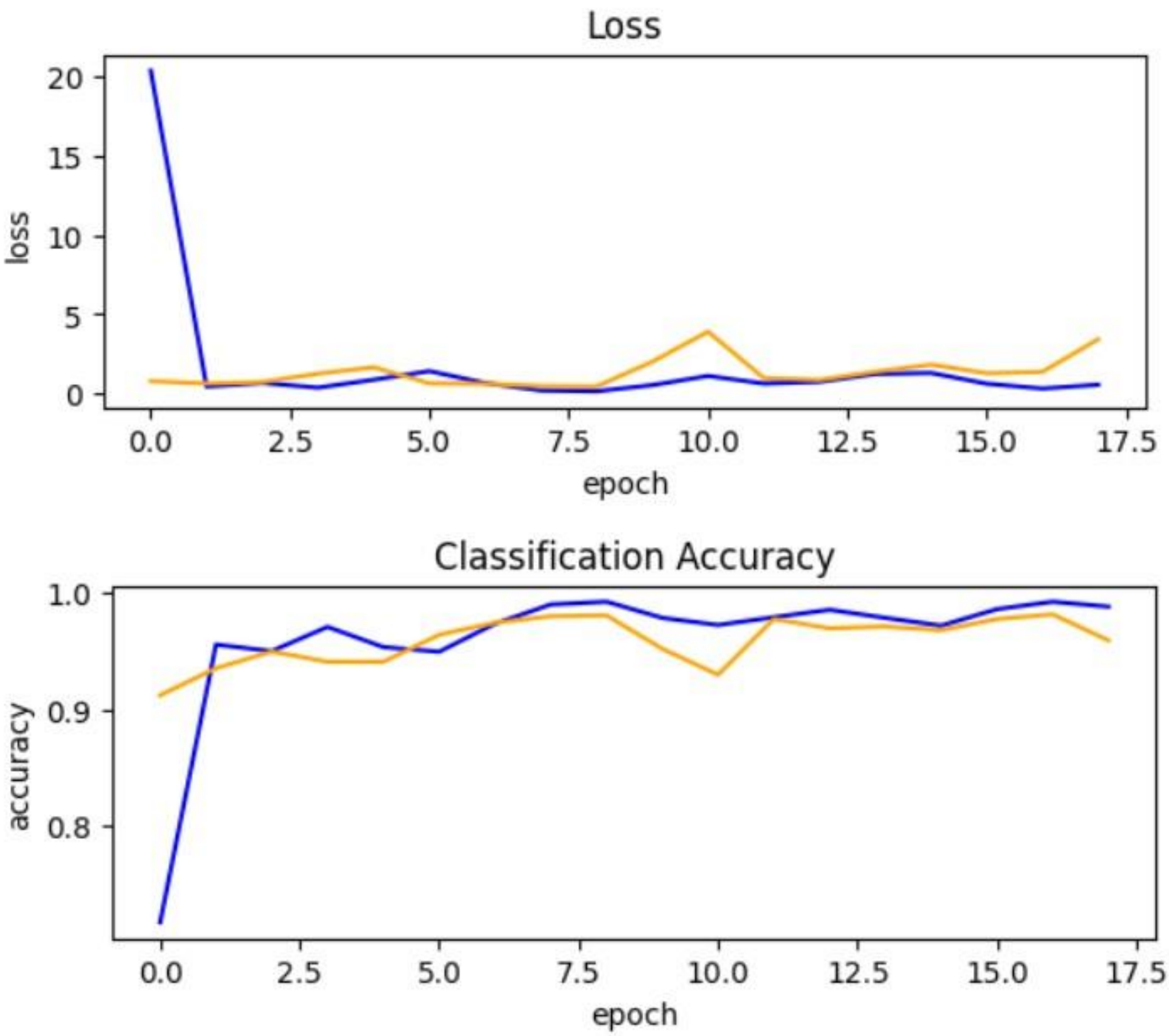


Figure 5.3.4: Training and Classification accuracy and loss over the epochs (Hybrid-Model).

**Confusion Matrix of the Models:**

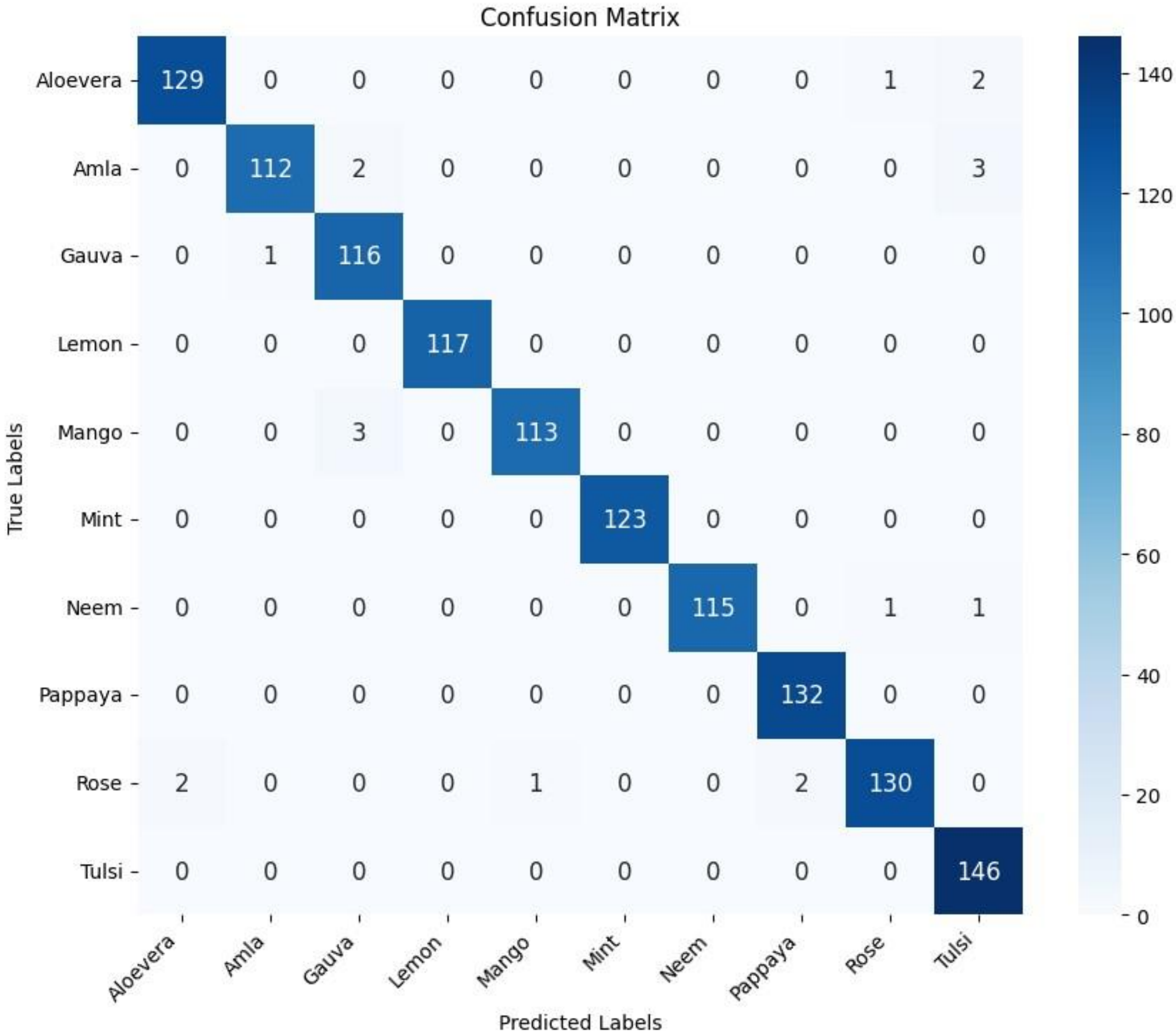


Figure 5.3.5: Confusion Matrix of VGG19

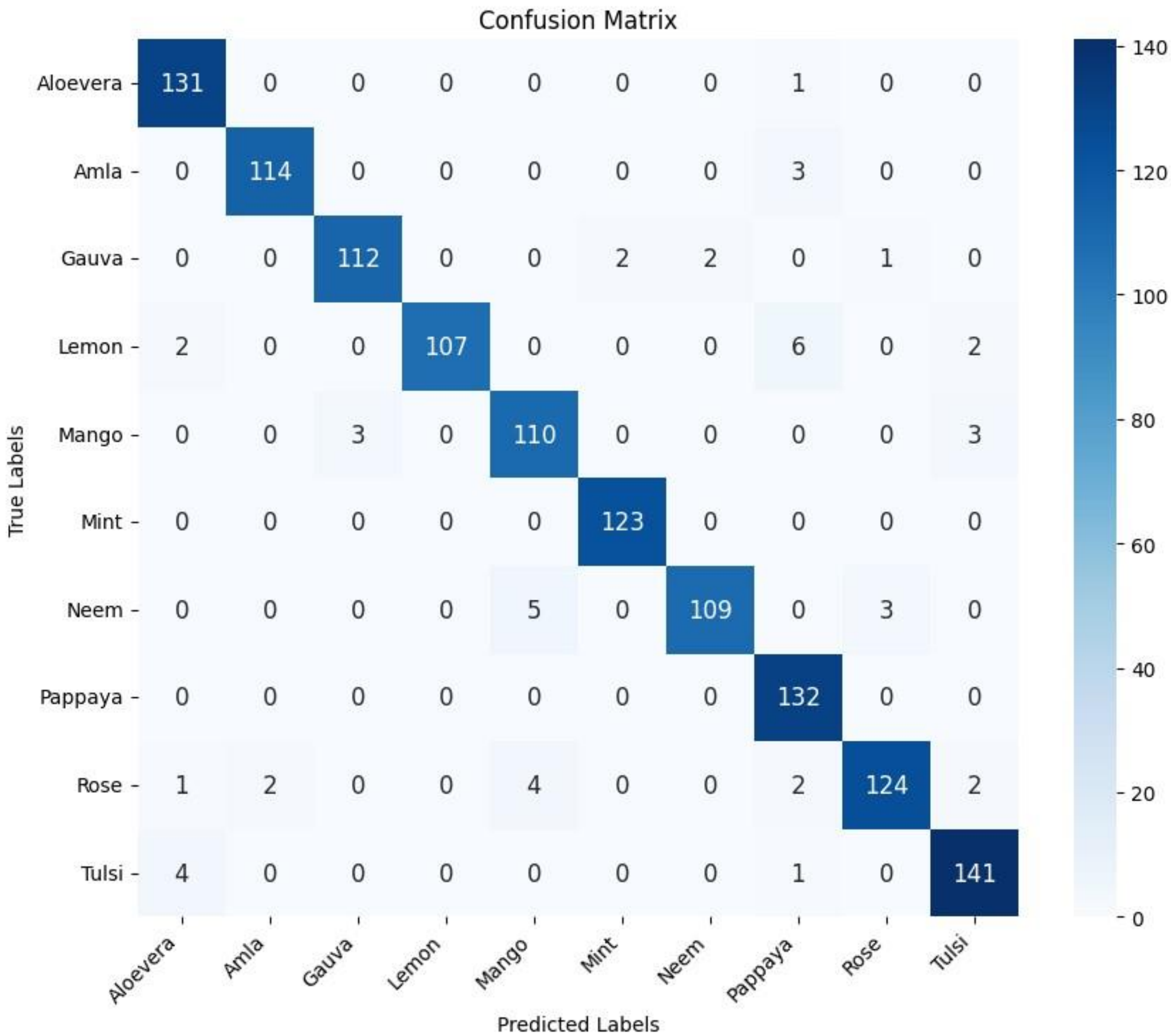


Figure 5.3.6: Confusion Matrix of Densenet201

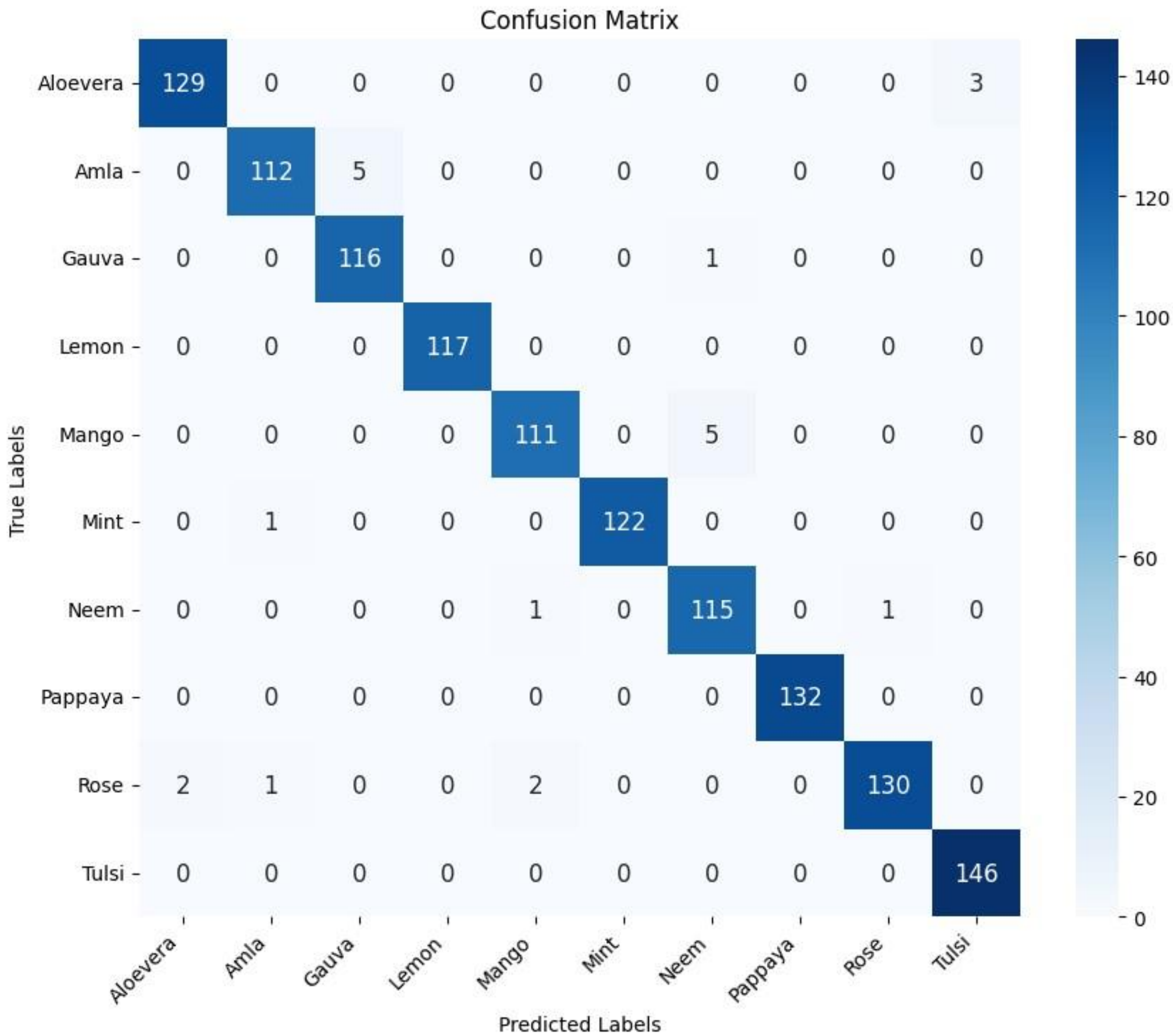


Figure 5.3.7: Confusion Matrix of Resnet152

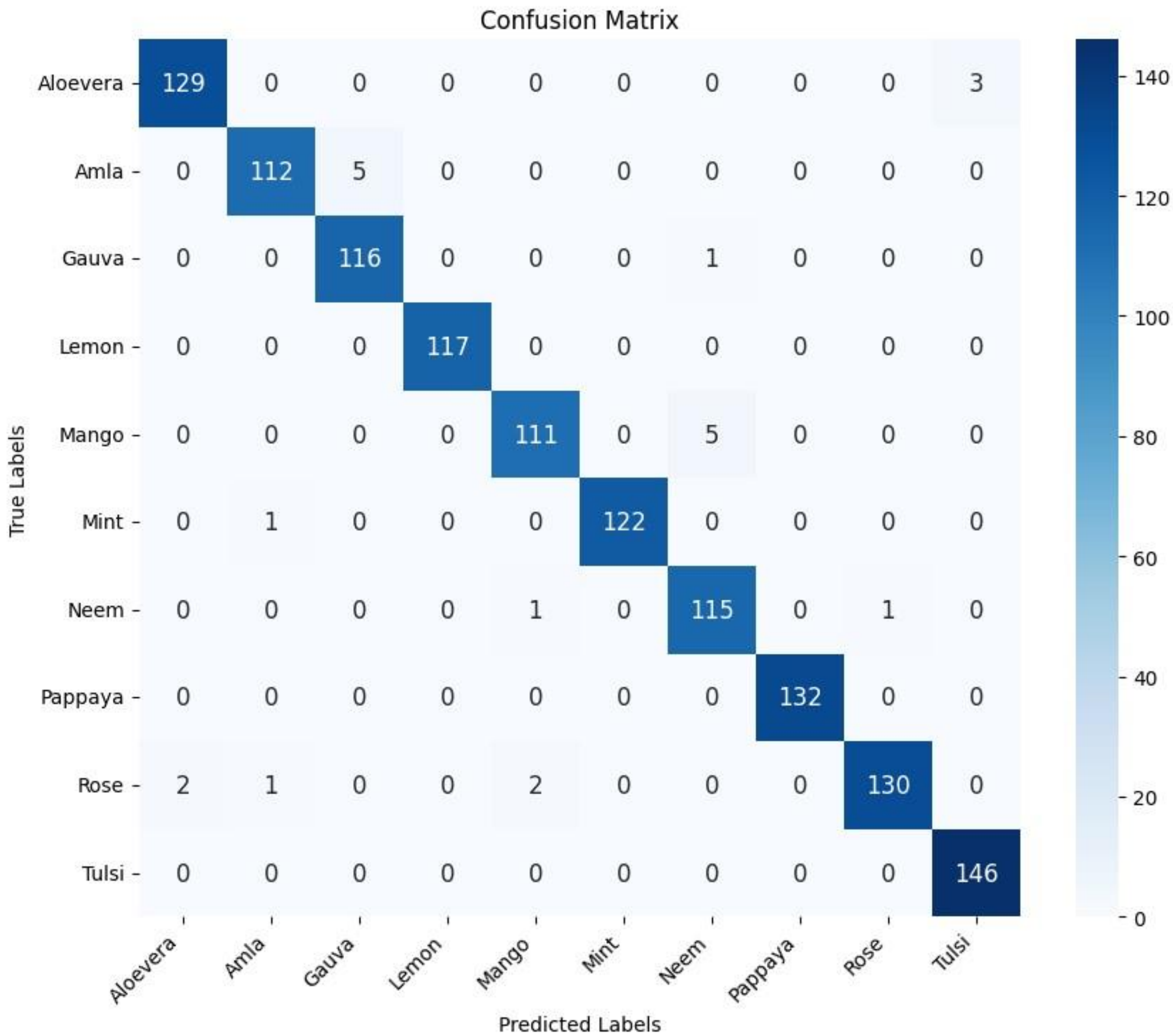


Figure 5.3.8 Confusion Matrix of Hybrid Model

## 5.4 Summary

In this study, we conducted a detailed evaluation of the performance of various deep convolutional neural networks (CNNs) and a hybrid model for the task of recognizing and segmenting images of two distinct types of medicinal herbs. We employed DenseNet201, VGG19, ResNet152, and a hybrid model that combines VGG19 and ResNet50 to classify medicinal plants based on leaf images, achieving notable accuracies of 96.08%, 97%, 98%, and 99.12% respectively.

TABLE 5.3.1: Accuracy for Classification of Individual CNN Networks and Hybrid Model in Detecting Medical Herbs Detection

| **Architecture** | **Model Accuracy** |
|---|---|
| **VGG19** | **97%** |
| **Densenet201** | **96.08%** |
| **Resnet152** | **98%** |
| **Hybrid Model** | **99.12%** |
| **Architecture** | **Model Accuracy** |

The hybrid model, which integrates VGG19 and ResNet50, achieved the highest accuracy of 99.12%, highlighting the advantage of combining different CNN architectures.

VGG19's deep, uniform architecture is effective in extracting detailed features from leaf images, while ResNet50's residual connections mitigate the vanishing gradient problem, allowing for the training of deeper networks. By integrating these two models, the hybrid approach capitalizes on VGG19's ability to capture fine-grained features and ResNet50's strength in handling complex, deeper representations, resulting in superior classification performance.

The training and validation loss curves for the hybrid model show a steady decrease, indicating effective learning and minimal overfitting. Similarly, the training and validation accuracy curves demonstrate consistent improvement, with the validation accuracy closely tracking the training accuracy, which signifies robust generalization to unseen data. The confusion matrix further supports the hybrid model's efficacy, showing high true positive rates and low false positive and false negative rates across all classes. Such high accuracy in medicinal plant classification is critical for accurate identification of plants with potential health benefits, such as those that can boost immunity and combat diseases. As new infectious diseases emerge, the need for integrating traditional medicinal knowledge with modern technological advancements becomes more pronounced. The success of the hybrid model in this study illustrates the potential of deep learning to enhance the precision of medicinal plant classification, thereby aiding in the discovery and utilization of natural remedies.

Our findings contribute significantly to the academic field by demonstrating the practical application of advanced deep learning techniques in healthcare. The hybrid model’s superior performance underscores the value of combining multiple neural network architectures to leverage their individual strengths. This study paves the way for future research and development in the area of medicinal plant classification, ultimately contributing to improved public health outcomes by harnessing the medicinal properties of plants through advanced technological means.

# CHAPTER 6
# Impact on Society, Environment and Sustainability

## 6.1 Impact on Life

The impact of implementing efficient image processing techniques with deep neural networks for the classification of medicinal herbs can significantly benefit human life in several ways:

- **Improved Healthcare:** Accurate classification of medicinal herbs ensures that herbal medicines are correctly identified and used, leading to more effective treatments for various health conditions.
- **Safety and Efficacy:** Proper classification reduces the risk of misidentification, ensuring that herbal remedies are safe and deliver the intended therapeutic benefits without adverse effects.
- **Access to Traditional Knowledge:** Preserving and accurately identifying medicinal herbs helps maintain access to traditional knowledge and cultural practices associated with herbal medicine, benefiting communities that rely on these remedies.
- **Promoting Sustainable Practices:** By facilitating the identification of medicinal plants, these technologies support sustainable harvesting practices, preserving biodiversity and ensuring the availability of medicinal herbs for future generations.
- **Public Health and Wellness:** Reliable classification contributes to public health initiatives by promoting the safe use of herbal products and supporting integrative healthcare practices that combine traditional and modern medicine.

## 6.2 Impact on Society & Environment

The impact of implementing efficient image processing techniques with deep neural networks for the classification of medicinal herbs extends beyond individual health benefits to broader societal and environmental impacts:

- **Conservation of Biodiversity:** Accurate classification aids in the preservation of medicinal plant species by facilitating their identification and conservation efforts. This helps maintain biodiversity, crucial for ecological balance and resilience.

- **Promotion of Sustainable Practices:** Automated classification systems support sustainable harvesting practices of medicinal herbs, reducing overexploitation and promoting responsible resource management.
- **Cultural Heritage Preservation:** By accurately identifying medicinal herbs, these technologies help preserve traditional knowledge and cultural practices associated with herbal medicine, benefiting communities that rely on these practices for healthcare and cultural identity.
- **Economic Opportunities:** Enhanced classification capabilities can stimulate economic opportunities in sectors related to herbal medicine, such as pharmaceuticals, agriculture, and eco-tourism, contributing to local economies.
- **Environmental Stewardship:** By reducing the need for invasive sampling or harvesting practices, automated classification systems minimize environmental impact and support ecosystem health.
- **Public Awareness and Education:** These technologies can raise awareness about the importance of medicinal plants and their conservation, fostering appreciation for natural resources and sustainable living practices.

### 6.3 Ethical Aspects

The research on "Implementing an Efficient Image Processing Technique With Deep Neural Networks for the Classification of Medicinal Herbs" is underpinned by a commitment to ethical considerations throughout its methodology. The use of plant image data entails a responsibility to respect intellectual property rights and ensure that all images are sourced with proper permissions, adhering to ethical guidelines and regulatory standards. Informed consent, where applicable, is obtained from contributors to maintain transparency and integrity. The potential societal impact of the research on public health underscores the importance of ethical deployment, ensuring that advancements in plant classification translate to improved health practices without exploiting traditional knowledge or natural resources.

The ethical dimension is further reflected in the transparent documentation of the research process, enabling scrutiny, reproducibility, and responsible knowledge dissemination. Additionally, fair compensation and benefit-sharing with local communities, particularly those with traditional knowledge of medicinal plants, are prioritized to ensure equity and justice. Sustainable harvesting practices are promoted to prevent environmental degradation and protect biodiversity, aligning the research with broader ecological and ethical standards.

Overall, ethical considerations are integral to the research's commitment to societal wellbeing and the responsible application of cutting-edge technologies in the field of medicinal plant classification. This holistic approach ensures that the benefits of the research are realized without compromising ethical standards or the rights of individuals and communities involved.

## 6.4 Sustainability Plan

The sustainability plan for the research on "Implementing an Efficient Image Processing Technique with Deep Neural Networks for the Classification of Medicinal Herbs" is designed to minimize environmental impact while ensuring ongoing positive societal contributions. Efforts will be directed towards optimizing computational efficiency and adopting energy-efficient algorithms to reduce the overall energy consumption associated with model training and deployment. Cloud computing solutions will be explored to further mitigate energy use, capitalizing on the efficiency of shared resources. Moreover, the research team is committed to leveraging eco-friendly practices in data management and storage. This includes utilizing data centers powered by renewable energy sources and implementing best practices for data archiving to minimize redundancy and unnecessary storage. The plan prioritizes ongoing awareness and integration of green computing principles, ensuring that technological advancements are aligned with environmental sustainability goals. Continuous evaluation and adaptation of sustainable strategies will be embedded in the research process. This involves regularly assessing the environmental impact of our computational processes and making necessary adjustments to enhance sustainability. By maintaining a commitment to responsible and eco-conscious scientific innovation, the research not only advances the field of medicinal plant classification but also contributes to broader environmental sustainability efforts

## 6.5 Summary

The analysis explores the wider effects of the newly developed medicinal herb classification system, encompassing its influence on human health, societal advantages, and environmental consequences. It also considers ethical concerns associated with the system's adoption and operation, emphasizing the importance of responsible deployment of technology.

# CHAPTER 7

# Conclusion and Future Work

## 7.1 Conclusions

The thesis titled "Implementing an Efficient Image Processing Technique with Deep Neural Networks for the Classification of Medicinal Herbs" explores advanced artificial intelligence applications in the classification of medicinal herbs based on leaf images. This research addresses the vital role of medicinal plants in traditional medicine practices such as Homeopathy, Unani, and Ayurveda, particularly in enhancing immunity during health crises like the COVID-19 pandemic. The study employs state-of-the-art algorithms including DenseNet201, VGG19, and ResNet152 and a Hybrid model combining VGG19 and ResNet50 to achieve classification accuracies of 96.08%, 97%, 98%, and 99.12% respectively. Using a dataset comprising 5,997 images across ten medicinal herbs, including Tulsi, Rose, and Aloe vera, the research implements a rigorous training, testing, and validation process. The training set, comprising 70% of the dataset, ensures robust model development, while the testing and validation sets verify the model's accuracy and generalization capabilities. Beyond classification accuracy, the study emphasizes the implications for healthcare, highlighting how improved classification of medicinal herbs can empower individuals to better understand and utilize immunity-boosting plants. This research not only contributes to the advancement of AI techniques in medical plant classification but also underscores ethical considerations, including privacy and informed consent, in deploying AI technologies in healthcare. In conclusion, this study not only enhances understanding of medicinal plants' therapeutic potential but also offers practical insights into leveraging AI for healthcare improvements, potentially impacting global health outcomes.

## 7.2 Further Suggested Works

Future research could focus on integrating multimodal data sources to enhance the robustness of deep-learning models in classifying medicinal plants. By incorporating textual descriptions of medicinal properties and spectral imaging data capturing detailed leaf characteristics, researchers can enrich feature representations beyond traditional image-based approaches. This approach holds promise for improving classification accuracy and refining the identification of subtle variations among different plant species. Exploring transfer learning techniques from related domains, such as agriculture and environmental sciences, offers another avenue for enhancing classification performance. Adapting pre-trained models to leverage domain-specific features could improve model generalization across diverse ecological contexts, addressing variability in plant appearances and growth conditions. Additionally, optimizing hybrid models that combine different deep learning architectures or ensemble techniques presents an opportunity to further enhance accuracy and resilience to noise in input data. Investigating novel combinations or refining existing hybrid approaches beyond those explored could push the boundaries of AI-driven plant classification. Longitudinal studies are essential to assess the long-term stability and adaptability of AI-based classifications in real-world environments. Conducting field testing and validation with botanical experts and traditional healers would validate the relevance and accuracy of identified medicinal plants, ensuring practical applicability and cultural sensitivity in healthcare practices. In conclusion, these research avenues aim to advance AI-driven plant classification, contributing to improved healthcare outcomes, biodiversity conservation efforts, and the sustainable use of natural resources.

### 7.3 Limitations

The project's limitations include the dataset's size and diversity, despite efforts with 5,997 images of ten herbs like Tulsi, Rose, and Aloe vera. Model interpretability remains a challenge despite high accuracy with DenseNet201, VGG19, ResNet152, and a Hybrid model. Ethical concerns, such as privacy and consent in AI healthcare applications, are acknowledged but require ongoing attention. Real-world deployment faces challenges in integration, scalability, and adaptation to diverse healthcare settings. Additionally, the model's focus on immunity-boosting herbs during crises like COVID-19 may limit its applicability to broader medicinal contexts. Addressing these issues is essential for advancing AI in medicinal plant classification responsibly.

# REFERENCES

[1] Sharrab, Y., Al-Fraihat, D., Tarawneh, M. and Sharieh, A., 2023, June. Medicinal Plants Recognition Using Deep Learning. In 2023 International Conference on Multimedia Computing, Networking and Applications (MCNA) (pp. 116-122). IEEE.

[2] Akter, R. and Hosen, M.I., 2020, December. CNN-based leaf image classification for Bangladeshi medicinal plant recognition. In 2020 Emerging Technology in Computing, Communication and Electronics (ETCCE) (pp. 1-6). IEEE

[3] Putri, Y.A., Djamal, E.C. and Ilyas, R., 2021, March. Identification of medicinal plant leaves using convolutional neural network. In Journal of Physics: Conference Series (Vol. 1845, No. 1, p. 012026). IOP Publishing.

[4] N.G. Gavhale and A.P. Thakare, "Identification of Medicinal Plant Using Machine Learning Approach," International Research Journal of Engineering and Technology (IRJET), vol. 7, no. 07, 2020.

[5] M. Ariful Hassan, M. Sydul Islam, M. Mehedi Hasan, S.B. Shorif, M. Tarek Habib, and M.S. Uddin, "Medicinal plant recognition from leaf images using deep learning," in Computer Vision and Machine Learning in Agriculture, Volume 2, Singapore, Springer Singapore, 2022, pp. 137-154.

[6] A. Sabu, K. Sreekumar, and R.R. Nair, "Recognition of ayurvedic medicinal plants from leaves: A computer vision approach," in 2017 Fourth International Conference on Image Information Processing (ICIIP), Dec. 2017, pp. 1-5.

[7] A. Begue, V. Kowlessur, U. Singh, F. Mahomoodally, and S. Pudaruth, "Automatic recognition of medicinal plants using machine learning techniques," International Journal of Advanced Computer Science and Applications, vol. 8, no. 4, pp. 166-175, 2017.

[8] D. Venkataraman and N. Mangayarkarasi, "Computer Vision Based Feature Extraction of Leaves for Identification of Medicinal Values of Plants," in IEEE International Conference on Computational Intelligence and Computing Research, 2016, pp. 978-1-5090-0612-0/16/$31.00 ©2016 IEEE.

[9] P. Poudel and S. Kumar, "Robust recognition and classification of herbal leaves," in ICESMART-2016, May 2016, vol. 05, special issue: 04.

[10] P. L. Chitra and S. James Pushparani, "SURF points Versus SIFT points in Identification of medicinal plants," International Journal of Engineering and Advanced Technology (IJEAT), vol. 9, no. 2, Dec. 2019.

[11] A N. Tunio, A. Memon, F. Khuhawar, and E. G. M. Abro, "Detection of Infected Leaves and Botanical Diseases using Curvelet Transform," 2019.

[12] A. Aakif and M. Khan, "Automatic classification of plants based on their leaves," Biosystems, Aug. 2015. DOI: 10.1016/j.biosystemseng.2015.08.003.

[13] M. M. Ghazi, B. Yanikoglu, and E. Aptoula, "Plant identification using deep neural networks via optimization of transfer learning parameters," Neurocomput., vol. 235, no. C, Apr. 2017, pp. 228-235.

[14] G. Jain and D. Mittal, "Prototype Designing of Computer-Aided Classification System for leaf Images of Medicinal Plants," Journal of Biomedical Engineering, DOI: 10.14738/jbemi.42.3053

## Appendix A Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

**Title:**
**IMPLEMENTING AN EFFICIENT IMAGE PROCESSING TECHNIQUE WITH DEEP NEURAL NETWORKS FOR THE CLASSIFICATION OF MEDICINAL HERBS**

**Student ID: [Student ID]**

### CO Description for FYDP

| CO | CO Descriptions | PO |
|---|---|---|
| **Phase -I** | | |
| **CO1** | Integrate recently gained and previously acquired knowledge to identify a **medical herbs detection** problem for the Final Year Design Project (FYDP) | **PO1** |
| **CO2** | Analyze different aspects of the goals in designing a solution for this FYDP | **PO2** |
| **CO3** | Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP | **PO4** |
| **CO4** | Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP | **PO11** |
| **Phase -II** | | |
| **CO5** | Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP | **PO3** |
| **CO6** | Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP | **PO5** |
| **CO7** | Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding. | **PO6** |
| **CO8** | Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks. | **PO7** |
| **CO9** | Implement ethical principles and adhere to professional standards and norms in this FYDP | **PO8** |

| | | |
|---|---|---|
| **CO10** | Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP. | **PO9** |
| **CO11** | Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP. | **PO10** |
| **CO12** | Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors. | **PO12** |

## Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

**Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):**

| SN | EP Definition | Attainment | CO | Justification (with Knowledge Profile) | References |
|---|---|---|---|---|---|
| **1.** | **EP1: Depth of Knowledge required** | Yes | CO1, CO2, CO3, CO5, CO6, CO7 and CO8 | This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like VGG19, ResNet150, and enhancing medical herbs detection accuracy. | **Page no:** [24-29] **Section:** [4.2] **Page no:** [16-18] **Section:** [3.2 B] |

| | | | | | |
|---|---|---|---|---|---|
| | | | | The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing CNN model. | **Page no:** [19-20] **Section:** [3.2] [24-29] |
| | | | | | **Section:** [4.2] |
| | | | | This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance medical herbs detection using deep learning, showcasing a comprehensive understanding of current methodologies. | **Page no:** [8-11] **Section:** [2.2, 2.3] |
| **2.** | **EP2: Range of Conflicting Requirements** | Yes | CO2, and CO7 | This project addresses **EP-2** by recognizing the hurdles in medical herbs detection, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies. | **Page no:** [12-13, 49] **Section:** [2.4,7.3] |
| **3.** | **EP3: Depth of analysis required** | Yes | CO2, and CO6 | This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing medical herbs detection amidst multiple potential approaches. | **Page no:** [27-37] **Section:** [4.2] |

| | | | | | |
|---|---|---|---|---|---|
| **4.** | **EP4: Familiarity of Issues** | Yes | CO8 | This project's interdisciplinary approach extends beyond computer science and engineering, impacting medical herbs necessity, contributing to advancements in public health and healthcare practices which indicates **EP-4**. | **Page no:** [30-41] **Section:** [5.2, 5.3] |
| **5.** | **EP5: Extends of application codes** | No | CO5 | N/A | N/A |
| **6.** | **EP6: Extends of stakeholders involved and conflicting requirements** | No | CO8 | N/A | N/A |
| **7.** | **EP7: Interdependence** | Yes | CO5 | This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in medical diagnostics which ensures **EP-7**. | **Page no:** [49] **Section:** [7.3] |

**Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:**

| SN | EA Definition | Attainment | CO | Justification | References |
|---|---|---|---|---|---|
| 1. | **EA1: Range of resources** | Yes | CO11 | Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in medical herbs detection through transfer learning and deep CNNs. | **Page no:** [25-26] **Section:** [3.5] |
| 2. | **EA2: Level of interaction** | No | | N/A | N/A |
| 3. | **EA3: Innovation** | No | | N/A | N/A |

| | | | | | |
|---|---|---|---|---|---|
| **4.** | **EA4: Consequences for society and the environment** | Yes | | This project contributes to society by improving healthcare through advanced medical herbs detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for data privacy. | **Page no:** [44-45] **Section:** [6.1,6.2] |
| **5.** | **EA- 5: Familiarity** | Yes | | This project expands upon existing research by examining a novel approach in medical herbs detection through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field. | **Page no:** [8-11] **Section:** [2.2, 2.3] |

**Addressing CO (4, 9, 10, and 12):**

| SN | COs | Attainment | Justification | References |
|---|---|---|---|---|
| **1** | CO4 | Yes | This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle. | **Page no:** [23] **Section:** [3.4] |
| **2** | CO9 | Yes | The project demonstrates adherence to ethical principles by prioritizing privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**. | **Page no:** [45-46] **Section:** [6.3] |
| **3** | CO10 | No | N/A | N/A |

| | | | | |
|---|---|---|---|---|
| **4** | CO12 | Yes | The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges. | **Page no:** [14-21, 24-29] **Section:** [3.2, 4.2, 4.3] |

report

ORIGINALITY REPORT

| 17% | 14% | 8% | 8% |
|---|---|---|---|
| SIMILARITY INDEX | INTERNET SOURCES | PUBLICATIONS | STUDENT PAPERS |

PRIMARY SOURCES

| | | |
|---|---|---|
| 1 | dspace.daffodilvarsity.edu.bd:8080<br>Internet Source | 6% |
| 2 | Submitted to Daffodil International University<br>Student Paper | 4% |
| 3 | www.researchgate.net<br>Internet Source | 1% |
| 4 | ijrpr.com<br>Internet Source | 1% |
| 5 | Stanojevic, Marija. "Domain Adaptation Applications to Complex High-Dimensional Target Data", Temple University, 2023<br>Publication | <1% |
| 6 | Submitted to University of Westminster<br>Student Paper | <1% |
| 7 | mafiadoc.com<br>Internet Source | <1% |
| 8 | www.coursehero.com<br>Internet Source | <1% |