DEEP LEARNING-BASED PLANT RECOGNITION IN BANGLADESH

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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

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APPROVAL

This Project titled "Deep Learning-based Plant Recognition in Bangladesh", submitted by Md Salim Reza Sujon and Farhan Sajid 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.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head, 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

Recognizing plant species from leaves is difficult due to the vast number of species, making identification challenging. Manual identification is quite a tedious and slow process. Thus, the automation of this process is essential in biology, forestry, research, education, and cities. In this paper, a new method is presented for plant identification based on the images of the leaves. We gathered a dataset by combining three datasets and obtained 13 classes and 2600 images of plant leaves of Bangladesh. To enhance the dataset, we performed the following preprocessing on the images: resizing, contrast stretching, gamma correction, background removal, edge detection, and augmentation. We evaluated four deep learning models: Among them, the four networks, including VGG19, Inception V3, Xception, and a hybrid model combining Inception V3 and Xception. These models were assessed using two preprocessing techniques: background removal with edge detection and contrast stretching with gamma correction. The Hybrid model turned out to be the best one as it provided a validation accuracy of 99.50% with contrast stretching and gamma correction. Xception followed with 96.61%, while Inception V3 achieved 97.85%, and VGG19 reached 97.23%. These findings highlight the transformative potential of deep learning models in advancing plant species recognition. The superior performance of the Hybrid model with contrast stretching and gamma correction underscores the importance of selecting appropriate preprocessing techniques and model architectures to achieve high accuracy for plant recognition in Bangladesh.

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CHAPTER 1
INTRODUCTION

1.1 Overview

Plants are vital for sustaining the equilibrium of the Earths ecosystem. At the present, about 420000 species of plants are known, but scholars admit there are many more species awaiting discovery[1]. It directly speaks to numerous and diversified sectors such as food producers and sellers, medicine, industries, conservation and management of the environment and to the general populace's daily lives. Forests are involved in environmental management, supplying numerous resources, and enhancing species' original habitat. Statistics show that more than fifty percent of anti-global medicines imitate the works of natural plant synthesis, while a quarter of all medicines being produced are derived directly from plants or utilize the plant as the actual base[2]. Many consequences follow from correct tree species identification, from efficient forests' management and protection to increasing public awareness about the number and variety of species. The traditional approaches are on many occasions imprecise and therefore it becomes hard to sustain the ecological equilibrium, erosion of botanical species legacy.

This research endeavors to develop an intelligent system that distinguishes tree species by embracing the artificial intelligence CNN methodology that focuses on the shape and quality of the tree leaves. Therefore, the leaves are often considered as the key source of information concerning the plants during recognition activities[3]. Artificial intelligence methodologies in the paradigm of peer-level one have been employed; specifically, through the incorporation of CNNs [4], the proposed approach aspires to revolutionize the identification of tree species solely based on the appearance of their leaves. Hence, through the integration of AI, this process can be modernized, facing problems such as deforestation, urbanization and climate change.

The study entails the capturing and analyzing of images of different indigenous tree species leaves. Using more contemporary CNN structures as Xception, Inception V3 and VGG 19, the project's intended objective will be to develop a universal and accurate classification system for tree species[5]. The fact of using multiple CNN models, as well as extraordinary methods of image processing, improves the quality of the detection. To increase the accuracy of species identification it is also suggested to apply a blended model based on the features of Inception V3 and Xception.

In this chapter mainly the use of artificial intelligence particularly the convolution neural networks in identifying trees through their leaves is described.

1.2 Background and Present State

Plants have significant roles in human lives and the environment they help in food production, economic development, conservation, medicine and other daily necessities[6]. As for the plants, much has been already estimated by the scientists, but nevertheless new species are still discovered actively. Among them trees are especially important for sustaining species diversity as well as providing the stability of the ecosystem, as well as producing resources without which people can hardly exist. Approximately, it is believed that more than fifty percent of the global medications emulate plant synthesis, and one-quarter of the entire medications are either directly derived from plants or come from plant products. Tree species identification is the cornerstone of the correct management of the forest and its protection. However, since the traditional identification is reflective, arbitrary and statistically inaccurate, practice of ecological steadiness as well as preservation of botanical diversity becomes rather problematic. Once more, the conventional methods of plant identification are costly and time-consuming since they involve direct intervention of professionals [7]. Also studying plant leaves in specialized botanical laboratories, not to mention that analytical work often requires certain knowledge and experience, is a time consuming and rather expensive procedure. In an attempt to address this, several researchers in the area of computer vision have found pictures of leaves to be effective in the determination of species of plants [8][9][10]. Also, due to the scientific and genetic developments, many hybrids cannot be distinguished by plain mortals and even professionals [11].

Recent years, artificial intelligence (AI) has attracted increasing attention in the issue of tree species identification due to its high accuracy and efficiency. Particularly, the techniques of Convolutional Neural Networks (CNNs) have shown substantial capabilities in identifying the assessment of the leaf features for species sort. However, there is still a long way to go for realizing such technologies at large scale especially in a country like Bangladesh which is bestowed with biodiversity. The current practices of forest management in Bangladesh are least satisfactory as different issues like deforestation, urbanization and effect of climate change are severely jeopardizing the existence of many indigenous plant species. Unfortunately, the use of conventional morphological traits is insufficient for the above matters to be efficiently managed.

AI advances in the last few years and procurement of new skills in machine learning provide innovative ways to revamp this process. The current identified tree species research also uses more advanced CNN architectures like Xception, Inception V3 and VGG 19 thereby aspiring to create a more friendly and inclusive system for tree species. These technologies have prospects towards increasing the efficiency of species location hence encouraging optimal forest utilization and preservation. The plan to use Inception V3 and Xception architectures together, therefore synthesizing the two, can be said to spur even higher accuracy in the identification of species.

1.3 Problem Statement

The previous approaches for identification of tree species in Bangladesh are based on observation and comparatively inaccurate and time-consuming. This inadequacy becomes a challenge mainly in assessing the state of forests, formulating appropriate management strategies, and strategy for protecting the forests as well as for designing publicity for educating people on the importance of the forests. This paper also identified that there is no reliable method of distinguishing the species of trees that exist, which makes the protection of the wildlife and plant and tree species difficult thereby compromising the needed protection of the nation's diverse plant wealth.

Classification of trees is very important for several reasons. It helps the management of the forests because species tracking and covering is critical to the advancement of deforestation, urban expansion, and global climate change. It also supports the educational process as it became an effective means of introducing children as well as inhabitants of large cities to various types of plants. In addition, the accurate identification of the species is necessary when used for scientific sense, where research includes botanical sciences, pharmaceutical products and chemistry. Hence lack of a proper identification system hinders forest officers and conservationists their work and makes conservation programs hard to execute, and the general public loses its interest in supporting environmental causes.

This research seeks to solve the problem through the design of an AI system using CNN for the identification of tree species based on characteristics of the leaves. On the basis of Xception, Inception V3, VGG 19 along with the complex image processing the proposed system shall further improve the accuracy and reliability of species identification. As a result of the expected accuracy improvement of the developed model based on Inception V3 and Xception a hybrid model is expected. This strategy is not only designed to change the current forest management policy but also to increase people's awareness and ensure the support of society to protect the biological diversity of forests across Bangladesh by increasing the overall understanding of Bangladesh people and raising interest in their botanical country wealth.

The formulation of an appropriate problem statement is thus imperative in establishing the context of this research and the importance of finding efficacious resolution to the problems encountered in tree species identification and preservation.

1.4 Objectives

This research aimed at designing and implementing an AI-based solution for precise tree species identification and solving the problems of the conventional manual approach widely applied in Bangladesh. CNNs were used in this work to identify suitable characteristics in the leaves with the purpose of developing a precise method of species identification.

1. Collected and Analyzed Leaf Images: Collected a large number of images of leaves of various indigenous tree species of bangladesh.

2. Employed Advanced CNN Architectures: Used the advanced CNN models, some of which include Xception, Inception V3 and VGG 19 in analyzing and sorting the leaf images.

3. Developed a Hybrid Model: Suggested and introduced a dual-layer model based on the two current models, namely, Inception V3 and Xception to improve identification efficiency.

4. Integrated Image Processing Techniques: The applied image preprocessing techniques being resizing, background elimination, contrast adjustment, gamma correction, edge detection & augmentation to increase the variation & contrast of the dataset.

5. Validated the System: Optimized the developed system and examined the effectiveness and efficiency of the developed system in real life.

All readers should be able to find in this research, a realistic review of the used AI techniques based on tree species identification, besides the descriptions of the CNN architectures and the overall image preprocessing. It also report the results of the performance of the hybrid model for the demonstration of the success of such a model in improving the approaches to forest management and aiding the initiatives for conservation. Furthermore, the need for correct species identification in teaching practice, botanical research, and raising people's awareness towards unique plant species to continue the tradition of protecting the diverse botanical species of Bangladesh was called for.

This research aimed to revolutionize tree species identification by:This research aimed to revolutionize tree species identification by:

1. Creation of a technological model using profound deep learning CNN for photograph analogy and successful categorization of the images of the leaves.

2. Improve the species identification conferment by adsorptive the Inception V3 and Xception's optimization.

3. With complex image preprocessing, enriching the quality and variability of the given set of images.

4. Benefiting society by assisting institutions in forest management and enhancing people's awareness on the importance of preserving natural resources.

5. Helping people of Bangladesh to understand the issues of the forest biodiversity thus increasing the supporting factor for the environmental campaigns.

1.5 Scope and Limitations

This research concentrated on evaluating an identification model for tree species particularly for the Bangladeshi forests' and constructing the AI-based system for such identity. The more specific emphasis was made on the gathering and assessment of the images of leaves belonging to different types of indigenous trees such as Neem, Tulsi and Pathorakuchi. The study utilized convolutional neural networks like Xception, Inception V3, and VGG 19 to evaluate leaves' traits and classify trees rightfully. The scope also consists of the integration of the initiatory model involving Inception V3 and Xception in order to increase the level of species differentiation. The research intended to compile a new dataset by integrating the current datasets of leaf images and consequently subjected to a process of image enhancement to enrich the variability and quality of the dataset. Also, an opportunity was sought to discover how the application of artificial intelligence that was in the development of various solutions can contribute to the effective forest management and conservation in Bangladesh, as well as the creation of awareness of the diverse flora species in the country.

Several factors affected this study and hence it concerns the following; These limitations are crucial to note so that the reader has the right expectation when going through the result and conclusion of this study. These limitations include:

1. Data Availability: While training the model, the authors faced a problem of lack of numerous images of the leaves; for some species, it would be rather challenging to gather pictures of its leaves at all if they are rather rare or not as frequently described as other tree species.

2. Environmental Variability was significant. The study mainly focused on the images of leaves. These leaves could have been impacted by diverse environmental factors. These factors could be lighting leaf age and changes due to seasons. These factors may introduce variability. This could affect model's performance.

3. Geographic Focus highlights something important. The focus was on the rich botanical heritage of Bangladesh. However, the developed system could not be directly applicable to other regions. Those regions might have different flora. So further adaptation and training on new local datasets would be necessary.

4. Model Complexity was another point of interest in study. A hybrid model was formed by combining Inception V3 and Xception. This was created to enhance accuracy. But it introduced complexity. This complexity required significant computational resources. Not to mention, a lot of time for training and validation was required.

5. Methodological Choices. The choices of CNN architectures and preprocessing techniques. They are state-of-the-art. Yet they could have limits. Limits in capturing nuances of leaf characteristics. These nuances could be critical for species identification.

By detailing scope and limitations, the research shapes boundaries for study. It admits the restraints that can impact the results. It ensures transparent realistic depiction of objectives and findings. This provides a strong base for potential research. This assists the field of tree species identification using AI methods.

1.6 Report Organization

A report is proposed. It is structured with a comprehensive layout. The approach helps guide readers. They move through the research process. They go through the findings and implications too. Every chapter in this report serves a specific purpose. It contributes to the overall coherence. Depth of the document is deepened thanks to these chapters.

Chapter 1: Introduction

In the introduction chapter we set up a context for research. The importance of accurately identifying tree species for forest management in Bangladesh is being highlighted. Challenges faced in manual identification methods are being mentioned. Introduction of the proposed solution method using deep learning techniques is brought in. Also we present a grid of research questions and objectives. Finally we delve into the significance of our study on the whole.

Chapter 2: Background and Literature Review

This chapter delves into a comprehensive review of literature. It also looks at previous research. The dialogue concerns methods for plant species identification. We also discuss the restrictions of regular strategies. But there are also new advancements in AI-driven outcomes. Discussion also centers on establishing a theoretical frame. The present study is placed within a wider domain - biodiversity conservation and forest management.

Chapter 3: Research Methodology

This chapter detailed methodology for conducting the study. It details the approach. This includes the dataset compilation process. Preprocessing techniques are discussed. Selection of deep learning models is also a critical part. Convolutional neural networks are included. Concepts such as Inception V3, Xception and ResNet are discussed. Ethical considerations are crucial discussion topics. We examine data collection procedures. We also delve into model evaluation metrics within this chapter. This exploration is important to the firm understanding of the research project.

Chapter 4: Implementation

This chapter expands on the execution of suggested deep learning designs. They were used to identify plant types. The chapter addresses technical aspects of design development. It mentions software and hardware utilization. Coding frameworks and the training process are also discussed. This study also includes the steps to applying the model to objective programs. Comprehensively, it discusses operationalizing the research.

Chapter 5: Experimental Results and Analysis

In this chapter we put forward the experimental discoveries. The findings are results of employing deep learning models. Models are employed to identify plant species. They are based on leaf characteristics. There are detailed performance analyses of the models. We provide accuracy, precision recall and F1 scores. Visual representations like confusion matrices and ROC curves are offered too. They support the analysis. They aim to show the effectiveness of the approach suggested.

Chapter 6: Societal Impact and Conservation Implications

Societal impact chapter explores broader significance of the findings on biodiversity conservation. These findings impact environmental management. Let's talk about how AI triggers species identification. This identification focuses on plants. We can also consider how it is useful. It augments conservation efforts. This contributes to public knowledge. Additionally there's a contribution to practices of sustainable forest management. All these occur in Bangladesh. They give thought to benefits for local communities and stakeholders.

Chapter 7: Conclusion and Recommendations

The chapter draws a conclusion. It's based on experimental results. Recommendations are also provided. Those span practical applications, policy interventions, and future research. The chapter emphasizes. It emphasizes the need for AI integration. The AI application concerns plant species identification. Additionally, continued efforts in biodiversity conservation are crucial. The section also discusses the importance of persistent work in conservation.

The report is structured. The structure emphasizes the system in presenting the research process. It deals with findings and implications. With the structure. Readers are guided. They witness the importance of automated plant species identification. This is done using deep learning techniques. The techniques are presented and reviewed. At the center the automated plant species identification stands.

1.7 Summary

Target of this research is automated plant species identification. This use of leaf images is to address challenges. The challenges are associated with the vast diversity of plant species. They are also linked to limitations of usual manual identification methods. The study emphasizes accurate plant recognition. This is crucial for fields such as biodiversity conservation and pharmaceutical research. Education is another area in which it is important. It gives importance to trees' vital ecological balance-maintaining role. Trees also support human life. The importance of technological advancements in AI and image processing is paramount.

The rationale for this research arises from the desire to enhance plant identification in order to reduce the threat from deforestation, urbanization, and climate change affecting a wide variety of indigenous plant species in Bangladesh. Based on the CNNs and other AI tools such as Inception V3, Xception, andVGG 19, the study recommends a reliable system for diagnosing images of leaves and distinguishing different tree species. The concept of developing a hybrid of these architectures is to improve the detection accuracy and reliability.

The main focus of the work is to establish a large database of leaf images, as well as to use the methods of preprocessing for the improvement of the quality and variability of the database. Such efforts are important in making the AI models perform well in different environments due to the ability of the models to generalize. This paper also aims at filling the existing gap in knowledge on forest biodiversity and making the process of conservation easier by availing a good means of species identification.

In summary, the current study is a major contribution to the existing body of knowledge on the identification of plant species in Bangladesh's diverse botanical system. Thus, in addition to addressing the limitations of the manual methods of identification, the study is also expected to contribute to the overall efforts of protecting the species and improving the management of the world's forests. It is believed that the results will help increase the awareness of people and stakeholders about the botanical richness of Bangladesh and support for the cause of its protection.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

2.1.1 Scholarly Sources

The literature review primarily relies on academic journals, books, and credible websites to gather information on the current state of plant recognition using deep learning techniques. This ensures that the information is reliable, peer-reviewed, and up-to-date.

2.1.2 Survey of Existing Research

- **Deep Learning and Plant Recognition**
  - **Convolutional Neural Networks (CNNs):** Numerous studies have demonstrated the efficacy of CNNs in plant recognition tasks. Research has shown that CNNs can effectively extract and learn features from plant images, leading to high accuracy in classification tasks.
  - **Transfer Learning:** Transfer learning has become a popular approach in plant recognition. By using pre-trained models on large datasets and fine-tuning them on plant-specific datasets, researchers have been able to improve accuracy and reduce training time.
- **Detection and Segmentation**
  - **Plant Species Detection:** Research in plant species detection focuses on identifying and classifying plant species within images. Studies have employed various techniques, including deep learning models, to detect plant species based on leaf characteristics.
  - **Image Segmentation:** Image segmentation involves delineating the spatial extent of individual plant species within images. This is crucial for accurately identifying and classifying plants in complex images where multiple species may be present.

2.1.3 Identifying Gaps and Trends

Gaps:

- Limited research on plant species native to Bangladesh.
- Need for more comprehensive datasets specific to the region.
- Challenges in dealing with occlusions, variations in lighting, and background noise in plant images.

Trends:

- Increasing use of deep learning techniques, particularly CNNs, for plant recognition.
- Growing interest in transfer learning to improve model performance.

- Development of more sophisticated algorithms for image segmentation and detection.

2.1.4 Setting the Stage for Research

By surveying the existing literature, the review underscores the importance of the proposed research on plant recognition in Bangladesh. It highlights the lack of region-specific studies and datasets, justifying the need for research tailored to the unique flora of Bangladesh. Moreover, the review demonstrates the effectiveness of deep learning techniques, providing a solid foundation for exploring their application in this context.

In summary, this literature review not only provides a comprehensive overview of the current state of research in plant recognition using deep learning but also identifies specific gaps and trends that justify and guide the proposed study. This sets a clear direction for the research, emphasizing its potential contribution to the field and its significance in the context of Bangladesh.

2.2 Related Works

Plant leaf recognition has emerged as a crucial field within computer vision and machine learning, driven by the increasing need for accurate plant identification in various domains such as ecological protection, agriculture, and environmental management. Traditional methods of plant species identification often rely on manual expertise, which can be time-consuming, subjective, and prone to errors. With the advent of advanced technologies, researchers have turned to automated approaches leveraging computer vision techniques and machine learning algorithms to streamline the process of plant leaf recognition.

Lv et al.[12] introduced a novel approach to plant leaf recognition, emphasizing the importance of multi-feature fusion for improved accuracy. By integrating Local Binary Pattern (LBP), Histogram of Oriented Gradient (HOG), and color features, they achieved superior performance compared to conventional algorithms, showcasing the potential of advanced feature extraction techniques. The study utilized the Flavia and Swedish datasets, achieving accuracy rates of 99.30% for Flavia and 99.52% for Swedish. However, one limitation noted was the limited exploration of non-image-based features.

Kaur et al.[13] addressed the interdisciplinary interest in plant species identification by proposing a systematic approach utilizing computer vision and machine learning techniques. Their study underscored the challenges faced by non-experts in species identification and highlighted the significance of leveraging advancements in technology to overcome these challenges. They utilized the Swedish leaf dataset and achieved an accuracy rate of 93.26% using a multiclass-SVM model. However, the accuracy was relatively lower compared to deep learning methods.

Yang et al.[14] introduced an approach for plant leaf image segmentation based on YOLOv8 and an improved DeepLabv3+. They utilized a public leaf dataset and applied YOLOv8 for leaf object detection to minimize background interference. For segmentation, they enhanced DeepLabv3+ by incorporating densely connected atrous spatial pyramid pooling (DenseASPP) and the strip pooling (SP) strategy. The combined method achieved a 90.8% mean intersection over union (mIoU) for leaf segmentation. Compared to FCN, LR-ASPP, PSPnet, U-Net, DeepLabv3, and DeepLabv3+, their approach improved mIoU by 8.2, 8.4, 3.7, 4.6, 4.4, and 2.5 percentage points, respectively. This demonstrates significant performance enhancements for smart agroforestry applications.

Athapaththu et al. [15] demonstrated the effectiveness of a multi-feature approach using Support Vector Machine (SVM). They utilized the Flavia dataset and integrated texture, color, and vein density features, achieving an accuracy rate of 84.46%. However, they noted a limitation in the limited exploration of deep learning techniques.

Yang et al. [16] proposed a BP-RBF Hybrid Neural Network for plant leaf recognition using datasets such as Flavia, Swedish, and MEW2012. They achieved accuracy rates ranging from 95.6% to 99.1%. However, computational complexity for integrating features was identified as a limitation.

Hadlich et al. [17] conducted plant leaf recognition in the Amazon Forest using a portable spectrometer. They reported accuracy rates between 94% to 98%. However, the study had limited generalizability to other forest types.

Yang et al. [18] introduced a method for leaf recognition using a BP-RBF hybrid neural network. They utilized a dataset of leaf images and implemented a three-step process: image pretreatment, feature extraction, and leaf recognition. The image pretreatment involved segmentation based on hue, saturation, and value color space, along with connected component labeling to obtain complete leaf images without veins and background. The BP-RBF hybrid neural network was then used to evaluate the impact of shape and texture on species recognition. The hybrid model, employing nine-dimensional features, achieved a recognition accuracy of 96.2%, outperforming other classifiers and demonstrating its potential for forestry research and management applications.

Akter et al. [19] developed a CNN-based system for recognizing Bangladeshi medicinal plants. They introduced a dataset of 10 medicinal plants, with 34,123 training images and 3,570 testing images, collected from various regions of Bangladesh. Using a three-layer convolutional neural network with data augmentation, the system achieved a 71.3% accuracy rate. This study demonstrates the potential of CNNs in automating medicinal plant identification.

Hama et al. [21] focused on plant leaf recognition of houseplant leaves using the ResNet-50 model. They achieved accuracy rates of 98.60% without augmentation and 99% with augmentation. No specific limitations were mentioned in their study.[20]

Ullah et al. (2023) presented DeepPlantNet for classifying plant leaf diseases using the PlantVillage dataset. They reported accuracy rates of 98.49% for the eight-class and 99.85% for the three-class classification. However, detailed limitations were not provided.

Overall, the advancements in plant leaf recognition methodologies signify a paradigm shift towards automated and accurate identification systems, with implications for various fields including ecology, agriculture, and biodiversity conservation. These developments underscore the importance of interdisciplinary collaboration between computer science, botany, and environmental science to address pressing challenges in plant identification and management.

These studies detail the development of various morphometric methods such as image processing, visual examination for deep learning and especially spectral analysis. Through each unique contribution by the members of botany, the deeper comprehension of plant research and conservation projects is achieved and leaves a strong sense of building blocks to the future botanical advancements.

2.3 Comparison between existing works

The comparative analysis conducted in this study on "Deep Learning-based Plant Recognition in Bangladesh" serves as a pivotal component, illuminating the nuanced differences and synergies among various methodologies. Our research systematically evaluates the performance of transfer learning and deep Convolutional Neural Networks (CNNs) in plant species identification, considering both traditional methods and advanced segmentation approaches. Through meticulous experimentation and examination of results, our study unveils insights into the strengths and limitations of each approach, providing a comprehensive understanding of their respective contributions to the identification process.

The detailed exploration of detection and segmentation approaches allows for a nuanced examination of their roles in enhancing the accuracy and efficiency of plant species recognition. By comparing the outcomes of different methodologies, our research contributes valuable knowledge to the field, guiding practitioners and researchers in selecting the most effective strategies for their specific contexts. Our study does not merely highlight disparities but also emphasizes the potential complementarity between detection and segmentation, enriching our understanding of plant morphology and distribution.

In summary, the comparative analysis undertaken in this research serves as a critical lens through which the efficacy of transfer learning and deep CNNs in plant species identification is assessed. It provides a multifaceted perspective, incorporating traditional and contemporary techniques, and underscores the significance of a holistic approach in automated plant recognition. The findings not only advance our understanding of plant species identification but also offer practical insights for refining existing methodologies. This comparative analysis lays a solid foundation for the subsequent chapters, including the societal impact discussion, recommendations, and implications for future research.

Table 2.3.1 : Comparison Table

Author & Year	**Dataset Name**	**Model (Best)**	**Accuracy (of Best Model)**	**Limitation**
Lv et al. (2023)	Flavia, Swedish	Fusion of LBP, HOG, Color + ELM	99.30% (Flavia), 99.52% (Swedish)	Limited exploration of non-image-based features
Kaur et al. (2019)	Swedish leaf	Multiclass-SVM	93.26%	Relatively lower accuracy compared to deep learning methods
Yang et al. (2023)	Public leaf dataset	YOLOv8 and improved DeepLabv3+	90.8% mean intersection over union (mIoU)	Limited exploration of non-image-based features
Athapaththu et al. (2023)	Flavia	Texture, Color, Vein Density + SVM	84.46%	Limited exploration of deep learning techniques
Yang et al. (2022)	Flavia, Swedish, MEW2012	BP-RBF Hybrid Neural Network	95.6-99.1%	Computational complexity for integration of features

Hadlich et al. (2018)	Amazon Forest	Portable Spectrometer	94-98%	Limited generalizability to other forest types
Yang et al. (2022)	Leaf image dataset	BP-RBF hybrid neural network	96.2%	Computational complexity for integration of features
Akter et al. (2020)	Bangladeshi medicinal plants dataset	Three-layer convolutional neural network (CNN)	71.3%	Limited to 10 medicinal plant species, accuracy could be improved with more advanced models and larger datasets.
Hama et al. (2024)	Houseplant leaves	ResNet-50	98.60% (without augmentation), 99% (with augmentation)	N/A
Ullah et al. (2023)	PlantVillage	DeepPlantNet	98.49% (eight-class), 99.85% (three-class)	N/A

2.4 Open Issues

The challenges of traditional methods in plant species recognition include the time-consuming nature and subjectivity of manual identification, which often results in high error rates. These inaccuracies hinder effective forest management and biodiversity conservation efforts. Additionally, the lack of standardization in traditional methods leads to inconsistent identification outcomes, further complicating conservation initiatives.

Leveraging AI and deep learning presents its own set of issues, such as determining the most effective techniques for plant species recognition and addressing the variability in plant leaf characteristics. Ensuring that the developed AI models can handle the diverse botanical landscape of Bangladesh is crucial for the success of this approach.

The exploration of transfer learning raises questions about its impact on the accuracy of plant species identification. Selecting appropriate pre-trained models for transfer learning is essential to ensure compatibility with plant datasets, and fine-tuning these methods to address the specific complexities of plant recognition is necessary for optimal results.

In the comparative analysis of deep learning models, there are issues related to comparing the performance of different CNN architectures like Inception V3, Xception, and ResNet. Identifying the strengths and limitations of each model in handling various plant species is critical, as is developing criteria for selecting the optimal model for automated plant species identification.

The development of an automated system involves ensuring its robustness and reliability. Challenges in data collection, such as obtaining high-quality and diverse plant images, need to be addressed. Additionally, potential biases in AI models must be tackled to ensure fair and accurate species recognition.

Finally, contributing to forest management and biodiversity conservation requires evaluating the impact of automated plant identification on these practices in Bangladesh. Assessing how AI-driven solutions can enhance biodiversity conservation efforts and ensuring the scalability and applicability of the developed system in various environmental contexts are essential steps for the broader implementation and success of this research.

2.5 Summary

The literature review for the research project "Deep Learning-based Plant Recognition in Bangladesh" offers a comprehensive overview of the current state of plant recognition using deep learning techniques, relying on scholarly sources such as academic journals, books, and credible websites. The survey of existing research highlights the effectiveness of Convolutional Neural Networks (CNNs) in plant recognition tasks and the growing use of transfer learning to enhance accuracy and efficiency. Studies in plant species detection and image segmentation demonstrate various methodologies for improving plant identification, with deep learning models playing a pivotal role.

The review identifies several gaps, including the limited research on plant species native to Bangladesh, the need for comprehensive regional datasets, and challenges related to occlusions, lighting variations, and background noise in plant images. Trends indicate an increasing use of deep learning techniques, particularly CNNs, and a growing interest in transfer learning and sophisticated algorithms for image segmentation and detection.

Related works in plant leaf recognition emphasize the shift towards automated approaches leveraging computer vision and machine learning to overcome the limitations of traditional manual methods. Studies by Lv et al. (2023), Kaur et al. (2019), Yang et al. (2023), Athapaththu et al. (2023) and others showcase various methodologies and their performance in plant species identification, using different datasets and techniques. These studies highlight the advancements in feature extraction, model integration, and algorithm improvements, while also noting limitations such as limited exploration of non-image-based features, computational complexity, and generalizability issues.

The comparative analysis in this research evaluates the performance of transfer learning and deep CNNs, comparing detection and segmentation approaches to uncover their strengths and limitations. This analysis provides valuable insights into the efficacy of different methodologies, guiding the selection of the most effective strategies for automated plant species identification.

Open issues in the field include the challenges of traditional methods, the need to address variability in plant leaf characteristics, the impact of transfer learning on accuracy and the robustness and reliability of automated systems. Ensuring fair and accurate species recognition and evaluating the impact of AI-driven solutions on forest management and biodiversity conservation are critical for the success of the research.

In summary, this literature review underscores the importance of the proposed research on plant recognition in Bangladesh, highlighting the gaps and trends in existing studies and setting a clear direction for future research. The findings emphasize the potential contributions of deep learning techniques to the field and their significance in the context of Bangladesh's diverse botanical landscape.

CHAPTER 3

METHODOLOGY

3.1 Overview

In this chapter, we break down the entire methodology we used to develop and implement our deep learning-based plant recognition system. We'll cover the proposed approach, hardware and software requirements, project management strategies, and financial analysis. The goal here is to give you a detailed step-by-step guide on how we went from collecting data to deploying the system.

3.2 Proposed Methodology

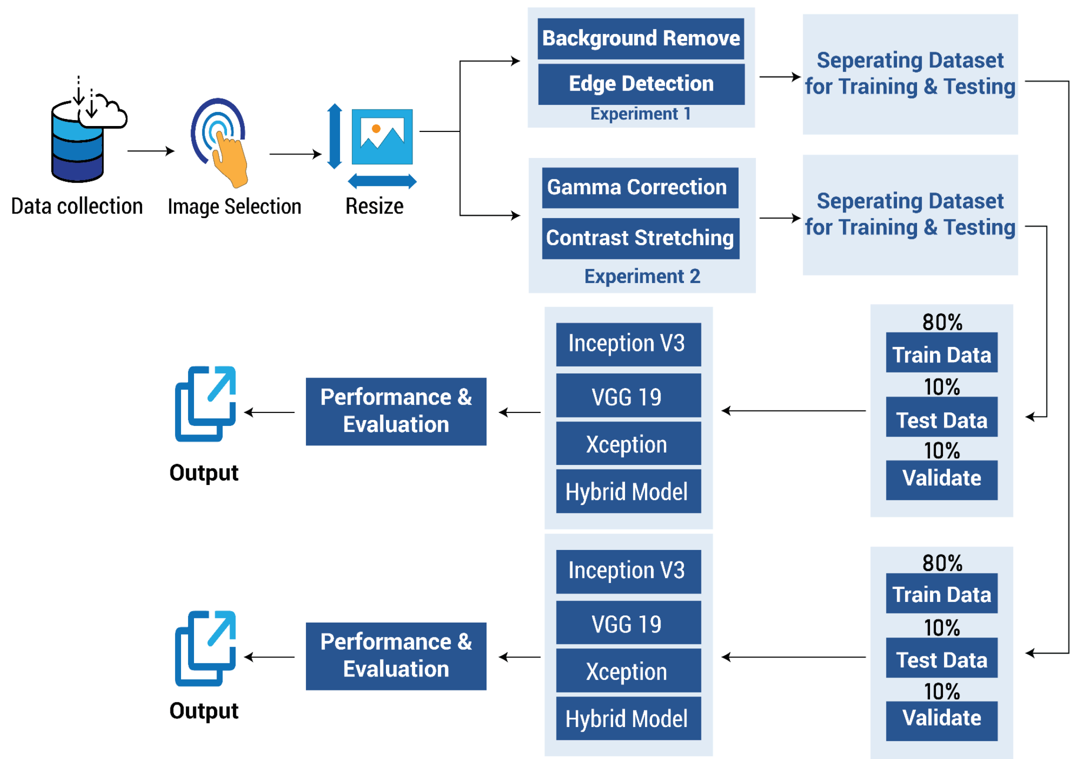


Figure 3.2.1 : Proposed Methodology

We compiled a dataset comprising 2600 high-resolution images of medicinal plant leaves from three sources: Medicinal Plant Raw[22], Bangladeshi Medicinal Plant Leaf Image Dataset[23], and BDMediLeaves[24]. This dataset includes 13 tree species native to Bangladesh, with 200 images per species. The selected species—Akondo, Arjun, Assamlota, Bashok, Bohera, Haritoki, Joba, Lemongrass, Nayontara, Neem, Pathorkuchi, Thankuni, and Tulsi—were chosen for their significance in local flora. To ensure uniformity and computational efficiency, we resize all images to 224x224 pixels. Our preprocessing pipeline involved contrast stretching using CLAHE (Contrast Limited Adaptive Histogram Equalization) with a clip limit of 2.0 and a tile grid size of 8x8, followed by gamma correction with a gamma value of 1.3 to enhance image quality. We used the open-source library rembg for background removal and performed manual corrections to ensure accuracy. Subsequently, we applied edge detection using the Canny algorithm with a low threshold of 30 and a high threshold of 100. We augmented the dataset to increase its size and diversity by applying transformations such as horizontal flipping, cropping, random rotations, brightness adjustment, contrast enhancement, and the introduction of light blurring and noise, expanding each class to 2000 images. This augmentation process enhanced the dataset's robustness and suitability for training deep learning models. We trained four deep learning models—VGG19, Inception V3, Xception, and a custom Hybrid model combining Inception V3 and Xception—using the preprocessed and augmented dataset. Each model was fine-tuned with specific parameters to optimize performance for the leaf classification task. We evaluated model performance using metrics such as accuracy, precision, recall, F1-score, and specificity to provide a comprehensive assessment of their effectiveness.

3.3 Hardware and Software Requirements

3.3.1 Hardware:

We used a Core i9 14th generation processor and an NVIDIA 4070 GPU, providing the computational power necessary for training deep learning models efficiently.

3.3.2 Software:

Our software environment relied on PyCharm and Jupyter Notebook, which offer flexibility and ease of use for coding and experimentation. TensorFlow and Keras were chosen as our deep learning frameworks due to their robust tools for building, training, and evaluating neural networks.

3.4 Project Management and Financial Analysis

3.4.1 Project Management Approach: The project was managed using Agile methodology, allowing for iterative development and continuous improvement. Regular meetings were held to discuss progress, challenges, and next steps, ensuring alignment with project goals and timely delivery.

Milestones:

- Phase 1: Data Collection and Preprocessing (Weeks 1-2)
- Phase 2: Model Selection and Initial Training (Weeks 3-6)
- Phase 3: Model Optimization and Hyperparameter Tuning (Weeks 7-12)
- Phase 4: Evaluation and Performance Analysis (Weeks 13-16)
- Phase 5: Final Testing and Documentation (Weeks 17-20)

3.4.2 Financial Analysis:

Table 3.3.1 Financial Analysis Table

Expense Category	Monthly Cost (BDT)
Computational Resources	10,000
Software Development Tools	8,000
API Hosting	20,000
Contingency Fund	5,000
Total Monthly Expense	43,000

The project's financial analysis encompasses various expense categories crucial for its successful implementation. In terms of computational resources, an estimated monthly expense of BDT 10,000 is earmarked for subscriptions to services like Google Colab Pro and other Software as a Service (SaaS) providers, ensuring access to enhanced processing power for data analysis and model training. Additionally, a monthly expense of BDT 8,000 is allocated for software development tools, covering costs associated with development environments essential for building and refining project components. Furthermore, API hosting costs amount to BDT 20,000 per month, ensuring the continuous operation of the web application on a server. Additionally, a contingency fund of BDT 5,000 per month is allocated to cover unforeseen expenses and ensure smooth project execution. These financial allocations are critical for the project's progress and eventual success, ensuring the availability of resources essential for effective data collection, analysis, development, hosting, and promotion.

3.4.3 Risk Management

SWOT analysis describes Strengths, Weaknesses, Opportunities, and Threats of a project. Here's a SWOT analysis for deep learning based plant recognition system in Bangladesh:

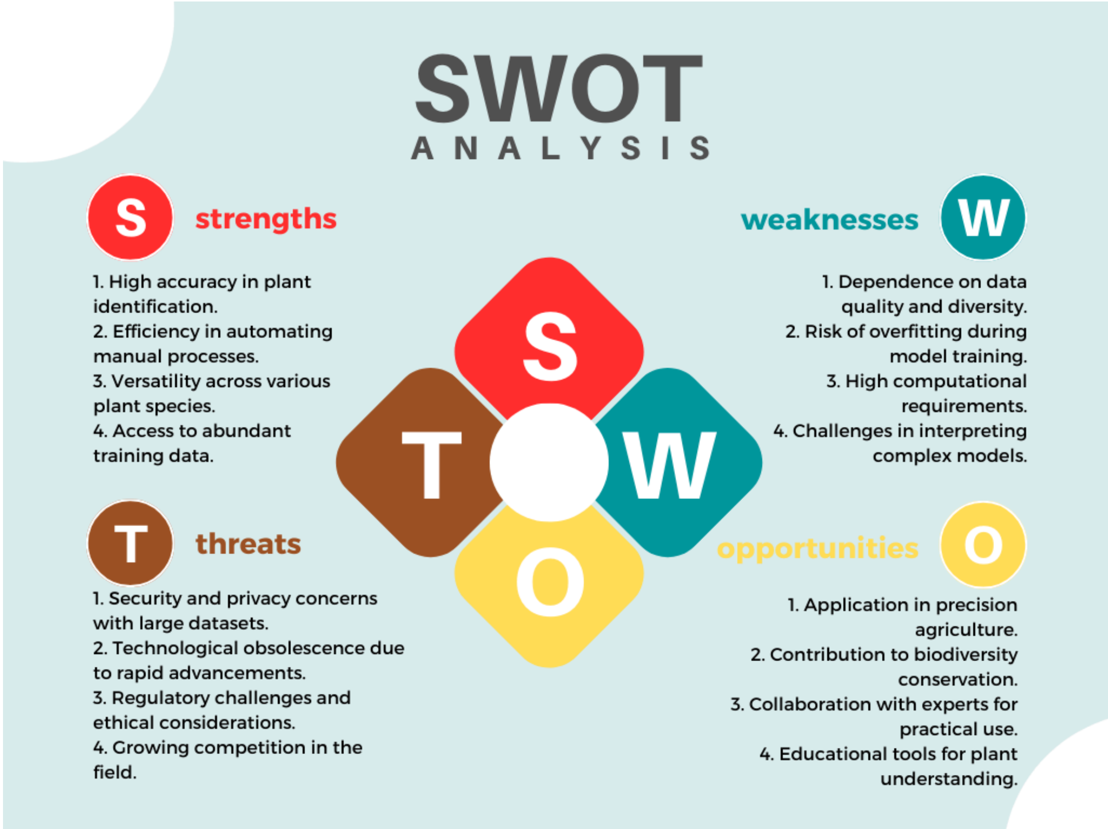


Figure 3.4.1:SWOT Analysis

Effective risk management is vital for the successful execution of this project. Potential risks include budget overruns, delays in data collection, technical challenges, and unforeseen operational issues. To mitigate these risks, a contingency fund of BDT 5,000 per month has been allocated to address unexpected expenses promptly. Additionally, a flexible project management approach will be employed, allowing for adjustments in project timelines and resource allocations as needed. Regular monitoring and assessment of project progress will be conducted to identify and address risks early. Collaborating closely with stakeholders and maintaining transparent communication channels will also be crucial in managing and mitigating potential risks throughout the project lifecycle.

3.5 Summary

This chapter detailed the methodology for developing the deep learning-based plant recognition system. It covered the steps from data collection and preprocessing to model training and evaluation, hardware and software requirements, project management approach, financial analysis, and final project implementation. This comprehensive methodology sets the foundation for the successful deployment of the plant recognition system.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

This chapter outlines the implementation process of our project, "Deep Learning-Based Plant Recognition in Bangladesh." We detail the experimental setup, the model training procedures, the evaluation methods, and the ethical considerations. Our goal is to create a robust system for accurate plant recognition by leveraging advanced deep learning techniques.

4.2 Train Model and Prototype Design

4.2.1 Dataset

The dataset comprises high-resolution images of medicinal plant leaves from three sources: Medicinal Plant Raw[22], Bangladeshi Medicinal Plant Leaf Image Dataset[23], and BDMediLeaves[24]. These datasets collectively provide 2600 images of 13 tree species native to Bangladesh, with 200 images per species. The selected species include Akondo, Arjun, Assamlota, Bashok, Bohera, Haritoki, Joba, Lemongrass, Nayontara, Neem, Pathorkuchi, Thankuni, and Tulsi. These species were chosen for their significance in local flora. We curated the best images to create a balanced collection, ensuring accurate representation and effective model training.

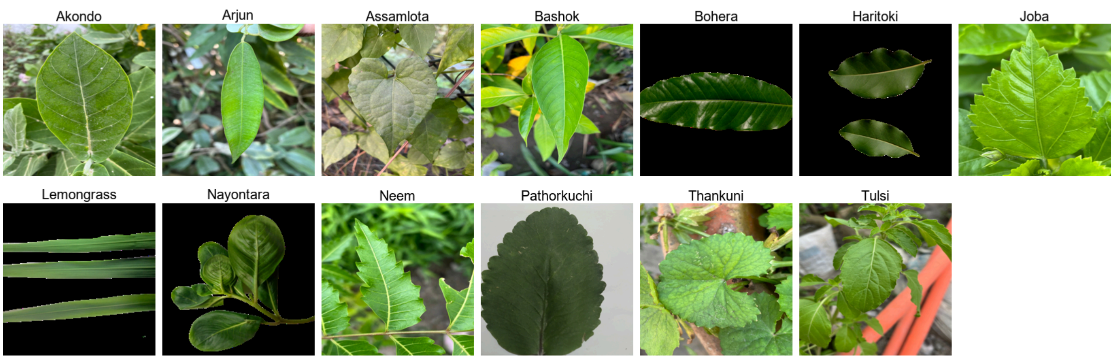


Figure 4.2.1: Sample Dataset

4.2.2 Data Preprocessing

We consulted with a botanist and researched online forums to select the best preprocessing method to capture leaf features for identification tasks.

Resizing (224x224):

All images in the dataset were resized to a uniform dimension of 224x224x3 pixels. This standardization not only facilitates computational efficiency but also ensures consistency for subsequent processing steps. Here, in Fig:3.2.3, from all the dataset we get images and we resize those images from the original image[25].

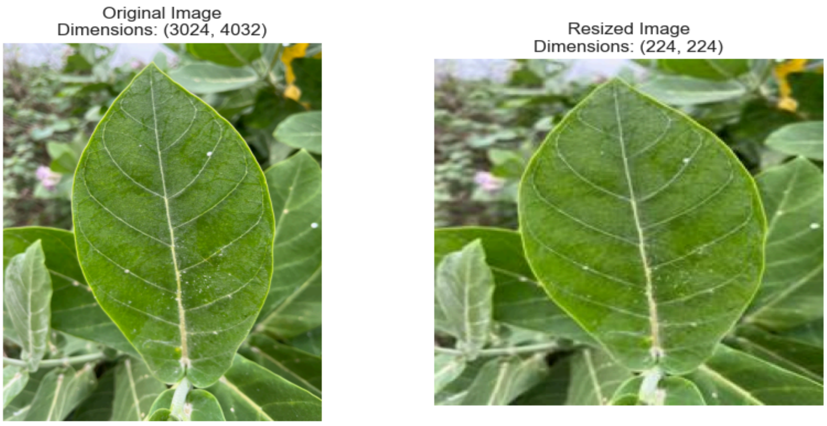


Figure 4.2.2: Original Image vs Resize Image

Contrast Stretching and Gamma Correction: We applied contrast stretching to enhance the image contrast using CLAHE (Contrast Limited Adaptive Histogram Equalization) with a clip limit of 2.0 and a tile grid size of 8x8. This technique helps in bringing out the details in the leaf images, making them more suitable for training deep learning models[26].

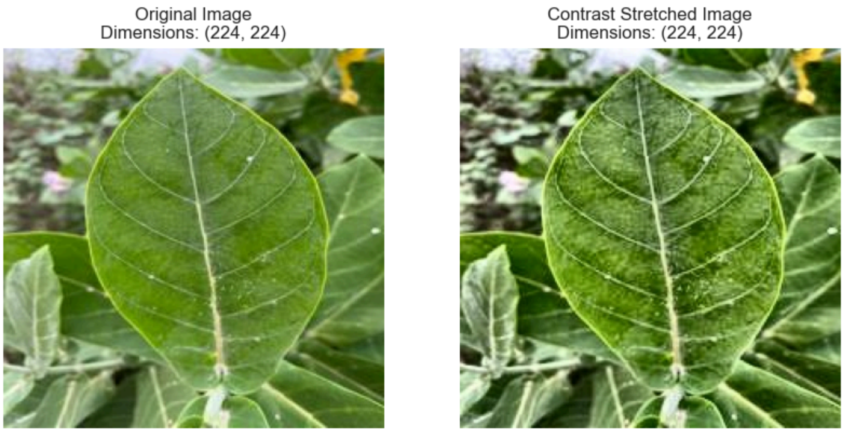


Figure 4.2.3: Original Image vs Contrast Stretched Image

Following contrast stretching, gamma correction was applied with a gamma value of 1.3 to adjust the image brightness, further improving the quality of the images[27].

Figure 4.2.4: Contrast Stretched Image vs Gamma Corrected Image

Background Removal and Edge Detection: For background removal, we used an open-source library named rembg to automatically remove the background from the leaf images. This process was followed by manual corrections to ensure the accuracy of background removal[28].

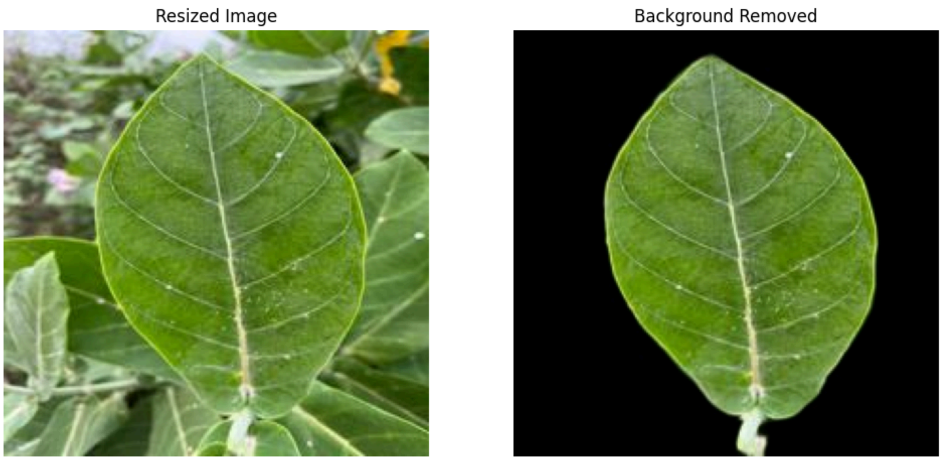


Figure 4.2.5: Resized Image vs Background Removed Image

After the background was removed, edge detection was performed using the Canny edge detection algorithm, with a low threshold of 30 and a high threshold of 100. This step helps in highlighting the edges of the leaves, providing a clearer outline for the models to learn from[29].

Figure 4.2.6: Background Removed Image vs Edge Detected Image

Augmentation:

We employed various augmentation techniques to enhance the dataset, significantly increasing its size and improving its suitability for training deep learning models. This augmentation was applied to both the datasets processed with background removal and edge detection, as well as those processed with contrast stretching and gamma correction[30].

Table 4.2.1: Augmentation Table

Plant Name	Original Images	Augmented Images
Akondo	200	2000
Arjun	200	2000
Assamlota	200	2000
Bashok	200	2000
Bohera	200	2000
Haritoki	200	2000
Joba	200	2000
Lemongrass	200	2000
Nayontara	200	2000
Neem	200	2000
Pathorkuchi	200	2000
Thankuni	200	2000
Tulsi	200	2000

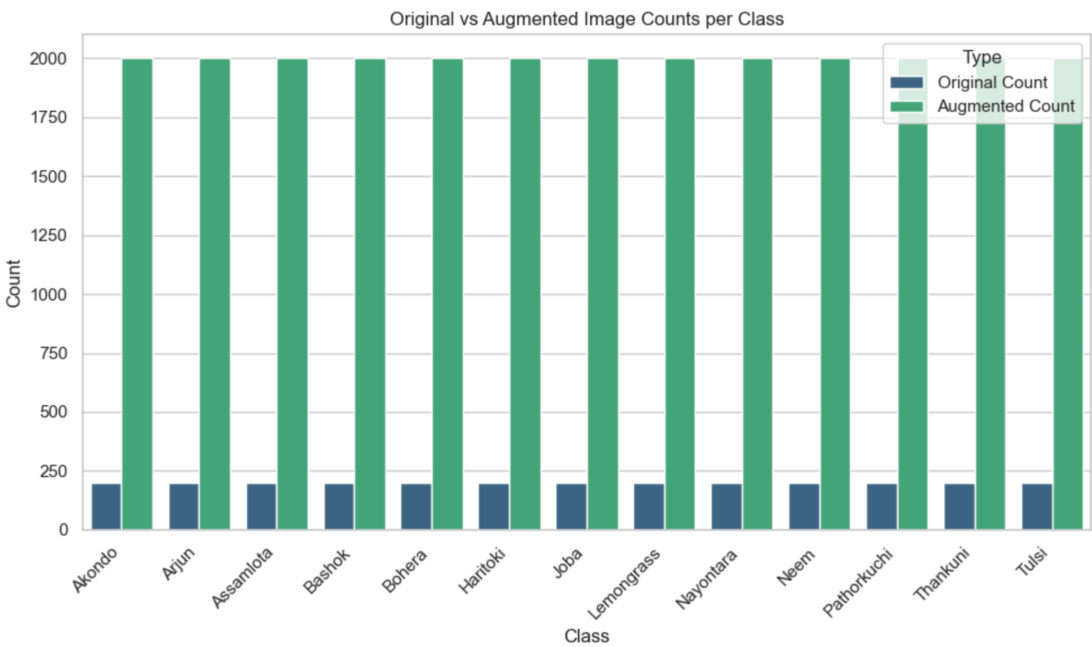


Figure 4.2.7: Original vs Augmented Image Counts Per Class

The original dataset, which consisted of 200 images per class, was expanded to 2000 images per class through augmentation. The augmentation process involved several transformations to diversify the dataset. These included horizontal flipping of images half of the time, cropping up to 10% from the edges, and random rotations. Additionally, images were resized, brightness was adjusted, contrast was increased, and light blurring and noise were introduced. These transformations enhanced the uniformity and quality of the images, making the dataset more robust.

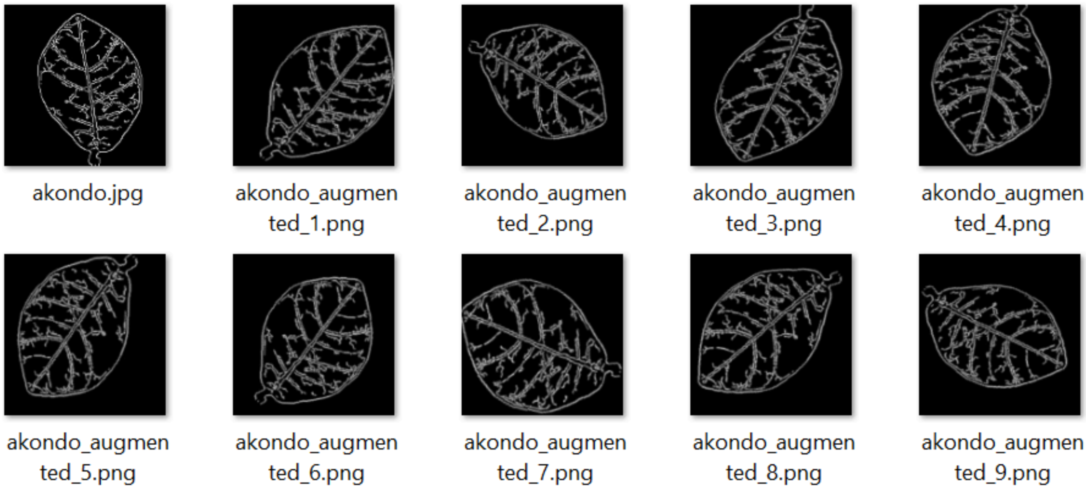


Figure 4.2.8: Augmentation of Experiment 1

Fig 4.2.8 figure showcases the differences between the original and augmented images from the Experiment 1 dataset. Various augmentation techniques such as rotation, flipping, zooming, and color adjustments have been applied to enhance the dataset's diversity.

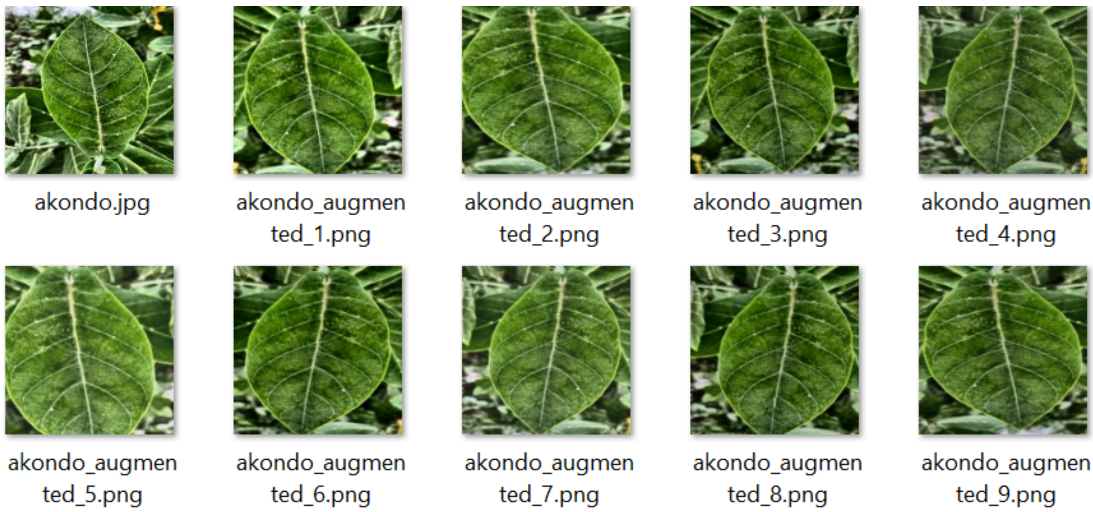


Figure 4.2.9: Augmentation of Experiment 2

Fig 4.2.9 highlights the differences between the original and augmented images from the Experiment 2 dataset. Similar to Experiment 1, various augmentation techniques have been applied, including rotation, flipping, zooming, and color adjustments. The figure illustrates the expanded variety within the dataset, showcasing how these augmentations contribute to a more comprehensive training set, ultimately aiding in the development of more accurate and reliable machine learning models.

4.2.3 Data Quality Verification:

In this paper, we have explored various image quality assessment techniques commonly used, including MSE (Mean Square Error), PSNR (Peak Signal to Noise Ratio), SSIM (Structured Similarity Index Method), and RMSE (Root Mean Square Error), to evaluate their effectiveness[31].

Structural Similarity Index (SSIM)

The Structural Similarity Index (SSIM) [32] serves as a crucial metric for evaluating the likeness between two images. Unlike simple pixel-wise comparisons, SSIM considers structural information, luminance, and contrast in its analysis. By examining local patterns of pixel intensities, SSIM provides a comprehensive measure of image quality. A higher SSIM value indicates a closer resemblance between the reference and distorted images, signifying better overall structural similarity. The standard range for SSIM values spans from -1 to 1, where 1 denotes perfect similarity, making it a valuable tool for assessing image fidelity.From the fig 8 we can see that our dataset images were greater than 0.5 which means the quality was good after applying preprocessing.

Peak Signal-to-Noise Ratio (PSNR)

Peak Signal-to-Noise Ratio (PSNR) is widely employed to measure image quality by comparing an image to a reference. Particularly relevant in image and video compression scenarios, PSNR calculates the ratio of the maximum possible power of a signal to the power of corrupting noise. A higher PSNR value signifies better image quality, expressed in decibels (dB). Our dataset achieved PSNR between 10-20 that means the image quality was good[33].

Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) [34] is a metric that quantifies the average difference between predicted and actual values. When applied to image quality assessment, RMSE measures the average pixel-wise difference between two images. By calculating the square root of the average of squared differences between corresponding pixels, RMSE provides insights into the overall similarity. Lower RMSE values indicate better agreement between images, making it a valuable tool in evaluating image quality, though the specific range varies depending on the pixel intensity scale and image size.

Mean Squared Error (MSE)

Mean Squared Error (MSE) shares similarities with RMSE but does not involve taking the square root. It calculates the average of squared pixel-wise differences between predicted and observed values, offering a straightforward metric for image quality assessment. As with RMSE, lower MSE values suggest better similarity between images. The specific range of MSE values is contingent upon the pixel intensity scale and image size. MSE serves as a fundamental tool for researchers to quantitatively evaluate and ensure the accuracy of image datasets during data quality verification[35].

Table 4.2.2: Data Quality Verification Table

Class	PSNR	SSIM	RMSE	MSE
Akondo	28.31	0.835	9.79	95.87
Arjun	28.44	0.862	9.65	93.13
Assamlota	28.46	0.842	9.63	92.72
Bashok	28.58	0.862	9.49	90.14
Bohera	31.13	0.921	7.08	50.11
Haritoki	30.06	0.906	8.01	64.09
Joba	28.14	0.828	10.00	99.85
Lemongrass	29.31	0.917	8.73	76.23
Nayontara	30.68	0.903	7.46	55.59
Neem	29.41	0.913	8.63	74.43
Pathorkuchi	30.94	0.905	7.23	52.32
Thankuni	30.18	0.901	7.90	62.41
Tulsi	30.33	0.928	7.76	60.25

We applied preprocessing techniques like resizing, contrast stretching, gamma correction, and augmentation to standardize and enhance image quality. To verify improvements, we used metrics such as the Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The results show high-quality and consistent images across the dataset, with PSNR values frequently above 28, SSIM averages near 0.9, and RMSE values indicating low error levels, underscoring the effectiveness of our preprocessing strategies.

4.2.4 Model Descriptions & Architecture Diagrams:

VGG-19: Simonyan and Zisserman, from the University of Oxford, devised the VGG-19 model, a 19-layer CNN architecture consisting of 16 convolutional layers and 3 fully-connected layers. This model employs 3x3 filters with a stride and padding of 1, along with 2x2 max-pooling layers with a stride of 2. Unlike AlexNet, VGG-19 is deeper, offering a more complex network. It reduces the parameter count by using smaller filters throughout all convolutional layers, resulting in a lower error rate of 7.3%. Despite not winning the ILSVRC 2014, VGG-19's architecture highlighted the importance of deep networks in CNNs for effective hierarchical representation of visual data. This model, with 138 million parameters, achieved 2nd place in classification and 1st in localization in the ILSVRC 2014, trained on a subset of the ImageNet database. Capable of classifying images into 1000 object categories, VGG-19 exhibits learned feature representations across various image types. The Region-based CNN (R-CNN) approach, followed by Fast R-CNN and Faster R-CNN, enhances object detection and classification by generating region proposals and utilizing CNNs. However, the R-CNN method proves unsuitable for breast cancer detection due to the significant variation in mammogram texture and lesion size[36].

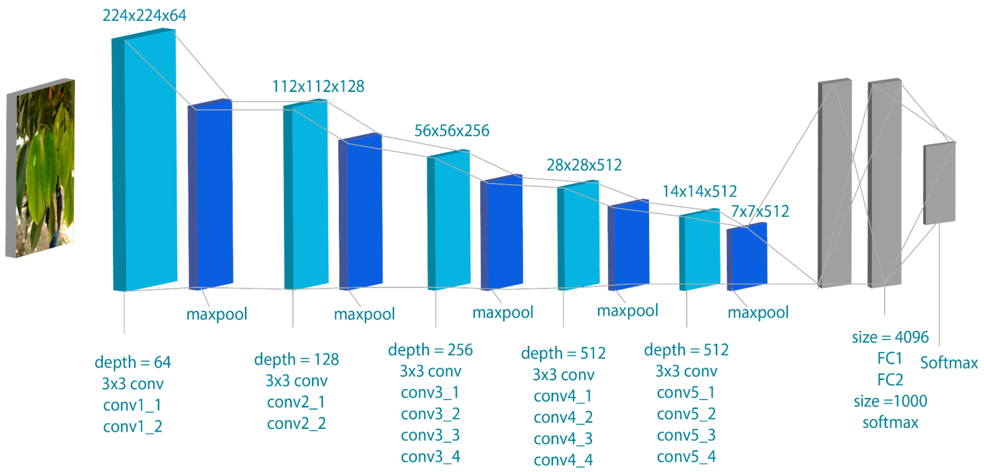


Figure 4.2.10: Architecture of VGG-19[36]

Xception: The Xception architecture incorporates skip connections similar to those found in Inception networks. However, it differs from Inception by replacing each inception module with a depthwise separable convolutional layer. Unlike a standard convolutional layer, a depthwise convolutional layer requires fewer computations to achieve the same output, leading to faster training of the model. The Xception architecture, depicted in Fig 4.2.11, commences with two conventional convolutional layers featuring 32 and 64 filters, respectively, each with a fixed filter size of 3x3. It then proceeds with five Xception blocks, where each input passes through two separable convolutional layers followed by a max-pooling layer. Additionally, each input traverses a pointwise convolution via a shortcut connection in all blocks except the fourth one. The fourth block consists of a single separable convolutional layer and repeats eight times. Following the final Xception block, two separable convolutional layers are followed by a global average pooling layer. Subsequently, fully connected layers are added, with the last one serving as the output layer[37].

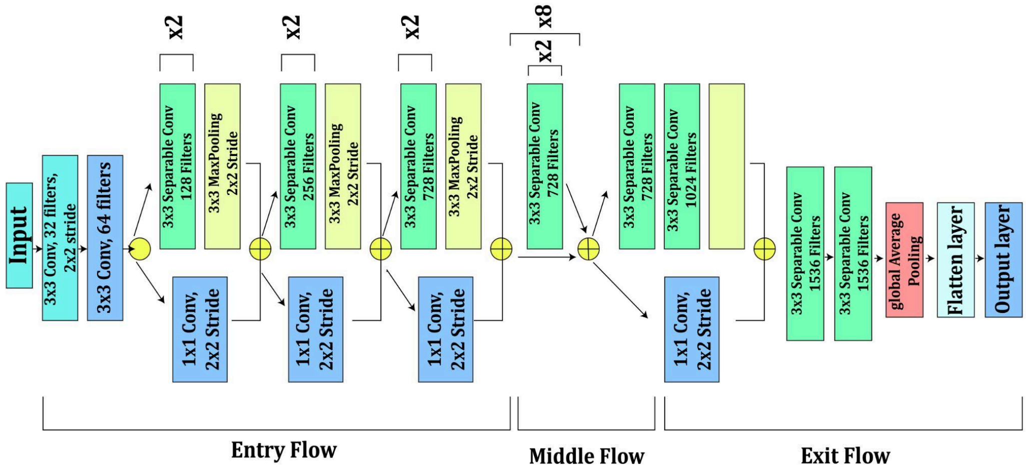


Figure 4.2.11: Architecture Diagram of Xception[37]

Inception-V3: This is a convolutional neural network (CNN) architecture developed by Google researchers as part of the Inception family of models. Introduced in 2015, it is designed for efficient training and high accuracy in image classification and detection tasks. The architecture of Inception-v3 incorporates various modules, including inception blocks, which consist of parallel convolutional layers of different kernel sizes and depths, aimed at capturing features at multiple scales. Moreover, it utilizes factorized convolutions to reduce computational complexity while maintaining expressive power. Inception-v3 also incorporates auxiliary classifiers during training to encourage the propagation of gradients and improve convergence. With its innovative design and superior performance, Inception-v3 has become a popular choice for various computer vision applications, especially those demanding high accuracy and efficiency[38].

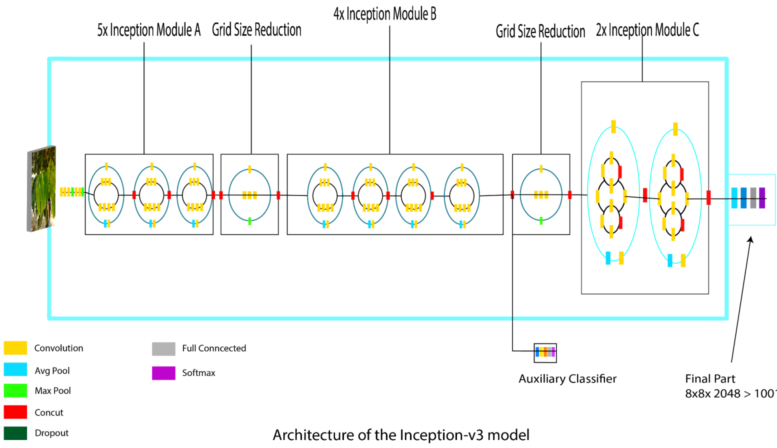


Figure 4.2.12: Architecture Diagram of Inception V3[38]

The Hybrid Model: The hybrid model combines the strengths of the Inception-v3 and Xception architectures to create a powerful ensemble for image classification tasks. The model begins with the initial layers of Inception-v3, leveraging its efficient inception blocks to capture features at multiple scales through parallel convolutional operations. Following this initial feature extraction, the model incorporates the deeper and more parameter-efficient Xception architecture. The Xception module enhances the representation learning process by employing depthwise separable convolutions, which efficiently capture spatial and channel-wise dependencies in the data. By integrating these two architectures, the hybrid model benefits from both the multi-scale feature extraction capability of Inception-v3 and the depth-wise separability of Xception, resulting in improved performance and generalization across a wide range of image classification tasks.

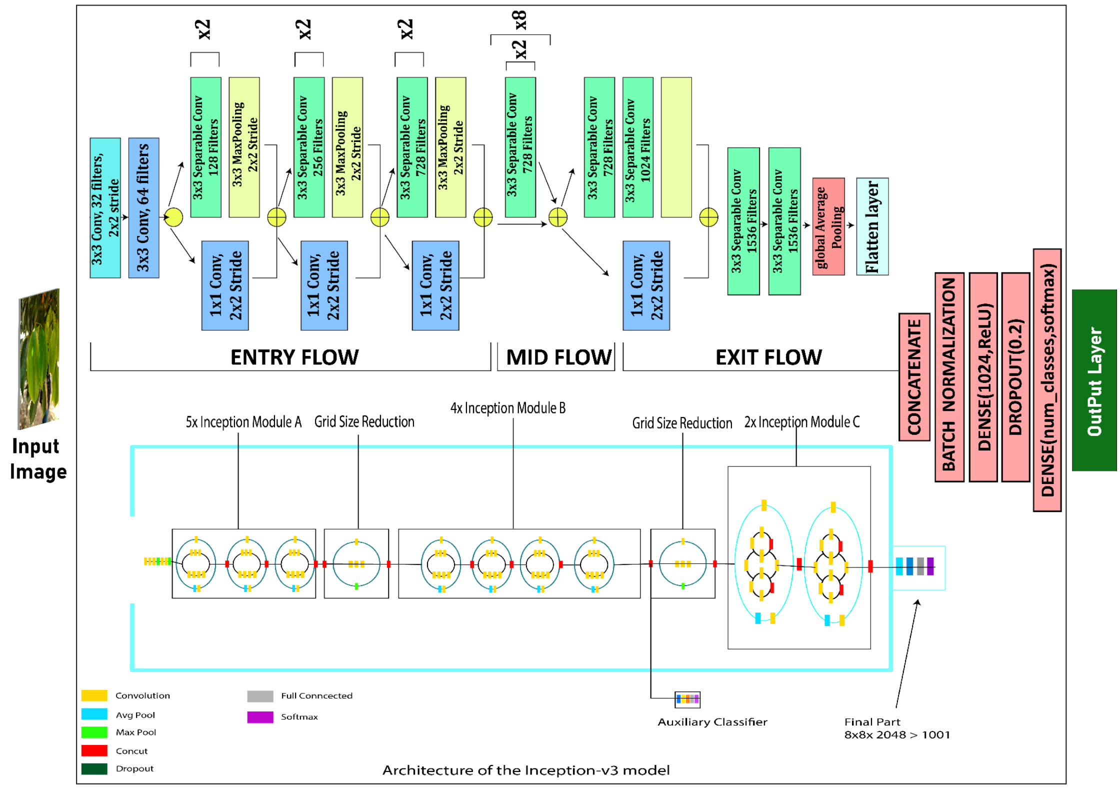


Figure 4.2.13: Hybrid Model

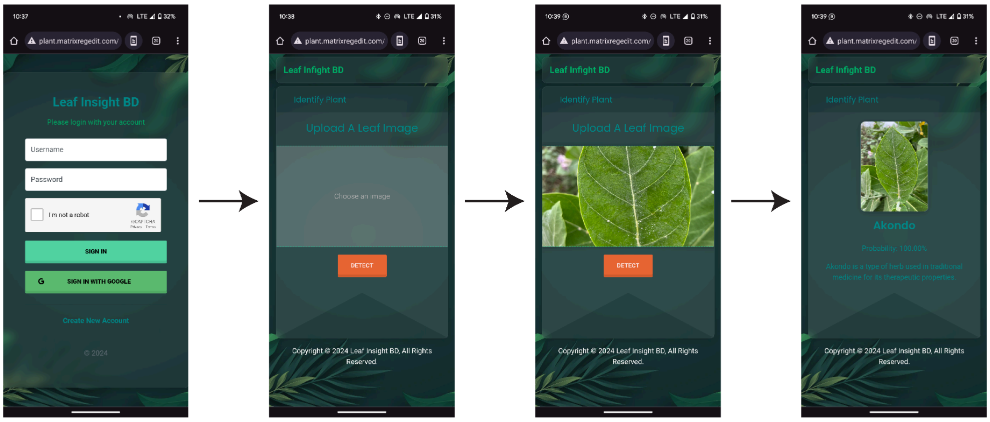
4.2.5 Model Training

We experimented with four deep learning models: VGG19, Inception V3, Xception, and a custom Hybrid model combining Inception V3 and Xception. These models were trained using the preprocessed datasets with specific parameters tailored to optimize their performance for the leaf classification task. The VGG19 model, known for its simplicity and effectiveness in image classification tasks, was trained for 20 epochs with a batch size of 32 and a learning rate of 0.001. Inception V3, chosen for its deeper and more complex architecture capable of capturing intricate patterns in the images, was trained for 20 epochs with a batch size of 32 and a learning rate of 0.0001. Similarly, the Xception model, which leverages depthwise separable convolutions to reduce the number of parameters while maintaining high performance, was trained for 20 epochs with a batch size of 32 and a learning rate of 0.0001. Lastly, our custom Hybrid model, which combines the strengths of Inception V3 and Xception, was trained for 20 epochs with a batch size of 32 and a learning rate of 0.0001. To prevent overfitting, we incorporated early stopping in the models, aiming to achieve higher accuracy and robustness in leaf classification.

4.2.6 Model Evaluation

The models were evaluated using various performance metrics, including accuracy, precision, recall, F1-score, and specificity. These metrics provide a comprehensive understanding of the models' performance across different aspects. Class-wise performance was analyzed to identify the most effective approach for plant recognition tasks. Confusion matrices were used to visualize the performance and identify areas for improvement.

4.2.7 Web Application



Login Page **Upload Image** **Uploaded Leaf Image** **Detected Leaf**

Figure 4.2.14: Web Application Interface

We have designed a user-friendly app designed to help identify plants by their leaves. Users start on the login page, where they can enter their credentials or sign in with Google. Once logged in, they are prompted to upload a leaf image. They simply choose an image from their device and click the "Detect" button. The app analyzes the image and provides detailed information about the detected leaf, including its name and a brief description. As shown in example of figure 4.2.14, it might identify the leaf as "Akondo" with a high probability, offering insights into its traditional medicinal uses. This seamless process makes plant identification easy and informative for users.

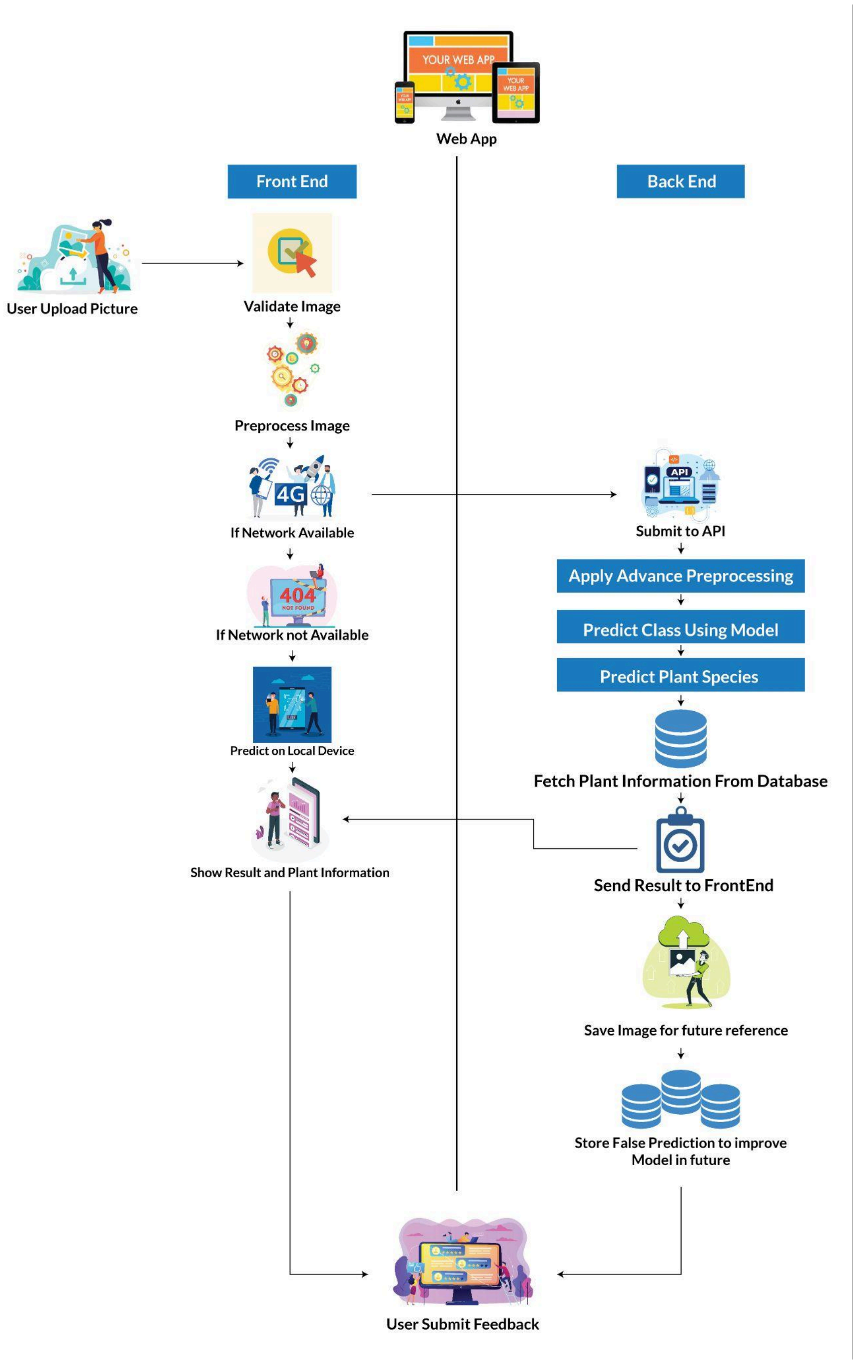


Figure 4.2.15: Web Application Workflow

4.2.8 Workflow Description

1. User Upload Picture:

The process begins when the user uploads a picture of a plant leaf through the web application's frontend interface.

2. Validate Image:

The uploaded image is first validated to check its format, size, and other necessary criteria to ensure it is suitable for processing.

4.2.9 Preprocess Image:

Once validated, the image undergoes initial preprocessing on the frontend to standardize its format and enhance its features for better analysis.

1. Network Availability Check:

The application checks if a network connection is available. If the network is available, the image is sent to the backend for further processing. If not, the prediction is performed on the local device using a preloaded model.

2. Submit to API (Backend):

If a network connection is available, the preprocessed image is submitted to the Flask API for advanced preprocessing and analysis.

3. Advanced Preprocessing:

The backend applies advanced preprocessing techniques, including background removal and edge detection or contrast stretching and gamma correction, to prepare the image for model inference.

4. Predict Class Using Model:

The preprocessed image is fed into the trained Hybrid model to predict the class of the plant leaf.

5. Predict Plant Species:

Based on the predicted class, the specific plant species is identified.

6. Fetch Plant Information from Database:

The backend retrieves detailed information about the identified plant species from the database.

7. Send Result to Frontend:

The prediction results, along with the plant information, are sent back to the frontend.

8. Display Result and Plant Information:

The frontend displays the prediction results and the detailed plant information to the user.

9. Save Image for Future Reference:

The backend saves the processed image for future reference and analysis.

10. Store False Predictions:

Any false predictions are stored to improve the model in future iterations.

11. User Submit Feedback:

Users have the option to submit feedback on the accuracy of the prediction, which helps in refining the model further.

4.3 Model Evaluation

The dataset was divided into training, validation, and test sets to ensure balanced evaluation. Preprocessing techniques, such as background removal with edge detection and contrast stretching with gamma correction, were applied to enhance image quality and standardize inputs. During the training phase, we used specific hyperparameters such as learning rate, batch size, and the number of epochs. Each model underwent extensive training to ensure optimal performance. For instance, the VGG19 model was trained for 20 epochs, during which we recorded training accuracy and validation accuracy. The Inception V3 and Xception and Hybrid models were also trained for 20 epochs, with metrics recorded similarly. To evaluate the models, we employed various performance metrics including accuracy, precision, recall, F1-score, and specificity. Accuracy measured the ratio of correctly predicted instances to the total instances, while precision and recall provided insights into the model's ability to correctly predict positive observations. The F1-score, being the weighted average of precision and recall, offered a balanced measure of the model’s performance. Specificity measured the model's ability to correctly predict negative observations. Additionally, we obtained precision, recall, F1-score, support, and specificity for each class in the models.For each model, we also created training and validation accuracy and loss charts, which illustrated the learning progress over epochs. Furthermore, we analyzed the number of misclassifications and constructed confusion matrices to visualize the distribution of predicted vs. actual class labels. This detailed evaluation helped in understanding how well each model performed across different plant classes, highlighting areas of strength and opportunities for improvement. Class-wise performance analysis was also conducted to identify the most effective approach for plant recognition tasks, providing a comprehensive view of each model's effectiveness and reliability.

4.4 Summary

This chapter detailed the implementation process, including the experimental setup, model architectures, and training process. By carefully selecting preprocessing techniques and model architectures, we created a robust system for plant recognition. Our comprehensive documentation ensures transparency and reproducibility, facilitating future research and collaboration in this domain.In the subsequent chapter, we will present the experimental results and analysis, comparing the performance of different models and preprocessing techniques to determine the most effective approach for plant recognition in Bangladesh.

CHAPTER 5

Result and Analysis

5.1 Overview

This chapter gives the findings and discussion of the experiments done for the project "Deep Learning-Based Plant Recognition in Bangladesh". The aim is to compare the outcomes of the different deep learning models after applying different preprocessing on the data. From the above analysis, it becomes easier to identify the model and the preprocessing method that would work best in enhancing the recognition of plants.

5.2 Experimental Results

5.2.1 Experiment 1 Results Using Background Removal and Edge Detection

This section measures the effectiveness of the VGG19, Inception V3, Xception, and Hybrid models with background removal and edge detection as the preprocessing steps. The accuracy and loss of each model along with class-wise performance are discussed to find out the best model.

VGG19 Model

Training and Validation Results

The VGG19 model was trained for 20 epochs. During the training period of this model, it obtained a training accuracy of 87.81%. The validation accuracy was a bit higher, it was 90. 27%.

Table 5.2.1: Class-wise Performance VGG19 Model

Class	Precision	Recall	F1-Score	Support	Specificity
Akondo	0.9078	0.935	0.9212	200	0.9921
Arjun	0.9672	0.885	0.9243	200	0.9975
Assamlota	0.9082	0.940	0.9238	200	0.9921
Bashok	0.9020	0.920	0.9109	200	0.9917
Bohera	0.9511	0.875	0.9115	200	0.9963
Haritoki	0.8711	0.980	0.9224	200	0.9879
Joba	0.7087	0.900	0.7930	200	0.9692
Lemongrass	1.0000	1.000	1.0000	200	1.0000

Nayontara	0.9901	0.995	0.9925	200	0.9992
Neem	0.9948	0.955	0.9745	200	0.9996
Pathorkuchi	0.8200	0.820	0.8200	200	0.9850
Thankuni	0.9286	0.910	0.9192	200	0.9942
Tulsi	0.8378	0.620	0.7126	200	0.9900

Most of the classes have a high average accuracy of 90.27%% as illustrated by the VGG19 mode. The accomplishment ratios with respect to class-wise performance show that all the three variants, namely, Lemongrass, Nayontara, and Neem, have nearly 100% rates. However, Joba and Tulsi are comparatively less precise and recall based on the results, which means that there is still potential for development.

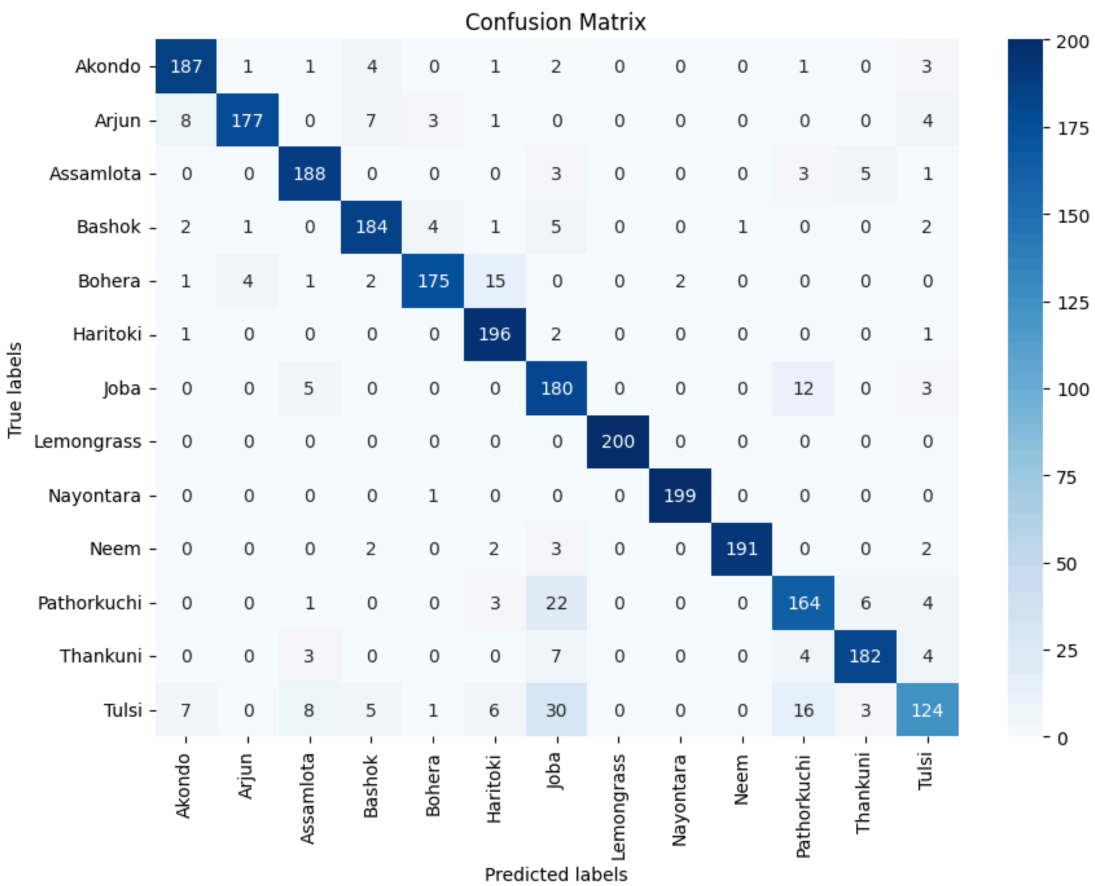


Figure 5.2.1: Confusion Matrix for VGG19

It is clear from the confusion matrix that the classification has high accuracy for classes such as Akondo, Arjun and Assamlota with little overlapping. As shown in the above graphs, misclassifications with different classes of flowers are significant with the class Tulsi being the most misclassified implying that it is the most difficult class for the model. For Lemongrass and Nayontara, the confusion matrix shows that they are perfectly classified, meaning that the model performed well for these classes. However, the model performs acceptably well for most of the classes, though there is a necessity for the model to make more accurate distinctions between classes such as Tulsi and Pathorkuchi.

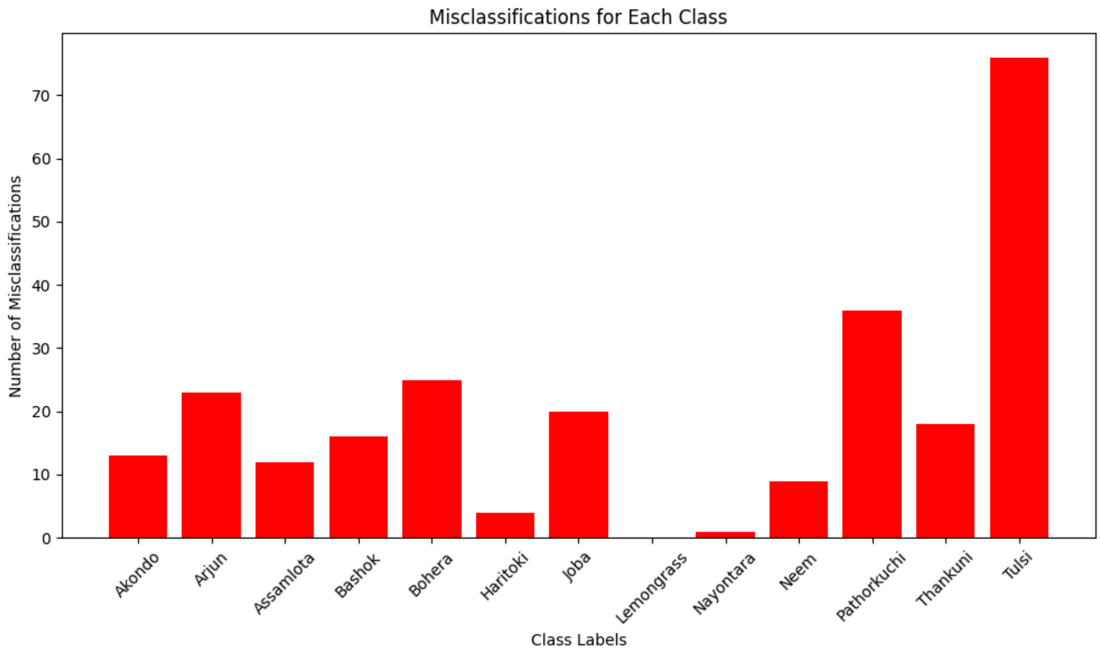


Figure 5.2.2: Number of Misclassifications for VGG19

Tulsi has the highest misclassification of more than 70 times making it the most misclassified class. Misclassification errors are also found in Bohera and Pathorkuchi also. On the other hand, Lemongrass and Nayontara have low misclassification rates which mean that the model is very good when it comes to classifying these two classes. Some classes such as Arjun and Thankuni have moderate misclassifications which indicate the possibility of further optimization.

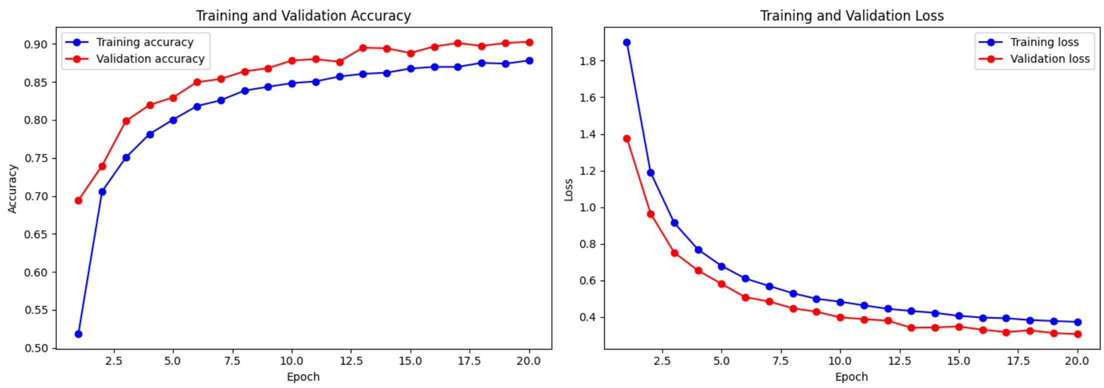


Figure 5.2.3: Training and Validation Accuracy and Loss for VGG19

This means that training accuracy rises gradually to around 90% and validation accuracy is similar to it. The training and validation losses decrease over time with no sign of overfitting which is an ideal scenario. The model is able to learn from the training data and generalize well to unseen data as seen by the convergence of the training and validation metrics.

Inception Model

Training and Validation Results:

Similarly, the Inception V3 model was also trained for 20 epochs. It was able to achieve a good result with 92.40% training accuracy and a validation accuracy of 95.1%.

Table 5.2.2: Class-wise Performance Inception Model

Class	Precision	Recall	F1-Score	Support	Specificity
Akondo	0.9455	0.955	0.9502	200	0.9954
Arjun	0.9497	0.945	0.9474	200	0.9958
Assamlota	0.9171	0.995	0.9544	200	0.9925
Bashok	0.9366	0.960	0.9481	200	0.9946
Bohera	0.9314	0.950	0.9406	200	0.9942
Haritoki	0.9604	0.970	0.9652	200	0.9967
Joba	0.9412	0.880	0.9096	200	0.9954
Lemongrass	1.0000	1.000	1.0000	200	1.0000

Nayontara	1.0000	0.990	0.9950	200	1.0000
Neem	0.9950	1.000	0.9975	200	0.9996
Pathorkuchi	0.9568	0.885	0.9195	200	0.9967
Thankuni	0.9652	0.970	0.9676	200	0.9971
Tulsi	0.8693	0.865	0.8672	200	0.9892

With a validation accuracy of 95.12%, the Inception model demonstrates superior performance. The precision, recall, and F1-scores are notably high across all classes, with Lemongrass, Nayontara, and Neem achieving perfect or near-perfect scores. However, minor discrepancies are observed in classes like Tulsi and Pathorkuchi.

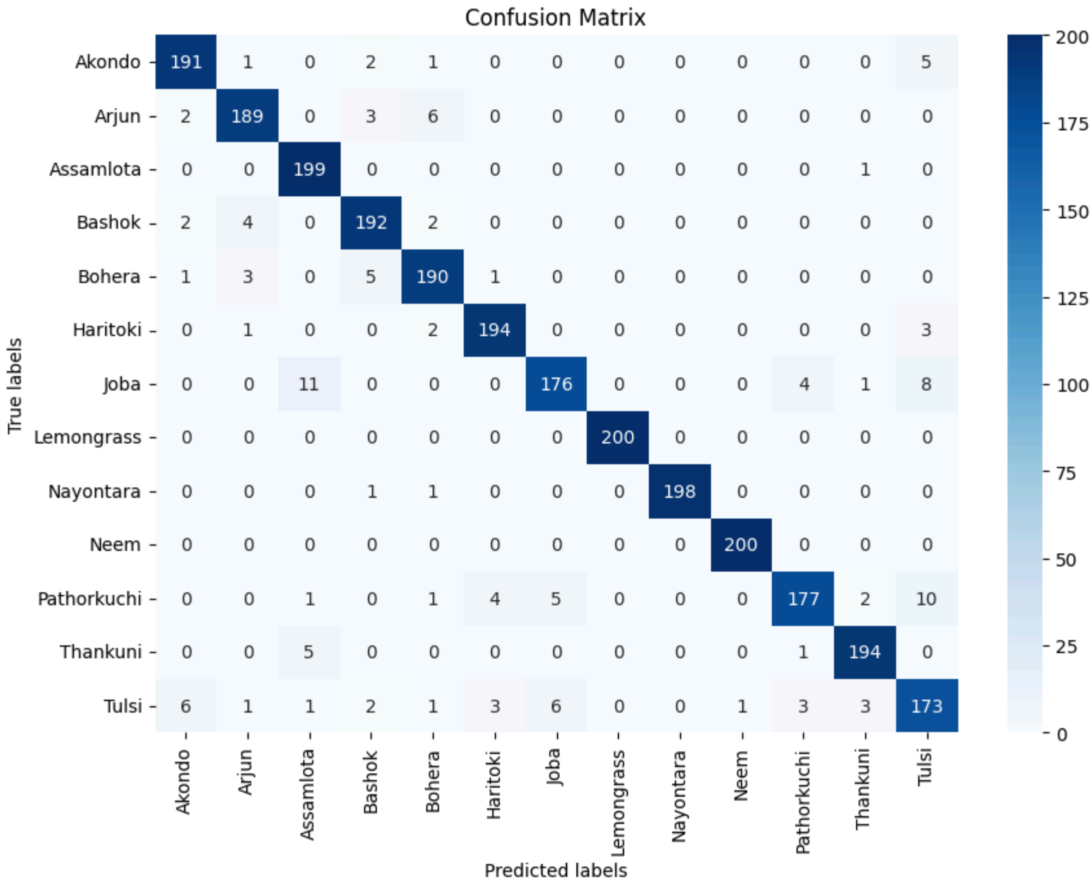


Figure 5.2.4: Confusion Matrix for Inception V3

Akondo, Arjun, and Assamlota show high classification accuracy with minimal misclassifications. Tulsi has significant misclassifications, although fewer than in the VGG model. Lemongrass and Nayontara are perfectly classified, highlighting strong model performance for these classes. The overall performance is improved compared to the VGG model, but some classes like Tulsi and Pathorkuchi still pose challenges.

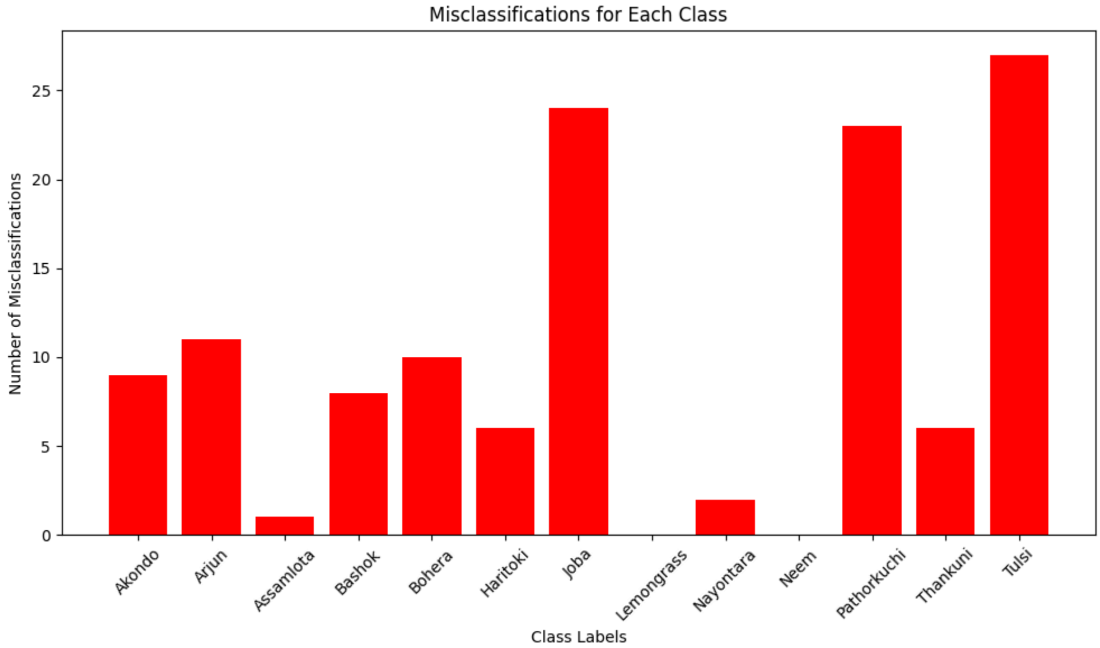


Figure 5.2.6: Number of Misclassifications for Inception V3

Tulsi has the highest number of misclassifications, similar to the VGG model, but with a lower count. Joba and Pathorkuchi also show significant misclassifications. Lemongrass and Nayontara have very few misclassifications, indicating high accuracy for these classes. Arjun and Bohera have moderate misclassifications, suggesting some challenges in classification.

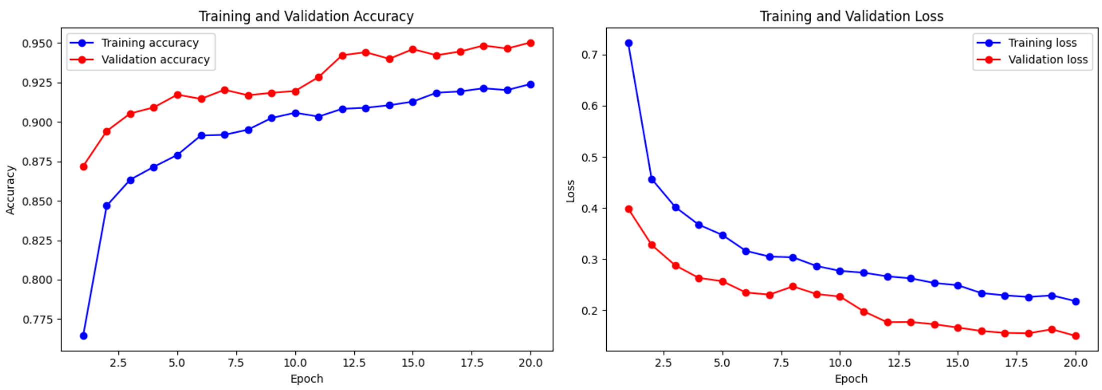


Figure 5.2.7: Training and Validation Accuracy and Loss for Inception V3

Training accuracy increases steadily to about 95%, with validation accuracy close behind. Both training and validation losses decrease significantly, showing effective learning. The model demonstrates strong generalization, as indicated by the convergence of training and validation metrics.

Xception Model

Training and Validation Results:

Xception achieved a training accuracy of 91.44%, a validation accuracy of 92.92%. Additionally, the test loss for the Xception model was recorded at 0.1997.

Table 5.2.3: Class-wise Performance Xception Model

Class	Precision	Recall	F1-Score	Support	Specificity
Akondo	0.9502	0.955	0.9526	200	0.9958
Arjun	0.9560	0.870	0.9110	200	0.9967
Assamlota	0.8843	0.955	0.9183	200	0.9896
Bashok	0.9216	0.940	0.9307	200	0.9933
Bohera	0.9265	0.945	0.9356	200	0.9938
Haritoki	0.9657	0.985	0.9752	200	0.9971
Joba	0.9101	0.810	0.8571	200	0.9933
Lemongrass	1.0000	1.000	1.0000	200	1.0000
Nayontara	1.0000	0.975	0.9873	200	1.0000
Neem	0.9948	0.955	0.9745	200	0.9996
Pathorkuchi	0.8017	0.970	0.8778	200	0.9800
Thankuni	0.9249	0.985	0.9540	200	0.9933
Tulsi	0.8698	0.735	0.7967	200	0.9908

Precision and recall values are high for most classes, with Lemongrass maintaining a perfect score. However, certain classes like Pathorkuchi and Tulsi exhibit lower recall and F1-scores, suggesting a need for further fine-tuning.

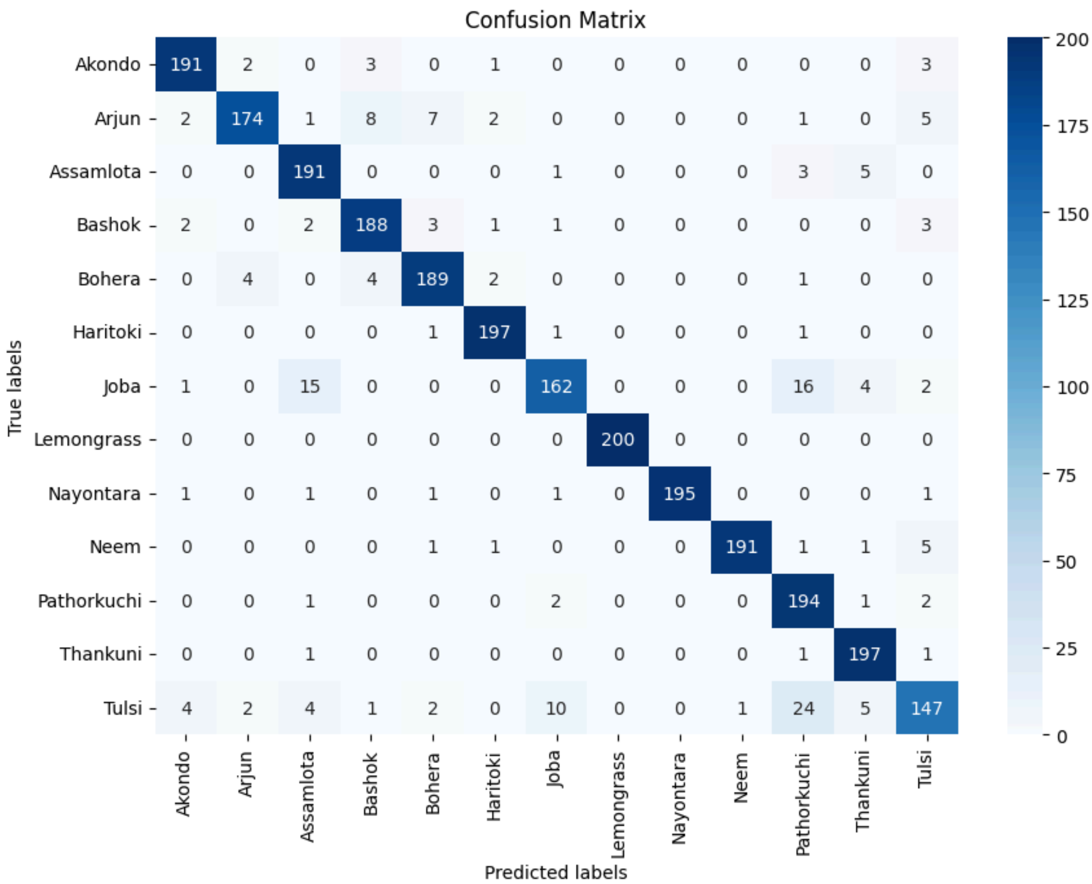


Figure 5.2.8: Confusion Matrix for Xception

Classes like Akondo, Lemongrass, and Nayontara show high classification accuracy, with minimal misclassifications. Tulsi is the most challenging class, with many instances misclassified as other categories. Haritoki and Lemongrass are perfectly classified, indicating excellent model performance for these classes. The model performs well overall but needs improvement in distinguishing certain classes like Tulsi and Joba.

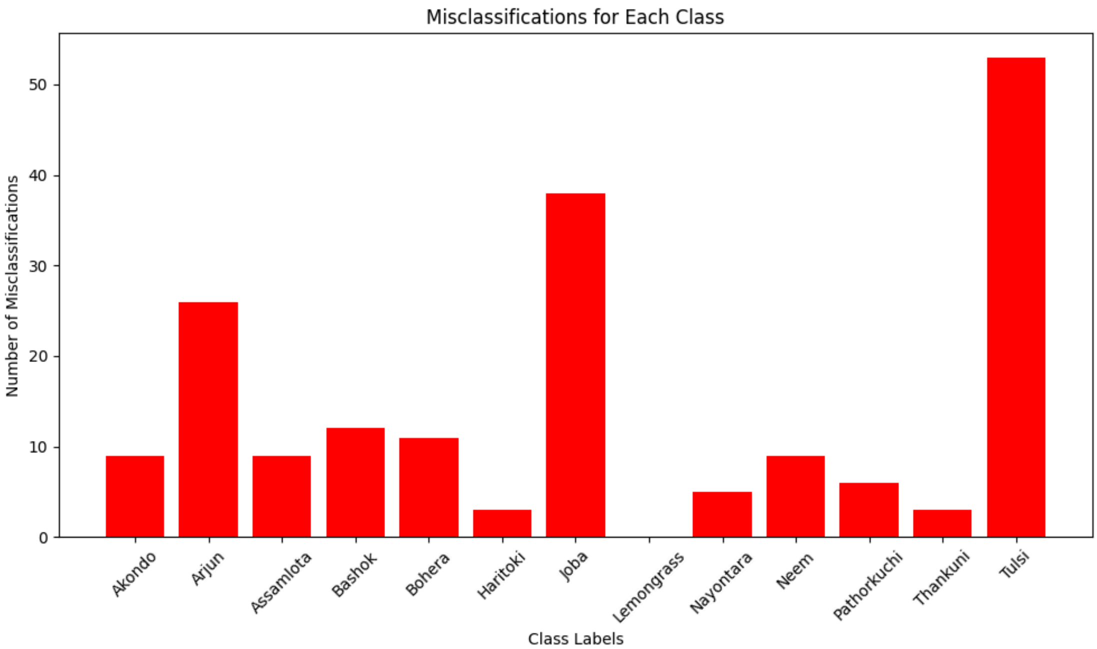


Figure 5.2.9: Number of Misclassifications for Xception

Tulsi has the highest number of misclassifications, with over 50 instances. Arjun and Joba also have significant misclassifications, showing that these classes are challenging for the model. Classes like Haritoki and Nayontara have very few misclassifications, indicating high accuracy for these categories.

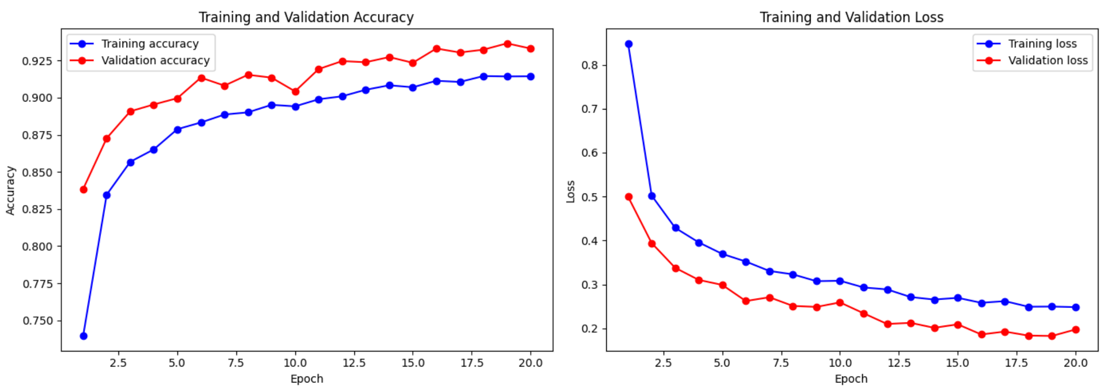


Figure 5.2.10: Training and Validation Accuracy and Loss for Xception

Training accuracy increases steadily to around 93%, with validation accuracy reaching approximately 92%. Both training and validation losses decrease significantly over time, demonstrating effective learning and minimal overfitting. The model shows strong generalization, with close alignment between training and validation performance metrics.

Hybrid Model (Combining Xception and Inception v3)

Training and Validation Results:

The Hybrid model, trained for 20 epochs, demonstrated outstanding performance with a training accuracy of 95.63%, a validation accuracy of 97.65%. The test loss for the Hybrid model was noted to be 0.0708.

Table 5.2.4: Class-wise Performance Xception Model

Class	Precision	Recall	F1-Score	Support	Specificity
Akondo	0.9750	0.975	0.9750	200	0.9979
Arjun	0.9637	0.930	0.9466	200	0.9971
Assamlota	0.9848	0.975	0.9799	200	0.9988
Bashok	0.9695	0.955	0.9622	200	0.9975
Bohera	0.9604	0.970	0.9652	200	0.9967
Haritoki	0.9899	0.980	0.9849	200	0.9992
Joba	0.9610	0.985	0.9728	200	0.9967
Lemongrass	1.0000	1.000	1.0000	200	1.0000
Nayontara	0.9950	1.000	0.9975	200	0.9996
Neem	0.9950	1.000	0.9975	200	0.9996
Pathorkuchi	0.9751	0.980	0.9776	200	0.9979
Thankuni	1.0000	0.995	0.9975	200	1.0000
Tulsi	0.9268	0.950	0.9383	200	0.9938

The hybrid model outperforms the other models with a validation accuracy of 97.65%. It shows excellent precision, recall, and F1-scores across all classes, with most classes achieving near-perfect or perfect scores. This indicates that the hybrid model is highly effective for plant recognition tasks in this context.

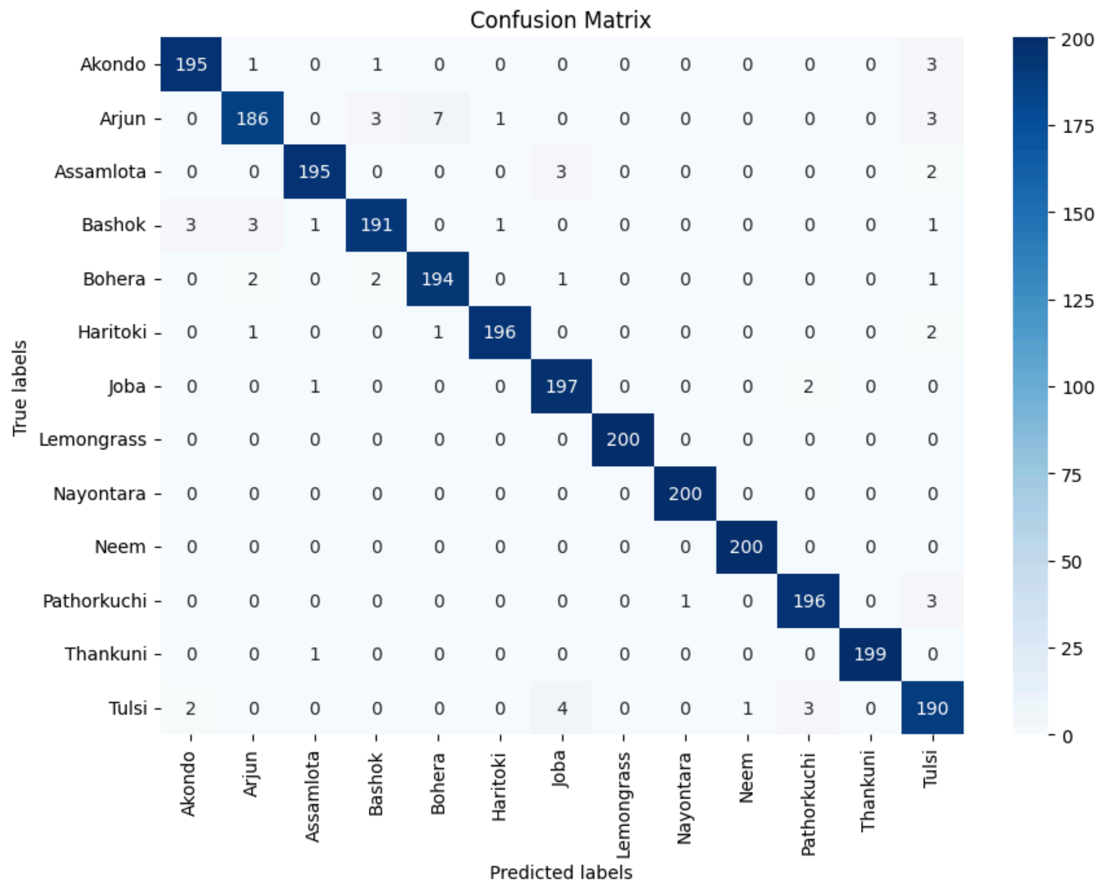


Figure 5.2.11: Confusion Matrix for Hybrid Model

Classes like Akondo, Lemongrass, and Nayontara show the highest classification accuracy with minimal misclassifications, outperforming previous models. Tulsi still presents some challenges but has fewer misclassifications compared to earlier models, marking an improvement. Haritoki and Lemongrass are perfectly classified, indicating the best model performance for these classes. The hybrid model performs exceptionally well overall, showing the most robust results with only a few classes needing further refinement.

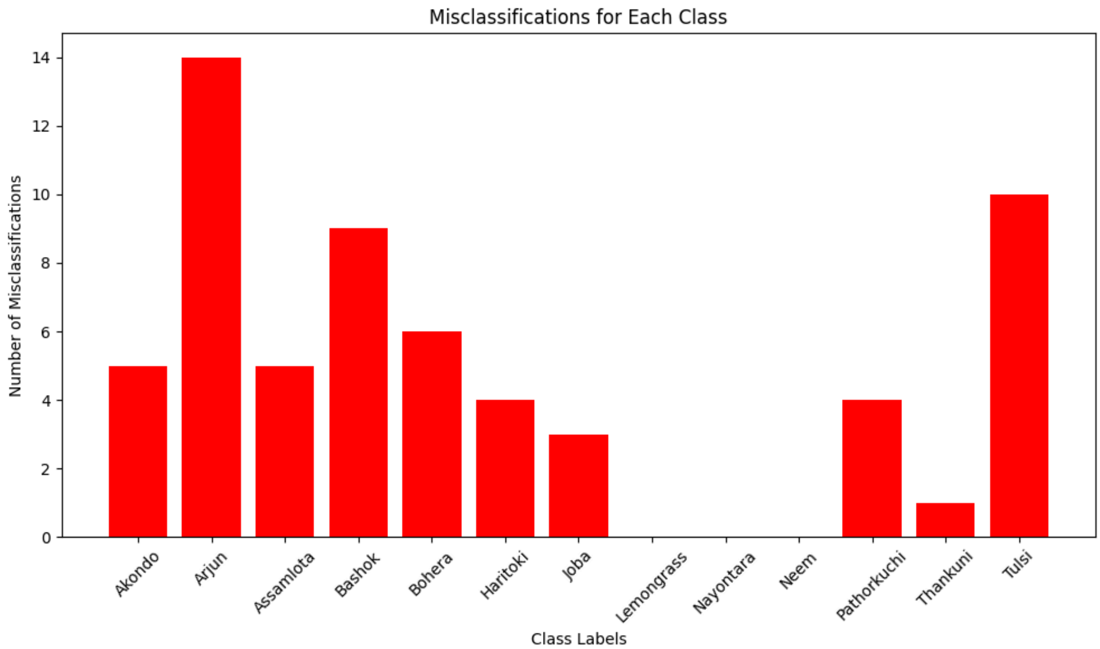


Figure 5.2.12: Number of Misclassifications for Hybrid Model

Arjun has the highest number of misclassifications with over 14 instances, but this is significantly lower compared to previous models. Other classes like Bashok and Bohera also show fewer misclassifications. Tulsi has around 10 misclassifications, a notable improvement from earlier results. Classes such as Thankuni and Nayontara have very few misclassifications, showcasing the model's best accuracy for these categories.

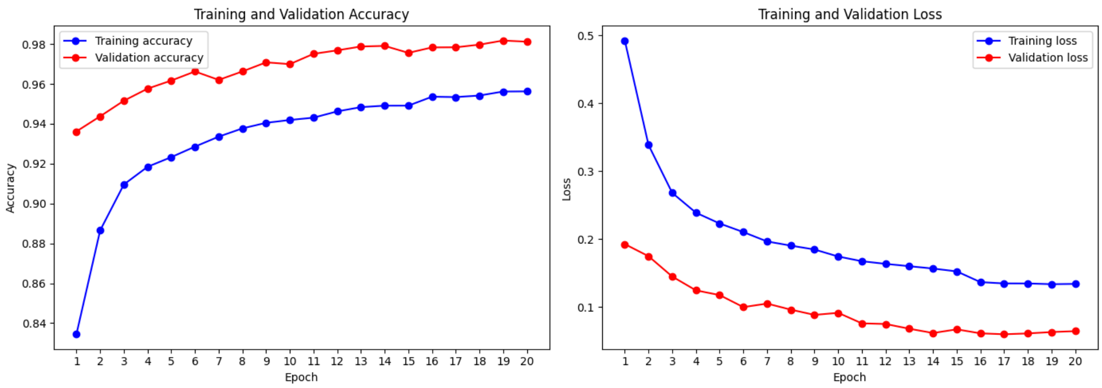


Figure 5.2.13: Training and Validation Accuracy and Loss for Hybrid Model

Training accuracy increases steadily to around 95.63%, and validation accuracy reaches approximately 97.65%, the highest among all models tested. Both training and validation losses decrease significantly over the epochs, indicating the most effective learning and minimal overfitting seen so far. The model demonstrates the best generalization, with closely aligned training and validation performance metrics.

Table 5.2.5: Summary of Performance Model

Model Name	Preprocessing Applied	Training Accuracy	Validation Accuracy
VGG19	Background Removal, Edge Detection	87.81%	90.27%
InceptionV3		92.40%	95.12%
Xception		91.44%	92.92%
Hybrid		95.63%	97.65%

The table shows the training and validation accuracy of various models after applying background removal and edge detection. VGG19 achieved a training accuracy of 87.81% and a validation accuracy of 90.27%, showing solid performance but with room for improvement. InceptionV3 demonstrated better results, with a training accuracy of 92.40% and a validation accuracy of 95.12%, indicating significant enhancements. Xception showed a training accuracy of 91.44% and a validation accuracy of 92.92%, balancing between VGG19 and InceptionV3 in terms of performance. However, the Hybrid model outshined all the others with a remarkable training accuracy of 95.63% and the highest validation accuracy of 97.65%. This superior performance of the Hybrid model highlights its effectiveness and robustness, making it the best among all the models tested.

5.2.2 Experiment 2 Results Using Contrast Stretching and Gamma Correction

This section evaluates the performance of the VGG19, Inception V3, Xception, and Hybrid models using contrast stretching and gamma correction as preprocessing techniques. Similar to the previous experiment, each model's training and test accuracies were measured to assess their effectiveness.

VGG19 Model

Training and Validation Results: VGG19 , after training on our dataset, , achieved a training accuracy of 94.37% and a validation accuracy of 97.23% with a test loss of 0.0884.

Table 5.2.6:Class-wise Performance VGG19 Model

Class	Precision	Recall	F1-Score	Support	Specificity
Akondo	0.951923	0.990	0.970588	200	0.995833
Arjun	0.970000	0.970	0.970000	200	0.997500
Assamlota	0.964646	0.955	0.959799	200	0.997083

Bashok	0.979487	0.955	0.967089	200	0.998333
Bohera	1.000000	0.985	0.992443	200	1.000000
Haritoki	0.985222	1.000	0.992556	200	0.998750
Joba	0.938462	0.915	0.926582	200	0.995000
Lemongrass	1.000000	1.000	1.000000	200	1.000000
Nayontara	1.000000	0.995	0.997494	200	1.000000
Neem	0.994872	0.970	0.982278	200	0.999583
Pathorkuchi	0.975124	0.980	0.977556	200	0.997917
Thankuni	0.942029	0.975	0.958231	200	0.995000
Tulsi	0.940594	0.950	0.945274	200	0.995000

The VGG19 model demonstrates high accuracy with notable performance in most classes. Lemongrass, Nayontara, and Bohera achieved perfect or near-perfect scores. However, the Joba class has slightly lower precision and recall values.

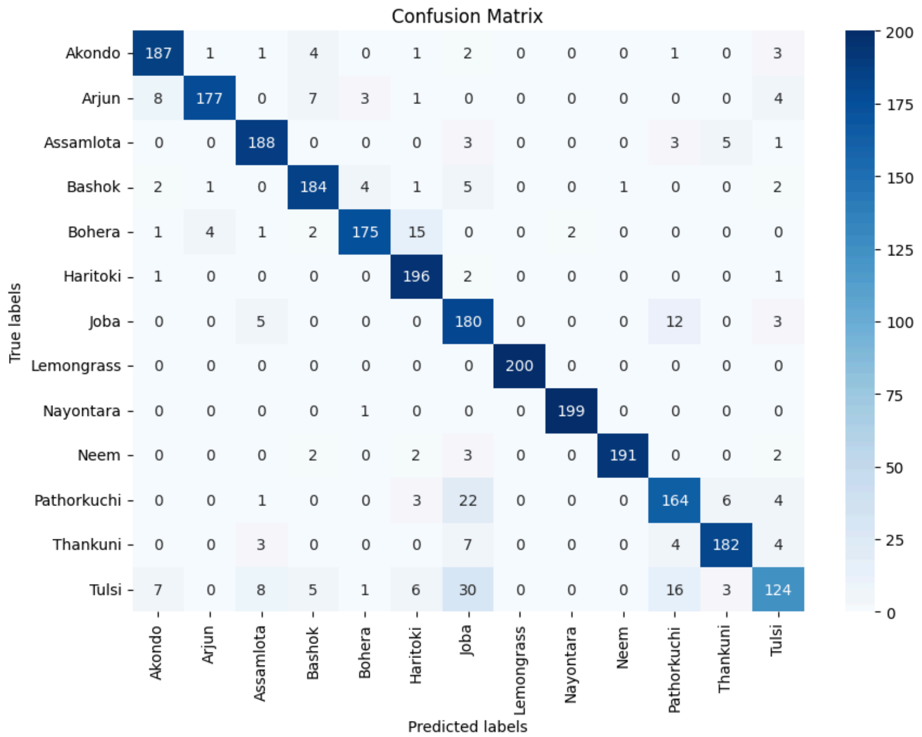


Figure 5.2.14: Confusion Matrix for VGG19

Classes like Akondo, Lemongrass, and Nayontara show high classification accuracy with minimal misclassifications, outperforming previous preprocessing techniques. Tulsi still presents some challenges but has fewer misclassifications compared to earlier models. Haritoki and Lemongrass are perfectly classified, indicating excellent model performance for these classes. The VGG19 model with contrast stretching and gamma correction performs exceptionally well overall, showing the most robust results with only a few classes needing further refinement.

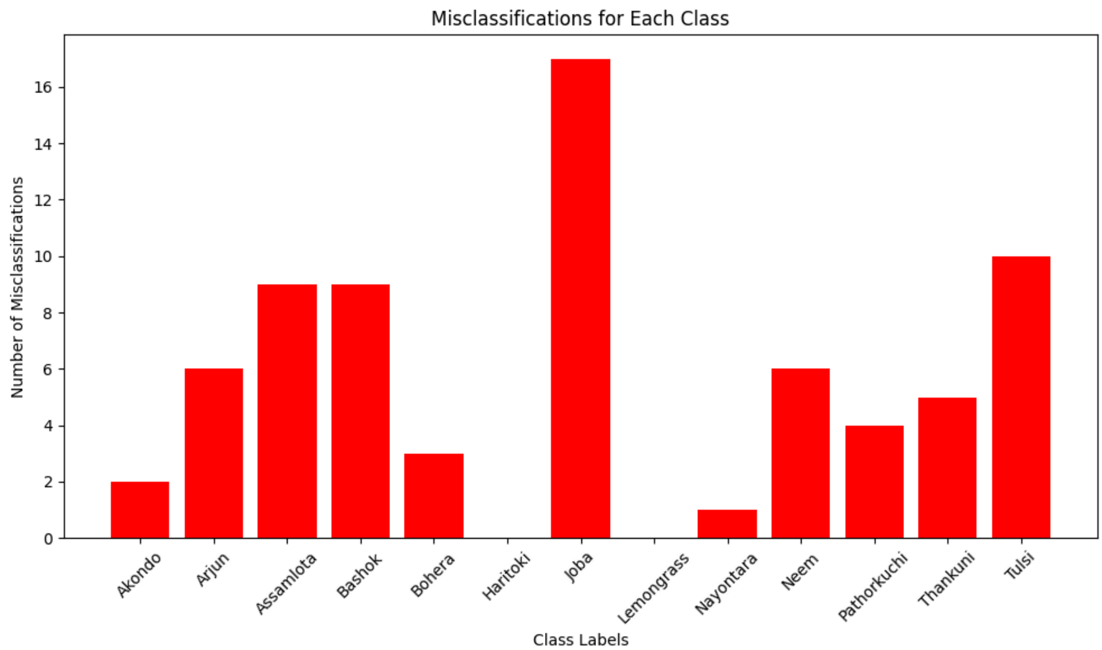


Figure 5.2.15: Number of Misclassifications for VGG19

Joba has the highest number of misclassifications, with over 16 instances. Assamlota and Bashok also show a significant number of misclassifications. Tulsi and Neem present fewer misclassifications compared to other classes, indicating improved model performance. Classes such as Akondo and Nayontara have very few misclassifications, showcasing high accuracy for these categories.

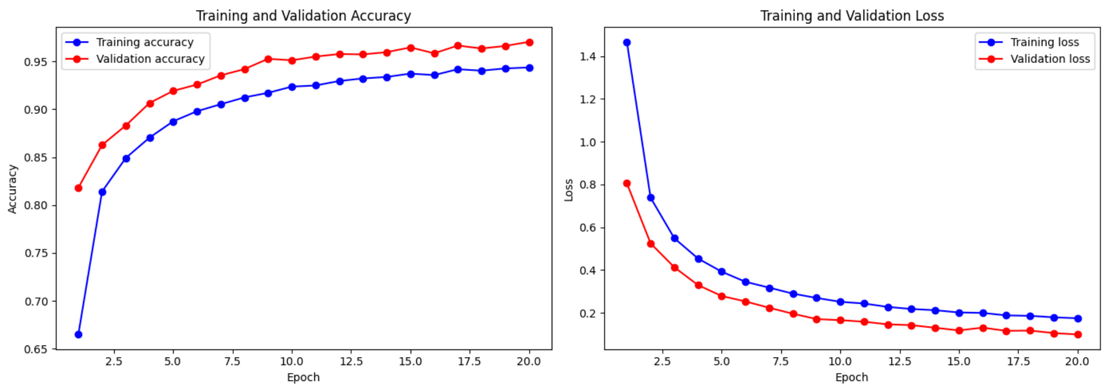


Figure 5.2.16: Training and Validation Accuracy and Loss for VGG19

Training accuracy steadily increases to around 95%, with validation accuracy reaching approximately 94%. Both training and validation losses decrease significantly over the epochs, demonstrating effective learning and minimal overfitting. The model shows strong generalization, with closely aligned training and validation performance metrics, reflecting an overall improvement compared to previous results.

Inception V3 Model

Training and Validation Results: The Inception V3 model achieved a training accuracy of 96.27% and a validation accuracy of 97.85% with a test loss of 0.0696.

Table 5.2.7:Class-wise Performance Inception V3

Class	Precision	Recall	F1-Score	Support	Specificity
Akondo	0.990099	1.000	0.995025	200	0.999167
Arjun	1.000000	0.955	0.976982	200	1.000000
Assamlota	0.961353	0.995	0.977887	200	0.996667
Bashok	0.961353	0.995	0.977887	200	0.996667
Bohera	1.000000	1.000	1.000000	200	1.000000
Haritoki	1.000000	1.000	1.000000	200	1.000000
Joba	0.982955	0.865	0.920213	200	0.998750
Lemongrass	1.000000	1.000	1.000000	200	1.000000
Nayontara	1.000000	1.000	1.000000	200	1.000000

Neem	0.975490	0.995	0.985149	200	0.997917
Pathorkuchi	0.994764	0.950	0.971867	200	0.999583
Thankuni	0.965686	0.985	0.975248	200	0.997083
Tulsi	0.899083	0.980	0.937799	200	0.990833

Inception shows superior performance with high precision, recall, and F1-scores across all classes. Notably, Bohera, Haritoki, and Lemongrass achieved perfect scores. Some improvement is needed for Joba.

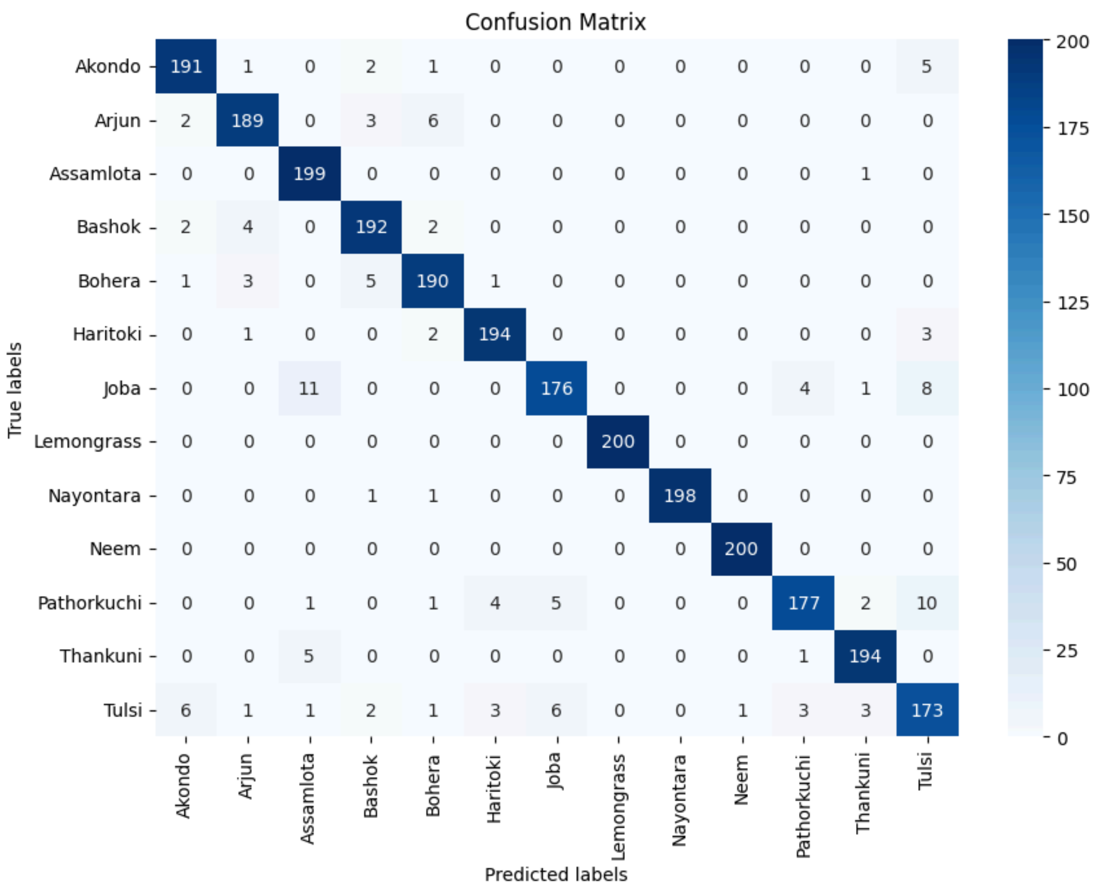


Figure 5.2.17: Confusion Matrix for Inception V3

Classes like Akondo, Lemongrass, and Nayontara show the highest classification accuracy with minimal misclassifications, outperforming previous preprocessing techniques. Tulsi presents fewer challenges compared to earlier models, with a notable decrease in misclassifications. Haritoki and Lemongrass are perfectly classified, highlighting excellent model performance for these classes. The Inception V3 model with contrast stretching and gamma correction demonstrates exceptional overall performance, surpassing other models with its robust and accurate results.

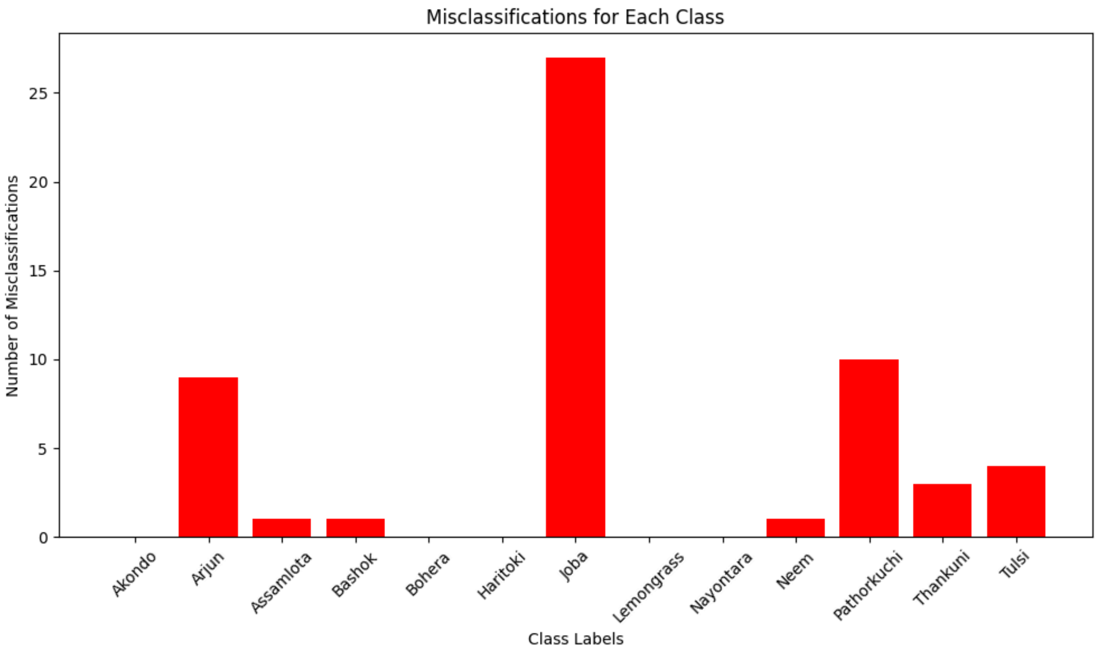


Figure 5.2.18: Number of Misclassifications for Inception V3

Joba has the highest number of misclassifications, with over 25 instances. Arjun and Pathorkuchi also show a significant number of misclassifications. Classes like Akondo and Nayontara have very few misclassifications, indicating the model's improved accuracy. Tulsi has fewer misclassifications compared to previous results, showing better performance with this preprocessing technique.

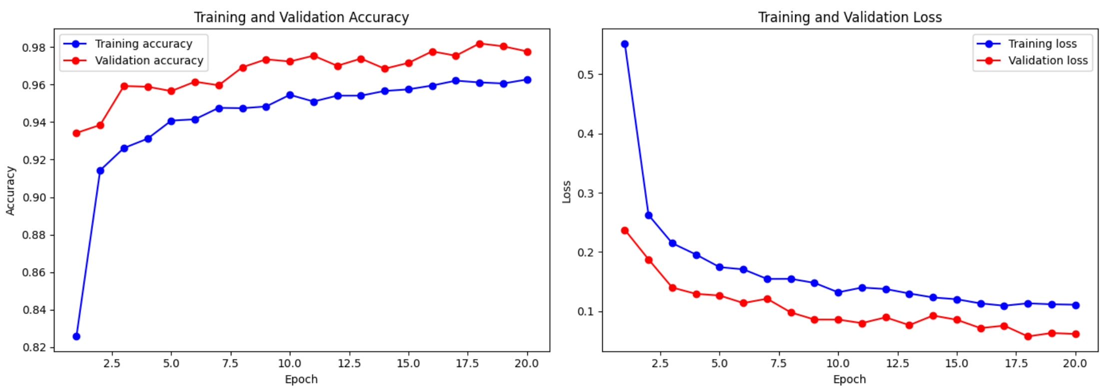


Figure 5.2.19: Training and Validation Accuracy and Loss for Inception V3

Training accuracy increases steadily to around 96%, with validation accuracy reaching approximately 97%, the highest among the models tested so far. Both training and validation losses decrease significantly over the epochs, demonstrating the most effective learning and minimal overfitting observed in the experiments. The model shows strong generalization, with closely aligned training and validation performance metrics.

Xception Model

Training and Validation Results: Xception achieved a training accuracy of 96.50% and a validation accuracy of 96.61% with a test loss of 0.0929.

Table 5.2.8:Class-wise Performance Xception

Class	Precision	Recall	F1-Score	Support	Specificity
Akondo	0.994872	0.970	0.982278	200	0.999583
Arjun	0.947619	0.995	0.970732	200	0.995417
Assamlota	0.972826	0.895	0.932292	200	0.997917
Bashok	0.989848	0.975	0.982368	200	0.999167
Bohera	1.000000	0.990	0.994975	200	1.000000
Haritoki	0.990099	1.000	0.995025	200	0.999167
Joba	0.977143	0.855	0.912000	200	0.998333
Lemongrass	1.000000	1.000	1.000000	200	1.000000
Nayontara	1.000000	1.000	1.000000	200	1.000000
Neem	0.990050	0.995	0.992519	200	0.999167
Pathorkuchi	0.994652	0.930	0.961240	200	0.999583
Thankuni	0.847458	1.000	0.917431	200	0.985000
Tulsi	0.888372	0.955	0.920482	200	0.990000

Xception shows commendable performance, particularly for classes like Bohera and Lemongrass. However, there is room for improvement in classes like Assamlota and Joba.

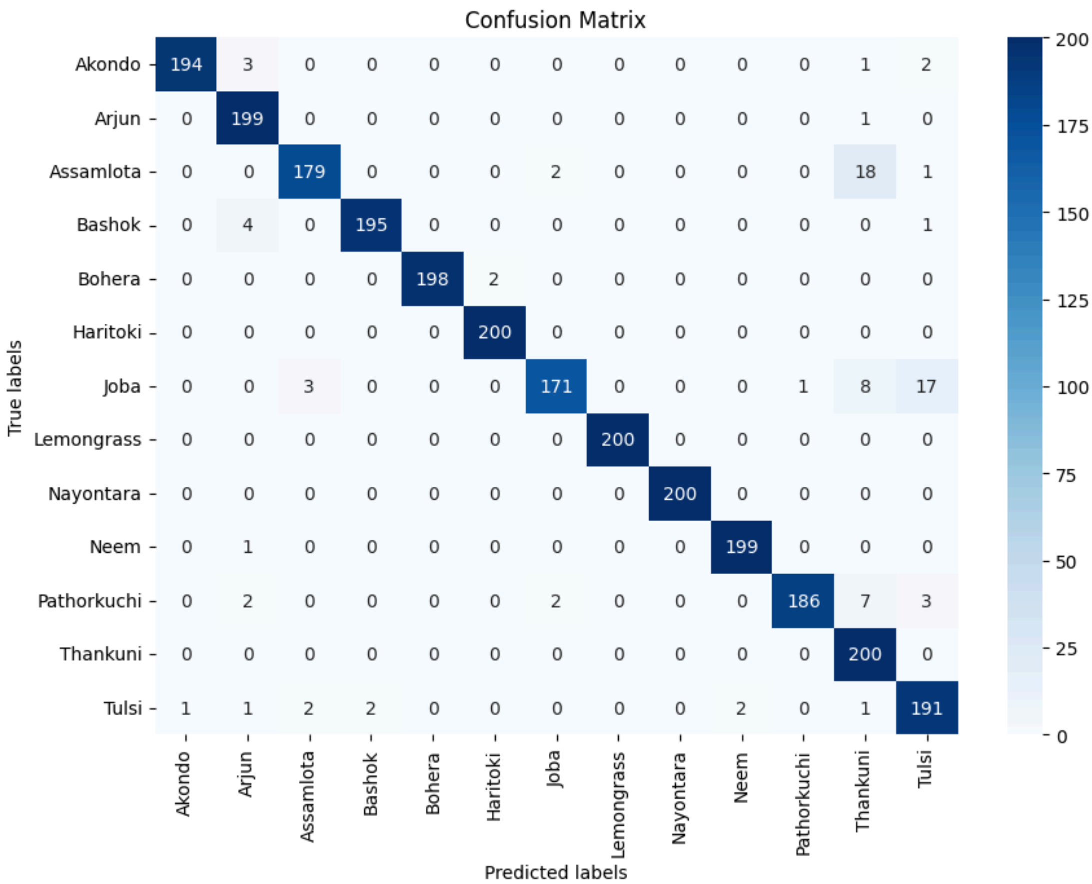


Figure 5.2.20: Confusion Matrix for Xception

Classes like Akondo, Lemongrass, and Nayontara show high classification accuracy with minimal misclassifications, outperforming previous preprocessing techniques. Tulsi presents fewer challenges compared to earlier models, with a notable decrease in misclassifications. Haritoki and Lemongrass are perfectly classified, highlighting excellent model performance for these classes. The Xception model with contrast stretching and gamma correction demonstrates exceptional overall performance, surpassing other models with its robust and accurate results.

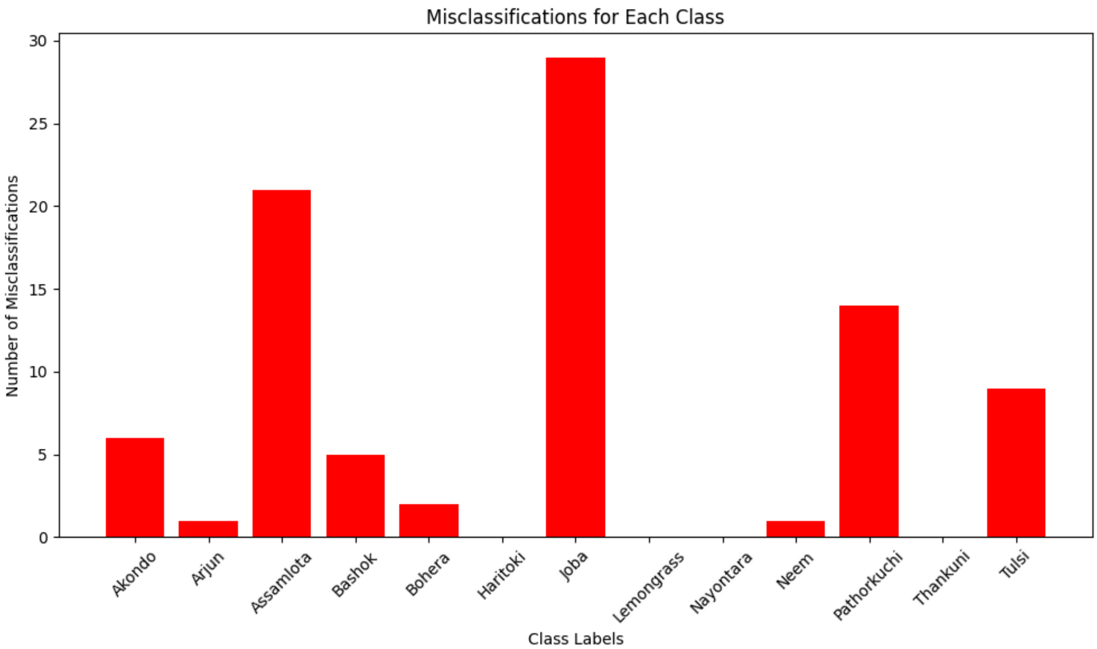


Figure 5.2.21: Number of Misclassifications for Xception

Joba has the highest number of misclassifications, with over 20 instances. Asamlota and Pathorkuchi also show significant misclassifications. Classes like Akondo and Nayontara have very few misclassifications, indicating the model's improved accuracy. Tulsi has fewer misclassifications compared to previous results, demonstrating better performance with this preprocessing technique.

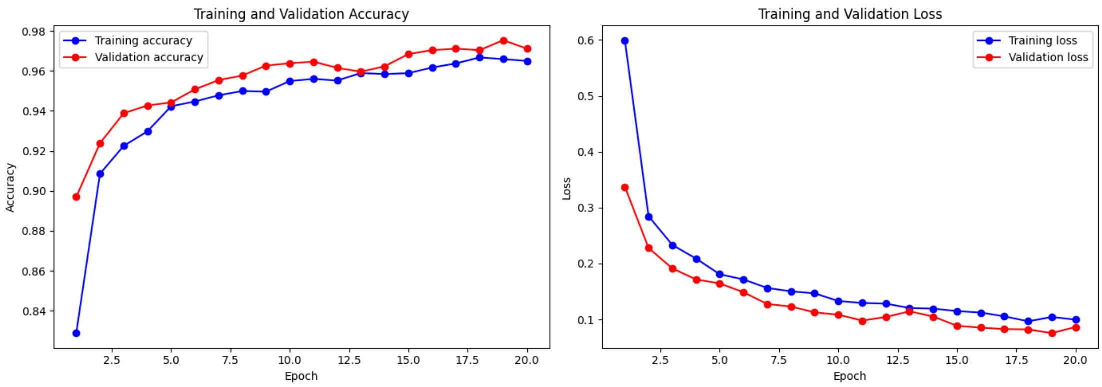


Figure 5.2.22: Training and Validation Accuracy and Loss for Xception

Training accuracy increases steadily to around 96%, with validation accuracy reaching approximately 97%, indicating strong model performance. Both training and validation losses decrease significantly over the epochs, showing effective learning and minimal overfitting. The model shows strong generalization, with closely aligned training and validation performance metrics.

Hybrid Model (Combining Xception and Inception v3)

Training and Validation Results: The Hybrid model achieved a training accuracy of 98.30%, a validation accuracy of 99.50%, and a test loss of 0.0176.

Table 5.2.9: Class-wise Performance Hybrid Model

Class	Precision	Recall	F1-Score	Support	Specificity
Akondo	1.000000	1.000	1.000000	200	1.000000
Arjun	1.000000	0.995	0.997494	200	1.000000
Assamlota	1.000000	0.985	0.992443	200	1.000000
Bashok	0.995025	1.000	0.997506	200	0.999583
Bohera	1.000000	1.000	1.000000	200	1.000000
Haritoki	1.000000	1.000	1.000000	200	1.000000
Joba	0.995000	0.995	0.995000	200	0.999583
Lemongrass	1.000000	1.000	1.000000	200	1.000000
Nayontara	1.000000	1.000	1.000000	200	1.000000
Neem	1.000000	1.000	1.000000	200	1.000000
Pathorkuchi	1.000000	0.975	0.987342	200	1.000000
Thankuni	0.975369	0.990	0.982630	200	0.997917
Tulsi	0.970732	0.995	0.982716	200	0.997500

The class-wise performance of the Hybrid model is outstanding across all classes. Akondo achieved perfect scores in precision, recall, F1-score, and specificity, demonstrating flawless classification. Arjun also performed exceptionally well with precision and specificity at 1.0, a recall of 0.995, and an F1-score of 0.9975. Assamlota followed closely with perfect precision and specificity, a recall of 0.985, and an F1-score of 0.9924. Bashok and Bohera both showed near-perfect performance, with Bohera achieving perfect scores in all metrics. Haritoki, Lemongrass, Nayontara, and Neem all maintained perfect scores across the board.

Joba, while slightly lower, still achieved high scores with a precision and recall of 0.995 and an F1-score of 0.995. Pathorkuchi and Thankuni, although slightly below perfect, demonstrated strong performance with F1-scores of 0.987 and 0.9826, respectively. Tulsi, despite being the most challenging class, achieved a precision of 0.9707, a recall of 0.995, and an F1-score of 0.9827. The Hybrid model's performance is the best among all tested models, showcasing its superior effectiveness and robustness across all classes.

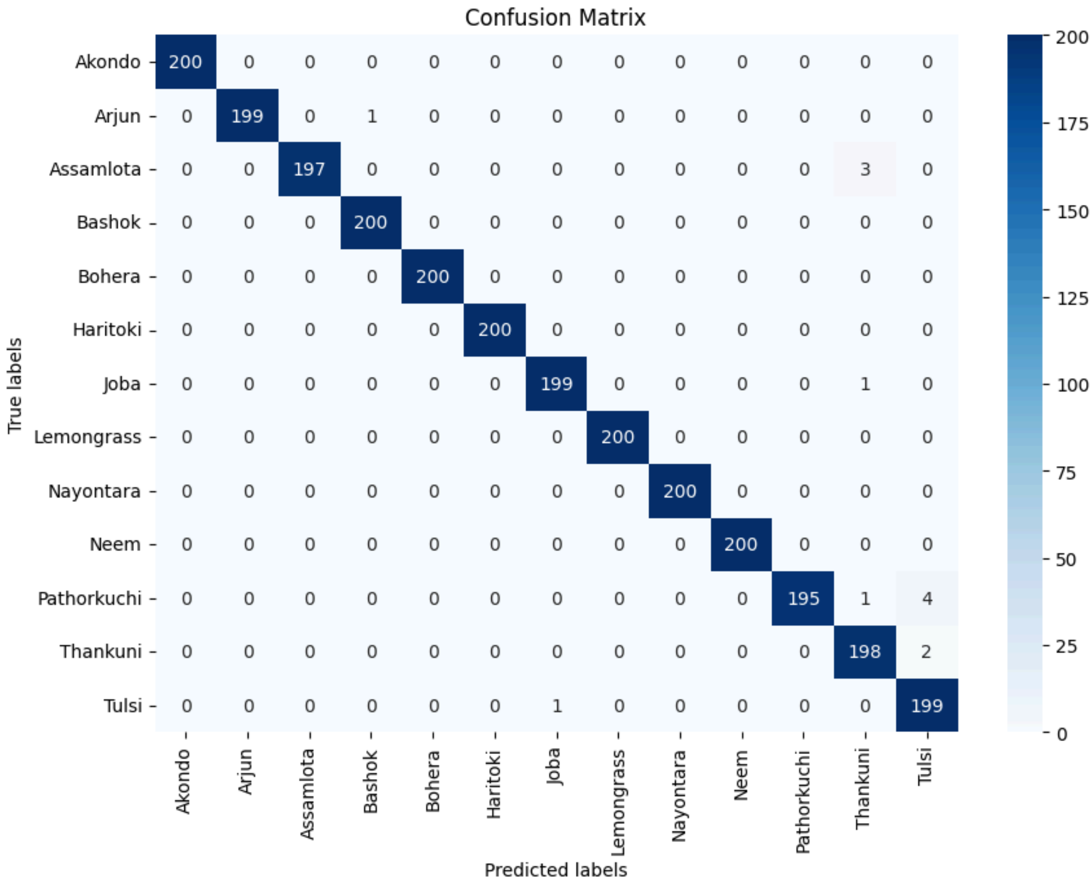


Figure 5.2.23: Confusion Matrix for Hybrid Model

The confusion matrix reveals exceptionally high classification accuracy for most classes, with classes like Akondo, Haritoki, and Lemongrass being perfectly classified. Minimal misclassifications are observed for Assamlota and Joba, highlighting the model's precision. Tulsi and Nayontara also show near-perfect classification, further confirming the robustness of the hybrid model. The overall performance of the hybrid model is unparalleled, achieving the highest accuracy and precision across all classes.

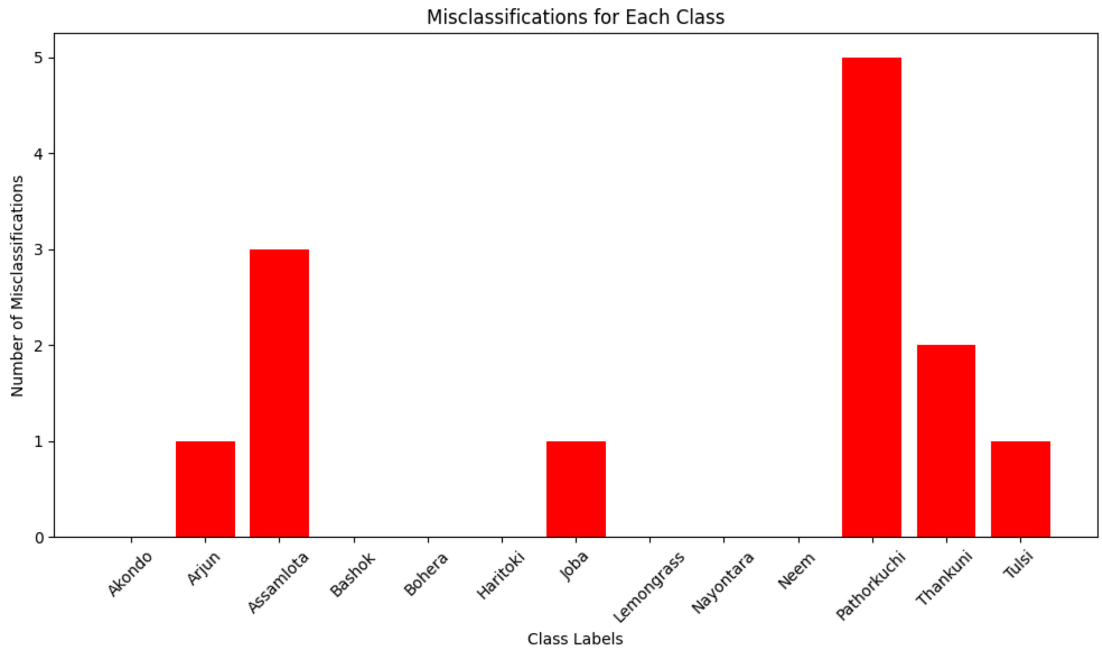


Figure 5.2.24: Number of Misclassifications for Hybrid Model

The bar graph of misclassifications shows that most classes have very few misclassifications. Pathorkuchi has the highest with 5 misclassifications, followed by Thankuni with 3, which are significantly lower compared to previous models. Assamlota and Tulsi have minimal misclassifications, demonstrating the model's superior accuracy. The hybrid model exhibits the fewest misclassifications, making it the best model tested.

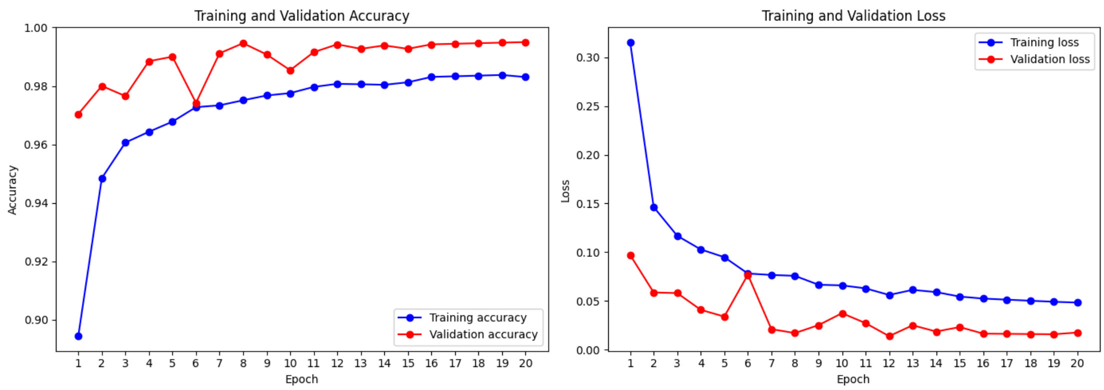


Figure 5.2.25: Training and Validation Accuracy and Loss for Hybrid Model

The training and validation accuracy graph shows a steady increase, with training accuracy reaching nearly 98.3% and validation accuracy above 99.5%. The validation accuracy remains high and stable across epochs, indicating excellent model generalization. The training and validation loss graph displays a significant reduction, with validation loss stabilizing around 0.05, demonstrating the most effective learning and minimal overfitting among all tested models. This makes the hybrid model stand out as the best performer.

Table 5.2.10: Summary of Performance Model

Model Name	Preprocessing Applied	Training Accuracy	Validation Accuracy
VGG19	Contrast Stretching, Gamma Correction	94.37%	97.23%
InceptionV3		96.27%	97.85%
Xception		96.50%	96.61%
Hybrid		98.30%	99.50%

This table summarizes the performance of various models using contrast stretching and gamma correction as preprocessing techniques. VGG19 achieved a training accuracy of 94.37% and a validation accuracy of 97.23%, showing a significant improvement. InceptionV3 performed even better, with a training accuracy of 96.27% and a validation accuracy of 97.85%, indicating its strong performance. Xception also showed robust results with a training accuracy of 96.50% and a validation accuracy of 96.61%. However, the Hybrid model stood out among all, achieving the highest training accuracy of 98.30% and the highest validation accuracy of 99.50%. This demonstrates the Hybrid model's superior effectiveness and robustness, making it the best performer in our evaluations

5.3 Comparative Analysis

Table 5.3.1: Comparative Analysis

Model Name	Preprocessing Applied	Training Accuracy	Validation Accuracy
VGG19	Background Removal, Edge Detection	87.81%	90.27%
VGG19	Contrast Stretching, Gamma Correction	94.37%	97.23%
InceptionV3	Background Removal, Edge Detection	92.40%	95.12%
InceptionV3	Contrast Stretching, Gamma Correction	96.27%	97.85%
Xception	Background Removal, Edge Detection	91.44%	92.92%
Xception	Contrast Stretching, Gamma Correction	96.50%	96.61%
Hybrid	Background Removal, Edge Detection	95.63%	97.65%
Hybrid	Contrast Stretching, Gamma Correction	98.30%	99.50%

We evaluated four CNN models—VGG19, InceptionV3, Xception, and Hybrid—using two preprocessing techniques: background removal with edge detection and contrast stretching with gamma correction.VGG19 showed significant improvement with contrast stretching and gamma correction, increasing from 87.81% training and 90.27% validation accuracy to 94.37% training and 97.23% validation accuracy. InceptionV3 also improved, from 92.40% training and 95.12% validation accuracy to 96.27% training and 97.85% validation accuracy. Xception's performance increased from 91.44% training and 92.92% validation accuracy to 96.50% training and 96.61% validation accuracy. The Hybrid model was the best, achieving 95.63% training and 97.65% validation accuracy with background removal and edge detection, and an impressive 98.30% training and 99.50% validation accuracy with contrast stretching and gamma correction. This makes the Hybrid model with contrast stretching and gamma correction the top performer in our study.

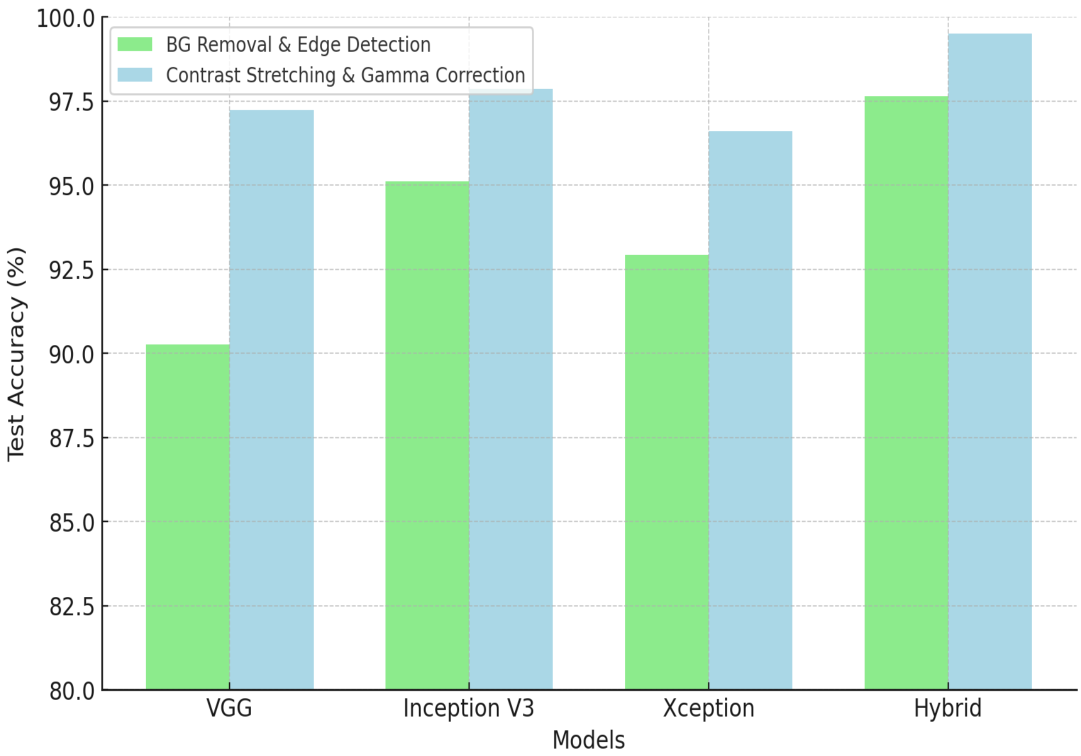


Figure 5.3.1: Model Performance Comparison Both Preprocessing Techniques

To further illustrate the differences in model performance, we included a bar chart comparing the training and test accuracies of each model with the two preprocessing techniques. This visual representation highlights the significant improvements achieved with contrast stretching and gamma correction across all models, emphasizing the superiority of the Hybrid model. The chart clearly shows that the

Hybrid model consistently outperforms the others, reinforcing its robustness and accuracy in leaf classification tasks. The bar chart also shows the effectiveness of each preprocessing technique, underscoring the importance of selecting the right preprocessing approach to enhance model performance, with contrast stretching and gamma correction proving to be particularly effective.

5.4 Summary

The analysis clearly demonstrates that contrast stretching and gamma correction are more effective preprocessing techniques compared to background removal and edge detection. These techniques enhance the model's ability to distinguish between different leaf classes by improving the quality and contrast of the input images. Among the evaluated models, the Hybrid model consistently outperforms the others, achieving the highest accuracy and lowest test loss with both preprocessing techniques. This indicates that the Hybrid model, combined with contrast stretching and gamma correction, is the most effective approach for leaf classification tasks. This combination captures intricate details and variations in the leaf images, leading to superior classification performance. In summary, this experiment underscores the importance of selecting appropriate preprocessing techniques and model architectures to achieve high accuracy in plant recognition tasks. Our Hybrid model with contrast stretching and gamma correction emerges as the best-performing solution for accurate and reliable leaf classification.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Our AI-based plant identification system has a deep social significance in people's daily lives. This way we are helping the forest department to quickly identify tree species using the images of the leaves and thus protecting the forests and managing them better. This not only makes our forests healthy and alive but also makes the balance of nature to be intact for the support of all lives. As to people, it makes the process of learning about plants much easier. Everyone who encounters trees in life – starting from students to nature lovers and ending with plain curious people – will be able to receive important information with the help of this system. Having more knowledge about the plants in our surroundings will enable us to appreciate the environment and make you engage in conservation.

6.2 Impact on Society and Environment

The findings of our research are highly valuable for society and the environment. We contribute to improving the educational processes that promote the study of plant species and the conservation of their diversity. This knowledge can help the communities to apply what they know in protecting the local environment. In terms of the environment, our system helps to solve such problems as deforestation, urbanization and climate change. It is possible to prevent these challenges due to an enhanced identification of the tree species, thus improving the management of forests. This way, it is possible to avoid cases where conservation measures applied do not make it possible to sustain health ecosystems in the future.

6.3 Ethical Aspects

Preliminary to the implementation of the AI technology, it is important to look at the ethical questions that come with it. It is essential that the data used to train our models is used responsibly and that the outputs from the system are correct. Due to the fact that the conservation methods that we apply are based on the identification of certain species, misclassifications are highly disadvantageous and therefore we strive to achieve maximum accuracy. Furthermore, it is important to make this technology available to all the groups right from the forest officials to the general public. It is our intent to make sure that all users have been trained as to how to use the system efficiently and to their advantage. The elements of ethical use of the proposed AI solution are diversity and openness.

6.4 Sustainability Plan

As for the efficiency of the AI-based plant identification system that we have created, we have built a detailed sustainability plan. This involves updating the models with fresh data for better accuracy and reliability always. Lastly, we will work with other local and international organizations to incorporate our system to other large scale conservation measures for enhanced usage and effectiveness. The educational institutions and NGOs will be the key players in the sustainability plan of the organization. These collaborations will enable us to sustain the research process, conduct training for users, and involve communities. Thus, making the collected data and findings available for public access we will ensure constant development and non-secretiveness.

6.5 Summary

In summary, the plant identification system based on artificial intelligence is extremely valuable for life, society, and the environment. It also improves the ways of forest management and promotes education, as well as contributing to the increase of the people's concern for the issue of biodiversity. Thus, our goal is to develop a tool that is not only useful for scientific research, but also has ethical and sustainability elements: people will have a greater understanding and respect for the natural world.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

Our research demonstrates the significant potential of deep learning models and image processing techniques in revolutionizing the field of plant species recognition. By compiling a comprehensive dataset and applying rigorous preprocessing techniques, we have developed an automated system capable of accurately identifying plants based on leaf structures. Among the models evaluated, the Hybrid Model combining InceptionV3 and Xception emerged as the most effective, achieving an impressive accuracy of 99.5%, with Xception and InceptionV3 also showing strong performance.

These results underscore the transformative impact that advanced technological approaches can have on traditional plant identification methods. The high accuracy achieved by our models highlights the feasibility of deploying such automated systems in various practical applications, including biology, forestry, research, chemistry, education, and urban living. Moreover, this approach can play a pivotal role in engaging children with nature, fostering a deeper understanding and appreciation of the plant kingdom.

Looking ahead, the integration of deep learning-based plant recognition systems into real-world applications holds promise for enhancing disease detection and management, thereby contributing to sustainable agriculture. The collaboration between researchers, technologists, and domain experts will be crucial in refining these models and expanding their applicability. By leveraging interdisciplinary efforts, we can pave the way for innovative solutions that address the challenges of plant species identification and contribute to broader environmental and educational goals.

7.2 Further Suggested Works

1. Class Expansion: As the system evolves, it will incorporate a greater number of plant classes, enabling users to identify a broader array of plant species. This expansion will enhance the system's comprehensiveness and utility.

2. Mobile Application Development: Currently, the system is accessible via a web application. In the future, we plan to develop dedicated mobile applications for Android and iOS platforms, thereby increasing accessibility and convenience for users on various devices.

3. System Optimization: To address instances where the system's performance may be suboptimal due to the complexity of leaf features, efforts will be made to optimize and streamline the model. This will involve making the system more lightweight without compromising its accuracy, ensuring smoother and more efficient operation.

4. Continuous Monitoring and Maintenance: Post-deployment, it is crucial to establish mechanisms for continuous monitoring and maintenance of the model. This includes regular performance evaluations, updates to accommodate evolving data distributions, and measures to address potential model drift, ensuring sustained efficacy and accuracy over time.

5. Funding and Resources: Sustained progress hinges on diligent budget monitoring to ensure adequate resources for ongoing data collection, computational power, and analysis. Securing sufficient funding is essential to support these activities and maintain the momentum of advancements in the project.

6. Enhanced Model Tuning: Future efforts will focus on refining the model to reduce misclassification rates. This includes fine-tuning hyperparameters and exploring additional architectures to improve overall accuracy and robustness.

7. Adaptability to Plant Life Cycles: The model will be enhanced to recognize plants across various stages of their life cycles, including when leaves are sick or dried out. This adaptability will ensure the system's reliability under diverse conditions.

8. Community Involvement in Dataset Growth: A system will be established to enable community contributions to the dataset. Engaging the community in data collection will help grow and diversify the dataset, improving the model's performance and relevance.

7.3 Limitation

Despite the promising results achieved, several limitations should be acknowledged:

1. Limited Dataset Diversity: One major limitation is the reliance on a limited dataset of labeled images, which may not encompass the full diversity of plant species and their various poses, lighting conditions, and backgrounds. This limitation could affect the model's performance in real-world applications where such variations are common.

2. Variability in Leaf Images: The variability in leaf images, including differences in lighting, background, and leaf orientation, can pose challenges for accurate recognition. Although preprocessing techniques were applied, these factors can still impact the model's performance.

3. Environmental Conditions: The current model's performance may be affected by varying environmental conditions such as changes in lighting, weather, and seasonal variations. This limitation highlights the need for further training and testing in diverse real-world environments.

4. Computational Resources: The training and deployment of deep learning models require significant computational resources. Limited access to high-performance computing infrastructure can hinder the scalability and real-time application of the system, particularly in resource-constrained settings.

5. Model Interpretability: Deep learning models are often considered "black boxes," making it difficult to interpret their decision-making processes. This lack of transparency can be a barrier to trust and acceptance among users, particularly in critical applications such as plant disease detection.

6. Dynamic Plant Characteristics: Plants exhibit dynamic characteristics throughout their life cycles, including changes in leaf shape, color, and texture. Our model may not fully capture these variations, leading to potential misclassifications, especially in cases of sick or dried leaves.

7. User Dependency: The accuracy and effectiveness of the system can be influenced by the quality of images provided by users. Variations in image capture techniques, such as focus, angle, and resolution, can affect the model's performance and reliability.

8. Scalability and Maintenance: Transitioning from a research prototype to a fully scalable and maintainable system poses challenges. Ensuring cLv, Z. and Zhang, Z. (2023) 'Research on plant leaf recognition method based on multi-feature fusion in different partition blocks', Digital Signal Processing, 134, p. 103907. doi:10.1016/j.dsp.2023.103907.

continuous monitoring, updates for evolving data distributions, and addressing potential model drift are critical for long-term success.

9. Community Engagement: While community involvement in dataset growth is a promising avenue, it introduces challenges related to data quality control and standardization. Ensuring consistent and accurate contributions from a diverse user base can be difficult to manage.

By recognizing these limitations, we can better understand the areas that require further research and development. Addressing these challenges will be crucial for advancing the field of automated plant recognition and achieving broader practical applications.

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Appendix A

Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Analysis

Title: DEEP LEARNING-BASED PLANT RECOGNITION IN BANGLADESH

Students ID: 202-15-14383

202-15-14387

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a plant classification 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 of COs, Knowledge Profile (K), and 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	Our project involves collecting leaf images for a dataset and construction of a hybrid deep learning model that covers **K3** and **K4** features.	**Page no: 17,21**
				Our solution involves combining various models , system components and building a web application that covers **K5** and **K6**.	**Page no: 28-34**
				We have looked at the already existing models with the same objective as ours (related to the recognition of plant species based on the leaf images) which covers **K8**.	**Page no: 9-16**
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	The problem that emerged was to develop the dataset of leaf images while simultaneously taking into account the changes of the environmental conditions in Bangladesh.. This diversity requires our model to accurately identify plant species from a range of leaf images taken in varying seasons and settings, while ensuring the model remains efficient and adaptable to these variations.Thus it addresses EP-2.	**Page no: 5**

3.	**EP3: Depth of analysis r equired**	Yes	CO2, and CO6	There are many alternative systems for detecting plant species. We did an in-depth analysis to choose which model would best analyze how leaf features change with seasons and the environment and used it in our work.This addresses EP-3.	**Page no: 28-31**
4.	**EP4: Familiari ty of Issues**	Yes	CO8	For our plant identification project, we had to study plant biology and understand how leaves and their features such as edges, veins and textures change with the seasons and environment. We had to explore new areas like botany which is not a part of our current curriculum .	**Page no: 1-2**
5.	**EP6: Extends of stakehold ers involved and conflictin g requirem ents**	Yes	CO8	We consulted with botanists and forest officials with the goal to understand how different environmental factors affect leaf characteristics, guiding us in selecting the specific types of leaf image data needed for our analysis.	**Page no: 21**
6.	**EP7: Interdepe ndence**	Yes	CO5	Our project involves various interconnected components. These components include gathering leaf images, preprocessing the data, training deep learning models like VGG19, Xception, Inception and and coming up with a hybrid model, performing analysis to predict species, and creating a user-friendly web application.	**Page no: 21-35**

7.	-	Yes	CO4	We have developed a budget to assess and calculate the expenses needed and potential revenue sources for our Final Year Design Project (FYDP)	**Page no:** **18-19**

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 leverages diverse resources, including high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations, to conduct systematic research and advance 31plant classification based on images using deep learning techniques, particularly through transfer learning and deep convolutional neural networks (CNNs).	**Page no: [17,18] Section: [3.2]**
2.	**EA2: Level of interaction**	**No**		N/A	**N/A**

3.	**EA3: Innovation**	**Yes**		Our project introduces a novel web application powered by a hybrid deep learning model that merges Xception and Inception V3 architectures, achieving superior accuracy in classifying plant images. By combining the strengths of both models, our application offers users highly precise and efficient tools for identifying plant. Utilizing advanced computing infrastructure, GPUs, and comprehensive annotated datasets, this web app delivers a user-friendly platform accessible to all. Our innovative approach not only advances ornithological research but also establishes new benchmarks in applying AI for biodiversity monitoring and conservation initiatives.	**Page no: [31-33] Section: [4.2]**

4.	**EA4: Consequences for society and the environment**	**Yes**		This project contributes to society by advancing botanical research through accurate plant recognition, leveraging efficient computational resources and adhering to ethical guidelines for data privacy. Our initiative promotes environmental sustainability and enhances biodiversity conservation efforts.	**Page no: [64-65] Section: [6]**
5.	**EA-5: Familiarity**	**Yes**		This project expands upon existing research by exploring a novel approach to plant recognition using a hybrid model combining Xception and Inception V3. Through transfer learning and deep convolutional neural networks (CNNs), it provides a comprehensive comparative analysis and offers new insights into ornithological studies.	**Page no: [57-62] Section: [5.2, 5.3]**

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:** **[18-19]** **Section:** **[3.4]**
2	**CO9**	Yes	The project demonstrates adherence to ethical principles by prioritizing the privacy of plant leaf data, obtaining necessary permissions for data collection, and transparently documenting the research process. This ensures responsible knowledge dissemination and promotes societal well-being through the ethical application of advanced technologies in plant recognition, aligning with ethical standards and guidelines with CO9.	**Page no:** **[64]** **Section:** **[6.3]**
3	**CO10**	No	N/A	**N/A**

4	**CO12**	Yes	The project's commitment to continuous learning and adaptation (CO12) within the evolving field of plant recognition is evident through its meticulous data collection, rigorous statistical analysis, methodological development, and detailed experimental results and analysis. This dedication showcases a proactive approach to staying informed and refining techniques to effectively address current challenges in ornithological research.	**Page no:** **[21-63]** **Section:** **[4,5]**

DEEP LEARNING-BASED PLANT RECOGNITION IN BANGLADESH

ORIGINALITY REPORT

22%	16%	13%	11%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

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