CAULIFLOWER DISEASE DETECTION USING A DEEP LEARNING APPROACH

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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 "Cauliflower Disease Detection Using a Deep Learning Approach", submitted by A.Z.M Amanullah Aman, ID No: 193-15-13503 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 14.07.2024.

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I hereby declare that this project has been done by me under the supervision of **Mr. Tanvirul Islam, Lecturer, Department of Computer Science and Engineering, Daffodil International University**. I 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

Cauliflower, a significant crop in global agriculture, is susceptible to various diseases that can severely impact yield and quality. Accurate detection and classification of the diseases are crucial for effective crop management and sustainable agricultural practices. This research paper explores the application of deep learning techniques for the detection and classification of cauliflower diseases from images.

The study investigates several state-of-the-art deep learning architectures, including CNN, EfficientNetB3, EfficientNetB7, EfficientNetV3, MobileNetV3, ResNet32, and ResNet50. These models were trained on a custom-collected dataset comprising five classes: Cauliflower Healthy, Cauliflower Healthy Leaf, Cauliflower Leaf Black Rot, Cauliflower Leaf Red Spot, and Cauliflower Spot Rot. Comprehensive image preprocessing, including augmentation and contrast enhancement, was employed to improve model robustness and generalization.

The performance of each model was evaluated using metrics such as precision, recall, and accuracy. MobileNetV3 achieved the highest accuracy of 99%, demonstrating its superior ability to distinguish between healthy and diseased conditions. This high accuracy underscores the potential of deep learning in supporting precise agricultural interventions.

By advancing our ability to accurately diagnose cauliflower diseases, this research contributes to improved crop management and productivity. The study also discusses challenges encountered during the process and suggests potential avenues for future research to enhance disease detection capabilities in real-world agricultural scenarios. The findings highlight the importance of integrating advanced technological solutions into farming practices to support sustainable agriculture and food security.

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Introduction

1.1 Introduction

Agriculture plays a critical responsibility in preserving food security and supporting economic success. Cauliflower, a routinely planted vegetable, is sensitive to different illnesses that can severely impair crop output and quality. Early and correct diagnosis of these diseases is vital for optimal crop management and minimizing losses. Traditional processes of disease identification typically rely on visual inspection by professionals, which can be laborious and prone to errors.

In recent years, developments in technology have opened the path for more efficient and trustworthy solutions. Deep learning, a type of artificial intelligence, has demonstrated enormous potential in the field of photo recognition and categorization. By employing deep learning methods, it is possible to construct automated systems that can efficiently recognize and classify plant diseases based on photographs of damaged leaves.

This research focuses on the detection of cauliflower diseases utilizing different deep learning models, including Convolutional Neural Networks (CNN), EfficientNetB3, EfficientNetB7, MobileNetV3, ResNet32, and ResNet50. These models are chosen for their proven efficacy in picture categorization tasks. The goal is to establish a reliable system that can aid farmers and agricultural professionals in diagnosing diseases at an early stage, hence enhancing crop management and productivity.

The project requires collecting a massive dataset of cauliflower leaf images, preprocessing these images to boost their quality, and enriching the dataset to improve the models' generalization skills. The performance of each model is evaluated based on criteria like as accuracy, precision, recall, and F1-score. Additionally, the project seeks to construct a user-friendly web interface that provides real-time disease detection by submitting leaf pictures.

By overcoming the hurdles of cauliflower disease identification with advanced deep learning techniques, this research seeks to contribute to the field of agricultural technology. The findings can potentially lead to more sustainable farming practices, lower crop losses, and increase food security. The next chapters will discuss the background, methodologies, experimental results, and broader implications of this work.

1.2 Motivation

Agriculture, being a significant contributor to the global economy, is a vital source of food, income, and employment. In middle-income nations, where a large number of farmers reside, agriculture accounts for 18% of the GDP and raises the employment rate to 53%. Over the past three years, the gross value added (GVA) by agriculture to the national economy has grown from 17.6% to 20.2%. This sector offers the largest share of economic growth. Early monitoring and accurate detection of crop diseases using an effective crop protection system can prevent losses in production quality.

Recognizing plant diseases is crucial and remains a significant focus in agriculture. Early detection can lead to better decisions in managing agricultural productivity. Infected plants typically display visible marks or spots on their stems, fruits, leaves, or flowers. Each type of infection and pest issue leaves distinctive patterns that help identify abnormalities. Detecting plant diseases requires expertise and labor. Additionally, manual inspection for identifying plant infections is subjective, time-consuming, and sometimes inaccurate. Misdiagnosis by farmers or specialists can result in the use of incorrect treatments, potentially damaging crop quality and polluting the environment.

The rise of computer vision has introduced various solutions to tackle the challenges of detecting plant diseases, as infected areas initially appear as spots and patterns on leaves. Researchers have devised multiple techniques to accurately identify and classify these diseases. Some of these techniques utilize conventional image processing methods, which involve manual feature extraction and segmentation.

1.3 Rational of the Study

The idea for this deep learning-based cauliflower disease detection investigation arises from the crucial need to efficiently solve agricultural concerns. Cauliflower, a major crop in worldwide agriculture, is susceptible to a variety of illnesses, which can significantly impair productivity and quality. Early and accurate recognition of these diseases is critical for prompt action and effective management, allowing farmers to reduce losses while enhancing crop health.

Traditional disease detection methods, which rely heavily on expert visual inspection, are time-consuming and error-prone. Because of the arbitrary nature of human assessment and the variety in disease presentation, these strategies can be ineffective. Automated systems that use deep learning, on the other hand, can deliver consistent, accurate, and timely disease detection, which is critical in modern agriculture.

This study aims to implement and compare many cutting-edge deep learning models, including CNN, EfficientNetB3, EfficientNetB7, EfficientNetV3, MobileNetV3, ResNet32, and ResNet50. The study uses a personally generated and well-annotated dataset to ensure high-quality data that accurately mimics real-world settings. The study's goal is to find the best effective model for illness detection in cauliflower while also offering significant insights into performance indicators such as precision, recall, and reliability.

The findings of this study have important consequences for the agricultural industry. Implementing a dependable deep learning-based disease identification system can provide farmers with tools to detect diseases early on, reduce reliance on expert consultations, and maximize resource utilization. This can result in better crop management, higher yields, and, eventually, increased food security.

Ultimately, the study tackles a critical need in agriculture by utilizing advanced deep learning techniques to improve disease detection in cauliflower. The discoveries may open the door for larger use in additional crops, contributing to more sustainable farming methods and increased productivity.

1.4 Research Questions

How accurate are deep learning models in detecting various cauliflower diseases?

This topic seeks to assess the efficacy of various deep learning algorithms (CNN, EfficientNetB3, EfficientNetB7, MobileNetV3, ResNet32, and ResNet50) in detecting and categorizing illnesses in cauliflower leaves with good precision and recall.

Which preprocessing strategies improve the quality and variety of cauliflower disease photos used in model training?

This subject analyzes how preprocessing processes such as gamma correction, Gaussian filtering, and histogram equalization, in addition to data augmentation strategies, improve the dataset for training deep learning models.

Which deep learning algorithm outperforms others in terms of precision, loss measures, and visuals for detecting cauliflower disease?

This topic compares the efficiency metrics and visual outputs of multiple models (confusion matrix, ROC-AUC curves) to determine the most effective illness detection algorithm.

How do we create a web-based application for real-time disease detection in cauliflower leaves?

This topic covers the practical application of research findings by creating a user-friendly web interface that allows users to input photos and receive real-time predictions on the disease state of cauliflower leaves.

What are the socioeconomic and environmental implications of using improved disease detection technology in agriculture?

This topic looks at the larger implications of deploying deep learning-based disease detection systems, such as the benefits to crop health, production improvement, and sustainable farming methods.

What are the guidelines and obstacles for future study into cauliflower disease detection with deep learning?

This question seeks to describe the study's findings, including any problems faced and effective techniques, in order to serve as a road map for additional studies in this area.

1.5 Expected Output

This research on cauliflower disease detection using deep learning is predicted to produce a variety of results, including technical, practical, and societal effects. These results include:

Accurate Disease Detection Models:

The creation of extremely accurate deep learning models (CNN, EfficientNetB3, EfficientNetB7, MobileNetV3, ResNet32, ResNet50) able to identifying numerous cauliflower diseases with high precision, recall, F1-score, and overall accuracy.

Comprehensive dataset:

A well-preprocessed and enhanced dataset of cauliflower photos, illness labels included, that may be used for future study and model training.

Performance metrics and visualizations:

Detailed performance metrics (accuracy, loss, confusion matrix, and ROC-AUC curves) and visualizations that demonstrate each model's effectiveness in detecting cauliflower disorders, allowing for comparison study and the optimal model selection.

Robust preprocessing pipeline:

An effective preprocessing pipeline that uses gamma correction, Gaussian filtering, histogram equalization, and data augmentation approaches to improve image quality and variety, hence boosting model performance.

User-friendly Web Interface:

Created a web-based program that allows users to upload photographs of cauliflower leaves and receive real-time disease forecasts, making it a useful tool for farmers and agricultural professionals.

Impact Assessment:

An assessment of the societal and environmental consequences of applying sophisticated disease detection technology in agriculture, including the possible benefits for crop health, yield improvement, and sustainable farming methods.

Guidelines For Future Research:

Comprehensive documents and insights that illustrate the problems, triumphs, and areas for development in cauliflower disease detection with deep learning, providing recommendations for future research and advancements in the field.

The project seeks to greatly advance the application of agricultural diagnostics by producing these results, which will provide practical resources and expertise that can improve crop management efficiency and sustainability.

1.6 Project Management and Finance

Effective project management and financial oversight are integral components of ensuring the success and sustainability of any endeavor, and they hold particular significance in the context of the proposed research. The project management aspect encompasses meticulous planning, coordination, and execution of tasks, ranging from data collection to model training and evaluation. A well-defined project plan will be devised to outline key milestones, allocate resources judiciously, and establishtimelines, fostering a structured and efficient workflow. Concurrently, robust financial management will be paramount to the project's viability, encompassing budgetary allocations for equipment, computational resources, and potential research collaborations. A transparent and judicious financial strategy will be implemented, ensuring optimal resource utilization while maintaining fiscal responsibility. These integrated approaches toproject management and finance are essential pillars that will empower the research team to navigate the complexities of the study effectively, ensuring that the allocated resourcesalign with the research objectives and facilitating the seamless progression of the project towards its goals.

Table 1.5.1: Cost Analysis

Task Description	Estimated Cost (BDT)
Miscellaneous	1000
Internet and Utilities	2,000
Documentation and Reporting	500
Total Estimated Cost	3500

1.7 Report layout

The proposed report is organized in a comprehensive manner to walk readers through the study process, findings, and consequences. Every section serves a particular purpose, which adds to the document's overall cohesion and depth.

Chapter 1: Introduction.

The very first section sets up for the investigation by explaining the importance of cauliflower illness detection. It covers the use of deep learning techniques like CNN, EfficientNetB3, EfficientNetB7, MobileNetV3, ResNet32, and ResNet50. The chapter discusses the research topics, aims, and overall framework of the study, highlighting the importance of good disease detection in agricultural.

Chapter 2: Background.

The background chapter provides a thorough review of the pertinent literature and prior research. This section provides a thorough knowledge of the fundamental theories, methodology, and technological breakthroughs associated with agricultural disease diagnosis using deep learning. It provides background for the current investigation and identifies knowledge gaps, particularly in the diagnosis of cauliflower illnesses.

Chapter 3: Research Methodology.

The research methods chapter describes the approach used for carrying out the study. It discusses the research design, data collection methods, preprocessing stages (gamma correction, Gaussian filtering, histogram equalization), data augmentation approaches, and model architecture. The chapter also examines the reasoning for selecting various procedures, ethical considerations, and potential constraints to the study.

Chapter 4: Experimental Results

This chapter describes the experimental results gained from the use of various deep learning algorithms (CNN, EfficientNetB3, EfficientNetB7, MobileNetV3, ResNet32, and ResNet50) in detecting cauliflower disorders. Detailed evaluations of the performance of several detection algorithms are provided, together with illustrations and statistical statistics (accuracy, loss metrics, confusion matrix, and ROC-AUC curve) to validate the results.

Chapter 5: The Impact on Society

The social impact chapter delves into the wider consequences of the research findings for agricultural and crop management. It examines how better disease detection technologies can benefit crop health, yield, and agricultural practices. Potential breakthroughs in agricultural technology are considered, as well as their societal ramifications, such as sustainable development and food security.

Chapter 6: Summary, Conclusion, Recommendations, and Implications for Further Research

This final chapter provides a summation of the full study. It highlights the important findings, reiterates the study's conclusions, and makes recommendations for practical use and further research. The ramifications for future studies are highlighted, giving a road map for scholars looking to build on the present investigation.

CHAPTER 2

Background

2.1 Preliminaries/Terminologies

In this part, we will define essential concepts from our study on cauliflower disease detection with deep learning algorithms. Deep Learning is a portion of machine learning that uses neural networks with multiple layers to acquire knowledge and make intelligent choices autonomously. Convolutional Neural Networks (CNNs) is a form of deep learning model that excels at tasks such as image classification due to their capacity to autonomously acquire spatial structures of features from input images. EfficientNet is a series of deep learning models noted for combining both precision and effectiveness, with variations such as EfficientNetB3, B7, and V3 providing varying levels of performance. MobileNetV3 is a compact deep learning model for mobile and edge devices that prioritizes precision and computational cost. A different kind of neural network is ResNet, which employs residual connections to build deeper networks. Variants such as ResNet32 and ResNet50 are noted for their excellent precision and durability in image categorization tasks.

2.2 Related Works

Crop diseases endanger the production of food, financial stability, and nutrition, threatening thousands of agricultural workers and critical crops. They emphasize the need for novel methodologies, such as deep learning, for better disease detection and mitigation strategies in agriculture. This section discusses the most current and significant research initiatives in this field.

In [1], researchers introduced an innovative framework that combines machine learning with deep learning, resulting in 40 distinct hybrid deep learning (HDL) algorithms. These HDL models showed impressive accuracy rates, ranging from 87.55% to 100%, when tested on the IARI-TomEBD dataset. To further validate the approach, the researchers conducted experiments using two publicly available datasets for diseased plants: PlantVillage-TomEBD and PlantVillage-BBLS.

In [2], a cutting-edge technique known as FC-SNDPN (Fully Convolutional - Switchable

Normalization Dual Path Networks) was proposed for the automated detection and identification of leaf diseases in agriculture. To mitigate the effects of intricate backgrounds on recognizing crop diseases and pests, the authors implemented a Full Convolutional Network (FCN) algorithm rooted in the VGG-16 framework for segmenting images of the target crops. The SNDPN approach combines the structural advantages of DenseNet and ResNet layers while integrating Switchable Normalization (SN) layers into the neural network. This innovative methodology, which merges SNDPN for disease detection with FCN for foreground segmentation, achieved a remarkable diagnostic accuracy of 97.59% on an enhanced dataset and highlighting the effectiveness.

In [3], a novel deep learning approach was introduced for detecting pests and diseases affecting mung beans. To address the challenge posed by the limited number of available mung bean crop images for training, the researchers utilized transfer learning, resulting in highly promising outcomes for swift and efficient disease and pest detection. The proposed model effectively identified six types of mung bean diseases and four distinct pests from both healthy and infected leaves collected across different seasons. During testing, the lightweight deep learning model for mung bean disease and pest identification achieved a remarkable average accuracy of 93.65%.

In [4], the researchers presented YOLO-Tobacco, an upgraded version of the YOLOX Tiny network, designed to detect brown spot disease in tobacco harvest photos taken in open fields. The goal was to pinpoint crucial diseased features and enhance the integration of multiple feature levels, allowing for the detection of densely affected areas at different scales. On the test set, YOLO-Tobacco achieved an average precision (AP) of 80.56%, outperforming other lightweight detection models like YOLOX-Tiny, YOLOv5s, and YOLOv4-Tiny by margins of 3.22%, 8.99%, and 12.03%, respectively.

In [5], MaizeNet was introduced as a deep learning (DL) technique for the precise identification and classification of various maize crop leaf diseases. This approach enhances the Faster-RCNN methodology by employing the ResNet-50 model with spatial channel attention as its backbone, allowing for the computation of deep keypoints which are then localized and classified into several categories. MaizeNet demonstrated significant performance, achieving 97.89% accuracy and a mean average precision (mAP) of 94%, underscoring its capability to accurately detect and identify diverse maize leaf diseases.

In [6], the classification of four specific cauliflower diseases—bacterial soft rot, black rot, buttoning, and white rust—was explored by researchers. Several Convolutional Neural Network (CNN) models were employed, and transfer learning was utilized to enhance performance. The dataset comprised approximately 2,500 images. Among the models tested, InceptionV3 was identified as the top performer, achieving an impressive test accuracy of 93.93%. This result was found to surpass the accuracy reported in similar recent studies.

In [7] described an online expert system based on machine vision for the detection of cauliflower illnesses. The technology analyzes photos recorded by smartphones and other devices, diagnosing illnesses and assisting cauliflower farmers.

In [8], a novel Lesion Proposal CNN based on Class-Attention, named CALP-CNN, was presented for the diagnosis of strawberry diseases. A class response map is utilized by CALP-CNN to identify the main lesion object and provide unique features of the lesions. With its cascade design, complex background challenges are addressed by CALP-CNN, and the risk of misclassifying similar but distinct instances is reduced.

In [9], a computer vision-oriented strategy was employed by researchers, integrating image processing, machine learning (ML), and deep learning (DL) techniques to lessen dependence on conventional methods for safeguarding paddy crops from diseases. The approach focused on image segmentation to identify infected areas of the rice plant, with disease identification carried out exclusively based on visual cues.

In [10], a lightweight CNN model named 'VGG-ICNN' was developed to identify crop diseases through images of plant leaves. This model has around 6 million parameters, which is considerably fewer than many current high-performance deep learning models. The effectiveness of the VGG-ICNN was evaluated using five different public datasets featuring a variety of crop types. These included multi-crop datasets like Embrapa and PlantVillage, with 93 and 38 categories, respectively, as well as single crop datasets for Maize, Rice, and Apple, each containing four or five categories.

In result, the aforementioned studies demonstrate considerable advances in the use of DL approaches for crop disease categorization, covering a variety of models. These models have showed excellent precision as well as effectiveness.

2.3 Comparative Analysis and Summary

In the Comparative Analysis and Summary section of my research report, I performed a thorough evaluation of numerous techniques pertinent to my topic. The emphasis has been on comparing various approaches, tools, and theoretical frameworks to determine their strengths, limitations, and overall efficacy. To accomplish this, I used a table-like structure to display the information clearly and concisely. This table contains important parameters such as performance measurements, scalability, cost-effectiveness, and applicability in many circumstances.

The comparative study tries to provide a comprehensive view by focusing not only on quantitative characteristics but also on qualitative factors such as ease of implementation and user satisfaction. By meticulously analyzing these various factors, I was able to gain valuable insights into which strategies are most suited for given situations. Furthermore, the summary synthesizes the important findings from the table, providing a unified narrative that connects the specific comparison data. This systematic approach guarantees that the reader understands the relative benefits and downsides of each strategy, allowing for more informed decision-making and laying the groundwork for the study's future suggestions and findings.

TABLE 2.3.1: Comparative Analysis Table

SI No.	**Study**	**Dataset**	**Classes**	Model	Accuracy
1	Barbedo et al. (2018) [c1]	Plant disease symptoms database	12 56 diseases under 12 classes	CNN GoogLeNet with tenfold crossvalidation	Accuracy: 84%
2	Gerardo et al. (2019) [c2]	Self-collected database	527 species of diseases under 5 classes	CNN	Accuracy: 96.5%
3	Yoon et al. (2017) [c3]	Self-collected database	9	Faster Regionbased CNN with SSD 1 and Region-based Fully Convolutional Network	Precision: 85.98%
4	K.P. et al. (2018) [c4]	Open dataset	58	CNN with pretrained VGG network	Accuracy: 99.53%

5	Yujin et al. (2019) [c5]	PlantVillage	38	VGG-16, Inception V4, ResNet with 50, 101, and 152 layers, and DenseNet with 121 layers	Accuracy: 99.75%
6	Lee et al. (2020) [c6]	PlantVillage	38	Pre-trained with ImageNet, GoogLeNet, and VGG16 models	Accuracy: 99.09%
7	Zhao et al. (2019) [c7[	AI-Challenger plant disease recognition	6	DenseNet-121	Accuracy: 93.71%
8	Song et al. (2020) [c8[	AI-Challenger plant disease recognition	4	Faster regional CNN	Accuracy: 98.54%
9	Chen et al. (2020) [c9]	Public database	7	Pre-trained models	Accuracy: 92%
10	Minz et al. (2019) [c10]	Self-generated database	4	Pre-trained CNN with SVM classifier	Accuracy: 91.37%

2.4 Scope of the Problem

The Cauliflower is a vital crop in the farming sector, which benefits financial stability and food security. But cauliflower plants are sensitive to a variety of illnesses that can significantly affect yield and quality. These infections, if not diagnosed and controlled early, can cause substantial losses in money for farmers and jeopardize food security.

Early diagnosis of cauliflower illnesses is critical for successful disease management. Traditional illness detection procedures, which include visual inspection by professionals, are costly, time-consuming, and susceptible to human error. As a result, there is a dire need for automatic and precise approaches to detect disease at early phases in order to limit harm and perform prompt therapies.

Deep learning algorithms, especially those intended for image analysis, present a viable approach for automating disease diagnosis in cauliflower plants. Using massive datasets of cauliflower photos, computer models can learn to recognize disease patterns with great accuracy. This study will investigate and analyze various deep learning models, including as CNN, EfficientNetB3, EfficientNetB7, EfficientNetV3, MobileNetV3, ResNet32, and ResNet50, to discover the best effective method for detecting cauliflower disorders.

Developing deep learning techniques for detecting diseases in agricultural contexts involves a number of obstacles. These include the requirement for high-quality and diversified datasets, computational capabilities for training complicated models, and assuring the models' durability and dependability in real-world scenarios. Addressing these problems is critical for creating a viable and scalable system that can be used in a variety of agricultural settings.

This study is aimed at contributing to the development of new methods for cauliflower disease diagnosis, resulting in enhanced crop care and increased agricultural productivity.

2.5 Challenges

Deep learning-based cauliflower disease detection study involves a number of obstacles. One key problem is acquiring and classifying a large and diverse dataset. Because the data set was collected individually, it is crucial to ensure that it includes all conceivable changes of disease symptoms under various environmental settings. This can be lengthy and labour-intensive.

Another problem is image preparation to improve clarity and ready them for use in deep learning models. Techniques like augmentation, scaling, and contrast enhancement have to be carefully employed to guarantee that the models obtain high-quality input data, as is critical for effective illness identification.

It is also difficult to choose and fine-tune appropriate deep learning models. CNN, EfficientNetB3, EfficientNetB7, MobileNetV3, ResNet32, and ResNet50 models all require careful hyperparameter setup, which necessitates substantial experimentation and computational resources. Balancing complexity of models and speed is crucial for avoiding overfitting and maintaining good accuracy.

Eventually, interpreting the findings and guaranteeing the model's applicability to real-world circumstances is difficult. Algorithms have to be sufficiently robust to accommodate previously unseen data with various illness presentations. To ensure the models' dependability and effectiveness in real applications, extensive validation and testing on a variety of datasets is required.

CHAPTER 3

Research Methodology

3.1 Research Subject and Instrumentation

Research Subject

This study focuses on identifying signs of cauliflower diseases utilizing deep learning techniques. Cauliflower, a vital agricultural crop, is sensitive to a variety of illnesses, which can have a substantial impact on productivity and quality. Early and accurate identification of these conditions is critical for their successful therapy and control. The study's goal is to provide a reliable and efficient approach for diagnosing cauliflower diseases through picture analysis utilizing deep learning models.

Instrumentation

To meet the goals of this study, numerous advanced algorithms for deep learning were used. The study used Convolutional Neural Networks (CNNs), which are fundamental deep learning algorithms that excel in picture task classification by automatically acquiring spatial hierarchies of features from input photos. Also, three distinct versions of the EfficientNet architecture were used: EfficientNetB3, which balances model accuracy and efficiency using a hybrid expanding method; EfficientNetB7, a bigger and stronger variant that provides higher accuracy; and EfficientNetV3, the most recent iteration that improves achievement via improved construction and better utilization of computational resources. Jupyter Notebook was used to implement and test these algorithms on a local PC. The collection included photos of cauliflower crops with different diseases, which were obtained directly to assure authenticity and relevance. The experimental setting entailed preprocessing the photos, training the models, then assessing their performance against standard criteria to establish the best effective approach for detecting cauliflower infections.

3.2 Data Collection Procedure

The data gathering approach for the cauliflower disease detection study was rigorously designed and carried out to guarantee that the data set provided both comprehensive and high-quality. The photographs were gathered individually from a variety of sources of information(Agricultural field, Groceries, Local markets), ensuring authenticity and relevancy. The full processes and tables below summarize the final count of photos after preprocessing and augmentation from the original images, as well as how they were distributed or splitting from the augmented images.

Data Collection Process

- Primary Data collection: Images were taken of cauliflower plants in various situations to represent an extensive variety of diseases and healthy states. This involved photographing various aspects of the plants to guarantee complete coverage. Here the table below contains 2160 original images from five class.

Table 3.2.1: Original Images of Cauliflower

Class	**Number of Images**
Cauliflower_Healthy	420
Cauliflower_Healthy_Leaf	624
Cauliflower_Leaf_Black_Rot	372
Cauliflower_Leaf_Red_Spot	372
Cauliflower_Spot_Rot	372
Total	**2160**

- Categories of Data:

  - Cauliflower_Healthy • Cauliflower_Healthy_Leaf
  - Cauliflower_Leaf_Black_Rot • Cauliflower_Leaf_Red_Spot
  - Cauliflower_Spot_Rot

(a) Cauliflower Healthy Leaf

(b) Cauliflower Healthy

(c) Cauliflower Spot Rot

Figure 3.2.1: Data sample of (a)Cauliflower Healthy Leaf, (b)Cauliflower Healthy and (c)Cauliflower Spot Rot

Image Preprocessing (Three types)

- Gamma Correction: It is a critical step in the image processing pipeline that ensures images are rendered in a way that aligns with human visual perception. By applying gamma correction, one can achieve consistent and accurate luminance across different display devices, enhancing the overall visual experience.

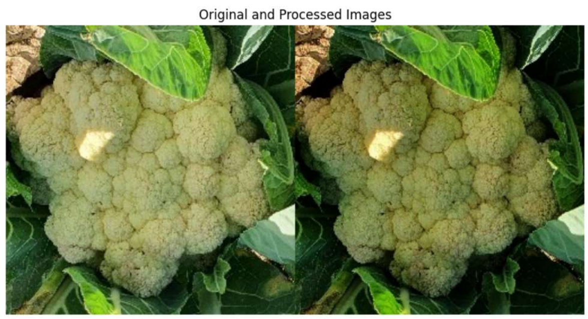

Figure 3.2.2: Data sample of Original and Processed Images

- Gaussian Filter: It is a fundamental tool in image processing, widely used for noise reduction and image smoothing. Its effectiveness lies in its simplicity and the ability to control the degree of smoothing through the standard deviation σ\sigma. While it has some limitations, such as edge blurring, it remains a valuable technique in the image processing toolkit.

Figure 3.2.3: Data sample of Gamma Correction and Gaussian Filter Image

- Histogram equalization: It is a fundamental technique in image processing that significantly enhances image contrast, making details more visible and improving the overall visual quality. It is widely used in various applications, including medical imaging, satellite imagery, and photography.

Figure 3.2.4: Data sample of Gaussian Filter and Histogram Equalization Image

Table 1: The complete number of images after augmentation.

After using picture augmentation techniques including rotation, flipping, and growing, the number of pictures in every class increased dramatically. This phase was critical in creating a diversified and wide sample to use for training deep learning algorithms.

Table 3.2.2: Images after augmentation

Class	Number of Images
Cauliflower_Healthy	2100
Cauliflower_Healthy_Leaf	2496
Cauliflower_Leaf_Black_Rot	2232
Cauliflower_Leaf_Red_Spot	2232
Cauliflower_Spot_Rot	2232
Total	**11292**

Table 2: Shows the final count of training images after splitting from augmentation.

Now we will split the images from the augmented images and use it as a training set. The table below depicts how photos were distributed across various categories in the instruction set.

Table 3.2.3: Training Images after splitting

Class	Number of Images
Cauliflower_Healthy	1680
Cauliflower_Healthy_Leaf	1872
Cauliflower_Leaf_Black_Rot	1860
Cauliflower_Leaf_Red_Spot	1860
Cauliflower_Spot_Rot	1860
Total	**9132**

Table 3: Shows the final count of valid images after splitting from augmentation.

Here we will split the images from the augmented images and use it as a valid set. The table below depicts how photos were distributed across various categories in the instruction set.

Table 3.2.4: Valid Images after splitting

Class	**Number of Images**
Cauliflower_Healthy	420
Cauliflower_Healthy_Leaf	624
Cauliflower_Leaf_Black_Rot	372
Cauliflower_Leaf_Red_Spot	372
Cauliflower_Spot_Rot	372
Total	**2160**

3.3 Statistical Analysis

A statistical examination of deep learning algorithms used to detect cauliflower leaf illnesses, evaluating Precision, Recall, F1-Score, and Accuracy in five investigations.

CNN has an overall accuracy of 0.92, with the highest score for detecting healthy cauliflower (F1-Score of 0.94) and the least accuracy in Cauliflower_Leaf_Red_Spot (F1-Score of 0.88).

EfficientNetB3 maintains a precision of 0.93, succeeding in Cauliflower_Spot_Rot (F1-Score of 0.97) while doing less on Cauliflower_Leaf_Black_Rot (F1-Score of 0.91).

EfficientNetB7 has a lower accuracy of 0.86, with a weak showing in Cauliflower_Leaf_Black_Rot (F1-Score of 0.75), but acceptable results in healthy leaves and spot rot.

MobileNetV3 obtains an excellent 0.99 accuracy, with perfect results in several categories, including Cauliflower_Healthy and Cauliflower_Spot_Rot (F1-score of 1.0).

ResNet32 and ResNet50 both have accuracies of 0.96, excelling in Cauliflower_Spot_Rot (F1-Score of 0.99), but performing somewhat worse in Cauliflower_Leaf_Black_Rot (F1-Scores of 0.92 and 0.87, respectively).

While all of the algorithms perform well in classifying cauliflower leaf illnesses, MobileNetV3 has the best overall accuracy and numerous perfect scores in crucial categories. CNN and EfficientNetB3 additionally show consistent performance, but with significant variation between illness studies. EfficientNetB7, despite its poorer overall accuracy, produces useful results in several categories. ResNet32 as well as ResNet50 are likewise quite effective, making them ideal for this application. This statistical analysis emphasizes the importance of choosing the appropriate algorithm depending on the disease categorization needs.

3.4 Proposed Methodology

This study tries to create an efficient method for detecting cauliflower infections utilizing deep learning techniques. The methodology comprises of numerous processes, involving gathering data, preliminary processing, augmentation, model training, evaluation, and implementation. Each stage is critical to ensure the model's correctness and resilience.

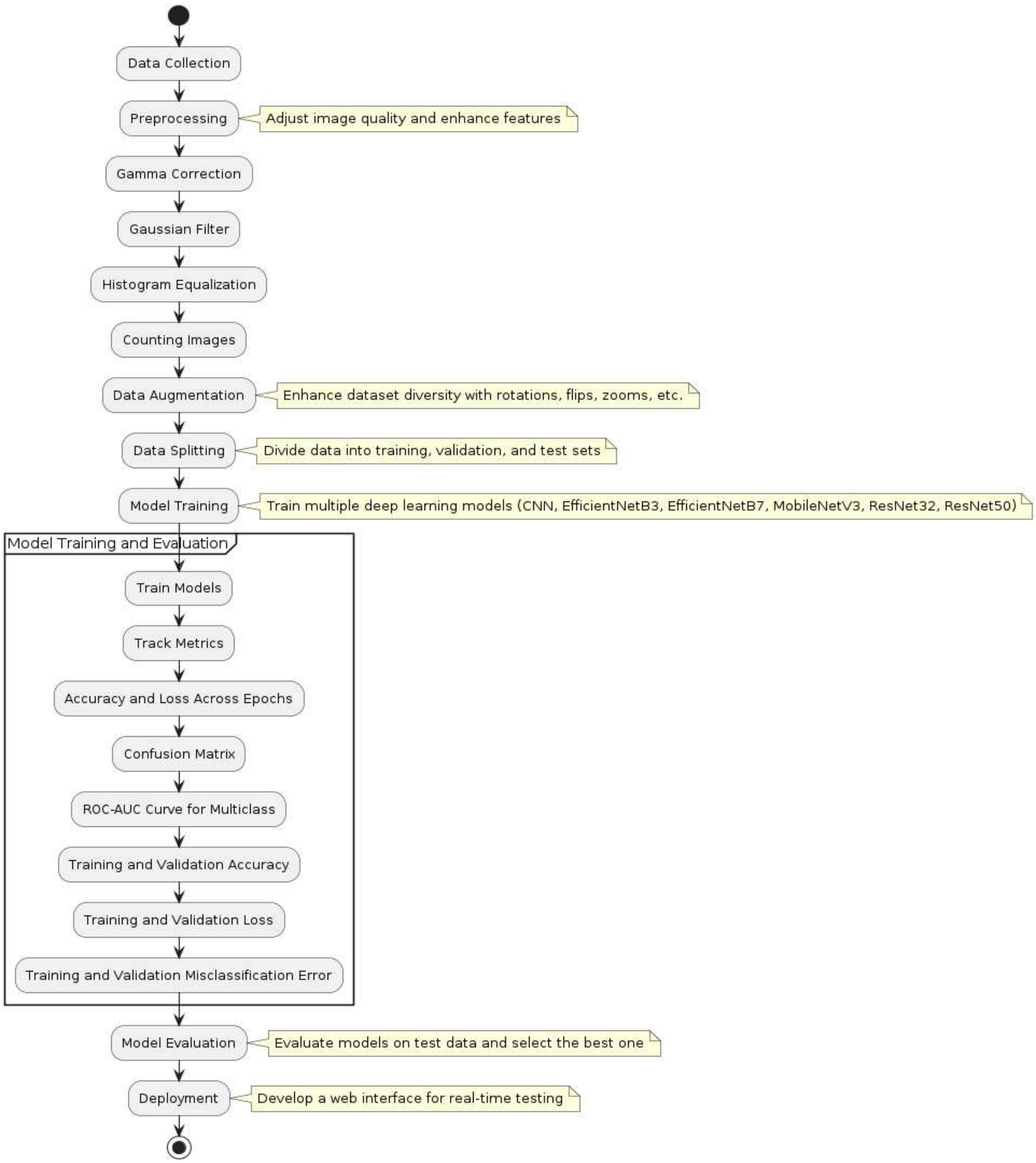

Figure 3.4.1: Proposed Methodology

3.5 Implementation Requirements

In this section, we will discuss the hardware, software, and other requirements needed to carry out the research on cauliflower diseased detection using various deep learning methods. The implementation was conducted on a local machine using Jupyter Notebook and datasets collected firsthand.

Hardware Requirements

1. Local Machine:
   - Processor:
     - Minimum: Dual-core processor
     - Recommended: Quad-core processor or higher for faster computation
   - Memory:
     - Minimum: 8 GB of RAM
     - Recommended: 16 GB or more for handling larger datasets and complex models
   - Storage:
     - Minimum: 20 GB free space for installing necessary software and storing data
     - Recommended: SSD for faster read/write operations
   - GPU (Optional but recommended):
     - NVIDIA GPU with CUDA support for accelerated deep learning computations
2. Internet Access:
   - A stable internet connection is required for downloading libraries, updates, and for any potential cloud backups or data sharing.

Software Requirements

1. Operating System:
   - Compatible with main operating systems that include Windows, MacOS, and Linux.
2. Python:
   - The language of programming used to create and run the code. Ensure that the

latest version is compatible with the essential libraries.

3. Jupyter Notebooks:
   - An open-source web software for generating and sharing documents with real-time code, equations, and narrative text.
4. Libraries and frameworks:
   - Keras: A high-level neural network API built on top of TensorFlow.
   - TensorFlow is a free machine learning framework designed for deep learning.
   - OpenCV: a set of tools for performing image processing tasks.
   - NumPy: a package for numerical computations.
   - Pandas: A data editing and analysis library.
   - Matplotlib is a plotting package for data visualization.
   - Scikit-learn: A library for machine learning and modeling of statistics.
   - Keras uses ImageDataGenerator for data enhancement and preprocessing.
5. Data Source:
   - Personal collection: The collection is made up of actual cauliflower diseased detection images that were obtained firsthand.

By meeting all of these computing and software requirements, the cauliflower diseased detection research may be successfully implemented on a local workstation with Jupyter Notebook. This configuration enables exploiting versatility and oversight of local assets while dealing with real, personally obtained datasets.

CHAPTER 4

Experimental Result

4.1 Experimental Setup

The full test environment was created on a computer at home utilizing Jupyter Notebook, which is an adaptable system to execute Python applications. The source code was split into sections, each of which performed a particular task during the assessment process. The dataset, which included photographs of cauliflower disease, had been collected personally and saved on a local machine.

The dataset was preprocessed using a range of approaches, including:

- Image Augmentation: To increase its scope and variety, methods like movement, tumbling, and magnification were used.
- Contrast and brightness Enhancement: Adjustments were done to increase the image quality and feature visibility.
- Image Resizing: Images were scaled to match the data specifications for deep learning models.

The data set was then separated into testing, validation, and training sets utilizing a proprietary approach to ensure that photos were distributed evenly among classes in each group.

The preprocessed dataset was used to build and train deep learning models like CNN, EfficientNetB3, EfficientNetB7, EfficientNetV3, MobileNetV3, ResNet32, ResNet50.

During the experiment, frameworks like TensorFlow and Keras were used to develop and train models. Additionally, tools such as Matplotlib and Seaborn were also used to show performance indicators and assess model performance.

4.2 Experimental Results & Analysis

Algorithms Used

CNN

Convolutional Neural Network (CNN) is an extension of artificial neural networks (ANN) that is mostly used to extract features from grid-like matrix datasets. For example, consider visual datasets such as photos or movies, in which data trends play a significant role. A convolutional neural network is made up of numerous layers, including the input layer, the convolutional layer, the pooling layer, and the fully connected layer. [26].

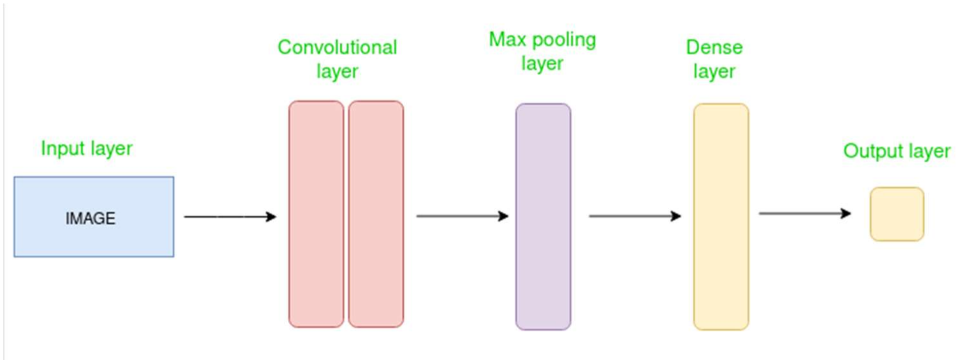

Figure 4.2.1: Working Principle of CNN [27]

EfficientNetB3

The architecture of boosted-efficientNet-B3. EfficientNet initially extracts picture features using convolutional layers. The process of attention is then used to reweight features, boosting the activation of key components. Next, we apply FF to the outputs of many convolutional layers. Images are then categorized using these fused attributes. [28].

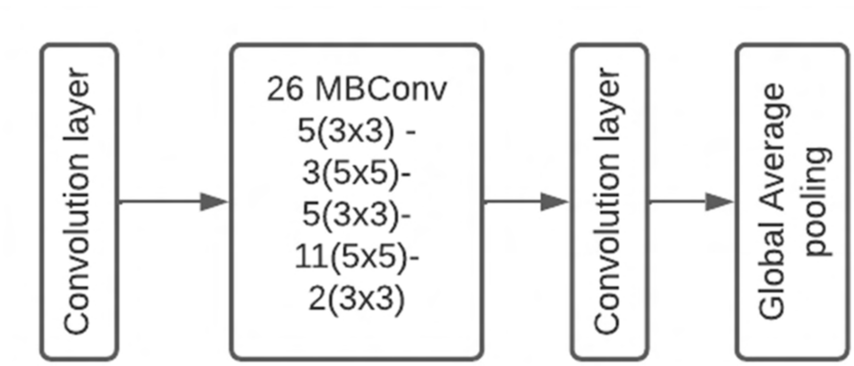

Figure 4.2.2: Working Principle of EfficientNetB3 [29]

EfficientNetB7

EfficientNetB7 is a member of the EfficientNet family of deep learning models, that are intended to achieve outstanding performance by optimizing accuracy and processing efficiency. EfficientNetB7 is one of the series' larger and more powerful models, with higher precision for image classification tasks. It employs a compound scaling strategy that equally scales every aspect of depth, width, and resolution, improving the model's capacity

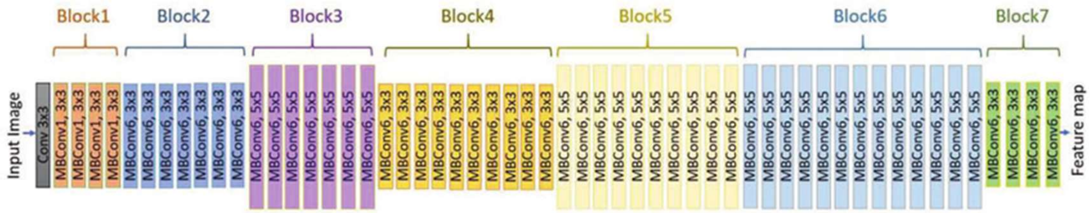

Figure 4.2.3: Working Principle of EfficientNetB7 [30]

to learn from data while not significantly increasing computational needs. [30].

MobileNetV3

MobileNetV3 is a network of convolutional neural networks that is tailored to mobile phone CPUs using a mix of hardware-aware neural network search (NAS) and the NetAdapt algorithm, which is then improved further by unique architecture developments. [31].

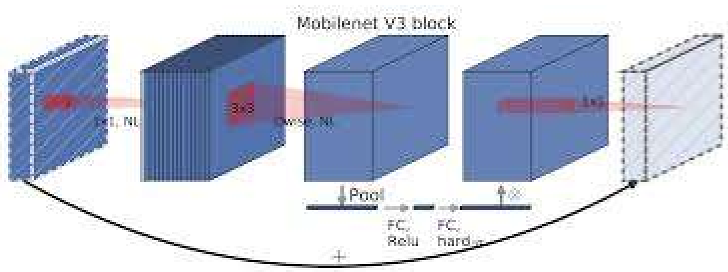

Figure 4.2.4: Working Principle of MobileNetV3 [31]

RestNet32

ResNet-32 is a convolutional neural network core derived from ResNet-34, ResNet-50, and ResNet-101. ResNet-32, as the name says, consists of 32 layers. It solves the issue of gradients disappearing by using an identity shortcut link which bypasses a couple of layers. The ResNet backbone may be adapted into a variety of applications, including picture categorization, as seen here. This ResNet-32 implementation was constructed using fastai, a low-code deep learning framework. [32].

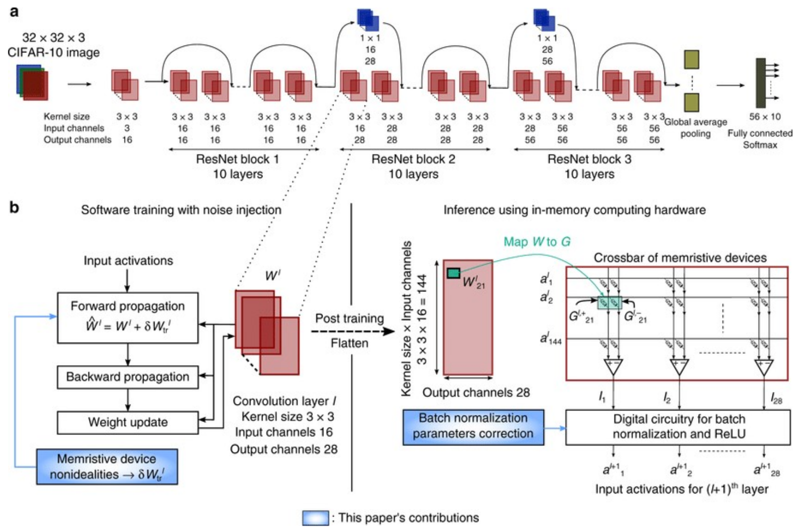

Figure 4.2.5: Working Principle of RestNet32 [33]

RestNet50

ResNet-50 is a CNN architecture from the ResNet (Residual Networks) family, which is a collection of models developed to handle the issues of training deep neural networks. ResNet-50, created by researchers at Microsoft Research Asia, is well-known for its depth and efficiency in picture categorization. ResNet topologies come in a variety of depths, including ResNet-18, ResNet-32, and so on, with ResNet-50 being a medium-sized form. [34]

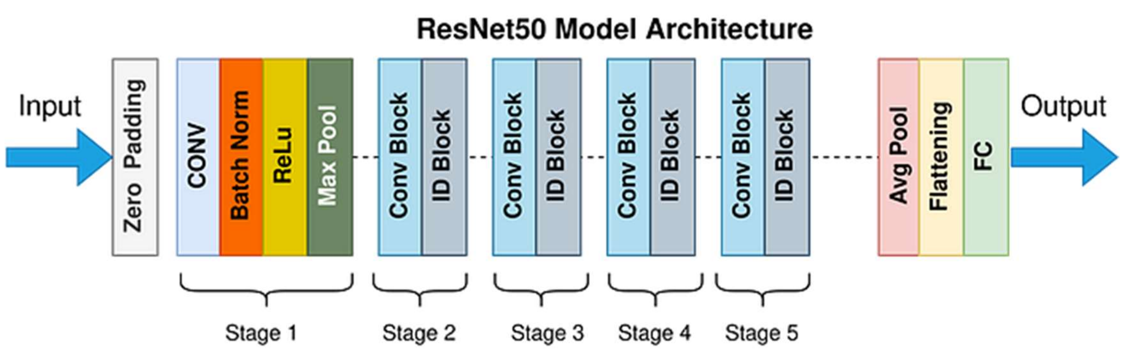

Figure 4.2.6: Working Principle of RestNet50 [35]

Experimental Result and Analysis

Experiment 1: CNN

The graphic depicts the training progress of a deep learning model across ten epochs, including accuracy and loss metrics for both the training and validation datasets. Initially, the model has a poor training accuracy of 0.4310 and significant loss values. As the epochs execution, both training and validation accuracy levels increase dramatically, reaching 0.9386 and 0.8801, accordingly, whereas loss values drop, indicating improved model performance.

Epoch	Time (s)	Accuracy	Loss	Val Accuracy	Val Loss
1	614	0.4310	3.5160	0.6167	0.8917
2	1330	0.6447	0.7788	0.7843	0.5395
3	1375	0.7998	0.4806	0.7852	0.5578
4	1226	0.8879	0.3021	0.8986	0.2892
5	1233	0.9386	0.1682	0.8801	0.4019
6	2122	0.9588	0.1153	0.9144	0.3181
7	1430	0.9692	0.0949	0.9301	0.2156
8	1310	0.9730	0.0771	0.9181	0.3581
9	1360	0.9780	0.0763	0.9370	0.2173
10	1235	0.9832	0.0485	0.9199	0.3168

Table 4.2.1: Accuracy and Loss Metrics Across Epochs for CNN

Confusion Matrix:

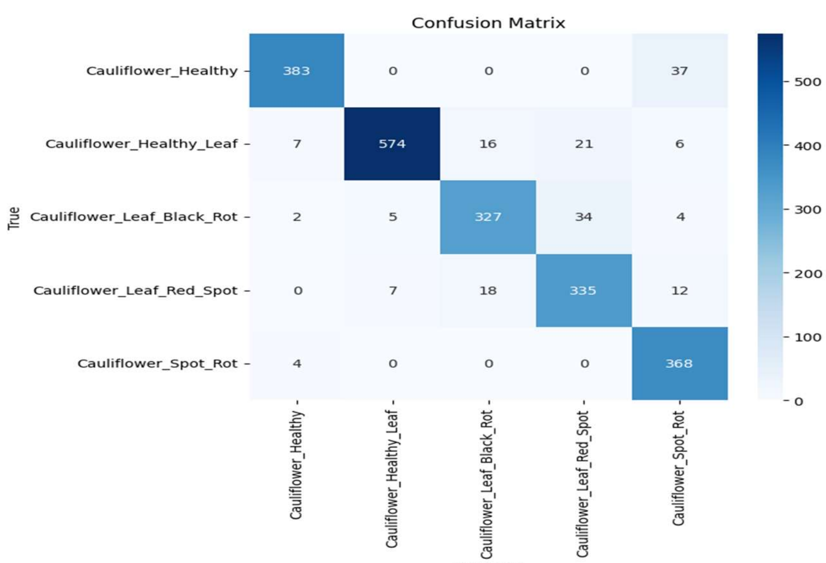

Figure 4.2.7: Confusion Matrix for CNN

ROC-AUC Curve for Multiclass

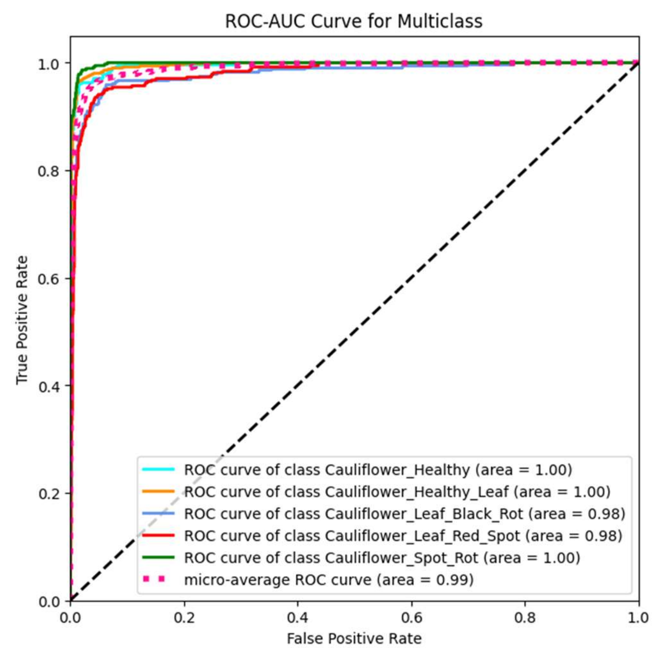

Figure 4.2.8: ROC-AUC Curve for Multiclass - CNN

Training and Validation Accuracy of CNN

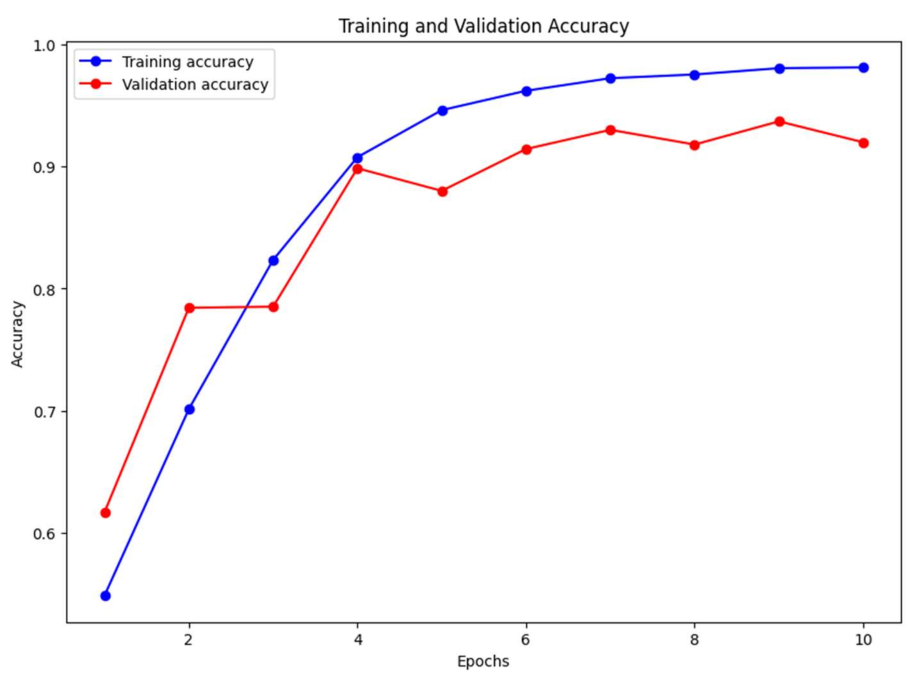

Figure 4.2.9: Training and Validation Accuracy of CNN

Training and Validation Loss of CNN

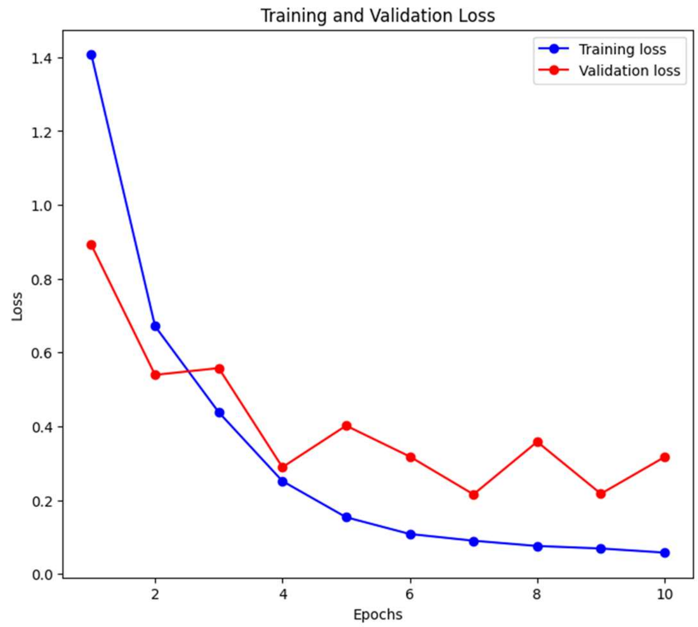

Figure 4.2.10: Training and Validation Loss of CNN

Training and Validation Misclassification Error or CNN

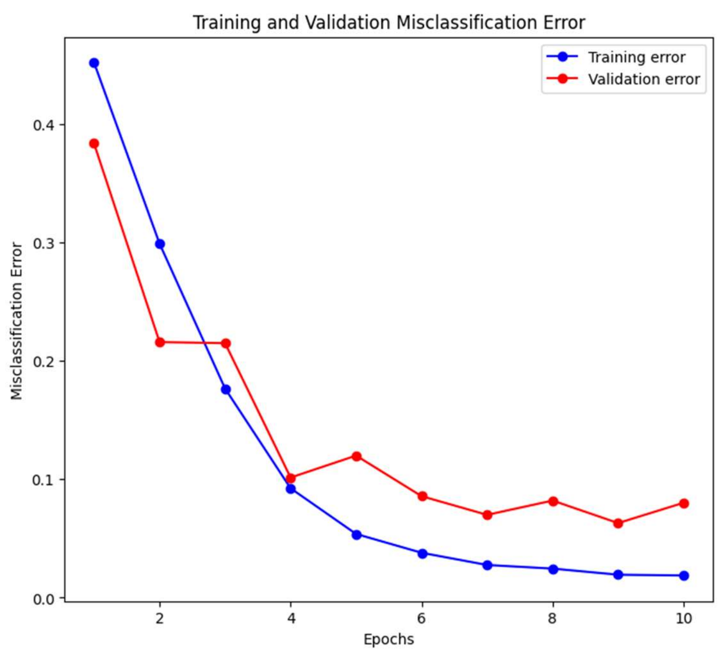

Figure 4.2.11: Training and Validation Misclassification Error or CNN

Experiment 2: EfficientNetB3

Accuracy and Loss Metrics Across Epochs for EfficientNetB3

Epoch	Time (s)	Accuracy	Loss	Val Accuracy	Val Loss
1	380	0.5989	0.8703	0.7597	0.5527
2	386	0.7344	0.5918	0.8051	0.4657
3	419	0.7700	0.5189	0.8468	0.3846
4	414	0.7923	0.4642	0.8708	0.3359
5	495	0.8190	0.4215	0.8838	0.3079
6	411	0.8318	0.3961	0.8963	0.2871
7	413	0.8368	0.3782	0.8824	0.3167
8	421	0.8534	0.3500	0.9204	0.2268
9	423	0.8657	0.3306	0.9194	0.2336
10	440	0.8701	0.3115	0.9306	0.2139

Table 4.2.2: Accuracy and Loss Metrics Across Epochs for EfficientNetB3

Confusion Matrix for EfficentNetB3:

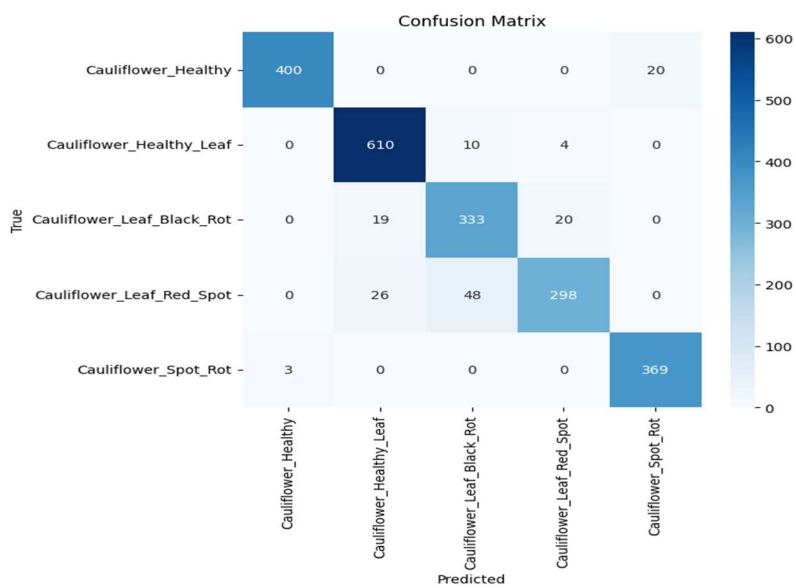

Figure 4.2.12: Confusion Matrix for EfficentNetB3

ROC-AUC Curve for Multiclass - EfficientNetB3

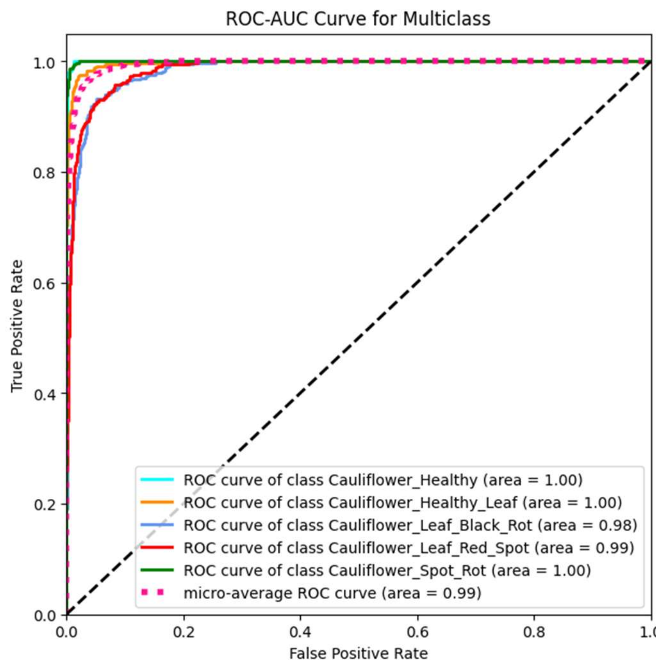

Figure 4.2.13: ROC-AUC Curve for Multiclass - EfficientNetB3

Training and Validation Accuracy of EfficientNetB3

Figure 4.2.14: Training and Validation Accuracy of EfficientNetB3

Training and Validation Loss of EfficientNetB3

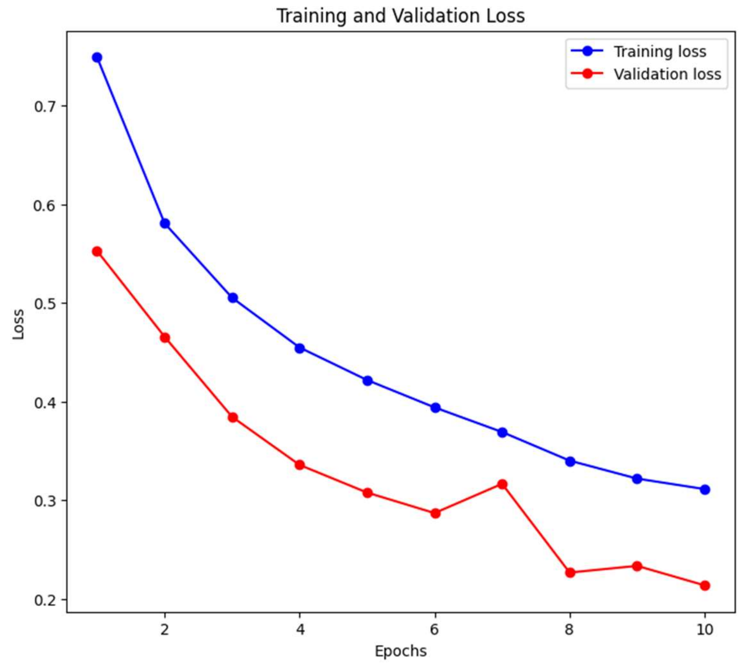

Figure 4.2.15: Training and Validation Loss of EfficientNetB3

Training and Validation Misclassification Error of EfficientNetB3

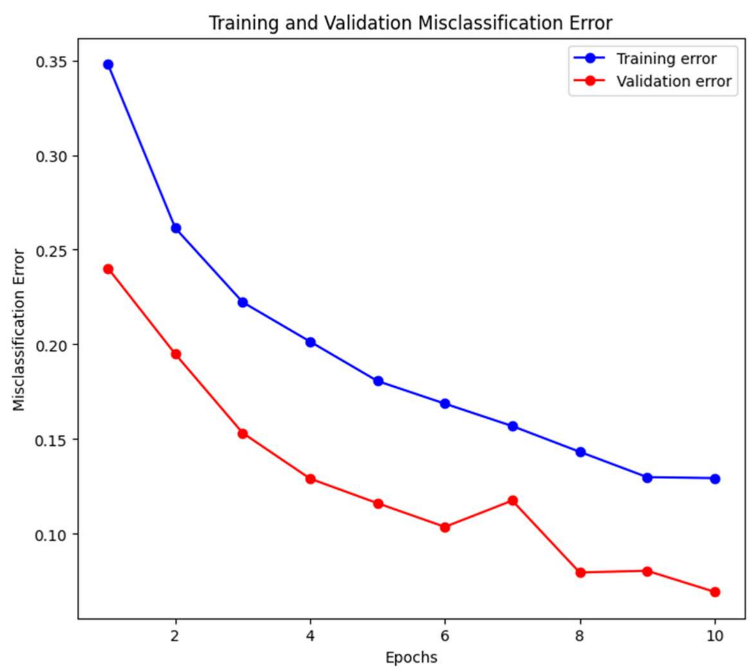

Figure 4.2.16: Training and Validation Misclassification Error or EfficientNetB3

Experiment 3: EfficientNetB7

Accuracy and Loss Metrics Across Epochs for EfficientNetB7

Epoch	Time (s)	Accuracy	Loss	Val Accuracy	Val Loss
1	1821	0.5418	0.9371	0.7176	0.6492
2	1537	0.7120	0.6592	0.7329	0.6208
3	1421	0.7381	0.6015	0.7847	0.5260
4	1550	0.7742	0.5493	0.7949	0.5019
5	2435	0.7825	0.5191	0.8194	0.4555
6	1559	0.7932	0.5017	0.8157	0.4530
7	13863	0.8063	0.4759	0.8384	0.4209
8	1254	0.8157	0.4570	0.8366	0.4205
9	698	0.8163	0.4439	0.8569	0.3795
10	942	0.8318	0.4240	0.8634	0.3631

Table 4.2.3: Accuracy and Loss Metrics Across Epochs for EfficientNetB7

Confusion Matrix for EfficientNetB7

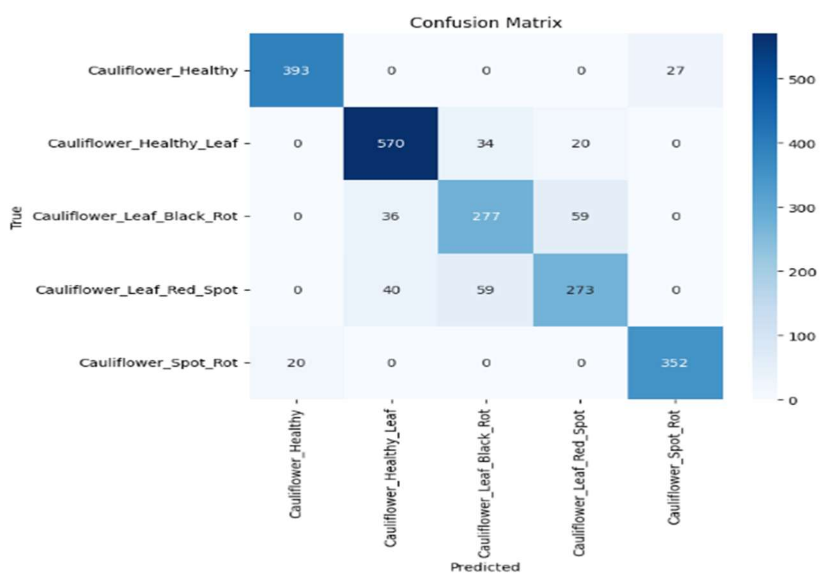

Figure 4.2.17: Confusion Matrix for EfficientNetB7

ROC-AUC Curve for Multiclass - EfficientNetB7

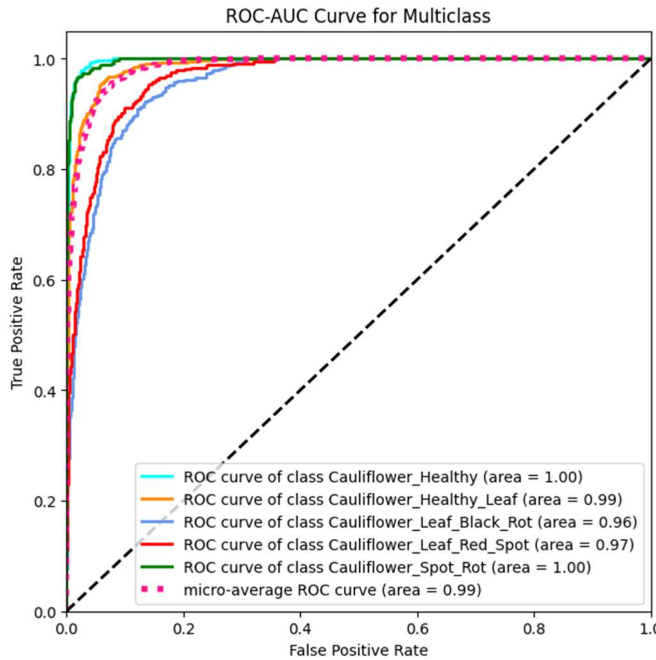

Figure 4.2.18: ROC-AUC Curve for Multiclass - EfficientNetB7

Training and Validation Accuracy of EfficientNetB7

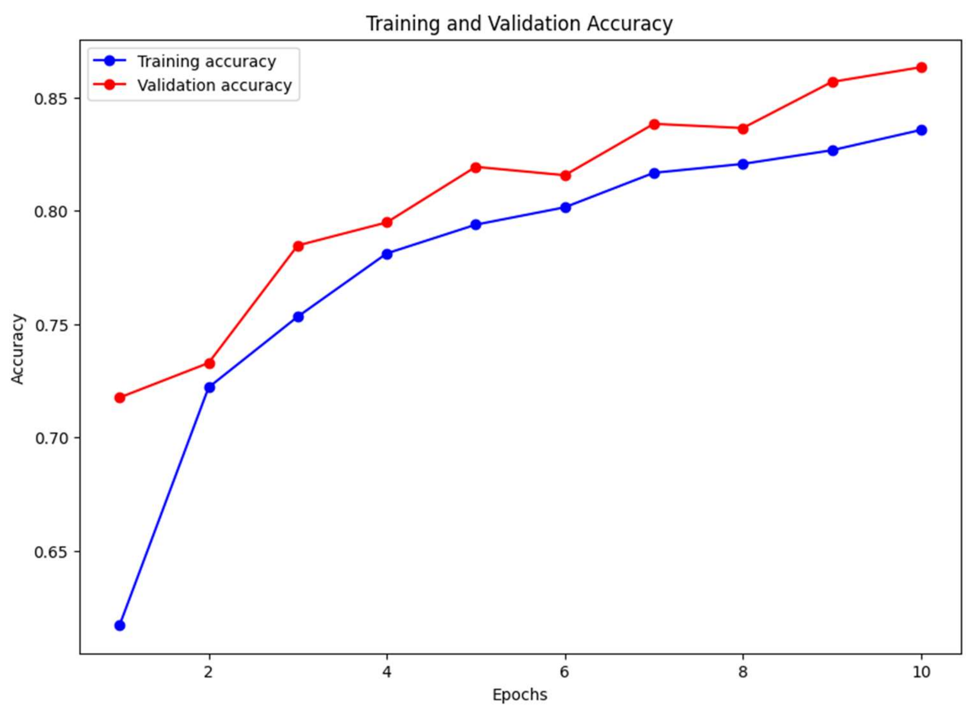

Figure 4.2.19: Training and Validation Accuracy of EfficientNetB7

Training and Validation Loss of EfficientNetB7

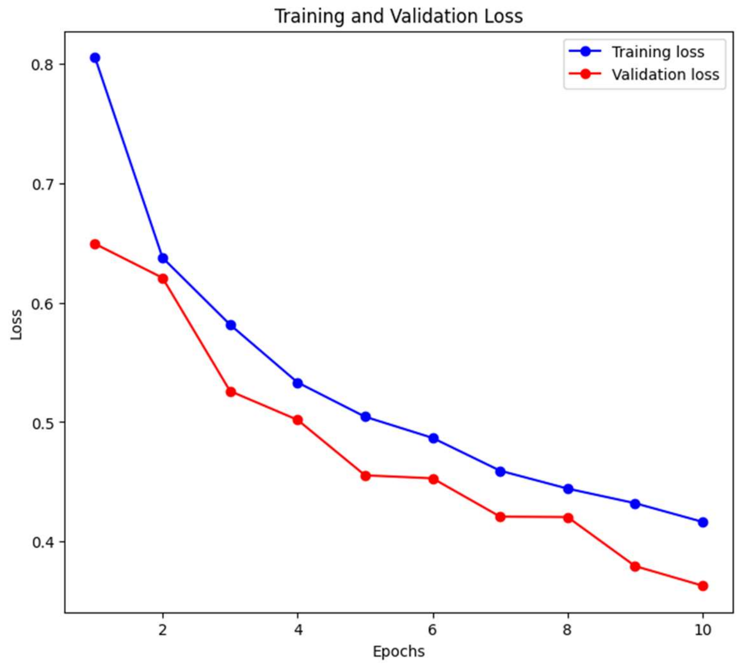

Figure 4.2.20: Training and Validation Loss of EfficientNetB7

Training and Validation Misclassification Error of EfficientNetB7

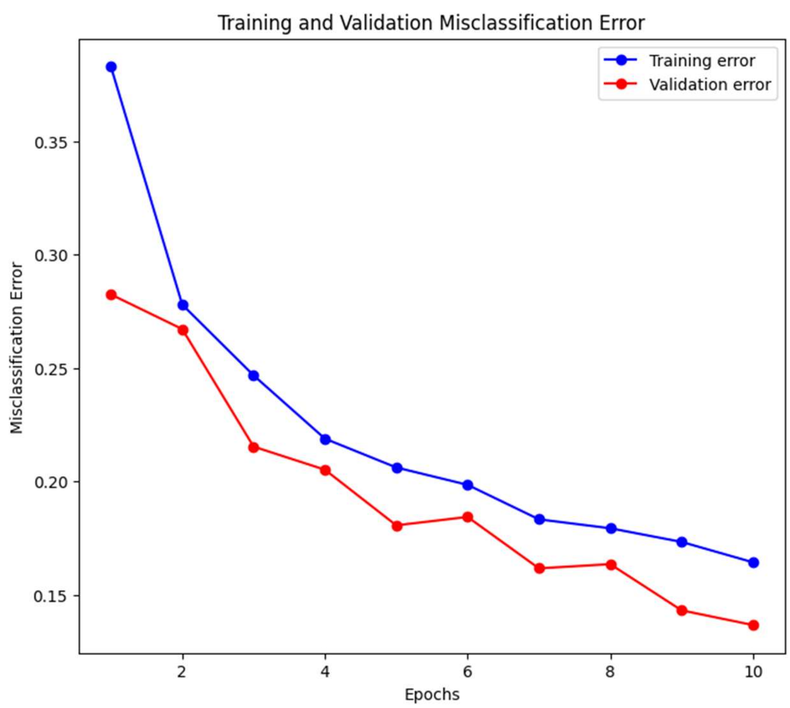

Figure 4.2.21: Training and Validation Misclassification Error or EfficientNetB7

Experiment 4: MobileNetV3

Accuracy and Loss Metrics Across Epochs for MobileNetV3

Epoch	Time (s)	Accuracy	Loss	Val Accuracy	Val Loss
1	142	0.7150	0.6392	0.9088	0.2553
2	80	0.9137	0.2426	0.9500	0.1529
3	72	0.9575	0.1370	0.9449	0.1458
4	83	0.9755	0.0861	0.9727	0.0815
5	83	0.9871	0.0526	0.9713	0.0725
6	81	0.9961	0.0296	0.9741	0.0742
7	82	0.9977	0.0199	0.9778	0.0595
8	82	0.9995	0.0131	0.9870	0.0477
9	121	0.9999	0.0078	0.9866	0.0435
10	128	1.0000	0.0052	0.9875	0.0458

Table 4.2.4: Accuracy and Loss Metrics Across Epochs for MobileNetV3

Confusion Matrix for MobileNetV3

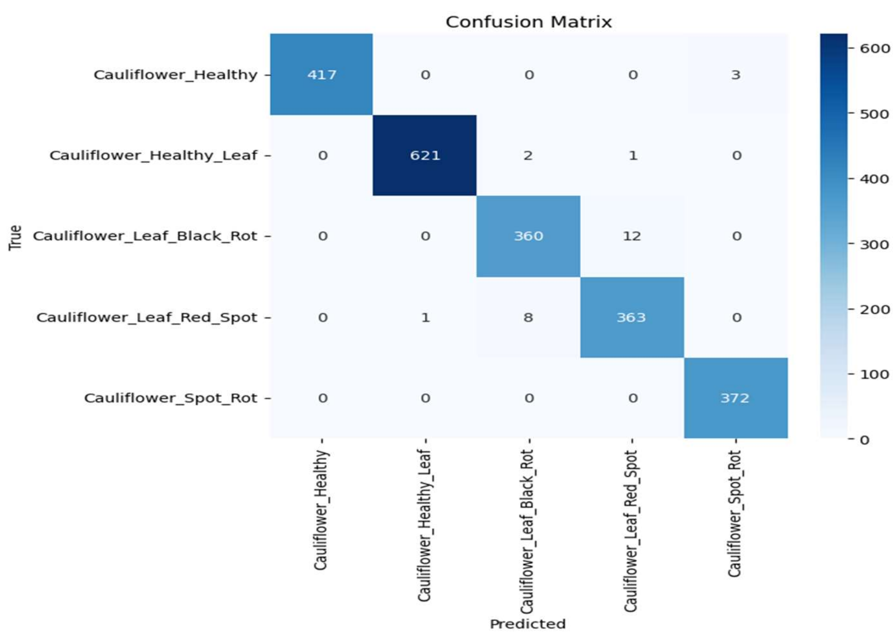

Figure 4.2.22: Confusion Matrix for MobileNetV3

ROC-AUC Curve for Multiclass - MobileNetV3

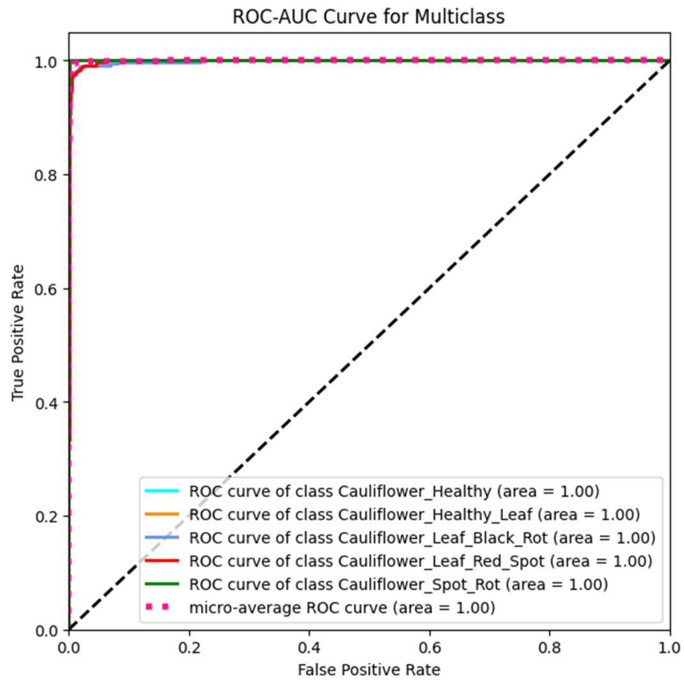

Figure 4.2.23: ROC-AUC Curve for Multiclass - MobileNetV3

Training and Validation Accuracy of MobileNetV3

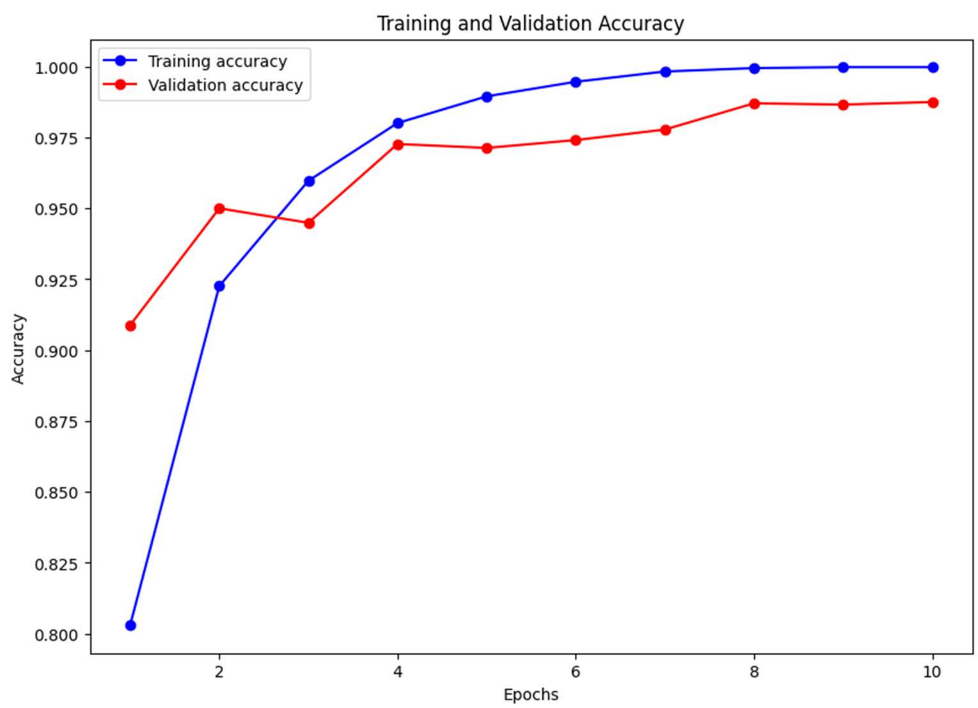

Figure 4.2.24: Training and Validation Accuracy of MobileNetV3

Training and Validation Loss of MobileNetV3

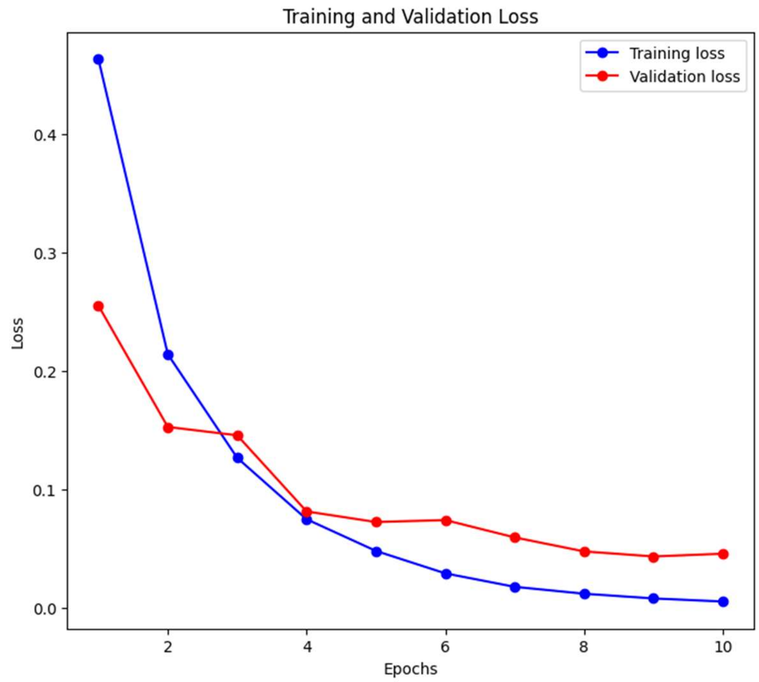

Figure 4.2.25: Training and Validation Loss of MobileNetV3

Training and Validation Misclassification Error of MobileNetV3

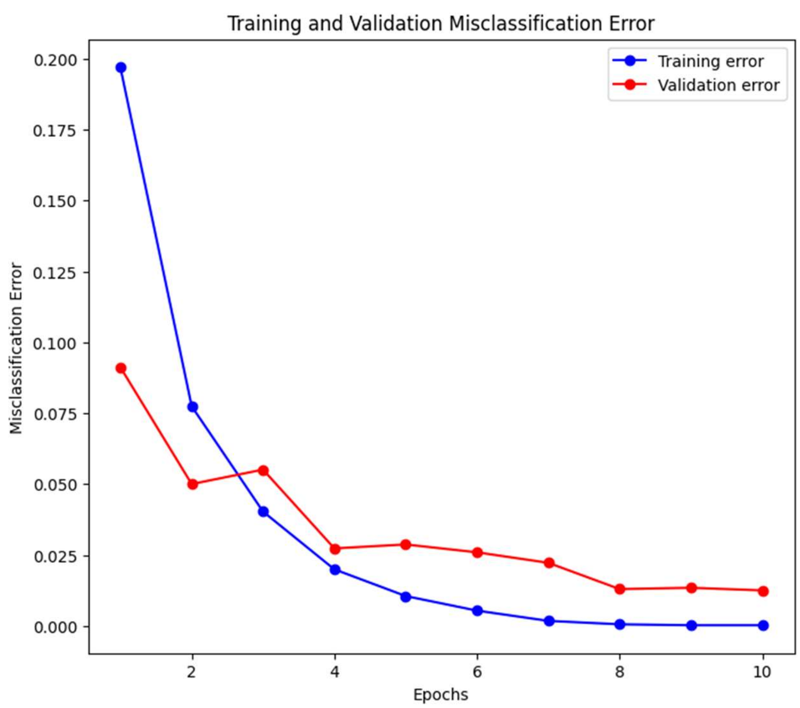

Figure 4.2.26: Training and Validation Misclassification Error or MobileNetV3

Experiment 5: RestNet32

Accuracy and Loss Metrics Across Epochs for ResNet32

Epoch	Time (s)	Accuracy	Loss	Val Accuracy	Val Loss
1	783	0.6558	0.9416	0.8491	0.3731
2	672	0.8244	0.4197	0.8968	0.2787
3	1485	0.8633	0.3299	0.9097	0.2348
4	749	0.8939	0.2667	0.9361	0.1737
5	673	0.9211	0.2048	0.9449	0.1580
6	673	0.9267	0.1868	0.9375	0.1582
7	666	0.9385	0.1566	0.9440	0.1504
8	669	0.9375	0.1636	0.9528	0.1228
9	12980	0.9469	0.1334	0.9528	0.1168
10	675	0.9462	0.1328	0.9565	0.1124

Table 4.2.5: Accuracy and Loss Metrics Across Epochs for RestNet32

Confusion Matrix for ResNet32

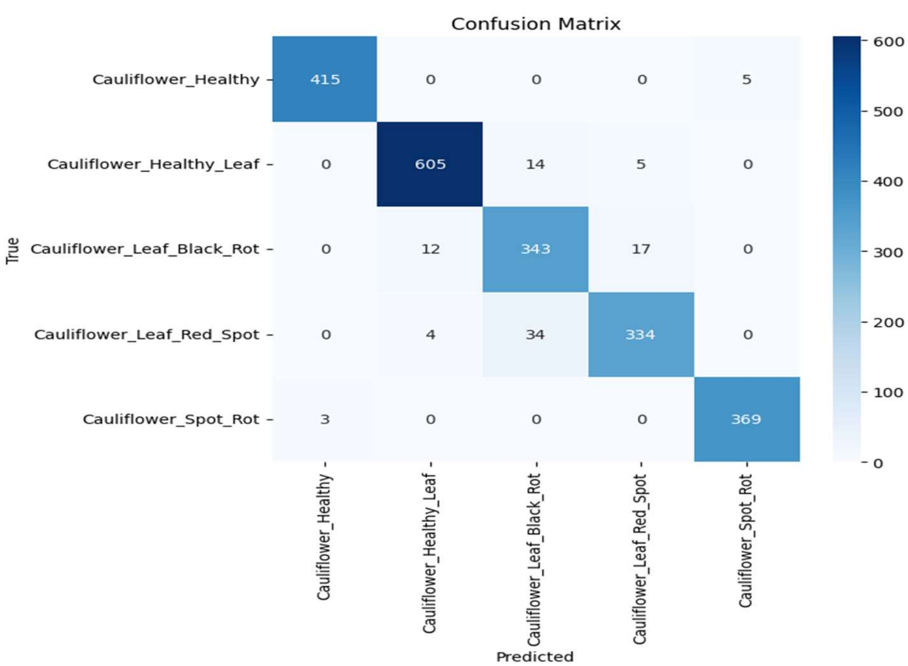

Figure 4.2.27: Confusion Matrix for RestNet32

ROC-AUC Curve for Multiclass - ResNet32

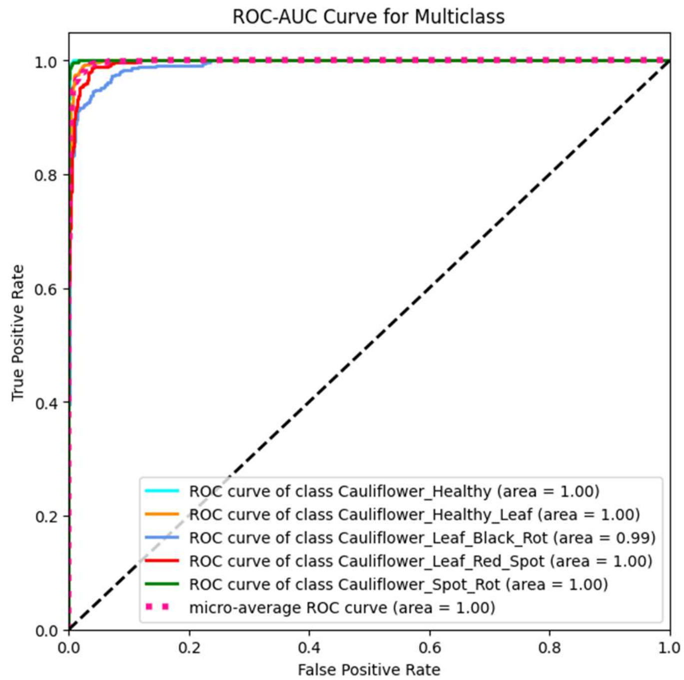

Figure 4.2.28: ROC-AUC Curve for Multiclass - RestNet32

Training and Validation Accuracy of ResNet32

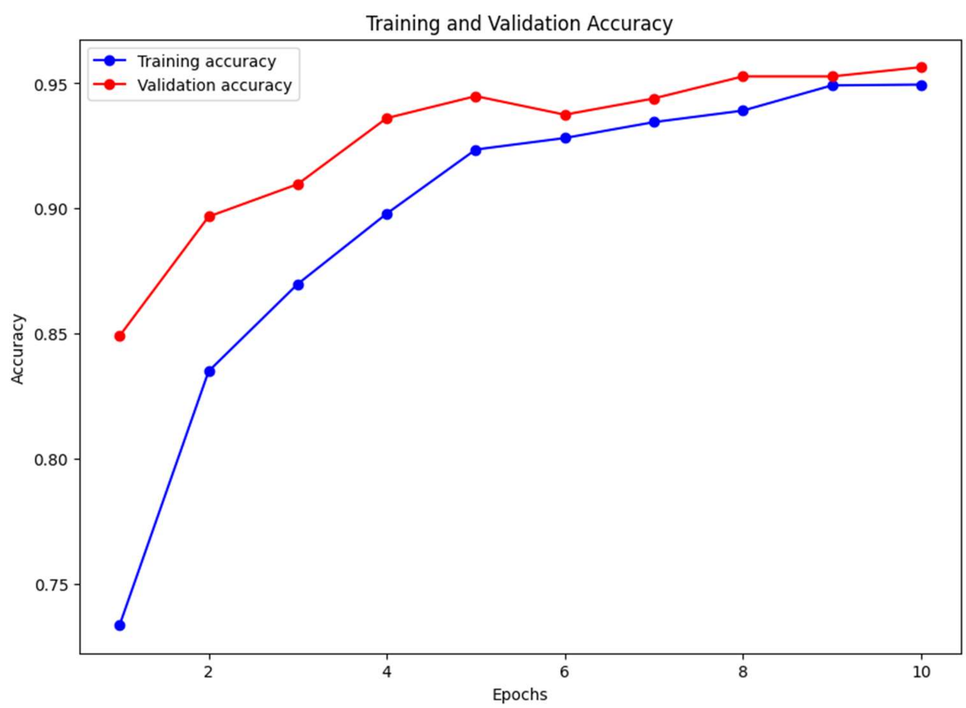

Figure 4.2.29: Training and Validation Accuracy of RestNet32

Training and Validation Loss of ResNet32

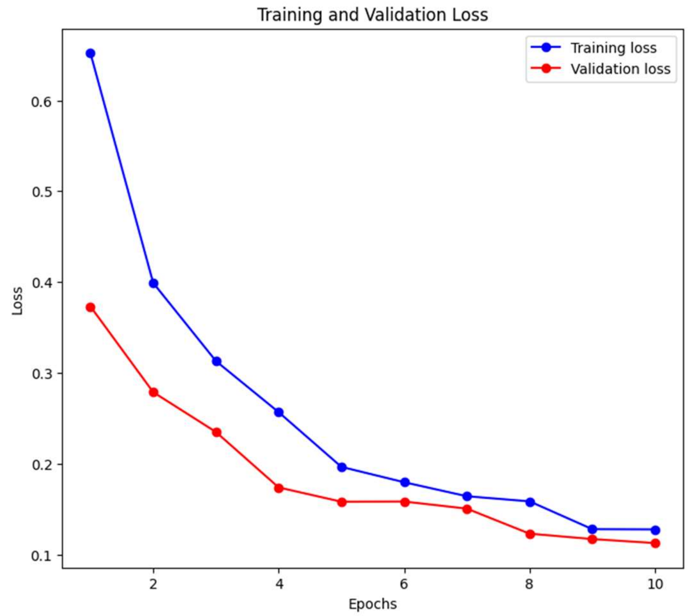

Figure 4.2.30: Training and Validation Loss of RestNet32

Training and Validation Misclassification Error of ResNet32

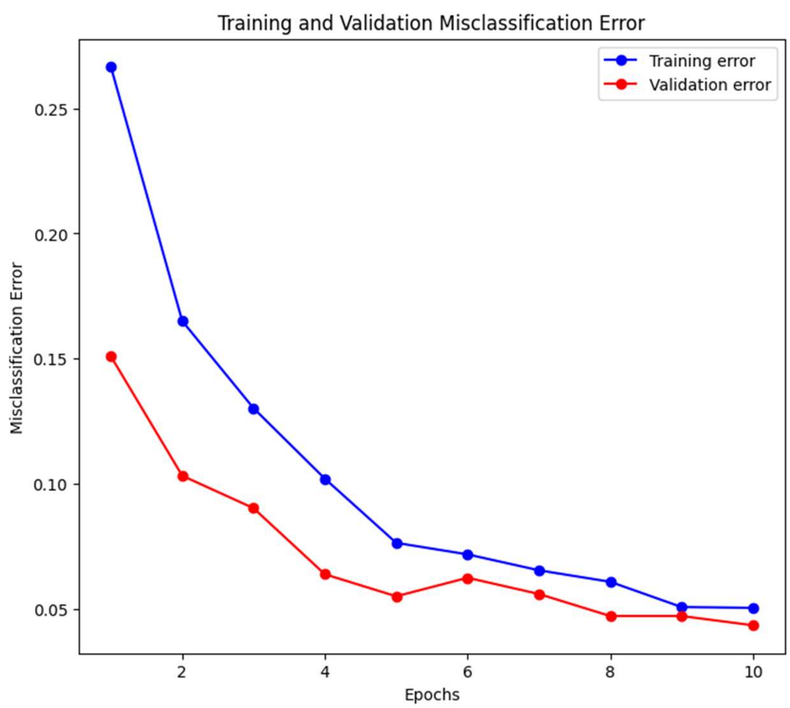

Figure 4.2.31: Training and Validation Misclassification Error or RestNet32

Experiment 6: RestNet50

Accuracy and Loss Metrics Across Epochs for ResNet50

Epoch	Time (s)	Accuracy	Loss	Val Accuracy	Val Loss
1	532	0.6508	0.9213	0.8412	0.3991
2	529	0.8102	0.4445	0.8968	0.2605
3	804	0.8708	0.3335	0.9144	0.2177
4	488	0.8940	0.2576	0.9319	0.1844
5	606	0.9176	0.2109	0.9301	0.1701
6	516	0.9265	0.1850	0.9426	0.1477
7	337	0.9384	0.1692	0.9403	0.1630
8	298	0.9375	0.1615	0.9569	0.1239
9	291	0.9409	0.1510	0.9597	0.1100
10	299	0.9466	0.1336	0.9556	0.1057

Table 4.2.6: Accuracy and Loss Metrics Across Epochs for RestNet50

Confusion Matrix for ResNet50

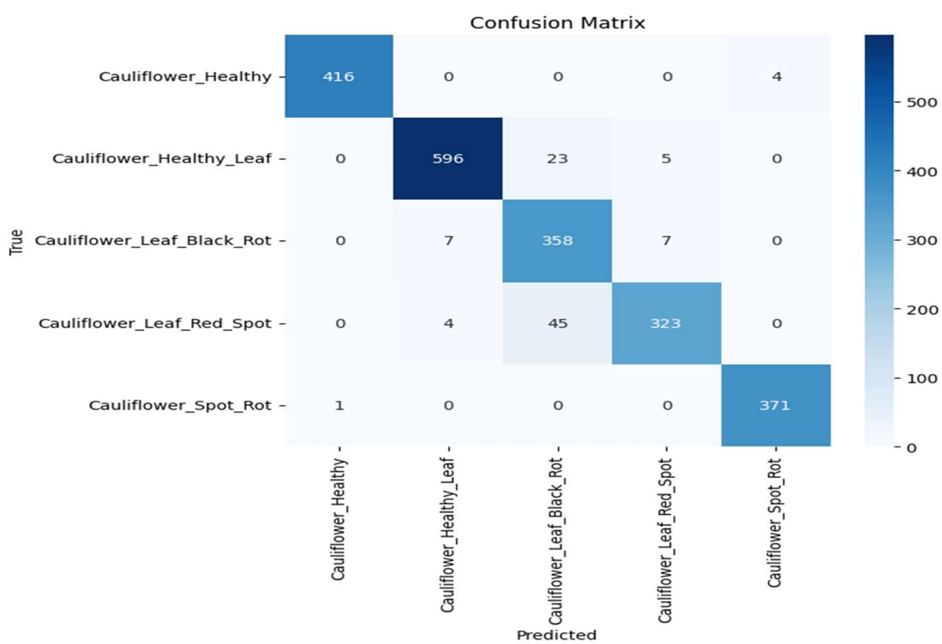

Figure 4.2.32: Confusion Matrix for RestNet50

ROC-AUC Curve for Multiclass - ResNet50

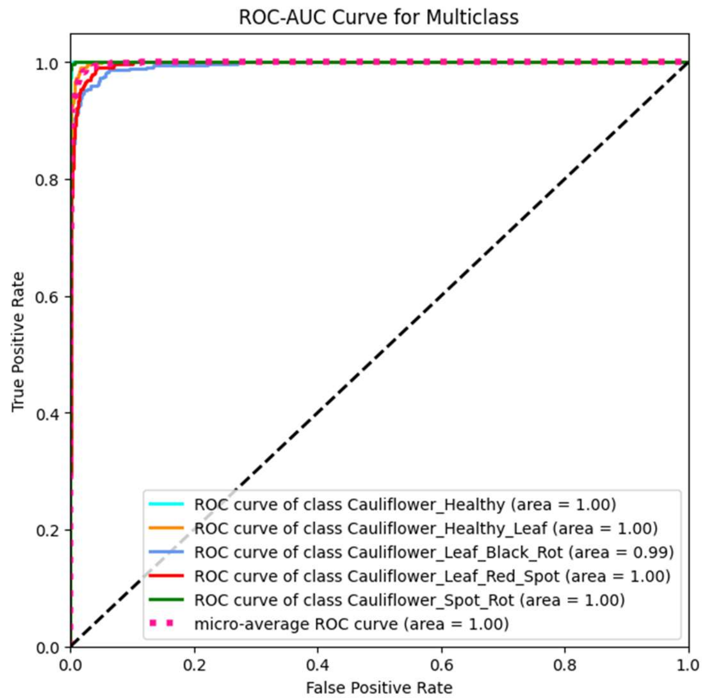

Figure 4.2.33: ROC-AUC Curve for Multiclass - RestNet50

Training and Validation Accuracy of ResNet50

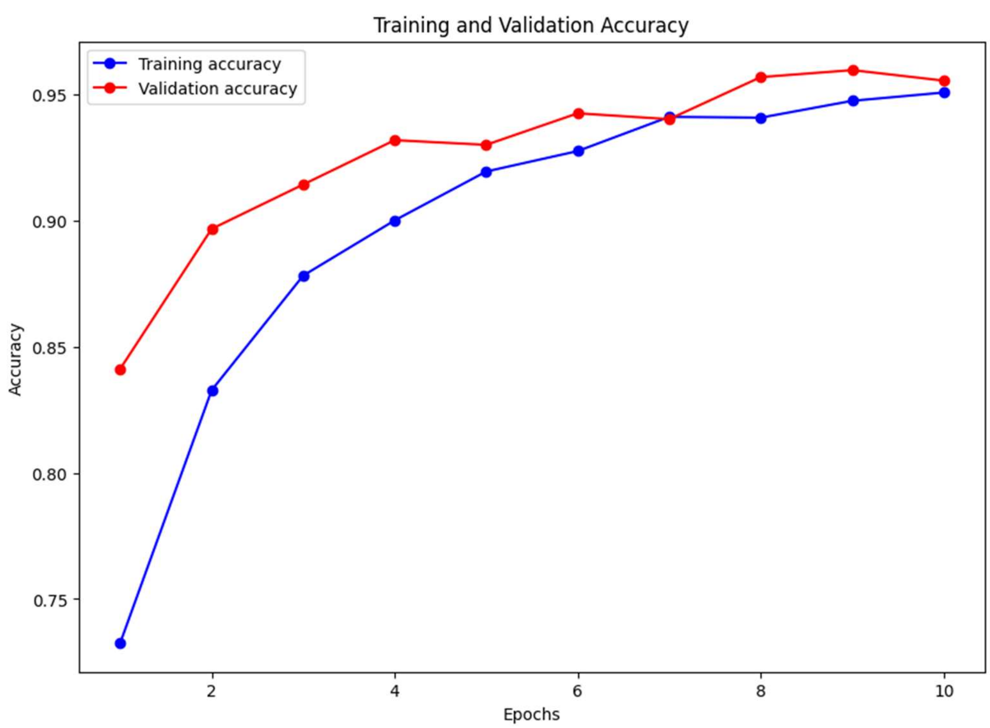

Figure 4.2.34: Training and Validation Accuracy of RestNet50

Training and Validation Loss of ResNet50

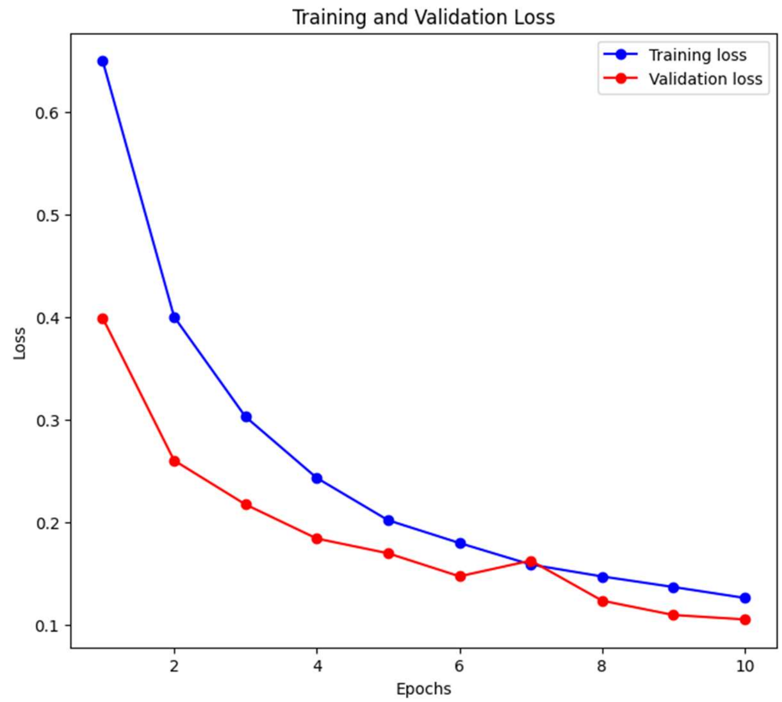

Figure 4.2.35: Training and Validation Loss of RestNet50

Training and Validation Misclassification Error of ResNet50

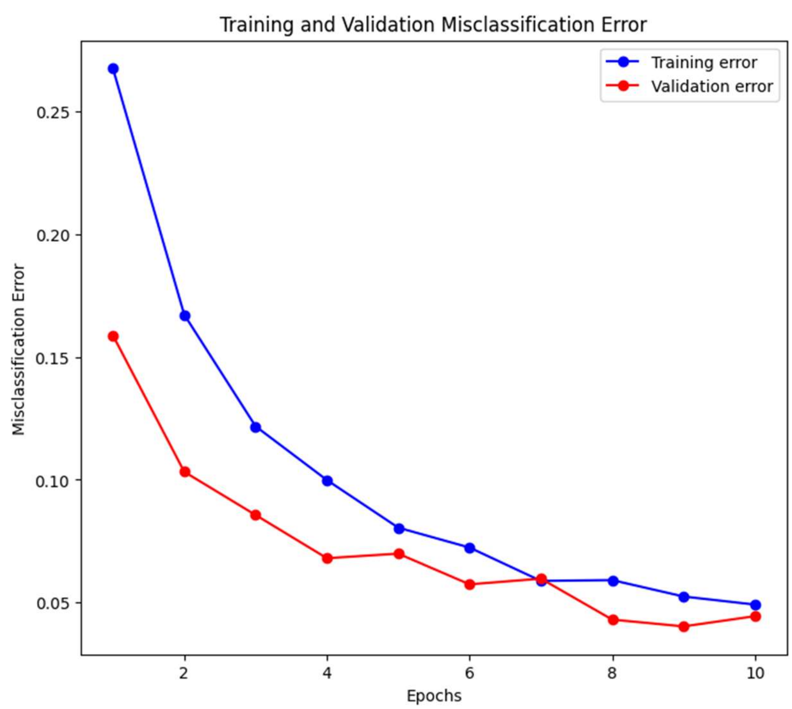

Figure 4.2.36: Training and Validation Misclassification Error or RestNet50

4.3 Discussion

The table compares multiple deep learning methods used to detect and classify illnesses in cauliflower leaves. The algorithms tested were CNN, EfficientNetB3, EfficientNetB7, MobileNetV3, ResNet32, and ResNet50. Precision, Recall, F1-Score, and Accuracy are presented for each algorithm in five distinct studies: Cauliflower_Healthy, Cauliflower_Healthy_Leaf, Cauliflower_Leaf_Black_Rot, Cauliflower_Leaf_Red_Spot, and Cauliflower_Spot_Rot.

MobileNetV3 has the highest overall accuracy, 0.99. It earns flawless scores (Precision, Recall, and F1-Score) in the Cauliflower_Healthy, Cauliflower_Healthy_Leaf, and Cauliflower_Spot_Rot investigations, showing extraordinary performance.

In general MobileNetV3 outperforms the other algorithms in terms of accuracy and performance across numerous studies, but EfficientNetB7 has the least overall accuracy.

Table 4.3.1: Performance Comparison of Different Algorithms

Algorithm	Study	Precision	Recall	F1-Score	Accuracy
CNN	Cauliflower_Healthy	0.97	0.91	0.94	0.92
	Cauliflower_Healthy_Leaf	0.98	0.92	0.95	
	Cauliflower_Leaf_Black_Rot	0.91	0.88	0.89	
	Cauliflower_Leaf_Red_Spot	0.86	0.9	0.88	
	Cauliflower_Spot_Rot	0.86	0.99	0.92	
EfficientNetB3	Cauliflower_Healthy	0.99	0.95	0.97	0.93
	Cauliflower_Healthy_Leaf	0.93	0.98	0.95	
	Cauliflower_Leaf_Black_Rot	0.85	0.9	0.87	
	Cauliflower_Leaf_Red_Spot	0.93	0.8	0.86	
	Cauliflower_Spot_Rot	0.95	0.99	0.97	
EfficientNetB7	Cauliflower_Healthy	0.95	0.94	0.94	0.86
	Cauliflower_Healthy_Leaf	0.88	0.91	0.9	
	Cauliflower_Leaf_Black_Rot	0.75	0.74	0.75	
	Cauliflower_Leaf_Red_Spot	0.78	0.73	0.75	
	Cauliflower_Spot_Rot	0.93	0.95	0.94	
MobileNetV3	Cauliflower_Healthy	1	0.99	1	0.99
	Cauliflower_Healthy_Leaf	1	1	1	
	Cauliflower_Leaf_Black_Rot	0.97	0.97	0.97	
	Cauliflower_Leaf_Red_Spot	0.97	0.98	0.97	
	Cauliflower_Spot_Rot	0.99	1	1	
ResNet32	Cauliflower_Healthy	0.99	0.99	0.99	0.96

	Cauliflower_Healthy_Leaf	0.97	0.97	0.97	
	Cauliflower_Leaf_Black_Rot	0.88	0.92	0.9	
	Cauliflower_Leaf_Red_Spot	0.94	0.9	0.92	
	Cauliflower_Spot_Rot	0.99	0.99	0.99	
ResNet50	Cauliflower_Healthy	1	0.99	0.99	0.96
	Cauliflower_Healthy_Leaf	0.98	0.96	0.97	
	Cauliflower_Leaf_Black_Rot	0.84	0.96	0.9	
	Cauliflower_Leaf_Red_Spot	0.96	0.87	0.91	
	Cauliflower_Spot_Rot	0.99	1	0.99	

CHAPTER 5
Impact on Society

5.1 Impact on Society

Pneumonia Agriculture is the backbone of many countries around the world, and proper crop management is critical to food security and economic stability. Cauliflower, a popular vegetable in many cuisines, is susceptible to a variety of diseases that can significantly reduce output and quality. Early and exact identification is critical for effective disease prevention and therapy. Deep learning models provide humanity with a game-changing opportunity to enhance the detection of cauliflower illness. From the perspective of a researcher, this essay looks into the social implications of utilizing deep learning algorithms to diagnose cauliflower illness.

One of the most evident benefits of using deep learning models to diagnose cauliflower sickness is greater agricultural yield. Traditional disease detection systems rely on manual examination by farmers or agronomists, which can be time-consuming, arbitrary, and error-prone. Deep learning models trained on massive datasets of images of both healthy and diseased plants may identify early disease symptoms quickly and correctly. Farmers are better able to control the spread of disease and prevent crop losses when they identify problems early and use appropriate solutions. The final result is an increase in total production, which promotes steady farmer income and food security.

Improved sickness diagnosis has huge economic benefits. Farmers may enhance harvests and potentially lower consumer costs by reducing crop losses due to disease. This will increase the market supply. Furthermore, the precision of deep learning models allows farmers to save money on inputs by using pesticides and fertilisers more effectively. This economic efficiency increases profitability from farm to market, across the whole agricultural supply chain. Furthermore, higher-quality products can improve market competitiveness and export potential by lowering the need for chemical treatments and developing greener crops.

The application of deep learning techniques to the diagnosis of cauliflower illness has far-reaching and profound social consequences. Improved farming yields, economic gains, reduced environmental damage, and improved community and farmer empowerment are just a few of the key outcomes that demonstrate the significance of this technological accomplishment. We can make a big contribution to agricultural transformation, food security, and equitable growth by doing new research and addressing associated issues.

5.2 Impact on Environment

The application of deep learning algorithms for cauliflower disease detection offers significant ecological benefits. The widespread application of pesticides and fertilizers in traditional disease management methods can lead to misuse and environmental degradation. Deep learning models enable precise, focused treatment by accurately recognizing the presence and severity of diseases. Because of this accuracy, less wasteful chemical use is necessary, reducing water and soil contamination.

In addition, deep learning models' early detection capabilities helps prevent diseases from spreading widespread. Producers may avoid protracted therapies by employing focused interventions rather than addressing issues at an early stage. This strategy reduces the quantity of carbon dioxide produced while conserving the environment.

The application of deep learning to disease detection helps to support sustainable agriculture approaches. These technologies help to preserve biodiversity and soil health by encouraging the more effective use of resources. Richer minerals lead to more resilient agricultural systems that can withstand the effects of climate change. Furthermore, less chemical runoff protects surrounding rivers, preserving aquatic habitats and avoiding disruption of the food chain.

Implementing deep learning models supports integrated pest management (IPM) strategies. Integrated Pest Management (IPM) is a pest-management strategy that integrates chemical, cultural, and biological treatments, with a focus on sustainable development. Deep learning provides the data-driven insights necessary to optimize these procedures and reduce reliance on hazardous drugs. The use of deep learning algorithms for cauliflower disease diagnostics, according to researchers, could pave the way for ecologically friendly agriculture. These developments provide a substantial contribution to the preservation and conservation of our natural ecosystems, as well as enhancing crop health and yield through better disease detection accuracy.

5.3 Ethical Aspects

Data privacy and security are two of the most pressing ethical concerns. Deep learning algorithms require extensive data collection, which may include crop photographs as well as information about agricultural sites and practices. It is critical to ensure that this data is collected with informed consent, stored securely, and used correctly. To ensure that producers' data is not misused or shared without their permission, strict data management standards and open practices are required.

Other ethical considerations include technical justice and accessibility. If powerful AI technologies are only available and cheap to large-scale or wealthy farmers, there is a risk that they will exacerbate pre-existing imbalances. It is critical to strive toward developing scalable and fairly priced alternatives that smallholder and marginal farmers can use. Offering training and assistance is necessary to ensure that all farmers, regardless of financial situation, may benefit from the technology. Deep learning applications raise fundamental questions regarding algorithmic bias. If the training data does not reflect the wide range of conditions under which cauliflower is grown, the models may perform poorly for specific groups or locations. Creating varied and complete datasets is critical for developing unbiased and equitable solutions.

The moral repercussions of deploying deep learning models must be considered. Such technologies have the potential to improve resource efficiency; nevertheless, they must be developed and used in a way that encourages ecologically benign agricultural practices rather than unwittingly supporting damaging ones.

Addressing these ethical considerations is critical to the appropriate deployment of deep learning algorithms for the detection of cauliflower illness. We can harness the benefits of AI in agriculture while upholding moral norms and ensuring reasonable and long-term outcomes for all parties involved by emphasizing data privacy, increasing accessibility and justice, decreasing algorithmic bias, and considering the environmental impact.

5.4 Sustainability Plan

A comprehensive methodology is required to ensure the long-term viability and performance of deep learning models for the diagnosis of mental sickness. To construct a strong and efficient system, this plan must consider community involvement, policy frameworks, technical systems, and skill development.

It is vital to have a robust technological infrastructure. This includes developing and monitoring high-quality databases on cauliflower ailments, as well as ensuring that data gathering and annotation techniques are consistent. The requisite processing power and storage can be achieved by utilizing cloud computing resources, making the system more accessible and extensible. Deep learning models must be updated on a regular basis to account for new pathogen variants and environmental changes.

It is critical to invest in farmer and agriculture professional capacity development. Farmers should be educated how to use AI technologies and mobile applications for disease detection through educational campaigns. Workshops and other forms of continual education could help them stay up to date on the latest advancements. Building a network of regional agricultural professionals can also help farmers deploy these technologies more widely.

It is critical to create a legislative and policy climate that encourages the use of artificial intelligence in agriculture. Policies should provide data security and privacy, protecting farmers' personal information while allowing data exchange for the sake of improving models. Government subsidies and incentives can make these technologies more accessible and cost-effective for smallholder farmers.

Deep learning model implementation necessitates significant involvement from the agricultural industry. Building acceptability and trust can be accomplished by launching awareness campaigns that highlight the benefits of AI technologies and early disease detection. Community support and engagement can be increased through collaborative initiatives with surrounding NGOs and farmers.

A range of methodologies are required to develop a long-term deep learning model-based plan for diagnosing cauliflower sickness. We can ensure that these innovative ideas have a positive long-term impact on agriculture by involving the general public, enacting supportive laws, improving capacity, and strengthening technical assistance.

CHAPTER 6
Summary, Conclusion,
Recommendation and Implication for Future Research

6.1 Summary of the Study

The study on deep learning models for cauliflower disease recognition examines the application of cutting-edge artificial intelligence techniques to identify and diagnose disorders affecting cauliflower crops. Crop diseases have a significant impact on agricultural productivity and economic stability, therefore this study aims to increase farmers' control and mitigation efforts by establishing a reliable and effective method for early disease detection.

The primary goals of the study are to develop, refine, and validate deep learning models capable of accurately identifying various types of cauliflower disorders from image data. To improve model accuracy and resilience, the study compares the performance of several augmentation approaches. Furthermore, the study investigates the use of these models in real-world agricultural scenarios.

Experimental stations and agricultural areas include a significant collection of images of cauliflower, both healthy and unwell. These images offer labels and categories based on various diseases. Data augmentation approaches are used to increase the quality and variability of training data. To evaluate performance indicators such as accuracy, precision, recall, and F1-score, models are trained on a portion of the dataset and then validated on a larger percentage. To assess the viability and efficacy of the best-performing models for real-time disease detection, they are tested in realistic agricultural settings.

The study found that deep learning models improve the accuracy of detecting cauliflower disease significantly. The models show efficacy in recognizing diseased plants in a timely and reliable manner, with excellent recall and accuracy rates. Field testing demonstrates that these models may be utilized in practice and assist farmers in treating diseases on time.

According to the study's findings, deep learning models offer a practical strategy for detecting cauliflower disease, which will have a substantial positive influence on crop productivity, financial stability, and sustainable agricultural practices. It is recommended that more research be conducted to refine these algorithms, diversify the datasets, and study interactions with bigger farming management processes.

6.2 Conclusions

The use of deep learning models to diagnose cauliflower sickness has revolutionary implications for many sectors of farming. The study's findings and real-world applications indicate significant advances in early and precise disease identification, which is critical for effective cultivation. Deep learning models surpass conventional techniques in terms of speed and accuracy, allowing for more timely actions due to their ability to process and analyze massive amounts of image data.

An significant finding is that agricultural output needs to be boosted. Deep learning algorithms assist farmers in detecting infections early and administering targeted therapies to halt disease progress and prevent crop damage. Higher harvests and higher-quality products are the result, increasing supply and farmer revenues.

In terms of economics, using deep learning for illness detection reduces the cost of labor-intensive physical inspections and unnecessary chemical use. Farmers can minimize input costs and boost overall profitability by optimizing resource utilization. Furthermore, the precision of these models helps environmentally friendly farming operations by reducing chemical runoff and ensuring ecosystem health.

Another significant result is that farmers can become stronger by utilizing readily available and simple-to-use equipment. Smallholder farmers can now access superior farming tools thanks to mobile apps and training programs that use cutting-edge artificial intelligence technologies. This fosters an inventive and ever-improving environment in agricultural techniques.

But there are still concerns to be addressed, including ensuring that it is inexpensive, scalable, and does not jeopardize data privacy. We must continue to focus on developing cost-effective alternatives while maintaining farmer confidence and collaboration.

To put it simply, deep learning models for detecting cauliflower sickness are a crucial advancement in agricultural technology that will significantly improve farmer empowerment, economic efficiency, environmental sustainability, and performance. To fully achieve these benefits and overcome the remaining challenges, more research and development will be required to ensure widespread acceptability and long-term profitability.

6.3 Implication for Further Study

Although deep learning algorithms have considerable potential for detecting cauliflower disease, further research is needed to improve and optimize their performance. Future study will focus on expanding and diversifying datasets. Many of the current models rely on constrained datasets that may not adequately reflect the breadth of illness characteristics and environmental factors. The models' durability and generalizability can be improved by include more photographs from various growth scenarios and geographic areas in these datasets.

Another important strategy for improving forecast accuracy is multi-modal data integration, which integrates imaging with ecological and subsurface data. This comprehensive strategy can aid in more accurate and context-sensitive ailment detection, allowing for personalized therapeutic plans.

More research is needed to determine the viability and economics of employing these models in real-world agricultural scenarios. By making affordable, user-friendly systems more accessible to smallholder farmers, research can drive wider usage.

At last, it's vital to consider the ethical implications and ensure data security and privacy. Researchers must develop frameworks that both protect farmers' data and foster technological confidence. Future study can tremendously benefit the sector by addressing these concerns, which will aid in crop management and environmentally friendly farming.

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Appendix A

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

Title: Cauliflower Disease Detection Using a Deep Learning Approach

Student ID: 193-15-13503

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a cauliflower disease detection problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

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

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

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	The project emphasizes fundamental engineering (K3) concepts through the use of deep learning, data augmentation techniques, including a range of architectures for image processing and categorization. The project demonstrates specialized understanding (K4) by integrating complex architectures to increase disease identification accuracy in cauliflower photos, which is essential for autonomous agricultural diagnostics.	**Page no:** [26-30] **Section:** [3.2] **Page no:** [1-7] **Section:** [1.1]
				The initiative employs the field of engineering and design (K5) in the form of an experimentation process diagram. The deep learning model (K6) is used in the project to address practices in engineering and technology.	**Page no:** [30] **Section:** [3.2(B)] **Page no:** [33]

					Section: [3.4]
				This endeavor contributes to K8 (Research Literature) by combining ideas from recent studies to improve disease detection in agriculture using deep learning, exhibiting a complete understanding of existing methodologies.	**Page no:** [5-7] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This work tackles EP-2 by examining the limitations of conventional disease detection methods in the agricultural sector, as well as the complexities of integrating deep learning. It uses comparative analysis to address challenges in understanding geographical distributions, providing insights for improving diagnostic procedures.	**Page no:** [23-24] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	The study addresses EP-3 by meticulously assessing trial findings, revealing Deep Learning as a particularly successful approach for enhancing diseases detection in cauliflower amongst multiple possible approaches.	**Page no:** [36-57] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's multifaceted strategy extends beyond engineering and computer science to influence agricultural practices and contribute to advancements in plant disease and crop management (EP-4).	**Page no:** [16-24] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's broad approach addresses high-level concerns by integrating a variety of components, including data collecting, statistical evaluation, and the recommended technique. This results in a comprehensive answer to difficult challenges in agricultural diagnostics, ensuring EP-7.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

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 study makes use of a variety of resources, including high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations, to assure systematic research and contribute to advances in cauliflower diseases detection using deep learning.	**Page no:** [33-35] **Section:** [3.5]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This study benefits society by improving agricultural practices through improved cauliflower disease detection methods, while also promoting environmental sustainability by utilizing efficient computational capacity as well as following to ethical safeguarding standards for the collected images.	**Page no:** [58-61] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This project expands on earlier research by studying a fresh technique for cauliflower illness detection utilizing deep learning, as shown by preliminary findings and a comprehensive comparison analysis, resulting in new insights into the subject.	**Page no:** [7-10] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses CO4 emissions by combining effective project management and financial control, assuring precise planning, resource allocation, and budget estimation to maximize resource usage throughout the study lifetime.	**Page no:** [13] **Section:** [1.6]
2	CO9	Yes	The project displays commitment to moral values by protecting image data privacy, getting relevant data gathering approvals, and fully describing the research process. This promotes responsible information sharing and social prosperity through the ethical application of innovative agricultural technology that meet CO9.	**Page no:** [60] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning (CO12) and adaptation within the dynamic technological landscape is reflected in its extensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, demonstrating a willingness to stay current and refine techniques to address modern challenges.	**Page no:** [26-34, 37-55] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

CAULIFLOWER DISEASE DETECTION USING A DEEP LEARNING APPROACH

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