MANGO LEAF DISEASE DETECTION USING DEEP LEARNING MODELS

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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 **"Mango Leaf Disease Detection Using Deep Learning Models"**, submitted by **Marjana Masfia** 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 us under the supervision of **Narayan Ranjan Chakraborty, Associate Professor and Associate Head, 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.

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ABSTRACT

The detection and classification of diseases affecting mango leaves are critical for maintaining crop health and ensuring optimal yield. Manual inspection methods are often time-consuming and prone to human error, necessitating the development of automated detection systems. In this study, I propose a novel approach utilizing image data analysis for the detection of mango leaf diseases. Leveraging advanced image processing techniques and convolutional neural networks (CNNs), our model can accurately classify various types of leaf diseases based on image features. Our study integrates advanced techniques such as EfficientNetB4, VGG19, VGG16, InceptionV3 and Xception. By extracting relevant features from mango leaf images and training the model on a diverse dataset, we achieve robust performance in disease detection. Additionally, we explore the integration of transfer learning to enhance the model's capability to generalize across different disease types and environmental conditions. Through rigorous experimentation and validation, our framework demonstrates promising results, offering a reliable tool for early disease diagnosis and effective management strategies in mango cultivation. This research contributes to the advancement of precision agriculture practices, facilitating timely interventions and ultimately improving crop health and yield. The study tested integrated models for image classification, revealing that VGG19, InceptionV3, VGG16, EfficientNetB4, Xception and our proposed model demonstrated exceptional performance. Our proposed model has the height accuracy at 98%, while VGG19, InceptionV3, VGG16 and EfficientNetB4 secured the top positions with 86.50%, 96.49%, 89.99% and 94.09% accuracy. Transfer learning models improved accuracy, but remained lower than proposed models. This research is significant for data scientists as it highlights the importance of continuous advancements in agricultural research.

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CHAPTER 1
INTRODUCTION

1.1 Overview

An artificial intelligence method for computer-aided diagnosis, such as the diagnosis of mango leaf disease, is called deep learning (DL). While professional researchers, farmers, and agricultural classification are criticized for being costly and time-consuming, deep learning (DL) has been demonstrated to be successful and efficient in the classification and detection of illnesses using photos Maheshwari et al. (2021). DL uses convolutional neural networks (CNNs) with multilayered, hierarchical, and block structures to extract low-, mid-, and high-level information from leaf disease image collections. The mango (Mangifera indica L.), a tropical fruit that is extensively grown, is prized for its delicious flavor, high nutritional value, and economic significance. Unfortunately, a number of diseases that affect the leaves of mango trees frequently compromise their quality and productivity, resulting in sharp drops in yield and revenue. Timely identification and accurate diagnosis of these illnesses are essential for facilitating timely treatments, improving crop management practices, and reducing the adverse effects on mango cultivation Ghosh et al. (2024). A training dataset from a separate activity is the foundation for transfer learning (TL). The last few layers, though, may be eliminated and retrained for the intended job Mia (2020). Deep learning's first few layers explain the characteristics of the tasks. It explains a situation where optimization in one context is improved by using knowledge from another. After that, look into the topology of the CNN architecture to find a model that will allow (TL) to categorize pictures. Testing and changing the dataset properties and network architecture may help determine the parameters influencing classification performance, even with constrained time and processing resources. Deep learning models are often not well trained with small data sets due to possible detrimental effects on the model's performance. The act of applying the parameters of a model built from a bigger dataset that is entirely unrelated to the one being utilized is known as transfer learning, according to Sanath Rao (2021). Notable gains are only observed when the segmentation issue is more difficult and there is a lower quantity of target training data available. It is generally not advised to train a deep learning model on a limited data set since this can have a deleterious effect on the model's accuracy. Transfer learning is exemplified by initializing a model with weights from another model's training on a larger dataset. Only when the segmentation problem is more difficult and there are less target training data available do the gains become statistically significant. Known as the "King of Fruits," mangos are a costly fruit crop that are grown all over the world. Because of its nutritional and economic importance, it is commonly consumed. India is the world's top producer of mangoes, accounting for over 40% of global production. However, pests and diseases pose serious problems for mango crops, leading to large output losses estimated to be between 30% and 40% S. Chouhan (2020). Particularly mango leaves are prone to a number of illnesses that have a big influence on mango yield. In South India, mango farming is an important agricultural activity that boosts the local economy. However, a number of leaf diseases frequently impede the development and yield of mango plants. If these illnesses are not identified and treated very away, they may result in large crop losses and decreased fruit quality. The labor-intensive, time-consuming, and error-prone nature of manual leaf disease inspection and diagnosis necessitates the development of automated and accurate disease detection systems M. Mia (2020). Plant disease identification technologies that are autonomous, accurate, quick, and affordable are therefore becoming more and more necessary. Leaf diseases are identified using machine learning and image processing. One area of machine learning that has gained popularity is deep learning, which has real-world uses. It provides an effective tool for classifying and diagnosing plant diseases through the use of deep neural networks. Plant categorization and illness detection are two image analysis tasks that have benefited from deep learning, particularly with regard to Deep Convolutional Neural Networks (CNNs).CNNs can automatically extract from the raw input pictures the discriminative features needed for intricate pattern recognition tasks Y. Nagaraju (2020).

Convolutional Neural Networks (CNNs)

Convolutional neural networks, or CNNs, use the term "convolution" to describe the mathematical blending of two functions to create a third function. With others, Trongtorkid, C. (2018). With this process, two sets of data are combined. While CNNs are made up of several layers, ANNs are made up of just one layer. CNNs have an input layer, several convolutional layers, pooling layers, a fully connected layer, and an output layer.

Convolutional layers, often referred to as filters or kernels, are used by the CNN architecture to transform incoming data into a feature map. CNNs are made to recognize more complex patterns, like faces and objects, in later layers after being trained to recognize simpler patterns, like lines and curves, at first. CNNs are popular in data science because of their track record in finding, classifying, and identifying objects in photos Mohanty group et al. (2016). There are no changes made to the CNN algorithm's processing units, parameterization, hyper-parameter optimization strategies, design patterns, or layer connections; it is utilized just as its creators and programmers intended. Notably, a number of scientists and programmers have continuously built and enhanced a well-known CNN network across several iterations. Kumar (2019). Transfer learning is a method that improves optimization in a new environment by utilizing information from a training dataset in a particular activity or sector. This method involves adding additional layers and training them for the particular target job, while discarding the last few levels of a pre-trained network. Task-specific attributes are captured in the first layers of the deep learning process. Transfer learning basically entails using knowledge from one environment to enhance performance in another Rajeshwari et al. (2020). We conduct an examination into CNN topologies with the goal of finding a model that can be used for transfer learning in image categorization. Experimenting and adjusting network topology settings and dataset features can assist find aspects impacting classification success, even with limited processing power and time. A deep learning model may perform less well if it is trained on a small dataset. In order to overcome this difficulty, transfer learning uses weights from another model that was trained on a different, bigger dataset to initialize a model Sharma et al. (2021). Notable advancements are especially noticeable when working with a smaller target training dataset and a more complicated segmentation challenge.

VGG19: One example of this is VGG19, a 19-layer variant of VGG that allows for explicit and effective spatial information transfer across neurons in the same CNN layer. This design is especially effective in situations when things have distinct forms. Using tiny (3×3) convolution filters to evaluate networks of increasing depth and capture both left/right and up/down orientations, VGG19 makes a substantial contribution. A Rectified Linear Unit (ReLU) is used after 1x1 convolution filters to perform a linear transformation of the input. After convolution, the spatial resolution is preserved because to the fixed convolution stride

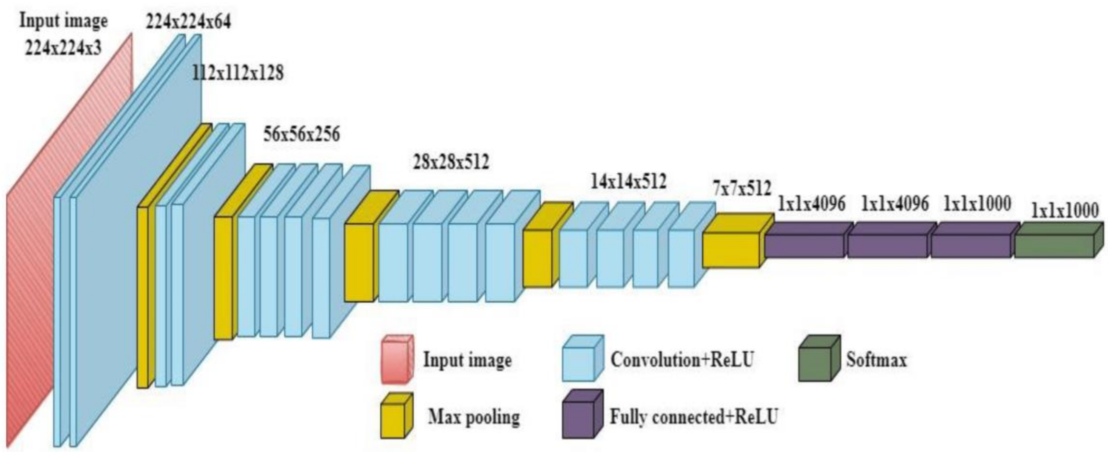

Figure 1.1.1: Architecture of VGG19 (Nguyen T-H 2022)

VGG16: The VGG16 architecture is a deep convolutional neural network that was proposed by the Visual Geometry Group (VGG) at the University of Oxford. VGG16, named for its 16 layers, is characterized by its simplicity and uniform architecture. It consists of 13 convolutional layers and 3 fully connected layers, along with ReLU activation functions and max pooling layers interspersed throughout. The convolutional layers use small 3x3 filters, which are stacked to create a deep network capable of learning complex features. Max pooling layers follow certain sets of convolutional layers to reduce the spatial dimensions, thereby decreasing the computational load and helping in hierarchical feature extraction. The fully connected layers at the end of the network help in combining these features to make final predictions. VGG16's uniform architecture and deep structure make it highly effective for image classification tasks, achieving significant performance on benchmark datasets like ImageNet. Despite its depth, VGG16 is computationally intensive due to its large number of parameters, but its design simplicity has made it a foundational model in the field of deep learning.

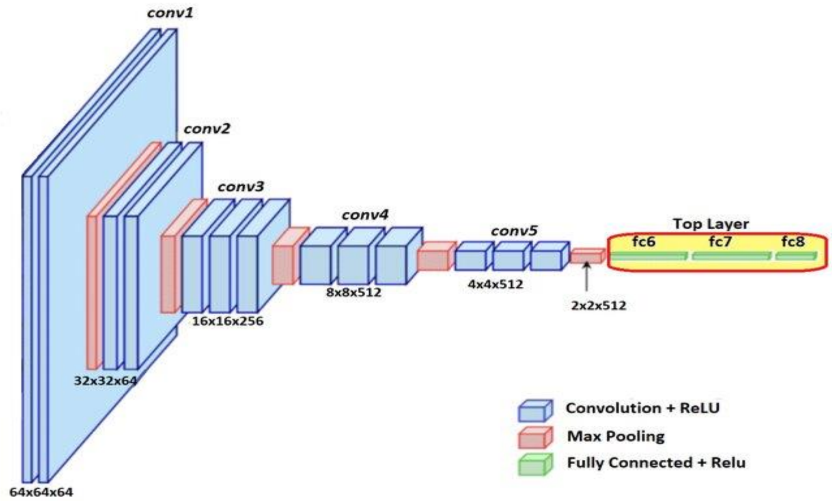

Figure 1.1.2: Architecture of VGG16 (Shaffi et al. 2023)

InceptionV3: The InceptionV3 architecture, developed by Google, is a deep convolutional neural network (CNN) designed for image classification tasks. It is an evolution of the original Inception architecture, also known as GoogLeNet, and introduces several enhancements for improved performance and efficiency. InceptionV3 incorporates the concept of 'Inception modules,' which consist of multiple convolutional filters of different sizes (1x1, 3x3, 5x5) operating in parallel, allowing the network to capture features at various scales within the same layer. This architecture reduces computational complexity by using 1x1 convolutions to decrease the dimensionality of the feature maps before applying larger convolutions, a technique known as dimensionality reduction. Additionally, InceptionV3 includes auxiliary classifiers for regularization and faster convergence during training, and it employs batch normalization to stabilize and accelerate the learning process. These design choices enable InceptionV3 to achieve state-of-the-art performance on various image recognition benchmarks while being computationally efficient and suitable for practical deployment.

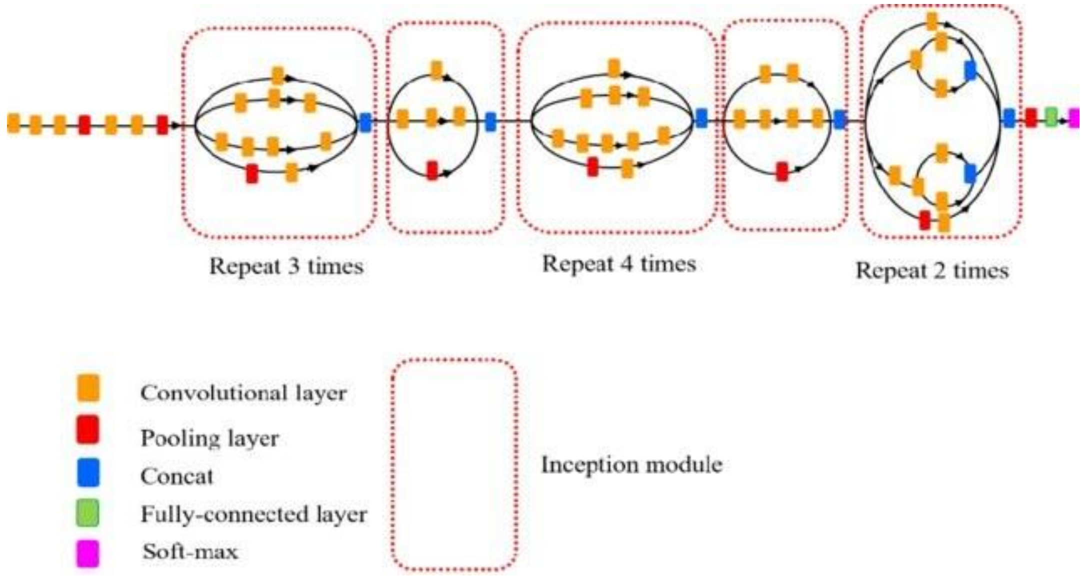

Figure 1.1.3: Architecture of InceptionV3 (Tian et al. 2018)

Xception: The Xception architecture, developed by François Chollet, is an advanced convolutional neural network (CNN) that builds upon the Inception architecture with depthwise separable convolutions, a more efficient variation of convolutions. Xception, short for "Extreme Inception," replaces the standard Inception modules with depthwise separable convolution layers, which decompose the convolution operation into two simpler operations: a depthwise convolution and a pointwise convolution. This results in a significant reduction in computational complexity and parameters while maintaining or improving model performance. The architecture consists of a series of entry flow, middle flow, and exit flow modules, with each flow designed to progressively abstract and capture features from the input images. Xception's design emphasizes efficiency and performance, making it well-suited for a variety of image recognition and classification tasks. The model leverages residual connections similar to those in ResNet, enhancing its ability to train deep networks effectively.

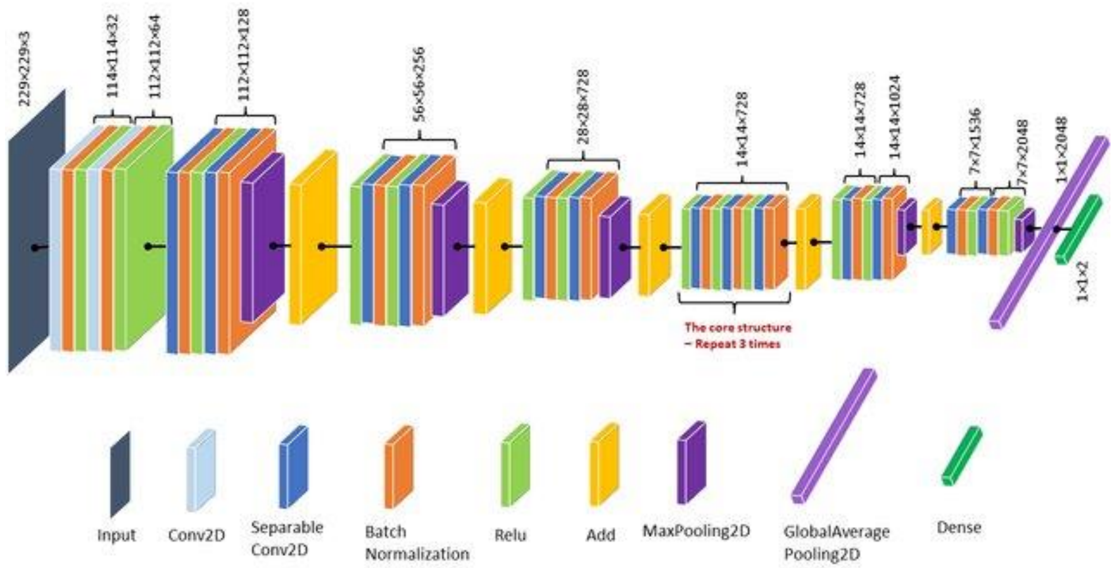

Figure 1.1.4: Architecture of Xception (Mehmood et al. 2021)

EfficientNetB4: EfficientNetB4 is part of the EfficientNet family of models, which are known for their efficient scaling methods, achieving high performance with fewer parameters and less computational cost compared to traditional CNN architectures. EfficientNetB4 employs a compound scaling method that uniformly scales all dimensions of depth, width, and resolution using a fixed set of scaling coefficients. It starts with a base EfficientNet architecture, characterized by the use of mobile inverted bottleneck MBConv blocks with squeeze-and-excitation (SE) optimization. These blocks efficiently balance the network depth and width, utilizing depthwise separable convolutions to reduce the number of parameters and computations. The EfficientNetB4 model further enhances performance by increasing the resolution of input images, deepening the network, and expanding its width. This model is pre-trained on ImageNet, which provides a strong initialization for various computer vision tasks. The final layers of EfficientNetB4 typically include a global pooling layer, followed by dense layers for classification, allowing it to effectively capture and process complex patterns in high-resolution images while maintaining computational efficiency.

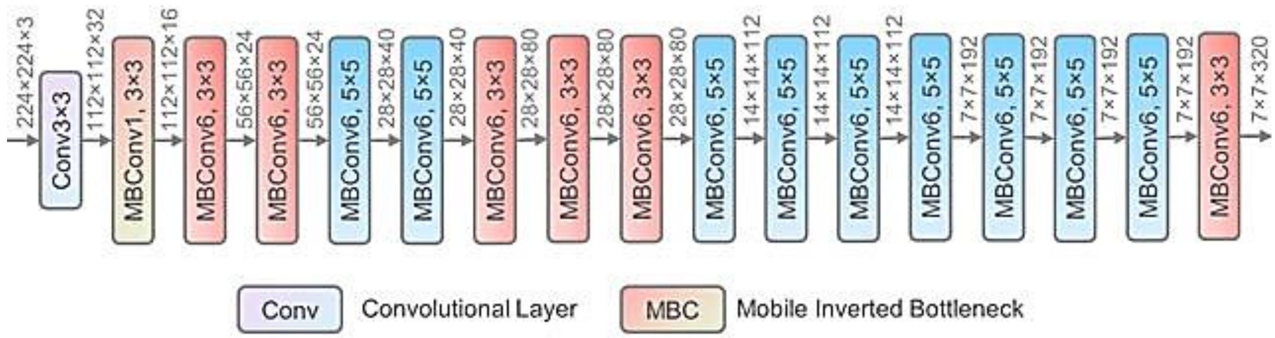

Figure 1.1.5: Architecture of EfficientNetB4 (Xu et al. 2021)

1.2 Background and Present State

The necessity to solve pressing issues in the fields of agricultural imaging and respiratory illness diagnostics is the base for the reasoning behind the "Mango Leaf Disease Detection Using Deep Learning Models" project. Leaf disease is still a major global crop health problem, and prompt and precise diagnosis is essential for management and treatment. The goal of this research project is to create a strong deep learning framework that can effectively classify subtypes of Mango Leaf Disease using visual data. This framework offers considerable advantages over current diagnostic approaches by aiming to attain high levels of subtype categorization accuracy, reliability, and efficiency. The model will identify pertinent characteristics and biomarkers from Mango Leaf Disease photos by utilizing convolutional neural networks (CNNs) and sophisticated image processing techniques, enabling accurate subtype categorization. In addition, the study seeks to determine the best architectural layouts and CNN model hyperparameters, as well as investigate how different preprocessing methods affect classification efficiency. In the end, a deep learning-based classification system that helps physicians correctly diagnose Mango Leaf Disease is anticipated as part of the output, which would enable tailored treatment plans and enhance tree health. The research findings will also improve our knowledge of the biology of mango leaf disease and develop computational pathology.

1.3 Problem Statement

A number of important elements are included in our suggested framework, such as feature extraction, data preprocessing, and classification utilizing cutting-edge deep learning architectures. To optimize the input for further analysis, we preprocess the picture data to improve contrast, eliminate noise, and standardize characteristics. Feature extraction is the process of using CNN models that have already been trained, such ResNet or VGG, to automatically extract discriminative features from the input photos and identify complex patterns that may be symptomatic of Mango Leafe Disease. These retrieved characteristics are used in the classification stage to develop an appropriate classification model. Using methods like transfer learning and fine-tuning, we leverage pre-trained CNN models' ability to learn intricate hierarchical representations from large-scale picture datasets to tailor them to the particular job of subtype categorization. Additionally, we explore ensemble learning methods to further enhance classification performance by combining multiple models' predictions.

1.4 Objectives

Mango leaf disease is still the world's biggest cause of mortality among mango plants, thus improving diagnostic tools and treatment approaches is imperative. This is the driving force behind this research. Conventional techniques for subtype categorization frequently depend on histological investigation, which can be laborious, subjective, and sensitive to variation across observers. On the other hand, deep learning models have proven to be remarkably effective in image analysis tasks, suggesting that they have the ability to overcome the drawbacks of traditional methods.

1. Enhance mango leaf recognition efficiency and accuracy using transfer learning techniques.

2. Compare the performance of CNNs in identifying mango leaf diseases and their role in diagnostics.

3. Assess the impact of transfer learning on the sensitivity and specificity of mango leaf disease detection.

4. Examine segmentation techniques for insights into disease features and spatial distribution.

5. Evaluate the pros and cons of various segmentation and detection techniques for improved diagnostics.

6. Advance state-of-the-art mango leaf disease diagnosis through comparative studies.

7. Apply study findings to improve agricultural imaging practices and real-world plant care.

1.5 Scope and Limitations

The necessity to fill in the significant gaps in the present understanding of Mango Leaf Disease diagnosis and subtype classification is the driving force for this work. Conventional techniques frequently lack the accuracy and efficiency needed to distinguish between the many subtypes of mango leaf disease, which causes delays in diagnosis and less-than-ideal treatment results. With the use of convolutional neural networks (CNNs), one of the deep learning techniques, this study aims to create a strong framework for classifying Mango Leaf Disease subtypes from visual data. By doing this, we want to transform the diagnosis process and give medical professionals fast, reliable insights that can inform individualized treatment plans and, eventually, lead to better patient outcomes in the fight against disease.

1.6 Report Organization

The suggested report has a thorough format that walks readers through the methodology, conclusions, and ramifications of the study. Every chapter has a distinct function and adds to the document's overall cohesion and depth.

Chapter 1: Introduction

The research is introduced in the first chapter, which also gives background information on the importance of detecting mango leaf disease, how deep CNNs and transfer learning are applied, and why a comparison of detection and segmentation techniques is necessary. It provides an overview of the study's goals, research questions, and general structure.

Chapter 2: Literature Review

A thorough analysis of pertinent literature and earlier research is provided in the background chapter. An extensive grasp of the theoretical underpinnings, practical approaches, and technical developments pertaining to deep CNNs, transfer learning, and the diagnosis of mango leaf disease is provided in this section. It lays forth the background for the present investigation and identifies knowledge gaps.

Chapter 3: Research Methodology

The strategy used to carry out the study is described in the research methodology chapter. It sheds light on the model architecture, data gathering techniques, study design, and the reasoning behind particular methodology selections. The ethical issues and potential constraints on the investigation are also covered in this chapter.

Chapter 4: Implementation

The experimental findings from using deep CNNs and transfer learning to identify mango leaf disease are presented in this chapter. Comprehensive evaluations of the effectiveness of various detection and segmentation techniques are offered, accompanied by graphical depictions and statistical metrics to corroborate the results.

Chapter 5: Result And Analysis

The research findings' wider implications for plant maintenance and agricultural diagnostics are examined in the chapter on social effect. It talks about how better ways to diagnose mango leaf disease can benefit plant care, treatment results, and plant care in general. Future technological developments and their effects on society are taken into account.

Chapter 6: Impact on Society

The whole report is summarized in this last chapter. It provides recommendations for real-world applications and more research in addition to summarizing the main results and restating the research's conclusions. Researchers interested in building on the current work might find a roadmap for future research by discussing the implications of the findings.

The reader is guided through the study process from the introduction to the wider implications and suggestions by this organized arrangement, which guarantees a logical flow of information. With transfer learning, it enables a thorough grasp of the study methodology and its possible effects on the academic and practical components of mango leaf disease detection.

Chapter 7: Conclusion and Future Work

The research findings' wider implications for plant maintenance and agricultural diagnostics are examined in the chapter on social effect. It talks about how better ways to diagnose mango leaf disease can benefit plant care, treatment results, and plant care in general. Future technological developments and their effects on society are taken into account.

1.7 Summary

Our suggested framework is important because it can give professionals a dependable instrument for quickly and accurately classifying Mango Leaf Disease subtypes, enabling individualized treatment plans and enhancing tree health. Using the enormous volumes of picture data found in academic libraries and medical archives, we can create deep learning models that are resilient and able to generalize across a variety of expert settings and trees by utilizing the collective knowledge included in these datasets.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

It is essential to lay a foundation through introductions and terminology clarifications in order to enable a thorough comprehension of the fundamental ideas and techniques used in this research on "Mango Leaf Disease Detection Using Deep Learning Models". The foundation of this work is transfer learning, a key idea in artificial intelligence that enables the model to use information gained from unrelated tasks for improved mango leaf disease identification. A key component of image analysis, deep convolutional neural networks (CNNs) are used to extract complex patterns from agricultural imaging. Detection is the process of identifying mango leaf disease in agricultural photographs, whereas segmentation is the process of defining the geographical boundaries of the afflicted regions. These terms are employed consistently throughout the study to investigate the connections between deep CNNs, transfer learning, and the comparison of detection and segmentation techniques. Before delving into the details of the study and grasping the subtleties of sophisticated procedures used in the diagnosis of mango leaf disease, it is imperative that readers have a shared knowledge of these first steps.

2.2 Related Works

Prior to our starting to use image databases for Mango Leaf Disease classification, several significant research initiatives were conducted. The tremendous insights and methods that these ground-breaking studies have given to the field have allowed for improvements in therapeutic efficacy and diagnostic precision. In a conference report published in 2022, Tariqul Islam M. and Tusher A.N. used a CNN model to identify plant illnesses in strawberries, potatoes, and grape leaves. This report makes it abundantly evident that several crop diseases are causing farmers to lose a significant amount of their agricultural yield. Farmers are unable to effectively diagnose plant diseases because they lack advanced technologies. The authors pre-sent the CNN algorithm in order to tackle this difficulty. About 5500 photos were utilized, and the accuracy percentage was 93.63%. In this case, 477 photographs were utilized to test the system while 5400 images were used to train the model Tariqul et al. (2022).

Sukanya S. In a conference article, Sukanya S. Gaikwada et al. employed the CNN algorithm to diagnose guava leaf disease (fungi-affected disorders). He reported in this research that guava leaf infections caused significant losses for the farmer growing guavas for commercial purposes. They thereby discourage the economic production of guava. The authors presented CNN algorithms here to overcome this problem. They obtained an accuracy of 66.3 percent by using about 4000 photos as source data. AlexNet and SqueezdNet were employed by the authors as pre-trained approaches to achieve relative resolution Gaikwad et al. (2021).

In a conference paper, Kien Trang et al. concentrated mostly on image processing (contrast enhancement, transfer learning, neural networks), using the Plant Village dataset to identify plant illnesses. Here, they attempted to quickly and precisely diagnose plant leaf illnesses so that the farmer might lessen their significant output losses. The authors mostly employed image processing and neural network techniques. They demonstrated in this presentation that their model's accuracy, which is 88.46%, is greater than the accuracy of the pre-trained model. To identify mango illnesses, they also concentrated on the mango dataset Kien (2019).

In their conference article, S. Ramesh et al. presented a contemporary algorithm (machine learning). The authors of this research attempted to illustrate the loss of rice output and the significant financial losses farmers experienced as a result of several illnesses. Farmers are unable to effectively diagnose infections because they lack advanced technologies. They attempted to use a machine learning-based strategy to solve this issue Raibongshi (2021).

They needed about 300 photos as a dataset to do their task, and they achieved an accuracy of 90%. Using a data mining methodology, Umar Ayub addressed an international conference in 2018 where he showed Pakistani farmers who were dealing with agricultural diseases Ramesh et al. (2018).

Techniques for segmentation, recognition, and identification were examined by Iqbal et al. They discovered that practically every approach is still in its early stages. Additionally, they covered nearly every approach now in use as well as its benefits, drawbacks, difficulties, and models of machine learning (ML) for illness detection and diagnosis Iqbal et al. (2018).

In their investigation on powdery mildew in strawberry leaves, Shin et al. used an artificial neural network (ANN) with accelerated ro-bust features (SURF) to reach an accuracy of 94.34%. On the other hand, their maximum classification accuracy using an SVM and GLCM was 88.98%. They employed two supervised machine learning techniques (ANN and SVM), HOG, SURF, and GLCM Shin et al. (2020).

Pane et al. used machine learning (ML) to detect the blue hue at a wavelength of 403–446 nm. They identified the healthy and unhealthy leaves of wild rocket, popularly known as salad greens, with precision Pane et al. (2021).

The Friedman test was utilized by Bhatia et al. to rank several classifiers, and the Nemenyitest was also employed for post hoc analysis. With an accuracy of 94.74%, they discovered that the MGSVM was the best classifier in their investigation Bhatia et al. (2021).

On pumpkin leaves, Lin et al.'s research shown that their findings were 3.15% more accurate than the conventional approach. To get findings that were 97.3% correct, they employed PCA Tariq et al. (2021).

An expert system was created by Kahlout et al. to identify illnesses on all citrus species, such as sooty mold and powdery mil-dew Kahlout et al. (2019). A computerized technique for segmenting and classifying citrus plant diseases was suggested by Sharif et al. They employed an optimal weight approach in the first section of their proposed system to identify unhealthy leaf portions. Second, a combination of texture, geometric, and color descriptors was used. Finally, they achieved 90% accuracy in selecting the best features using a hybrid feature selection strategy that used the PCA approach known as entropy Sharif et al. (2018).

A system for categorizing mango plant leaves with anthracnose (disease) was presented by Udayet al. For this challenge, they employed a multiple layer convolutional neural network (CNN). The technique was used on 1070 photos that they had taken using their own devices and cameras. The categorization accuracy increased to 97.13% as a result Singh et al. (2019).

In 2019, Kestur et al. introduced Mango ne t, a deep learning-based segmentation technique. This strategy yields findings that are 73.6% accurate Kestur et al. (2019). Using a CNN, Arivazhagan et al. demonstrated 96.6% accurate results Arivazhagan et al. (2018). Neither feature extraction nor preprocessing were done in this suggested method. Unhealthy areas for mango diseases, such as redrust, anthracnose, powdery mildew, and sooty mold, were identified by Srunitha et al. (2018).

2.3 Comparison between existing works

An essential part of this research on "Mango Leaf Disease Detection Using Deep Learning Models" is the comparison analysis that illuminates the subtle distinctions and complementary aspects of different approaches. In order to identify mango leaf illness, the study rigorously assesses the effectiveness of deep Convolutional Neural Networks (CNNs) and transfer learning, taking into account both conventional techniques and cutting-edge segmentation strategies. By means of rigorous testing and analysis of experimental outcomes, the study reveals discernments about the merits and demerits of every methodology, furnishing a thorough comprehension of their distinct inputs to the diagnostic procedure.

The in-depth examination of segmentation and detection strategies allows for a detailed investigation of their functions in improving the precision and effectiveness of mango leaf disease identification. The study adds significant knowledge to the area by comparing the results of various approaches, helping researchers and practitioners choose the best tactics for their particular situations. The study goes beyond only highlighting differences; it also highlights how detection and segmentation may work in tandem to improve our comprehension of the features and geographic distribution of farms impacted by mango leaf disease.

In conclusion, this research's comparison study provides a crucial prism through which to evaluate the effectiveness of deep CNNs and transfer learning for the identification of mango leaf disease. It presents a complex picture, combining old and new methods, and emphasizes the value of a comprehensive strategy in agricultural diagnostics. The findings provide useful insights for improving current diagnostic techniques in addition to advancing our knowledge of mango leaf disease detection. The present comparative study establishes a firm basis for the societal effect debate, recommendations, and implications for further research in the following chapters.

TABLE 2.3.1: Comparative Analysis Table

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Tariqul Islam M. et al.	InceptionV3, ResNet50, ,Custom CNN	93.63%
2.	Sukanya S. Gaikwada et al.	R-CNN, Fast R-CNN	66.3%
3.	Kien Trang et al.	CNN	88.46%
4.	S. Ramesh et al.	CNN	88.3%.
5.	Umar Ayub et al.	Proposed model	90%
6.	Our proposed work	pre-trained models (InceptionV3, EfficientnetB4, Xception, VGG19, and VGG16) with one custom model	98%

2.4 Open Issues

This study's focus on "Mango Leaf Disease Detection Using Deep Learning Models" broadens the problem's scope to include agricultural diagnostics in general and farm illnesses in particular. The necessity to fill in the significant gaps in the present understanding of Mango Leaf Disease diagnosis and subtype classification is the driving force for this work. Conventional techniques frequently lack the accuracy and efficiency needed to distinguish between the many subtypes of mango leaf disease, which causes delays in diagnosis and less-than-ideal treatment results. With the use of convolutional neural networks (CNNs), one of the deep learning techniques, this study aims to create a strong framework for classifying Mango Leaf Disease subtypes from visual data. By doing this, we want to transform the diagnosis process and give agricultural professionals fast, reliable insights that can inform individualized treatment plans and, eventually, lead to better plant outcomes in the fight against disease. The scope includes the difficulties in detecting mango leaf disease using conventional approaches, which may have limits with regard to overall diagnostic accuracy, sensitivity, and specificity.

2.5 Summary

Research has concentrated on solving problems including class imbalance, interpretability of model predictions, and generalization to different types of trees. Our research seeks to enhance tree results and expert decision-making in the battle against Mango Leaf Disease by expanding on the foundation established by these prior efforts and refining and advancing Mango Leaf Disease categorization approaches.

CHAPTER 3

METHODOLOGY

3.1 Overview

The results of a sophisticated automated detection system that was painstakingly customized for Mango Leaf Disease and prodromal symptoms are presented in this part, which forms the foundation of this thesis. The core of this breakthrough is the combination of Mango Leaf Disease detection patterns, which are facilitated by a variety of advanced deep learning models, such as NasNetMobile, Xception, VGG19, and VGG16. This section follows a deliberate split strategy and examines two main elements that are similar to the feature-based detection techniques of Mango Leaf Disease. This careful separation makes it possible to analyze each model's performance in-depth inside its own modality, offering insightful information about the subtleties of feature patterns. Simultaneously, it promotes a complete perspective on the amalgamation of different modalities, emphasizing the possible synergy for an all-encompassing method of detecting mango leaf disease.

3.2 Proposed Methodology

The convolutional neural network (CNN) designed for image classification with an input shape of 299x299 pixels and three color channels (RGB). The architecture begins with an input layer followed by three convolutional blocks. The first block applies a 2D convolution with 32 filters of 3x3 kernel size and ReLU activation, followed by a 2x2 max-pooling layer to reduce the spatial dimensions. This pattern is repeated in the second block with 64 filters and the third block with 128 filters, each time further abstracting the spatial features through max-pooling. After the convolutional layers, the model flattens the feature maps into a 1D vector, which is then processed by a fully connected dense layer with 128 neurons and ReLU activation. To prevent overfitting, a dropout layer with a 20% dropout rate is included. The final layer is a dense output layer with 5 neurons and a softmax activation function, making it suitable for multi-class classification with 5 distinct classes. The model is compiled using the Adam optimizer and categorical cross-entropy loss function, with accuracy as the evaluation metric. This CNN is designed to efficiently capture and process image features, making it well-suited for tasks requiring classification

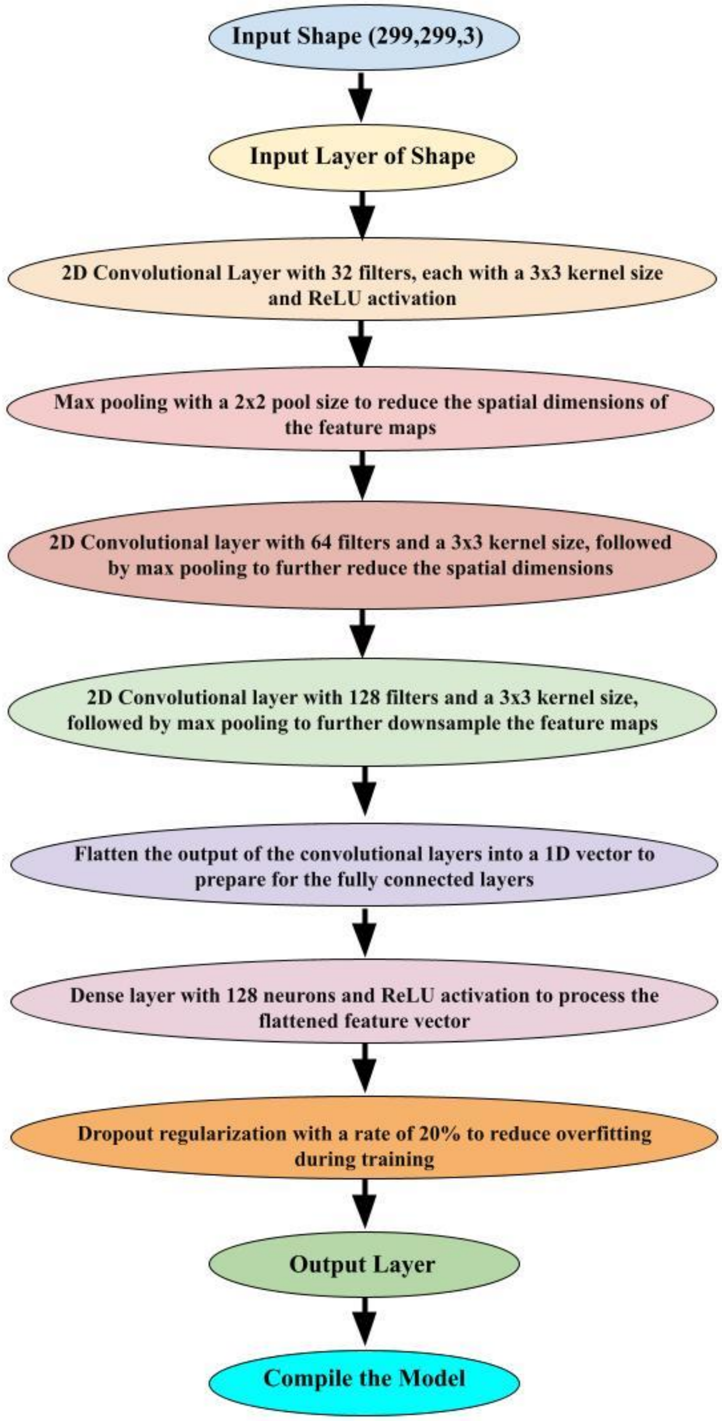

Figure 3.2.1: Flow work of proposed model

3.3 Software Requirement

The tests for this study were conducted on Google CoLab using the Kera's library. TensorFlow, one of the greatest deep learning frameworks, was used to handle machine learning methods on Python. Each model was developed by Google and trained on a Tesla graphics processing unit (GPU) in the cloud before being made available through the Google Collaboratory framework. The Collaboratory framework provides up to 16GB of RAM (random-access memory) and about 360GB of GPU in the cloud for research use. The models employed in this study's architectures for mango leaf disease detection include our suggested model, InceptionV3, Vgg19, Vgg16, EfficientNetB4, and the original Vgg19. From each category, one architecture was selected.

The study makes use of frameworks and programming languages like TensorFlow and Python to create deep learning models and related techniques. Deep learning tasks are quite complicated, and computational infrastructure—which includes GPUs for rapid processing—is essential to successfully addressing them.

Here's an overview of the materials used in Anaconda, Jupyter Notebook, NumPy, Pandas, Matplotlib, and Seaborn:

Anaconda: Anaconda is a distribution of the Python and R programming languages for scientific computing, aimed at simplifying package management and deployment.

- Anaconda Navigator: A desktop graphical user interface (GUI) that allows users to manage environments, packages, and channels easily.

- Conda: A package manager that installs, runs, and updates packages and their dependencies.

- Python Interpreter: The core Python programming language, including standard libraries and additional scientific computing packages.

- Jupyter Notebook: An interactive computing environment for creating and sharing documents that contain live code, equations, visualizations, and narrative text.

Jupyter Notebook: Jupyter Notebook is an open-source web application that allows you to create and share documents containing live code, equations, visualizations, and narrative text.

- Markdown Cells: For text-based documentation and explanation.

- Code Cells: For writing and executing Python code interactively.

- Output Cells: Display the output of executed code, including text, images, plots, and interactive widgets.

- Kernel: The computational engine that executes the code contained in the notebook.

NumPy: NumPy is a fundamental package for scientific computing in Python. It provides support for arrays, mathematical functions, linear algebra operations, random number generation, and more.

- ndarray: An efficient multidimensional array object that supports mathematical operations.

- Mathematical functions: Functions for array manipulation, mathematical operations, linear algebra, Fourier transforms, and random number generation.

Pandas: Pandas is a powerful data manipulation and analysis library for Python. It provides data structures and functions for efficiently working with structured data.

- DataFrame: A two-dimensional labeled data structure with columns of potentially different data types, similar to a spreadsheet or SQL table.

- Series: A one-dimensional labeled array capable of holding any data type.

- Data manipulation functions: Functions for reading/writing data, cleaning, filtering, transforming, aggregating, and merging datasets.

Matplotlib: Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. It provides a MATLAB-like interface for plotting.

- pyplot module: A collection of functions that provide a MATLAB-like interface for creating plots and visualizations.

- Figure and Axes objects: Components of the plot where data and visual elements are rendered.

- Various types of plots: Including line plots, scatter plots, bar plots, histogram plots, pie charts, etc.

Seaborn: Seaborn is a statistical data visualization library built on top of Matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics.

- Simplified plotting functions: Functions that allow users to create complex plots with minimal code.

- Statistical visualization functions: Functions for visualizing statistical relationships, distributions, and categorical data.

- Styling and customization options: Options for customizing the appearance of plots, including colors, styles, and themes.

There are several prerequisites that must be met in order for the research project "Mango Leaf Disease Detection Using Deep Learning Models" to be implemented successfully. These implementation requirements cover aspects like data gathering and model assessment in addition to hardware and software components.

Hardware Requirements:

- **Advanced computing resources:** The availability of a computer infrastructure capable of handling the complex tasks involved in deep learning and image analysis, with sufficient processing power and memory.

- **Graphics Processing Unit (GPU):** In order to significantly reduce the amount of time required for model creation, a GPU is essential for accelerating the training of deep Convolutional Neural Networks (CNNs).

Software Requirements

- **Deep Learning Frameworks:** Utilize well-known deep learning frameworks like PyTorch or TensorFlow for CNN model development, training, and evaluation.

- **Python Programming Language:** Make use of Python's adaptability and popularity while constructing deep learning algorithms and doing data analysis.

- **Image Processing Libraries:** Use image processing libraries for pre-processing and picture augmentation, such as OpenCV, in your work.

Data Collection:

- **Diverse and Representative Dataset:** Compile a thorough set of agricultural photos comprising both healthy and sick examples to guarantee the stability and applicability of the created models.

- **Annotated Dataset**: Make sure that labeled data with explicit annotations indicating the presence or absence of mango leaf disease is available for model training and validation.

Model Training and Evaluation

- **Transfer Learning Models:** Transfer learning frameworks can be implemented by using pre-trained models, such as those learned on ImageNet. This method improves mango leaf disease diagnosis by utilizing current information.

- **Evaluation Metrics:** Establish and use appropriate metrics for assessing model performance, such as accuracy, precision, recall, and F1 score, for both detection and segmentation tasks.

Ethical Considerations:

- **Farm confidentiality and data protection:** adherence to legal requirements and ethical guidelines to protect the privacy and security of farm data used in research.

- **Informed consent:** obtaining the informed consent of those whose agricultural photos are included in the collection, as applicable.

Documentation and Reproducibility:

- **Code Documentation:** Thorough documentation of the implementation code to guarantee future cooperation, clarity, and repeatability.

- **Version Control:** using version control tools (like Git) to keep an orderly development process and keep an eye on codebase alterations.

By fulfilling these implementation criteria, the study may be carried out methodically and thoroughly, guaranteeing the accuracy of the findings and advancing the use of deep CNNs and transfer learning to identify mango leaf disease.

3.4 Project Management and Finance Analysis

- **Project Objective:** Mango leaf disease is still the world's biggest cause of mortality among mango plants, thus improving diagnostic tools and treatment approaches is imperative. This is the driving force behind this research. Conventional techniques for subtype categorization frequently depend on histological investigation, which can be laborious, subjective, and sensitive to variation across observers. On the other hand, deep learning models have proven to be remarkably effective in image analysis tasks, suggesting that they have the ability to overcome the drawbacks of traditional methods.

- **Project Timeline:** Selecting the study domain and title with attention is a crucial initial step in every research endeavor. Both time and meticulous attention to detail are needed for this. After then, we start gathering and analyzing pertinent papers, a procedure that typically takes two months to finish. We are now working on maintaining the dataset and hope to have it completed by March 2024. After obtaining the dataset, we will proceed with preprocessing and coding chores before putting our work into practice.

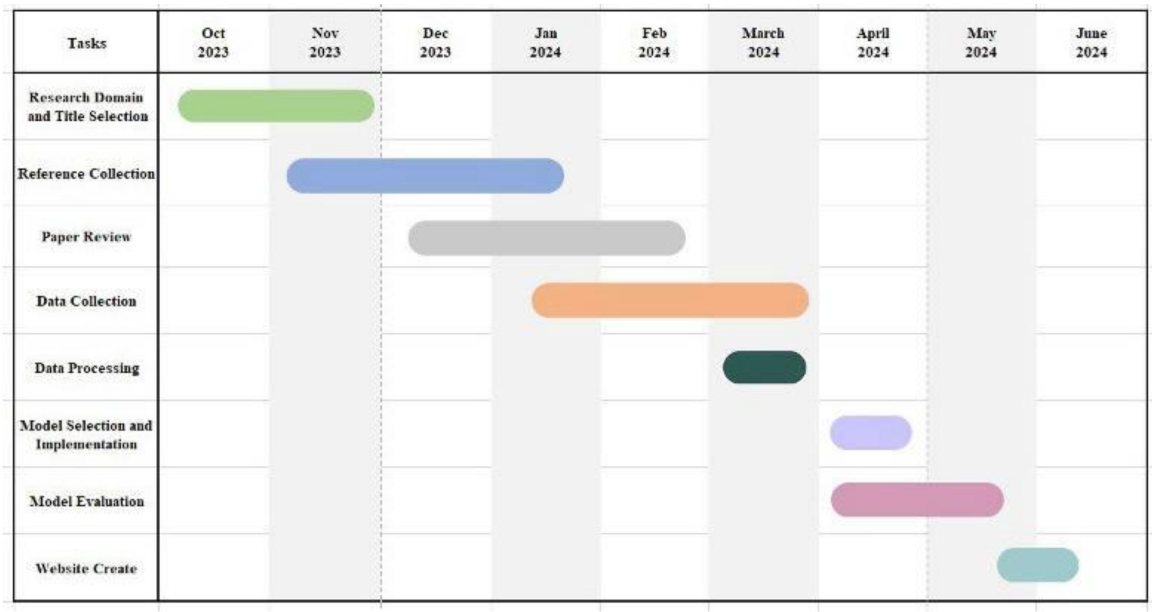

Figure 3.4.1: GAN Chart of Project Management

- **Resource Planning:**

A. Equipment and Tools:

- High-performance Computers for Model training and testing
- Anaconda
- Jupyter Notebook
- Python 3.10

B. Software and Technologies:

- HTML, CSS
- Django
- Flask

C. Data and Content:

- Collect dataset using mobile phone camera.
- Existing Deep Learning Model architecture documentations
- Existing work documentations

D. Training and Skill Development:

- Skill on data pre-processing and deep learning model architecture.
- Skill on model evaluation and comparison.

To get the work successfully, there is several type costings like copying cost, transport cost, Domain and hosting cost. And I have made those cost from self-funded.

Table 3.1: Financial Analysis

SL NO	Components	Estimated Cost (BDT)
1	Data Set Collection (Transport)	10000
2	Communication	2000
3	Internet	3000
4	Literature Review	2000
5	GPU	40000
6	RAM (16GB)	15000
7	Documentation	3500
8	Electricity Bill	3000

9.	Contingency: 10% of the adjusted	7850
	Total Estimated Cost	**86350**

3.5 Summary

The study aims to develop a deep learning framework for accurately classifying Mango Leaf Disease subtypes using image data. It will collect a diverse dataset, implement optimized convolutional neural networks, explore transfer learning techniques, and assess utility by comparing with existing methods, with the goal of improving trees outcomes.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

The results of a sophisticated automated detection system that was painstakingly customized for Mango Leaf Disease and prodromal symptoms are presented in this part, which forms the foundation of this thesis. The core of this breakthrough is the combination of Mango Leaf Disease detection patterns, which are facilitated by a variety of advanced deep learning models, such as NasNetMobile, Xception, VGG19, and VGG16. This section follows a deliberate split strategy and examines two main elements that are similar to the feature-based detection techniques of Mango Leaf Disease. This careful separation makes it possible to analyze each model's performance in-depth inside its own modality, offering insightful information about the subtleties of feature patterns. Simultaneously, it promotes a complete perspective on the amalgamation of different modalities, emphasizing the possible synergy for an all-encompassing method of detecting mango leaf disease.

4.2 Train Model

Datasets

Remove the Train, Test, and Val folders in order to build the dataset. We have collected 2000 JPG images for five different classes. The classes were Anthracnose, Bacterial Canker, Die Back, Healthy and Sooty Mould. We have collected 400 images per class.

Figure 4.2.1: Mango Leaf Disease Image

The data count plot is shown below:

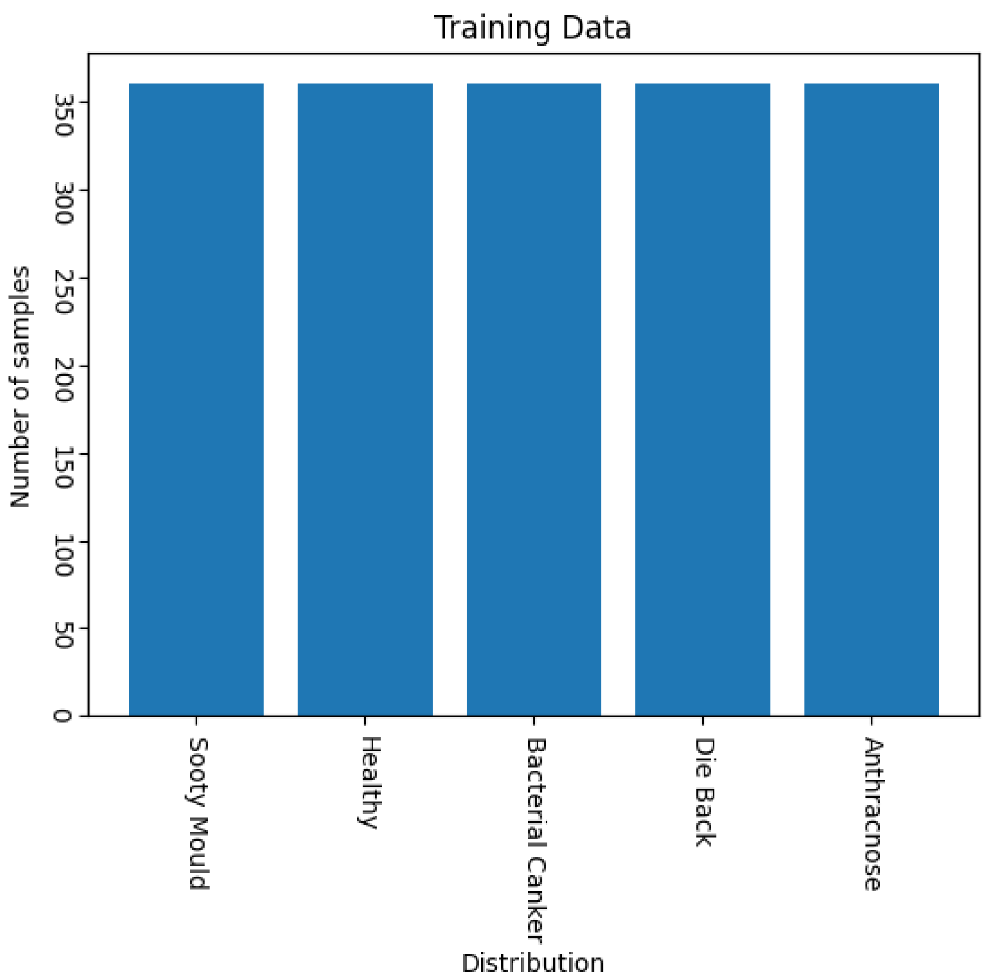

Figure 4.2.2: Mango Leaf Disease Image Count

Process of Experiments

Gathering information from the images of mango leaves is the first step in the suggested framework. When there is insufficient data for deep neural networks to train and perform better, data augmentation technology is sometimes utilized to solve the issue. Below is a summary of the experiment's intended methodology:

Image Acquisition:

Mango leaf disease Data for the model assessment was provided by Image Database. Targeted website pictures were employed in this step. A detailed analysis of the dataset photographs was conducted to ensure white backgrounds. Images in color are set on white backdrops.

Image Augmentation:

This is where picture enhancing is used. Picture augmentation is the process of adding new data while preserving the label data in an already-existing dataset. The model's ability to accommodate unknown inputs is improved by expanding the data set, hence improving its generalization. Through the use of data augmentation, our training data objectives were satisfied. But employing brightness, contrast, saturation, scaling, cropping, flipping, and rotation, color and position were enhanced. Data augmentation techniques included random spins between -20 and 20 degrees, accidental rotations of 90 degrees, distortion, bending, reversals of vertical and horizontal planes, skating, and conversion of luminous intensity. Ten enhancements were applied to each original image. Certain adjustments enhance a diverse image.

Training:

In this stage, a CNN learner model is produced. Using EfficientNetB4, Xception, InceptionV3, VGG16, and Vgg19, a model was trained on the dataset and its classification accuracy tested. All representations were trained for three epochs (10 iterations) using Early Stopping call-backs. The number of epochs without development until training is completed is known as patience. 0.0001 is the learning rate.

Classification:

In this stage, neural networks (EfficientNetB4, Xception, InceptionV3, VGG16, and Vgg19) were utilized to automatically detect cell diseases. The neural network's demonstrated efficacy in a wide range of practical applications led to its selection for classification. The experiments are displayed in Figure 3.2.3.

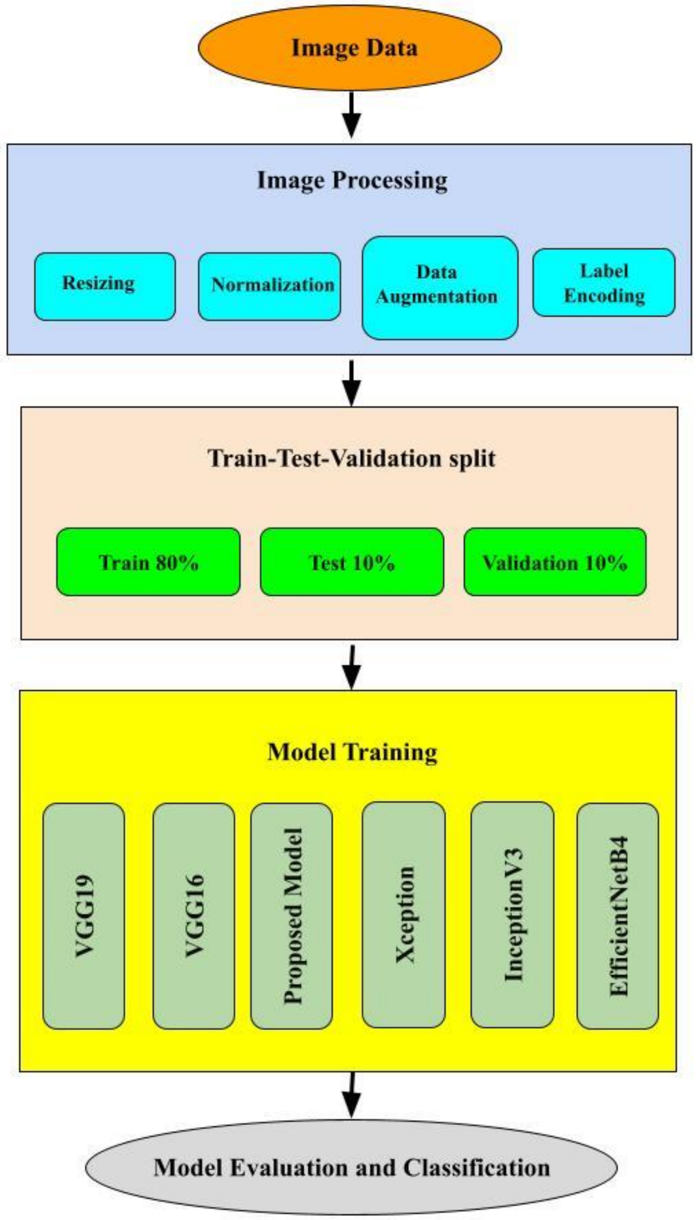

Figure 4.2.3: Methodology of the work

Results:

Two parts based on the transfer learning, and proposed methodologies show the experiment outcomes.Several measures for the performance of machine learning classification models are used to assess CNN base approaches. Evaluation criteria include accuracy, precision, recall, F1-score, and confusion matrix (CM).

4.3 Model Evaluation

Accuracy:

Accuracy of the classification model is one metric. The anticipated percentage of the model is its accuracy. The proportion of correctly categorized images to total samples is known as accuracy. Equation of accuracy.

Accuracy=(TP+TN)/(TP+TN+FP+FN)

Precision:

Accuracy is the probability of a positive label and the number of positive labels. The precision indicates the number of positively predicted cases with accuracy. It is useful to be precise when FP is more important than FN. In terms of math, this equation:

Precision=TP/(TP+FP)

Recall:

The number of correctly categorized positive predicted events is measured by recall or sensitivity. Recall is a useful statistic in cases where FN outperforms FP. An further statistic for classification accuracy that accounts for both recall and precision is the F1-score. Since recall and accuracy are harmonic means, a thorough comprehension of these two metrics may be obtained from the F1 score. When Precision and Recall are equal, it performs best. To calculate it, utilize the following equation:

Recall=TP/(TP+FN)

F-1 Score:

A recall-precision measure of classification accuracy is the F1 score. The F1-score provides a comprehensive view as it is the harmonic mean of Precision and Recall. When precision and recall are equal, they are ideal. Formula:

F-1 Score=2*(Precision*Recall)/(Precision+Recall)

Specificity is defined as the proportion of individuals with a negative test result who do not have the illness. A very particular test works well for ruling out most leaf who don't have the illness. This is why a positive result on an extremely specialized test might rule out the disease for a particular individual. Below is the equation:

$$\text{Specificity} = TN / ((TN+FP))$$

The model can only imitate the training set of data so closely before it starts to lose its capacity for generalization. A specific table format known as the confusion matrix (CM) can be used to evaluate the performance of an algorithm. Critical predictive criteria including memory, specificity, precision, and accuracy are illustrated using CM. Confusion matrices can very handy since they provide straightforward evaluations of values such as TP, FP, TN, and FN. Based on the research questions, the subsequent sections address the research questions of this investigation.

4.4 Summary

To extract significant insights from the experimental data, the statistical analysis carried out in this study on "Mango Leaf Disease Detection Using Deep Learning Models" is essential. Strict statistical techniques are utilized to measure and evaluate the effectiveness of different detection and segmentation strategies in the diagnosis of mango leaf disease. The gathered data's primary trends and variability are summarized by descriptive statistics like mean and standard deviation. Furthermore, inferential statistics—such as confidence intervals and hypothesis testing—help validate the observed distinctions and similarities among various approaches. In addition to provide a quantitative foundation for evaluating the efficacy of transfer learning deep Convolutional Neural Networks (CNNs) in mango leaf disease detection, the statistical analysis highlights the importance of the findings. These studies establish the foundation for expanding the findings to a larger population of agricultural images while also validating the experiment's resilience.

CHAPTER 5

RESULT AND ANALYSIS

5.1 Overview

An intricately planned arrangement of hardware, software, and data resources is used in the experimental setting for the study "Mango Leaf Disease Detection Using Deep Learning Models" in order to carry out thorough studies. The computational core is made up of high-performance hardware, which includes a strong central processing unit (CPU) and a potent graphics processing unit (GPU). Transfer learning models are implemented in a Python programming environment using deep learning frameworks, like TensorFlow or PyTorch. The experimental dataset is carefully preprocessed, standardized, and normalized after being gathered from a variety of agricultural photographs to provide a reliable and representative input for training and assessing the model. A crucial component of the model setup is the usage of deep Convolutional Neural Network (CNN) architectures that have already been trained, along with some fine-tuning for the purpose of detecting mango leaf disease. To maintain ethical standards, ethical issues like as informed consent and farm data protection are incorporated into the setup. Extensive documentation is kept throughout the experimental process, covering code details, model architecture, hyperparameters, and findings, in order to promote future cooperation and openness in the field of advanced mango leaf disease diagnosis.

5.2 Experimental Results

The five pre-trained CNN networks—EffectiveNetB4, VGG19, VGG16, Xception, InceptionV3, and the suggested model—are contrasted in this section. Performance in classification comes first. The overall metrics of those models are then examined. gathering, explanations, likely causes, and areas for result improvement.

Table 5.1: Comparison of Accuracy for Mango Leaf Disease Detection

Architecture	Training Accuracy	Model Accuracy
EfficientNetB4	**98.27%**	**94.99%**
VGG19	**71.73%**	**86.5%**
VGG16	**75.56%**	**89.99%**
Xception	**41.67%**	**68.50%**
InceptionV3	**96.50%**	**96.49%**
Proposed Model	**94.51%**	**98%**

Table 2 presents a comparative study of various pre-trained deep Convolutional Neural Network (CNN) architectures, including EfficientNetB4, VGG19, VGG16, Xception, InceptionV3, and the proposed model. The analysis sheds light on the accuracies of each CNN architecture for the detection of mango leaf disease. Interestingly, the results reveal that the suggested model had the greatest accuracy, at almost 98%. The models that performed the best were InceptionV3 and EfficientNetB4, with the maximum accuracy of 96.49% and 94.99%, respectively. This demonstrates their remarkable ability to identify patterns of mango leaf disease in farming photos. This subtle variation in accuracy highlights how crucial it is to choose the right CNN architecture with care when it comes to mango leaf disease detection as it has a direct impact on the accuracy and dependability of the diagnostic procedure.

Training and Validation Accuracy and loss of CNN Networks:

displays the accuracy of the training and validation of the original model, with the number of epochs on the x-axis and the accuracy and loss percentages on the y-axis. The graphic shows a sufficient separation of training and validation data with no overfitting.

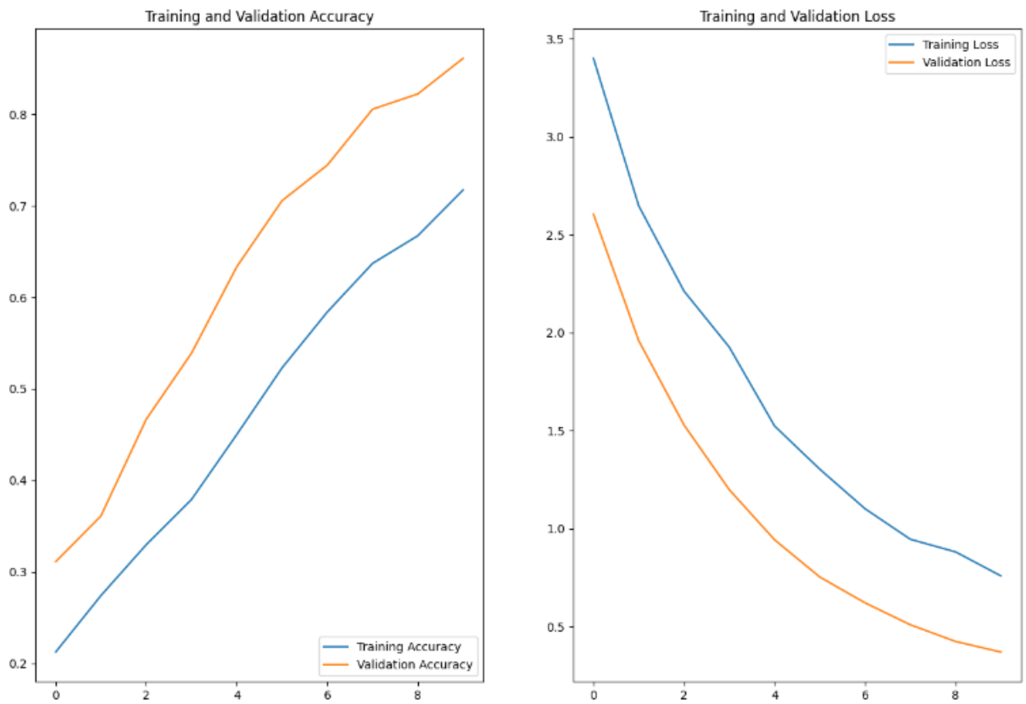

Figure 5.2.1: VGG19 model training and validation Accuracy and loss for epochs

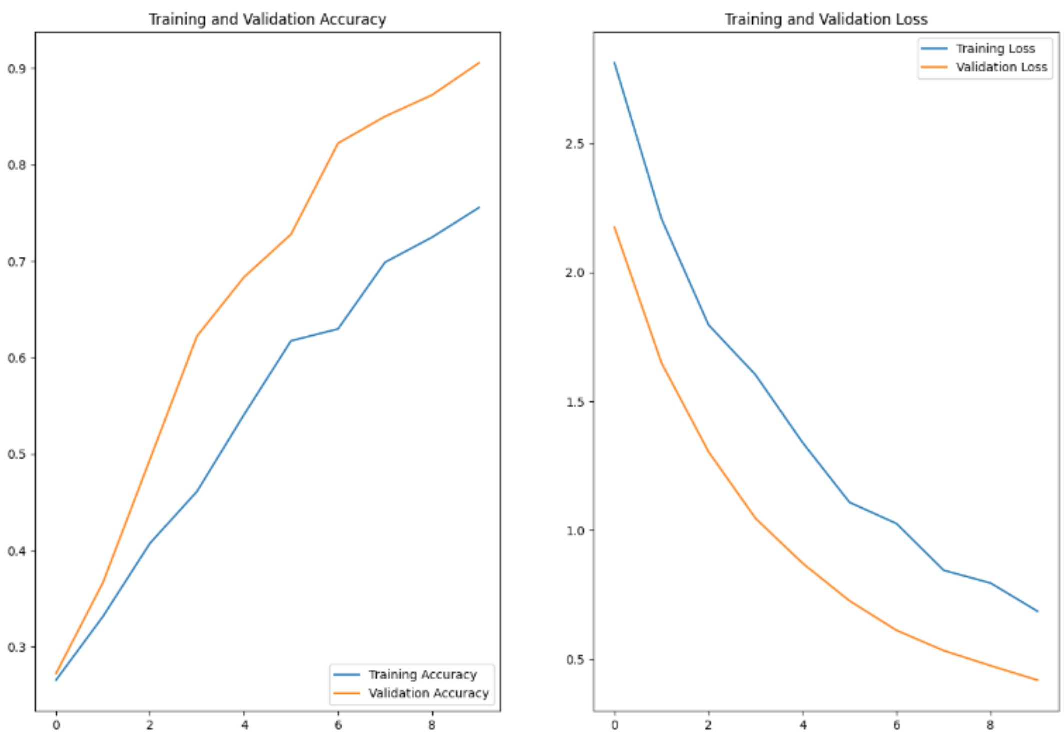

Figure 5.2.2: VGG16 model training and validation Accuracy and loss for epochs

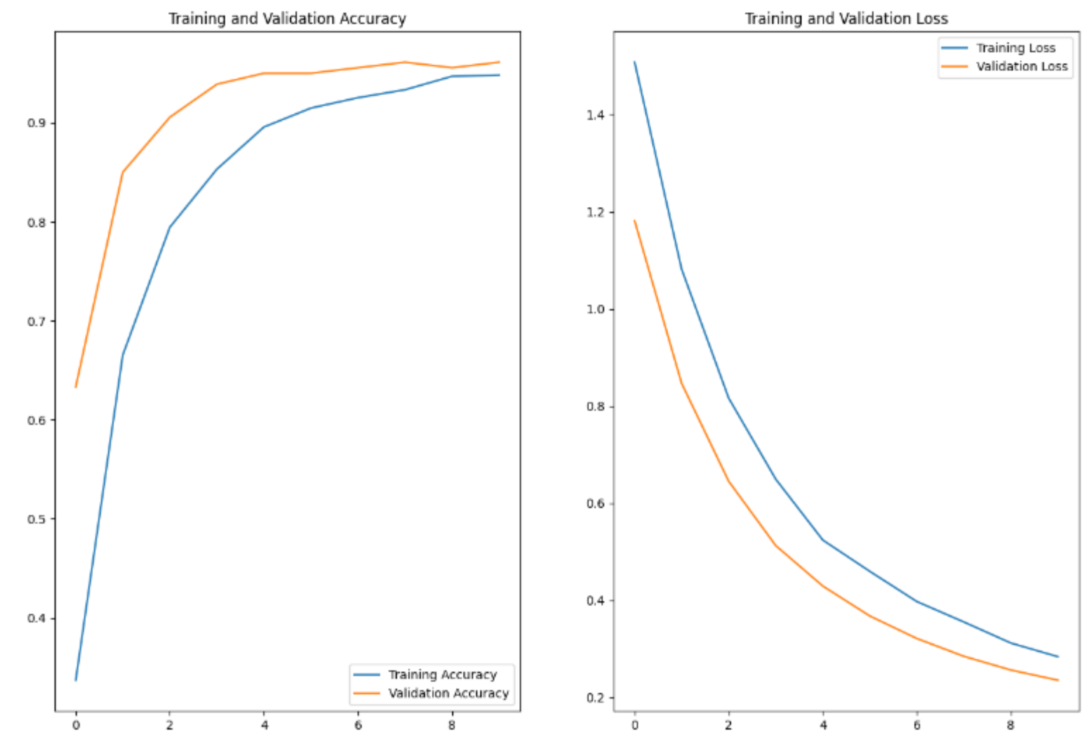

Figure 5.2.3: InceptionV3 model training and validation Accuracy and loss for epochs

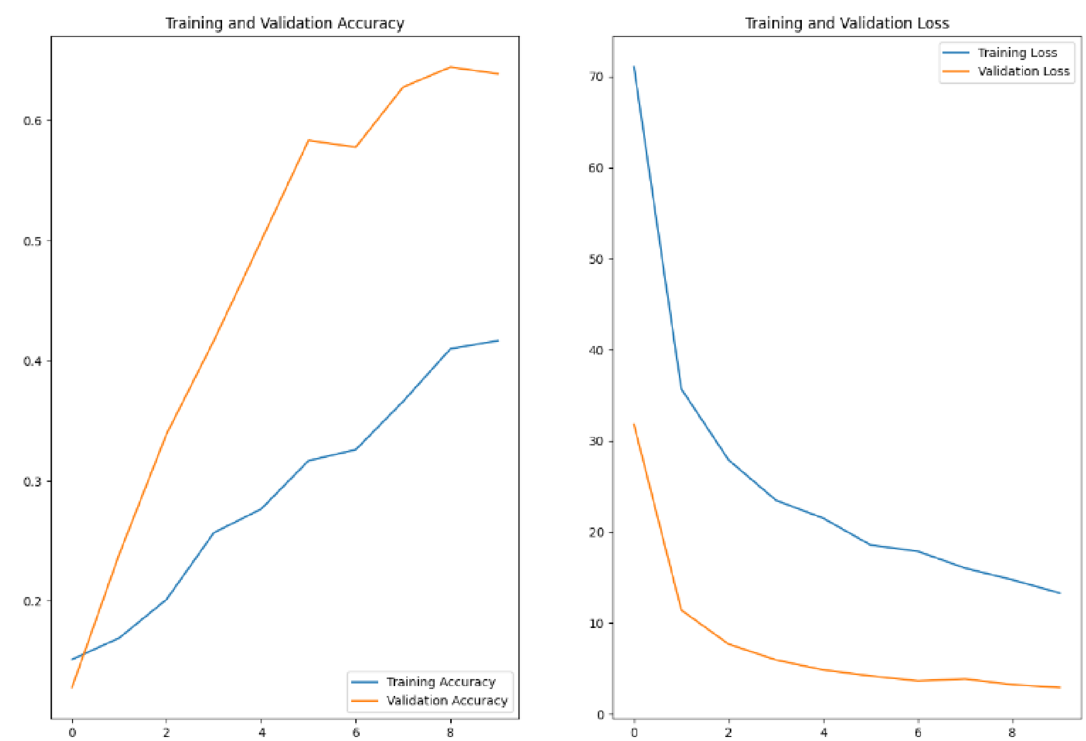

Figure 5.2.4: Xception model training and validation Accuracy and loss for epochs.

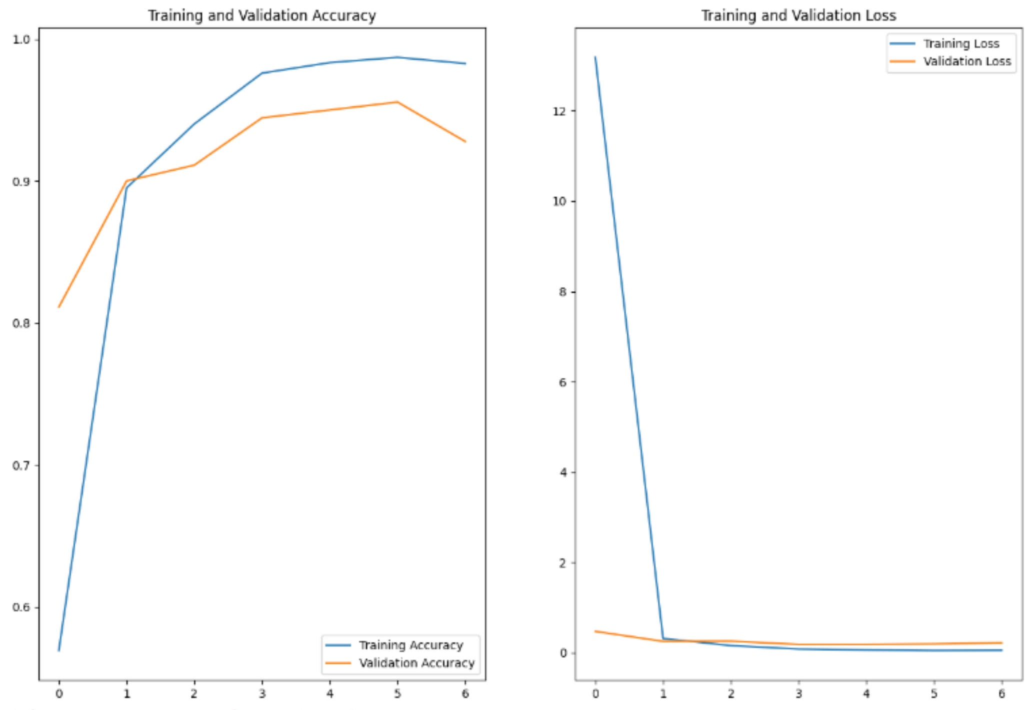

Figure 5.2.5: EfficientNetB4 model training and validation Accuracy and loss for epochs

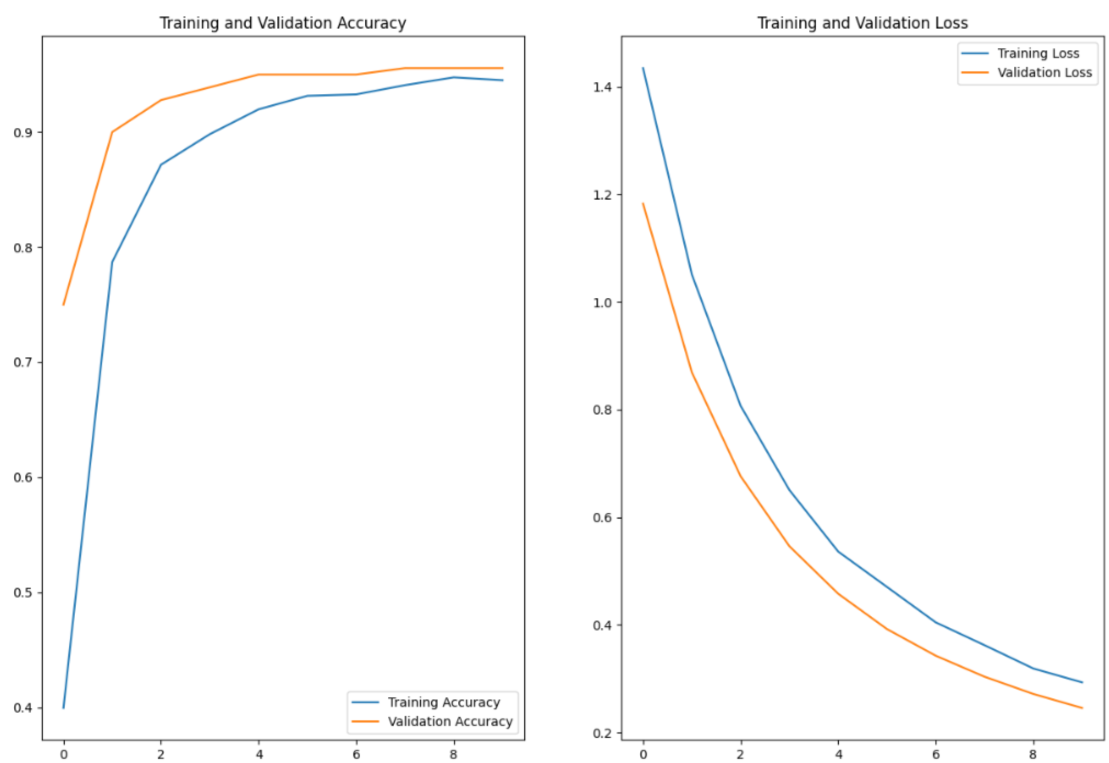

Figure 5.2.6: Proposed model training and validation Accuracy and loss for epochs.

Confusion Matrix after Original CNN:

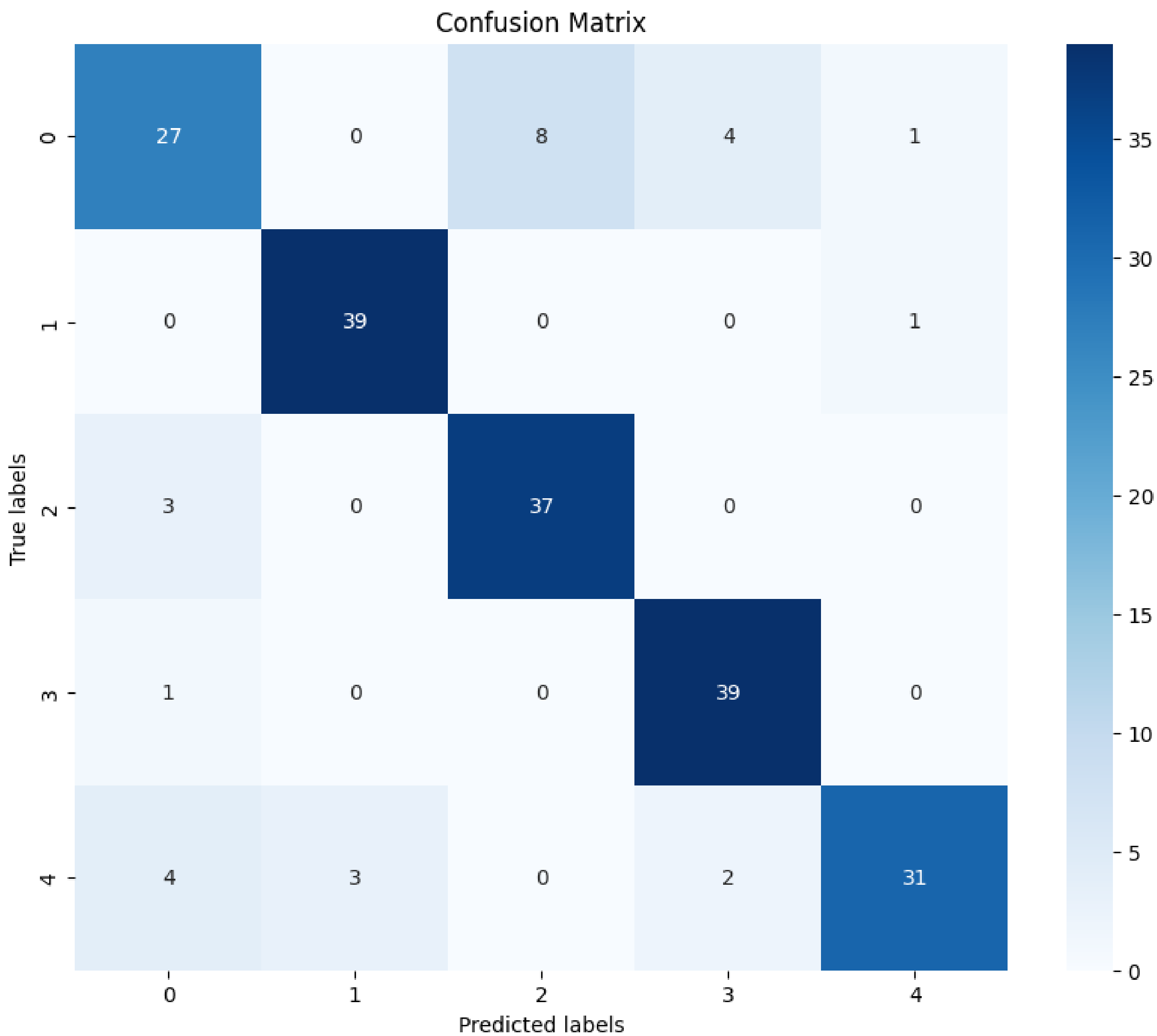

Figure 5.2.7: Confusion Matrices for VGG19

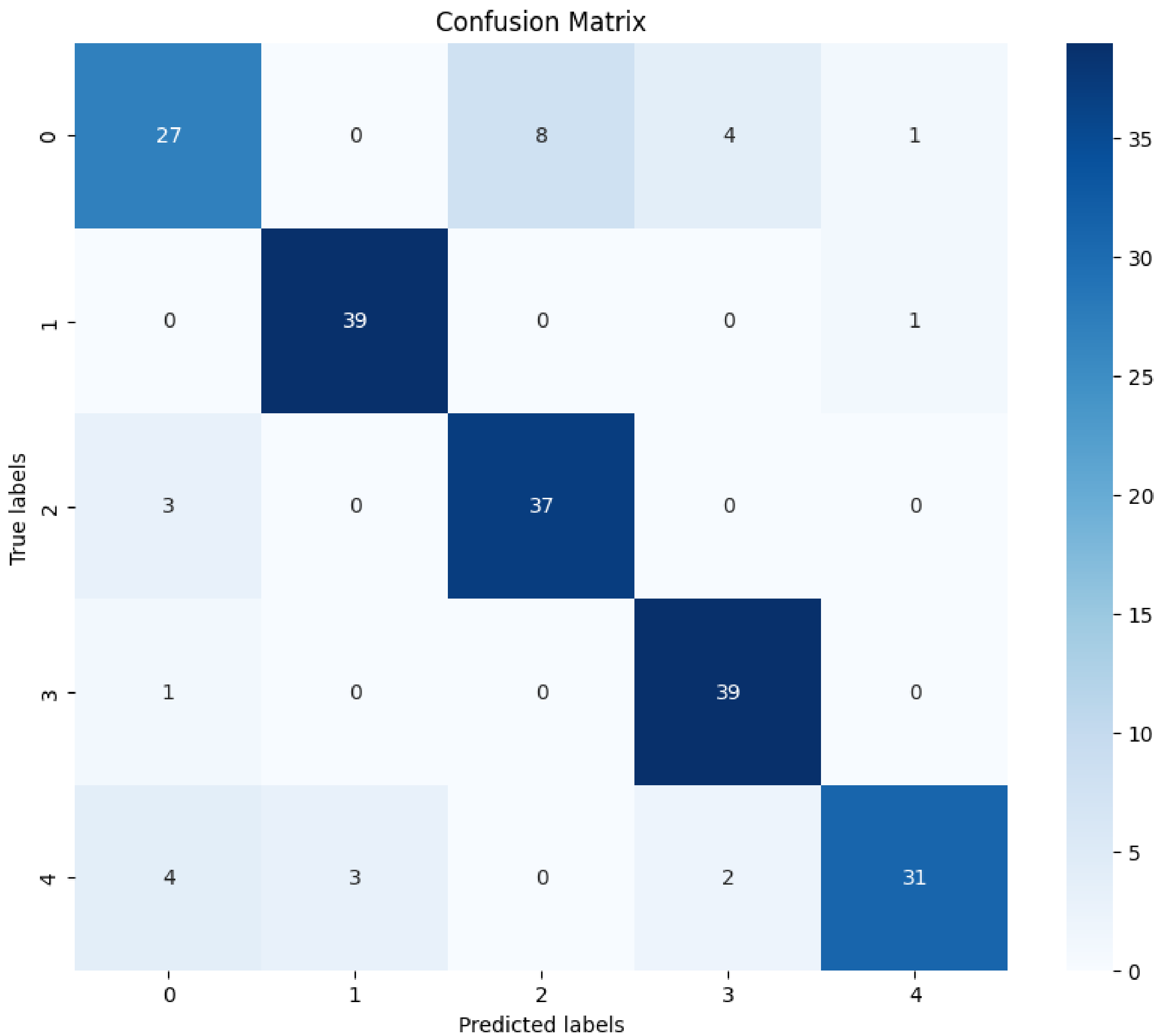

Figure 5.2.8: Confusion Matrices for VGG16

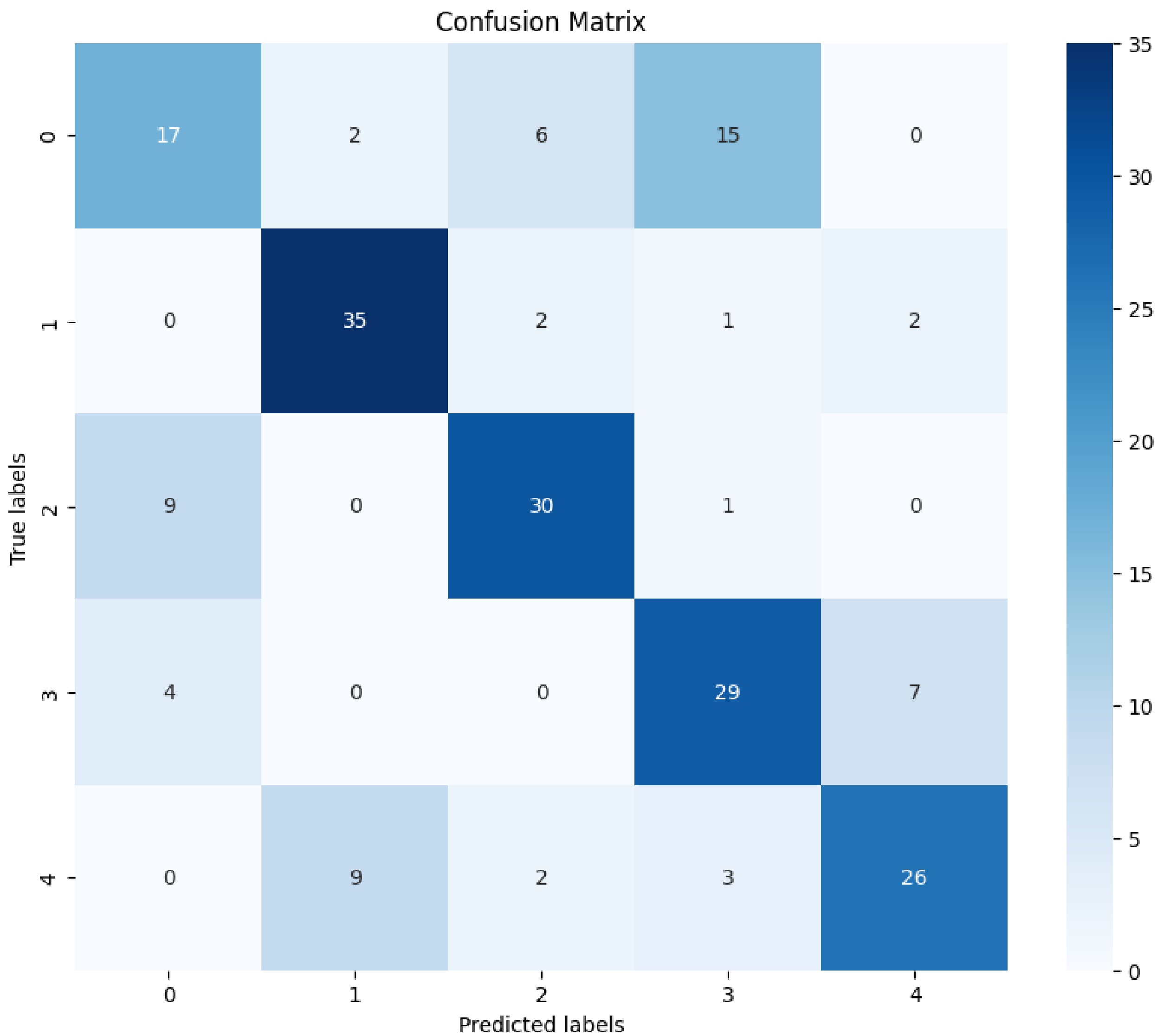

Figure 5.2.9: Confusion Matrices for Xception

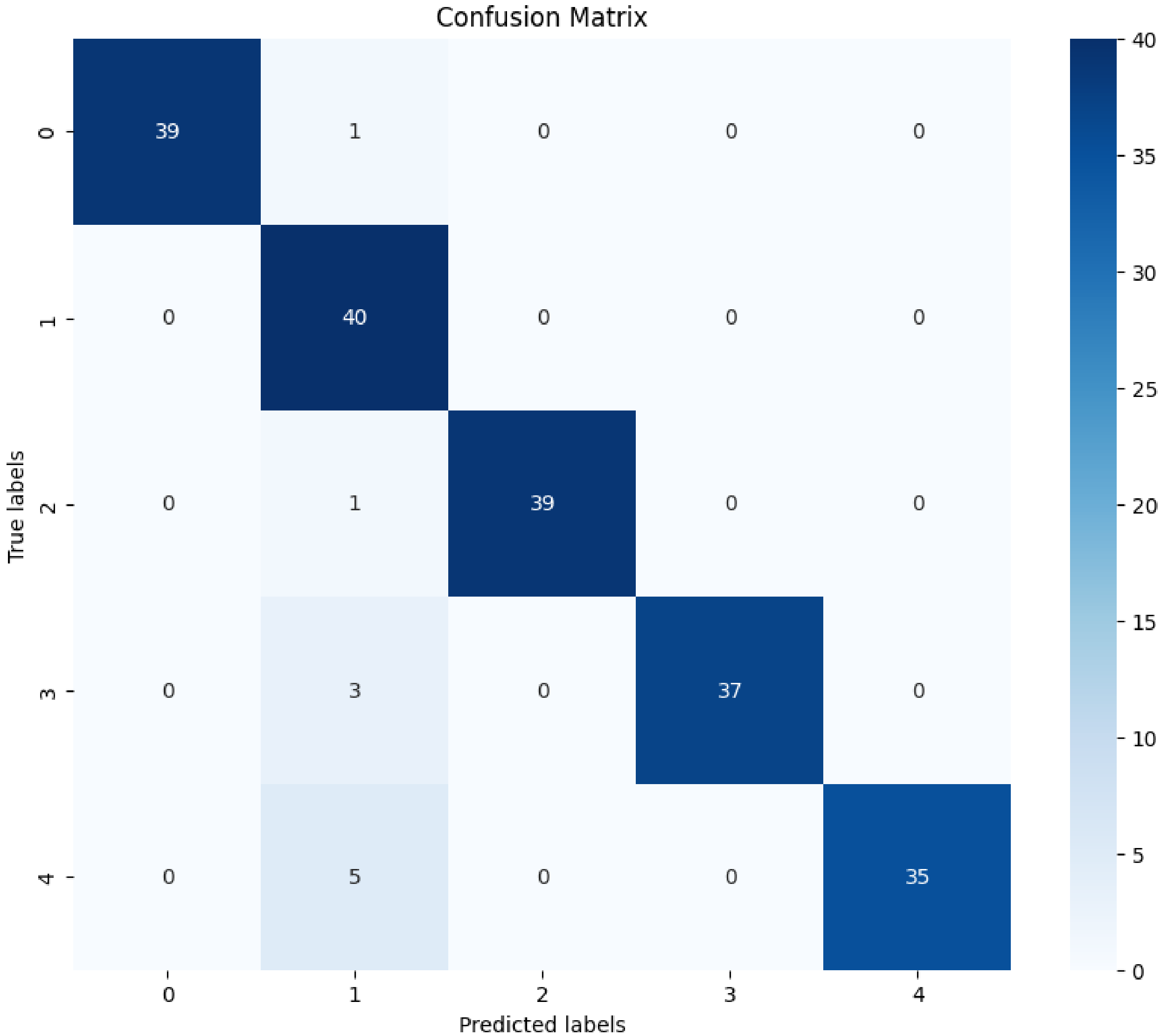

Figure 5.2.10: Confusion Matrices for EfficientNetB4

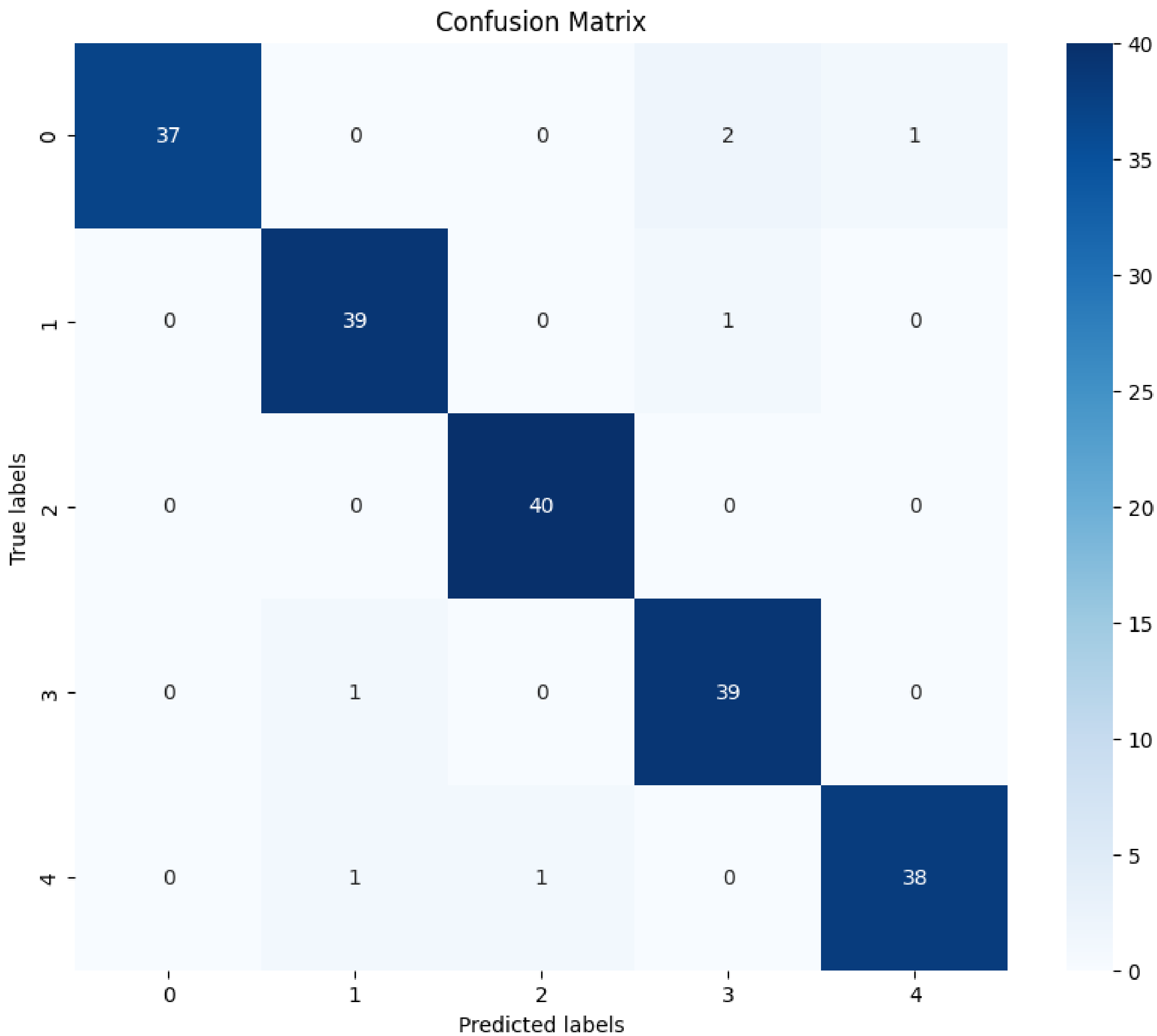

Figure 5.2.11: Confusion Matrices for InceptionV3

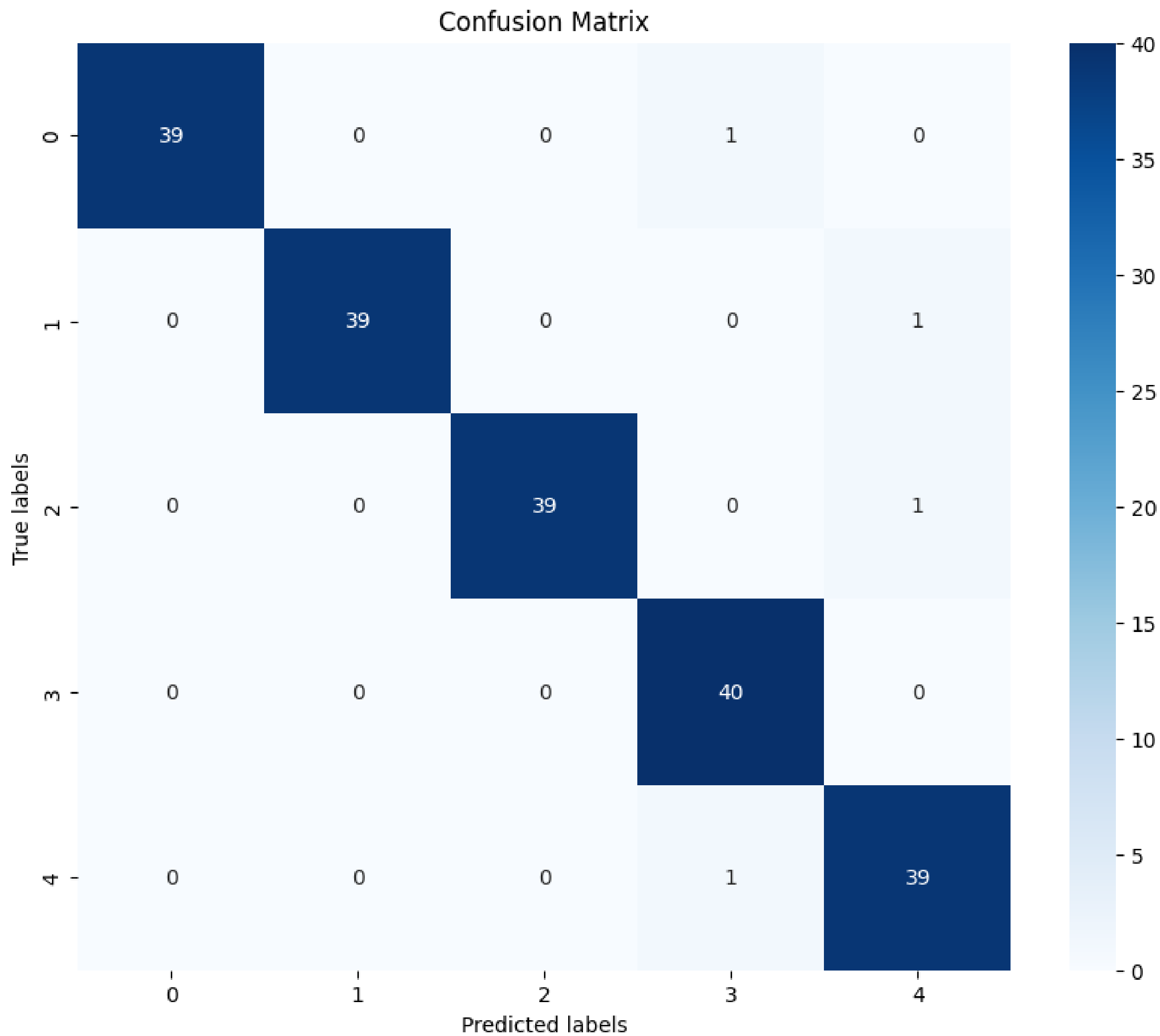

Figure 5.2.12: Confusion Matrices for Proposed Model

5.3 Performance Analysis

This extensive study investigates how well deep convolutional neural networks (CNNs) recognize and segment photos of mango leaf disease into two different categories: afflicted and normal. The research uses a clever augmentation technique to create eleven pictures from a single shot, using a sizable collection of 2000 original photos. The paper investigates the usefulness of original CNNs and transfer learning approaches models in the field of mango leaf disease detection. Specifically, the study examines the calculation of detection and segmentation, acknowledging them as separate steps in the diagnostic pipeline. Five well-known CNN-based models—EfficientNetB4, VGG19, VGG16, Xception, and

InceptionV3—as well as one suggested model are put through a rigorous testing process on the five classes of mango leaf diseases. Surprisingly, the suggested model comes out on top, with an astounding 96% accuracy, as seen in Figure 4.2.21. The study clarifies the complex effects of transfer learning by showing that accuracy decreases when the input image differs from the ImageNet Dataset's training set. Interestingly, different background noise levels and the use of different augmentation techniques separately with test sets are found to be possible causes of worse performance.

5.4 Summary

This extensive study investigates how well deep convolutional neural networks (CNNs) recognize and segment photos of mango leaf disease into two different categories: afflicted and normal. The research uses a clever augmentation technique to create eleven pictures from a single shot.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The study "Mango Leaf Disease Detection Using Deep Learning Models" holds transformative potential for agricultural diagnostics, promising significant societal and healthcare benefits. By leveraging advanced AI techniques, particularly transfer learning Convolutional Neural Networks (CNNs), the project aims to enhance the accuracy and efficiency of mango leaf disease detection. This advancement enables farmers to make informed decisions, leading to quicker therapeutic interventions, reduced misdiagnoses, and streamlined plant care. As a result, it could lower plant care costs and mitigate disease-related impacts, benefiting both individual farmers and the broader agricultural community. Additionally, the research's focus on ensemble models and comparative methodologies paves the way for practical diagnostic solutions that are affordable and accessible, especially in underprivileged regions with limited resources. This democratization of advanced plant care technology aligns with global efforts to improve plant health equity and reduce disease disparities, thereby enhancing the well-being of diverse communities worldwide. Despite the environmental concerns associated with the high energy demands of training deep learning models, ongoing advancements in sustainable computing and renewable energy integration promise to balance technological progress with ecological responsibility.

6.2 Impact on Society

The study "Mango Leaf Disease Detection Using Deep Learning Models" has far-reaching ramifications that might have a big influence on society and healthcare, going well beyond academic boundaries. Advanced artificial intelligence approaches have the potential to transform agricultural diagnostics and enhance farm outcomes and societal benefits by accurately and promptly detecting mango leaf disease. The goal of the project is to improve the accuracy and efficiency of mango leaf disease detection by utilizing transfer learning

Convolutional Neural Networks (CNNs), empowering farming practitioners to make more confident judgments.

In terms of plant health, the research has a very significant social influence. More reliable and accurate diagnostic techniques might be used to speed up therapeutic interventions, minimize misdiagnoses, and simplify plant care. Consequently, related plant care expenses, and disease-related consequences may be lessened. An additional layer of practicality is added by the research's emphasis on ensemble models and comparative analysis of various methodologies, which open the door to the creation of optimal diagnostic solutions that can be easily incorporated into actual plant care settings.

Furthermore, the potential for underprivileged groups and areas with limited resources for plant care is presented by the affordability and accessibility of enhanced approaches for detecting mango leaf disease. Geographical barriers may not be an obstacle for the technology created by this research, since it may provide advanced diagnostic capabilities to places where conventional agricultural infrastructure could be scarce. The overall objective of lowering disease inequalities and enhancing overall plant care equality is furthered by this democratization of advanced plant care technology, which is in line with plant health efforts. To summarize, the significance of this discovery for society resides in its ability to bring about the advent of precision medicine, namely in the identification and treatment of mango leaf disease. Using state-of-the-art technology, the research holds the key to real gains in plant health outcomes, accessibility, and the general well-being of varied communities worldwide. It also increases the scientific knowledge of respiratory illness diagnoses.

The energy used in training and implementing these sophisticated models is what has an influence on the environment. The substantial computing demands lead to higher energy usage and a carbon footprint, particularly in situations involving big datasets and intricate model structures. Thus, the study raises questions about how using cutting-edge technologies in plant care may affect the ecosystem.

It's important to remember, though, that developments in cloud computing techniques, sustainable computing methods, and hardware efficiency are always changing. As the environmental implications of AI applications become more apparent to researchers and developers, efforts are being made to optimize hardware and algorithms for energy efficiency. By combining green computing techniques with renewable energy sources, data centers may reduce their environmental effect and bring technical advancements into line with ecological concerns.

In conclusion, the research's environmental effect is a factor to consider even if its primary contributions are to the development of agricultural diagnostics. Plant care innovations will continue to be socially and ecologically responsible as long as attempts are made to strike a balance between technical innovation and environmental sustainability.

6.3 Ethical Aspects

The "Mango Leaf Disease Detection Using Deep Learning Models" research is grounded in a technique that prioritizes ethical issues throughout. When using farm photos, care must be taken to protect farm privacy and confidentiality, placing a strong emphasis on following legal and ethical requirements. When required, informed consent—a fundamental component of moral research procedures—is duly acquired. The significance of ethical deployment in ensuring that advances in diagnostics translate to better farm treatment without violating individual rights is highlighted by the research's potential social effect on plant care. Transparent documentation of the research process facilitates responsible knowledge sharing, examination, and reproducibility—an additional way in which the ethical dimension is expressed. In general, ethical issues are essential to the research's dedication to societal welfare and the conscientious use of state-of-the-art technology in the field of plant care.

6.4 Sustainability Plan

The research project "Mango Leaf Disease Detection Using Deep Learning Models" has a sustainability strategy that aims to reduce its negative effects on the environment while maintaining its beneficial effects on society. In order to lower the overall energy consumption related to model training and deployment, efforts will be focused on improving computational efficiency, implementing energy-efficient techniques, and investigating cloud computing options. The research team is also dedicated to utilizing environmentally friendly methods for data management and storage. In order to balance technical breakthroughs with environmental sustainability, the strategy places a high priority on continuous awareness of and integration of green computing concepts. The research method will incorporate ongoing assessment and modification of sustainable approaches, demonstrating a dedication to ethical and environmentally conscientious scientific innovation.

6.5 Summary

The study "Mango Leaf Disease Detection Using Deep Learning Models" aims to revolutionize agricultural diagnostics and enhance farm outcomes through the application of advanced AI techniques, particularly transfer learning Convolutional Neural Networks (CNNs). By improving the accuracy and efficiency of mango leaf disease detection, the research empowers farmers to make informed decisions, leading to faster therapeutic interventions, reduced misdiagnoses, and streamlined plant care, ultimately lowering costs and mitigating disease impacts. The study's emphasis on ensemble models and comparative methodologies facilitates the development of practical diagnostic solutions that are both affordable and accessible, especially benefiting underprivileged regions with limited resources. This democratization of advanced plant care technology aligns with global efforts to enhance plant health equity and reduce disease disparities, thereby improving the well-being of diverse communities worldwide. While the environmental impact of training deep learning models is a concern due to high energy demands, ongoing advancements in sustainable computing and renewable energy integration offer a path towards balancing technological progress with ecological responsibility.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

Plant diagnosis is not possible without the early and precise identification and categorization of mango leaf disease. The major focus of this research is a thorough performance assessment of Deep Convolutional Neural Networks (D-CNN) in the areas of segmentation and mango leaf disease detection. Our work highlights the usefulness of a CNN-based segmentation strategy, especially demonstrating its success with smaller and less sophisticated datasets. Notably, there is a dearth of studies specifically focused on the identification of mango leaf disease in the corpus of information now in existence. As such, our comparative analysis is of great importance and holds great potential for making significant advances in the field of managing mango leaf disease. We explore the effectiveness of several CNN models, including transfer learning approaches, in the categorization of mango leaf disease. The findings highlight the fact that the six networks—EfficientNetB4, VGG19, VGG16, Xception, InceptionV3, and the suggested model—perform better together than they do alone in terms of accuracy. It is important to highlight, nevertheless, that although the framework was generally effective, there were certain cases of projections that were not correct. Thus, there is a strong need for future research projects to investigate other tactics like contrast-enhancing or other image-processing techniques.

In addition, we suggest that picture segmentation be added before classification in order to improve the CNN models' capacity to extract relevant features. While the recommended ensemble is computationally more costly than known CNN baselines due to the training of six CNN models, the potential for increased accuracy outweighs this expense. Future research might investigate methods such as snapshot ensemble to lessen the computing load. This work essentially contributes to the advancement of mango leaf disease diagnosis techniques by providing valuable insights that have the potential to greatly influence clinical practice and stimulate more study in the constantly developing field of agricultural image analysis.

7.2 Further Suggested Works

The results of this study on the detection and segmentation of mango leaf disease using Deep Convolutional Neural Networks (D-CNN) offer insightful information and create new research directions. A noteworthy recommendation for future research is to investigate different image-processing techniques, such contrast enhancement, to deal with the erroneous predictions that the ensemble framework sometimes produces. Furthermore, as a possible improvement for CNN models in feature extraction, the use of segmentation techniques prior to classification is proposed. Furthermore, future studies should look at the use of methods like snapshot ensemble to lessen the strain on computer resources given the computational intensity of the suggested methodology. This suggests the need for more effective and scalable ensemble approaches in order to improve or preserve accuracy without sacrificing computing effectiveness.

Although the identification of mango leaf disease was the major emphasis of this study, considering the paucity of previous research in this field, further targeted studies are needed. To further advance our understanding of this crucial field of agricultural diagnostics, future research on mango leaf disease detection techniques should include unique designs, a variety of datasets, and practical clinical applications. To sum up, the research implications for mango leaf disease detection are to refine image-processing strategies, investigate effective ensemble techniques, and broaden the research scope. These actions will enhance the field of agricultural image analysis and promote improvements in diagnostic efficiency and accuracy.

7.3 Limitations

The study titled "Deep Learning Models for Detection of Mango Leaf Disease" offers an extensive investigation of cutting-edge AI methods within the field of agricultural diagnosis. The study examines the efficacy of deep Convolutional Neural Networks (CNNs) in identifying and classifying five types of mango leaf disease images: normal and afflicted, using a dataset of 2000 original pictures. Six CNN-based models are carefully tested in this study, with the suggested model earning noteworthy accuracy ratings. Examining transfer learning reveals subtle differences in accuracy when the input image differs from the training set. The study supports suggestions for augmentation-based updates by highlighting the advantages of ensemble models over individual designs and recognizing the effect of dataset size on prediction skills. The study notes environmental concerns and lays out a sustainability strategy to lessen related effects, even as it promises improvements in the accuracy of mango leaf disease identification. The correct application of artificial intelligence in healthcare is highlighted by ethical factors such as informed consent and plant privacy. Overall, the study's findings have significant implications for enhancing agricultural productivity and healthcare accessibility globally, in addition to adding to the body of knowledge on respiratory illness diagnosis.

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Appendix A

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

Title: Mango Leaf Disease Detection Using Deep Learning Models

Student ID: 201-15-3746

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a mango leaf 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 plant health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

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

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

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

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like VGG19 and EfficientNetB4, enhancing mango leaf disease detection accuracy in agricultural images, crucial for computer-aided diagnosis.	**Page no:** [19-20] **Section:** [3.2] **Page no:** [1-8] **Section:** [1.1, 1.2]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing CNN model.	**Page no:** [29-33] **Section:** [4.2] **Page no:** [1-8]

					Section: [1.1]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance mango leaf disease detection using deep learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [13-17] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in mango leaf disease detection, including limitations of traditional methods and the complexities of integrating transfer learning CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [10-17] **Section:** [1.5, 2.4]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing mango leaf disease detection amidst multiple potential approaches.	**Page no:** [35-45] **Section:** [5.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting agricultural diagnostics in respiratory diseases like mango leaf disease, contributing to advancements in plant health and farm care practices which indicates **EP-4**.	**Page no:** [13-17] **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 comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in agricultural diagnostics which ensures **EP-7**.	**Page no:** [19-25] **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 project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in mango leaf disease detection through transfer learning CNNs.	**Page no:** [21-24] **Section:** [3.3]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving plant care through advanced mango leaf disease detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for farm data privacy.	**Page no:** [47-49] **Section:** [6.1, 6.2, 6.3]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in mango leaf disease detection through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [13-17] **Section:** [2.2, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [25] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing farm privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced plant care technologies which comply with **CO9**.	**Page no:** [47-49] **Section:** [6.2,6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [19-27, 47-49] **Section:** [3.2, 3.3, 3.4, 6.2, 6.3]

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