A COMPUTER VISION APPROACH FOR BANANA LEAF DISEASE CLASSIFICATION

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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 "**A Computer Vision Approach for Banana Leaf Disease Classification**", submitted by **Anik Dash Akash** and **Md. Iftekhar Hossain** 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 **15-07-2024**.

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We hereby declare that this project has been done by us under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

This study investigates the potential of computer vision approach for classifying banana leaf diseases - Cordana, Pestalotiopsis, Sigatoka in the context of regional variations. We collected a dataset of banana leaf images from Habiganj, Sylhet, Bangladesh, to account for these variations and employed data augmentation techniques to enrich its size and diversity. Five pre-trained CNN architectures (VGG19, VGG16, ResNet50, MobileNetV1, MobileNetV2) were evaluated for their disease classification performance. The evaluation compared the models' performance with and without image preprocessing. Our findings highlight the exceptional performance of MobileNetV2, achieving an impressive 94.41% accuracy on raw, unprocessed data. This accuracy further improved to 96.41% after image preprocessing, demonstrating the model's robustness and resilience to variations that might be encountered in real-world applications. These results emphasize the potential of CNNs, particularly lightweight architectures like MobileNetV2, for accurate banana leaf disease classification using computer vision. This study provides valuable insights for developing future plant disease identification systems, ultimately contributing to improved disease management and promoting sustainable agricultural practices.

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CHAPTER 1
Introduction

1.1 Overview

Bangladesh, a prominent agricultural nation in Asia, cultivates bananas, a highly sought-after fruit throughout the region. Bananas contribute a significant 16% to global fruit production and boast valuable bioactive molecules and antioxidant content. The World Health Organization suggests every person to take 400 grams of fruits and vegetables on each day [1]. India produces 27% of banana in the world which is the largest in the world [2], Bangladesh cultivates 833,309 tones on 48,850 hectares of land [3]. Unfortunately, banana plants face diverse disease threats. These diseases not only reduce crop yield but also diminish fruit quality, impacting farmers' livelihoods. Numerous infections from throughout the world can cause leaf spot diseases, which cause large annual crop losses. On the other hand, many of these exhibit characteristic symptoms on leaves and fruits. Early and accurate detection of such diseases is crucial for implementing effective management strategies. Traditional methods rely on visual inspection by trained personnel, a process that can be time-consuming, subjective, and prone to errors.

Convolutional Neural Network (CNN) models, including ResNet50, VGG19, VGG16, MobileNetV1, and MobileNetV2, are investigated in this study. Every model, distinguished by its distinct architecture, goes through extensive testing before and during augmentation. The results, which are expressed as accuracy percentages, show how well these CNN models perform in the challenging task of identifying illnesses of banana leaves. This research explores the application of convolutional neural networks (CNNs) approach for classifying healthy banana leaves and three common diseases prevalent in Bangladesh: Cordana leaf spot, Pestalotiopsis leaf spot, and Sigatoka disease. We address the regional variations in disease presentation by utilizing a dataset specifically collected from Habiganj, Sylhet, Bangladesh. This ensures the model is trained on images that reflect the local disease patterns. Unlike traditional methods, CNNs excel at extracting features from image data, making them suitable for automated disease detection in banana leaves.

Through this research, we hope to contribute to the development of accurate and efficient deep learning models for banana leaf disease classification in the Bangladeshi context. This advancement can empower farmers with a powerful tool for early disease detection, enabling them to take timely action and safeguard their crops.

1.2 Background and Present State

Banana leaf diseases pose a significant threat to global banana production, leading to yield losses and economic hardship for farmers. Early and accurate disease identification is crucial for effective disease management and maintaining crop health. Traditionally, disease diagnosis relies on visual inspection by trained professionals, which can be time-consuming, subjective, and require expertise.

Challenges of traditional methods:

- **Subjectivity:** Diagnosis accuracy depends on the experience and expertise of the inspector.
- **Time-consuming:** Field inspection and lab analysis can be slow, delaying treatment implementation.
- **Limited accessibility:** Expert personnel might not be readily available in all areas.

Advancements in image processing and machine learning offer promising solutions:

- **Automated disease detection:** Machine learning algorithms can analyze digital images of banana leaves to detect and classify diseases.
- **Improved accuracy and efficiency:** Automated systems can achieve high accuracy and analyze large numbers of images quickly.
- **Early detection:** Machine learning can potentially detect diseases at earlier stages, allowing for more effective treatment.

Present State:

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), are at the forefront of banana leaf disease classification research. These algorithms excel at extracting features from images and can achieve high classification accuracy.

Transfer learning is a widely used approach where pre-trained CNN models are fine-tuned for banana leaf disease classification. This leverages pre-existing knowledge from large image datasets and reduces training time on specific diseases.

Several studies have demonstrated the effectiveness of CNN-based approaches for classifying various banana leaf diseases, including Sigatoka, Bunchy Top Virus, and Bacterial Wilt.

1.3 Problem Statement

One of the most popular and nutrient-dense fruits, bananas are produced and consumed worldwide, but banana leaf diseases pose a danger to these industries. Numerous diseases frequently affect banana crops. Leaf spot diseases are caused by a variety of infections that can arise anywhere in the world and result in significant annual crop losses. Numerous leaf spot diseases are commonly documented, such as the sigatoka diseases: Cordana leaf spot [4], Exserohilum leaf spot [5], Plantain zonate leaf spot [6], banana freckle disease [7], yellow sigatoka (Pseudocercospora musicola), black sigatoka (Mycosphaerella Fijiensis), and Eumusae leaf (Mycosphaerella Eumusae) spot [8]. However, because they necessitate personal inspection and specialized knowledge, the detection and diagnosis of these disorders are frequently difficult. It is crucial to identify these illnesses early on to minimize yield losses and guarantee food security. Banana leaf image collection and analysis technologies now in use are expensive, time-consuming, and require specialized knowledge. Consequently, a reliable and automatic deep learning system for categorizing photos of banana leaves with various illnesses is required.

Traditional methods of identifying banana leaf diseases, while valuable, have limitations. Visual inspection by trained personnel is time-consuming, subjective, and prone to human error, potentially leading to missed diagnoses or delays in implementing effective disease management. However, existing deep learning models for banana leaf disease classification might be trained on datasets from other regions. These models may not generalize well to Bangladesh due to potential variations in disease presentation, such as specific strains or environmental factors. This limitation can lead to inaccurate diagnoses in a Bangladeshi context.

Our research addresses this gap by utilizing a specifically curated dataset collected from Habiganj, Sylhet, Bangladesh. This dataset captures the local disease patterns prevalent in this region, ensuring the model is trained on images that accurately represent the banana leaf diseases farmer's encounter. In conclusion, this research is driven by the need for a more accurate, efficient, and objective approach to banana leaf disease classification specific to Bangladesh. In this study we aim to overcome the limitations of traditional methods and contribute to the development of a valuable tool for farmers and agricultural stakeholders.

1.4 Objectives

Bananas are vital to Bangladesh's agriculture, but banana diseases pose a significant threat to Bangladesh's agriculture productivity, impacting both local sustenance and global trade. Traditional disease detection methods for bananas are cumbersome and subjective, often leading to yield loss. In response, our research aims to revolutionize disease detection. Our main objective is to make a smart system that can quickly and accurately find diseases on banana leaves. To detect these diseases, visual detection is commonly used instead of laboratory analysis as laboratory analysis is a comparatively time-consuming method. So, our aim is not to replace laboratory methods. Our aim is to make visual detection faster. For this we will leverage convolutional neural networks (CNNs). Firstly, we'll gather lots of pictures of banana leaves and develop a comprehensive dataset of banana leaf images. Then, our primary aim is to create a robust system capable of accurately identifying and categorizing banana leaf diseases, including healthy leaves, Cordana, Pestalotiopsis or Sigatoka and compare the result with some pre-trained CNN models. After analyzing its accuracy, robustness, and computational efficiency, we can ensure the effectiveness of CNNs for banana leaf disease. Once it's working well, we can use it to help our agricultural economy by detecting the disease.

1.5 Scope and Limitations

This research focuses on utilizing a self-collected dataset of banana leaf images from Habiganj, Sylhet, Bangladesh for classifying three specific diseases: Cordana, Pestalotiopsis, and Sigatoka. We explore the effectiveness of transfer learning with pre-trained Convolutional Neural Network (CNN) architectures for this task.

Scope:

- **Disease Classification:** This study targets the classification of three prevalent banana leaf diseases: Cordana, Pestalotiopsis, and Sigatoka.
- **Data Collection:** We leverage a self-collected dataset of banana leaf images from a specific region in Bangladesh to account for potential regional variations in disease presentation.
- **Transfer Learning:** The research employs transfer learning with pre-trained CNN models (VGG19, VGG16, ResNet50, MobileNetV1, MobileNetV2) for disease classification.
- **Performance Evaluation:** The performance of various CNN architectures is compared with and without image pre-processing to assess the impact on classification accuracy.

Limitations:

- **Disease Range:** The study is limited to classifying three specific banana leaf diseases. Other diseases might require further investigation and model development.
- **Dataset Size:** While the research utilizes a self-collected dataset, increasing the dataset size and diversity could potentially improve model generalizability.

- **Generalizability:** The model's performance might be limited to the specific region where the data was collected. Further validation on data from diverse geographic locations would be beneficial.
- **External Factors:** The study doesn't account for external factors that might affect image quality, such as lighting variations or camera angles. Future work could explore methods for handling these variations.
- **Real-world Deployment:** While the research demonstrates the potential of the approach, integrating the model into a mobile application for real-world use by farmers is not covered in this study.

These limitations highlight areas for future research to further refine and improve the banana leaf disease classification system.

1.6 Report Organization

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

Chapter 1: Introduction

The research is introduced in the first chapter, which also gives background information on the importance of classifying banana leaf diseases, how CNNs are used, and why a comparative analysis is necessary. It provides an overview of the study's background and present state, problem statement, objectives, scope and limitations, and overall framework.

Chapter 2: Literature Review

A thorough analysis of pertinent literature and earlier research is provided in the background chapter. A comprehensive understanding of the theoretical underpinnings, practical approaches, and technological developments pertaining to CNNs, and the classification of banana leaf disease is provided in this section. It lays out the background for the current investigation and identifies knowledge gaps.

Chapter 3: 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, research 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 implementation of different CNN models, training model, Testing the model and evaluation and overview are in this section.

Chapter 5: Result and Analysis

The experimental findings from the classification of banana leaf disease using several CNNs are presented in this chapter. Comprehensive evaluations of the efficacy of various methodologies are provided, accompanied with graphical depictions and statistical metrics to corroborate the results.

Chapter 6: Impact on Society, Environment and Sustainability

The chapter on societal impact delves into the wider consequences that the research findings hold for the fields of agriculture and agricultural diagnostics. It talks about how better techniques for classifying leaf diseases can increase food security, have a positive impact on farming practices, and give farmers in Bangladesh more authority. Future technological developments and their effects on society are considered.

Chapter 7: Conclusion and Future Work

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. A path for academics interested in building upon the current study is provided in the discussion of the implications for future research.

1.7 Summary

Bananas are a vital crop, but banana leaf diseases significantly impact yield and quality. Traditional disease identification methods are time-consuming, subjective, and require expertise. This research addresses these limitations by exploring automated disease classification using Convolutional Neural Networks (CNNs).

The introduction highlights the rise of machine learning, particularly CNNs, for accurate and efficient disease detection in banana leaves. It emphasizes the importance of transfer learning for leveraging pre-trained models and reducing training time. Existing research on CNN-based banana leaf disease classification is acknowledged.

The problem statement identifies the need for regionally specific datasets to account for variations in disease presentation. This research addresses this by utilizing a self-collected dataset from Bangladesh.

The objectives are to classify specific banana leaf diseases (Cordana, Pestalotiopsis, and Sigatoka) using transfer learning with CNN architectures. The scope and limitations section outlines the focus on these three diseases, the self-collected dataset, and the chosen CNN models. It acknowledges limitations like the number of diseases covered and the dataset size.

Finally, the introduction summarizes the key points, emphasizing the importance of regionally specific data and transfer learning for banana leaf disease classification. It highlights the contribution of this research to advancements in plant disease identification.

CHAPTER 2

Literature Review

2.1 Overview

The classification of banana leaf diseases, including Cordana leaf spot, Pestalotiopsis leaf spot, and Sigatoka disease, has been significantly enhanced by advancements in deep learning, especially Convolutional Neural Networks (CNNs). Deep learning algorithms, inspired by the brain, learn patterns from large datasets, with CNNs being particularly effective for image recognition. They automatically extract relevant features from images, making them ideal for classifying diseases. Transfer learning, where a pre-trained model on a large dataset is adapted for a new task using a smaller dataset, improves training efficiency. Data augmentation, which increases dataset size and diversity through transformations like flipping and rotation, helps models generalize better.

Performance metrics such as accuracy, precision, recall, and F1 score evaluate the effectiveness of these models. Studies have successfully applied CNNs to identify various plant diseases, with models achieving high accuracy rates. For instance, Bhuiyan et al. reported the first occurrence of Pestalotiopsis Microspora-induced banana leaf blight in Bangladesh, and subsequent research has employed aerial images and machine learning algorithms for disease identification. Models using deep neural networks, transfer learning, and hybrid CNNs have demonstrated impressive accuracy, contributing to more effective agricultural practices and disease management.

2.2 Related Works

Previously, features created by various feature extraction techniques, such as Histogram of Oriented Gradients (HoG) [10], Scale-Invariant Feature Transform (SIFT) [9] and Speeded Up Robust Features (SURF) [11], were used for object detection and picture categorization. However, with the use of Convolutional Neural Networks (CNN), automatic object detection and image categorization have evolved dramatically in recent years [12], [13].

Bhuiyan et al. [14] reported the first occurrence of Pestalotiopsis Microspora-induced banana leaf blight in Bangladesh in 2022. Aerial pictures can be utilized with various machine learning algorithms to identify banana plants and their main illnesses [15].

Another deep transfer learning-based method for detecting banana pests and disease from banana field images [16].

Sujithra et al. used deep neural networks to diagnose leaf problems in bananas and sugarcane [17]. The proposed models can identify between black and yellow Sigatoka infestations on banana leaves. Region-Based Convolutional Neural Network and Gabor Extraction can both detect banana leaf diseases [18].

Gopinath et al. [19] proposed an approach for classifying plant leaf disease that employs the Convolutional Recurrent Neural Network Classifier algorithm. Scientists used their technology to discern between healthy and diseased leaves of a variety of plants, including bananas, peppers, potatoes, and tomatoes.

Md. Abdullahil Baki Bhuiyan et al [20] suggested a rapid, lightweight convolutional neural network for the identification of three common banana leaf diseases in 2023, and it did extremely well in diagnosing banana leaf diseases from pictures, with a total accuracy of 96.25%. Their model outperforms some of the most advanced convolutional neural networks, including ResNet-101, EfficientNetB0, MobileNetV3, InceptionNet-V3, ResNet-50, and VGG16.

Ilham Rahmana Syihad et al. [21] suggested a CNN method for identifying banana plant diseases based on banana leaf images using ResNet50 and VGG-19 models, with the ResNet50 model achieving an incredible 94% accuracy and the VGG-19 model doing well with 91% accuracy.

In 2023, Samridhi et al. [22] created a model to identify sigatoka leaf spot disease in bananas using CNN, which achieved an accuracy of 96.41%.

In 2020, A. Criollo et al. [23] introduced a convolutional neural network (CNN) to identify illnesses in banana plants, which was trained on RGB pictures of banana leaves. Three models were examined: one without regularization, one with dropout, and one with weight regularization. Despite the limited data, they concluded that CNN without any regularization technique outperformed the other models in predicting banana plant infections.

In 2022, K. Lakshmi Narayanan et al. [24] suggest a hybrid CNN for banana disease detection, assisting farmers in using the enabling fertilizers necessary to prevent illness in its early stages.

In 2020, S. L. Sanga et al. [25] introduced a mobile-based deep learning model for banana disease detection. The models have good accuracy, ranging from 95.41% for InceptionV3 to 99.2% for Resnet152.

In addition to a DCNN Classifier model based on the VGG16 architecture, Prasad, K.V. et al. [26] employed convolutional neural networks (CNN) for damaged grape leaf recognition in 2024, both using and not using augmentation approaches. The CNN models' capacity for generalization can be enhanced and overfitting problems can be reduced with the help of augmentation. Because it adds additional Convolutional Neural Network (CNN) layers with training and test accuracy rates of 99.18 and 99.06%, and because it uses the VGG16 architecture, the Deep Convolutional Neural Network (DCNN) model performs better than other models.

A reliable method, ResNet-34 based Faster-RCNN, was presented by Nawaz et al. [27] in 2022 to identify and categorize tomato plant leaf diseases. The technique was tested on the PlantVillage Kaggle dataset, a publicly accessible standard database, and achieved a 99.97% accuracy rate.

Wu, Q. et al. presented a soybean leaf disease classification method in 2023 [28] that was built on ConvNeXt and an attention module. Four CBAM attention modules were included in the CBAM-ConvNeXt network, an upgraded network model for soybean leaf diseases. Compared to the six deep learning comparator models, ConvNeXt (66.41%), ResNet50 (72.22%), Swin Transformer (77.00%), MobileNetV3 (67.27%), ShuffleNetV2 (59.89%), and SqueezeNet (72.92%), it has an average recognition accuracy of 85.42%.

In 2020, Ani Brown Mary et al. [29] created a model using Enhanced Gabor Feature Descriptor. This model used an improved Gabor filter for extracting features from photos of damaged plants. Furthermore, KNN classifiers are used to categorize illnesses. Classification trials on sick datasets show that the suggested method outperforms the SIFT and SURF feature descriptors.

A concatenated neural network of the extracted features of VGG16 and AlexNet networks was proposed by Bezabh, Y.A. et al. [30] in 2023 to develop a fully connected layer pepper disease classification model with a 100% training classification accuracy, 97.29% validation accuracy, and 95.82% testing accuracy.

By using the quickest single-stage object identification model, YOLOv7, to train on the diseased tea leaf dataset gathered from four renowned tea plantations in Bangladesh, Soeb, M.J.A. et al. [31] offered an artificial intelligence-based solution to the problem of tea leaf disease detection in 2023. The suggested algorithm was able to distinguish between healthy and diseased tea leaf segments and automatically identify five different kinds of tea leaf illnesses. 97.30% of classifications are accurate overall. The proposed model performs better than the latest ones.

2.3 Comparison between existing works

This section delves into a comparative analysis of existing approaches for banana leaf disease classification.

Traditional Methods vs. Machine Learning

Traditional methods for banana leaf disease detection rely on visual inspection by trained personnel. While these methods are simple and require no specialized equipment, they are prone to human error and subjectivity. Additionally, manual inspection can be time-consuming and labor-intensive, particularly for large farms.

Machine learning offers a more objective and automated approach. Techniques like Support Vector Machines (SVM) and k-Nearest Neighbors (kNN) have been employed for banana leaf disease classification. These methods involve feature engineering, where relevant characteristics (e.g., color, texture) are manually extracted from images and used to train the model. While promising results have been achieved using machine learning, the reliance on manual feature engineering can be a limitation.

Machine Learning vs. Deep Learning (CNNs)

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized image classification tasks, including disease detection in various agricultural applications. Unlike machine learning methods, CNNs eliminate the need for manual feature engineering. They automatically learn relevant features directly from image data through convolutional layers. Studies have shown that CNNs achieve superior accuracy compared to traditional machine learning approaches in banana leaf disease classification. However, training deep learning models often requires large datasets and significant computational resources, which might be limitations for resource-constrained settings.

Transfer Learning for Improved Efficiency

Transfer learning techniques leverage pre-trained CNN models on vast generic image datasets for new tasks like banana leaf disease classification. This approach reduces training time compared to training a model from scratch. Research has explored using pre-trained models like VGG16 and ResNet50 with promising results, demonstrating the effectiveness of transfer learning in achieving good accuracy with smaller, disease-specific datasets.

In summary, Machine learning offers improved objectivity and automation, but relies on manual feature engineering. Deep learning with CNNs achieves superior accuracy by automatically learning features yet requires substantial computational resources and large datasets. Transfer learning improves efficiency by leveraging pre-trained models but might not capture regional disease variations. To address these limitations, this research proposes a hybrid CNN model that utilizes a local dataset from Bangladesh, combines the strengths of multiple pre-trained architectures, and incorporates data augmentation techniques. This approach aims to achieve a balance between accuracy, efficiency, and generalizability, making it a potentially valuable tool for banana leaf disease classification in the Bangladeshi context. This comparative analysis sets the stage for the subsequent chapters, providing a solid foundation for the societal impact discussion, recommendations, and implications for future research.

Table 2.3.1: Comparative Analysis Table

SL No	**Author Name**	**Used Algorithm and Image Type**	**Best Accuracy with Algorithm**
1.	Md. Abdullahil Baki Bhuiyan et al. [20]	MobileNetV3, EfficientNetB0, ResNet-50, BananaSqueezeNet, ResNet-101, VGG-16, Inception-V3 on banana leaves	BananaSqueezeNet = 96.25%
2.	Ilham Rahmana Syihad et al. [21]	ResNet50, VGG-19 on banana leaves	ResNet50 = 94%
3.	Samridhi et al. [22]	CNN on on banana leaves	CNN = 96.41%
4.	A. Criollo et al. [23]	CNN without regularisation, CNN with Dropout, CNN with weight regularization on banana leaves	CNN without regularization = 87.5%
5.	K. Lakshmi Narayanan et al. [24]	Proposed CNN+FSVM, CNN+RF, SVM+PCA, SVM+Haar-WT, CNN, ANN, Random Forest, SVM on banana leaves	Proposed CNN+FSVM = 99%
6.	S. L. Sanga et al. [25]	VGG16, Resnet18, Resnet50, Resnet152, InceptionV3 on banana leaves	Resnet152 = 99.8%
7.	Selvaraj, M.G. et al.	Faster R-CNN InceptionV2, SSD MobileNetV1,	Faster R-CNN

	[16]	Faster R-CNN ResNet50 on banana leaves and pest	ResNet50 = 99%
8.	J. Sujithra et al. [17]	Histogram-based, H + U-Net, U-Net based, CRUN-MP on banana and sugarcane leaves	CRUN-MP = 99.2%
9.	Ani Brown Mary et al. [29]	Enhanced Gabor, Gabor, Log Gabor, SHIFT, SURF on banana leaves	Enhanced Gabor = 98.12%
10.	Nawaz et al. [27]	ResNet-34 based Faster-RCNN on tomato plant leaves	Faster-RCNN (RESNET-34) = 99.97%
11.	Prasad, K.V. et al. [26]	DCNN Classifier model based on VGG16 on grape leaves	DCNN = 99.06%
12.	Wu, Q. et al. [28]	CBAM-ConvNeXt, ResNet50, ConvNeXt, Swin transformer, MobileNetV3, ShuffleNetV2, SqueezeNet on soybean leaves	CBAM-ConvNeXt = 85.42%
13	Bezabh, Y.A. et al. [30]	CNN, VGG16, VGG19, ResNet50, ResNet101, ResNet152, InceptionResNetV2, DenseNet121, Concatenated CNN model on pepper leaves	Concatenated CNN model = 95.82%
14	Soeb, M.J.A. et al. [31]	YOLOv7 (YOLO-T), Improved YOLOv5, CNN, Deep CNN (LeNet), DNN, Improved DCNN, CNN (LeafNet) tea leaves	YOLOv7 (YOLO-T) = 97.30%

2.4 Open Issues

Banana leaf diseases pose a significant threat to banana production in Bangladesh, causing substantial crop yield losses and impacting fruit quality. Early and accurate detection of these diseases is crucial for implementing effective disease management strategies and minimizing these losses. This research focuses on three prevalent fungal diseases affecting banana leaves in Bangladesh: Cordana leaf spot, Pestalotiopsis leaf spot, Sigatoka disease. These diseases manifest with distinct visual characteristics on banana leaves. However, accurate differentiation, particularly between early stages of these diseases, can be challenging for traditional visual inspection methods.

The scope of this research is to develop and evaluate a robust and accurate method for classifying these three banana leaf diseases using different convolutional neural network (CNN) models. This study aims to address the limitations of existing approaches:

- Human Error: Eliminate subjectivity and inconsistencies associated with visual inspection by trained personnel.

- Feature Engineering: Overcome the need for manual feature extraction required in traditional machine learning methods.
- Limited Dataset Size: Address potential limitations arising from datasets that might not be sufficiently large or diverse for training deep learning models.
- Regional Variations: Capture the specific disease characteristics prevalent in Bangladesh, potentially improving generalizability compared to models trained on generic datasets.

By addressing these limitations, our study has the potential to be a valuable tool for:

- Early Disease Detection: Enabling farmers to promptly identify diseases and take timely action to minimize crop losses.
- Improved Disease Management: Supporting the development of targeted interventions based on the specific disease identified.
- Enhanced Food Security: Contributing to increased banana production and a more stable food supply in Bangladesh.

2.5 Summary

The reviewed literature confirms the effectiveness of Convolutional Neural Networks (CNNs) for banana leaf disease classification. Studies have demonstrated successful classification of various diseases using pre-trained CNN models and transfer learning techniques.

However, limitations exist in current research. Datasets used in existing works might not be regionally representative, potentially affecting generalizability. Additionally, some studies focus on a limited range of diseases, neglecting others prevalent in specific regions.

By addressing these limitations, this research aims to contribute valuable insights for banana leaf disease classification in Bangladesh and paves the way for further advancements in the field.

CHAPTER 3

Methodology

3.1 Overview

The methodology for the research project "A Computer Vision Approach for Banana Leaf Disease Classification" involves leveraging machine learning methods in Python. The models include VGG19, VGG16, ResNet50, MobileNetV1, and MobileNetV2. This study investigated the potential of Convolutional Neural Networks (CNNs) for classifying banana leaf diseases (Cordana, Pestalotiopsis, Sigatoka) with a focus on potential regional variations in disease presentation and to extract intricate patterns from images, thereby enhancing diagnostic accuracy. This chapter contains details about about our dataset, how we collected it, image augmentation, what was done before preprocessing, about the preprocessing of images, what was done after preprocessing, hardware and software requirements, different methods, libraries and frameworks we used, and our project management and financial analysis of this work. The overview of our methodology is: A dataset of banana leaf images (healthy and diseased) was collected from Habiganj, Sylhet, Bangladesh, to account for regional disease presentation. Dataset augmentation was done to balance the dataset. Five pre-trained CNN architectures (VGG19, VGG16, ResNet50, MobileNetV1, MobileNetV2) were selected applied for the classification task using a separate validation set to prevent overfitting. Image preprocessing techniques were applied as needed to improve image quality and potentially enhance model performance. Trained models were evaluated on a held-out test set for unbiased assessment. The most effective architecture for banana leaf disease classification was identified. A comparative analysis of different CNN models is conducted to understand their strengths and weaknesses, aiming to develop more reliable and efficient diagnostic tools that account for regional variations in disease presentation.

3.2 Proposed Methodology

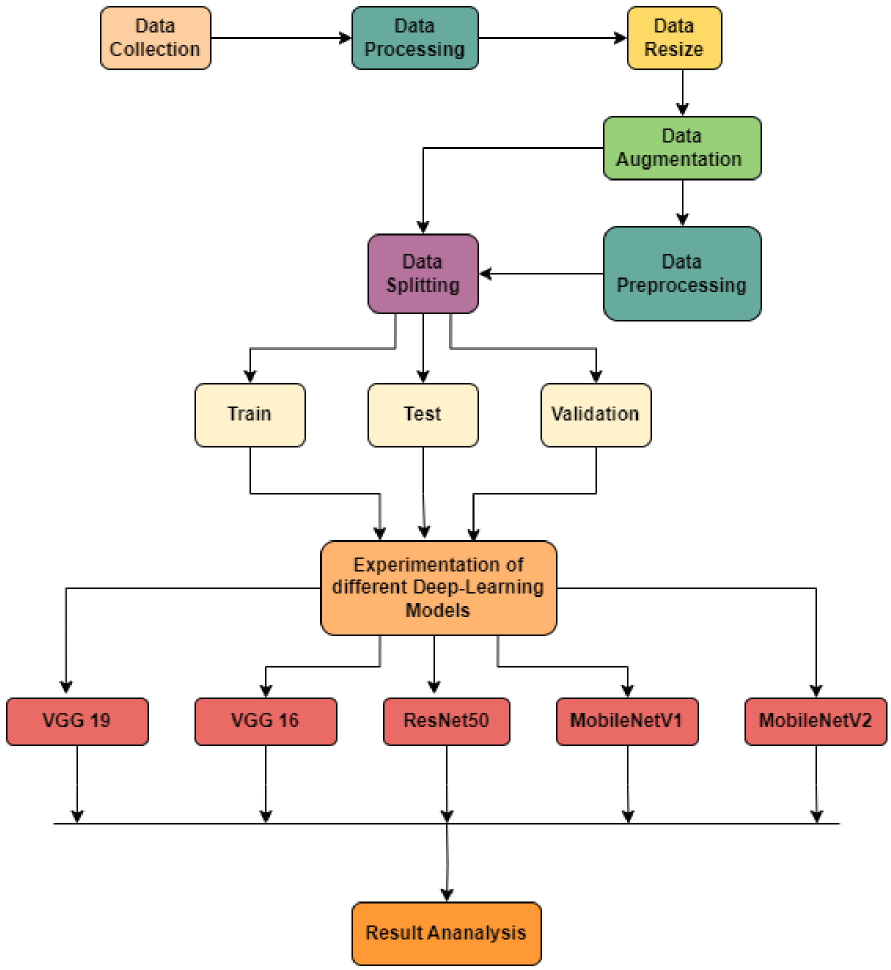


Figure 3.2.1: Proposed Methodology

This image illustrates the workflow for a deep learning project, detailing each step from data collection to result analysis. Initially, data is collected and processed to ensure consistency, followed by resizing the images to maintain uniformity. The data is then augmented to increase variability and preprocessed for normalization and preparation.

Next, the data is split into three sets: 60% for training, 25% for validation, and 15% for testing. The training set is used to train various deep learning models, the validation set is used to fine-tune the models' parameters, and the test set evaluates the models' performance.

Different deep learning models, including VGG19, VGG16, ResNet50, MobileNetV1, and MobileNetV2, are experimented with to determine their effectiveness. Finally, the results from these models are analyzed to select the best-performing one, ensuring a thorough and rigorous approach to model development and evaluation.

3.2.1 Design approach

In our research, we mainly apply a two-phase design approach such as preprocessing and post-processing model implementation to see how well different models can identify banana leaves diseases. This two- fold approach underscores the importance of proper preprocessing techniques in refining model accuracy and effectiveness.

3.2.2 Before Performing preprocessing

At first, we wanted to see how well five different types of computer brain models, called Convolutional Neural Networks (CNNs) architectures. The aim was to evaluate how well these models could identify diseases of banana leaves without any enhancements or standardization to the dataset. The raw images, categorized into healthy, Cordana, Pestaliopsis and Sigatoka were utilized to train and evaluate the CNN models. This approach allowed for a baseline evaluation of the model's performance directly on the original, unaltered dataset, providing insights into their initial capabilities before any preprocessing techniques were applied. This also helps us understand how good the models were without doing anything special to the pictures first.

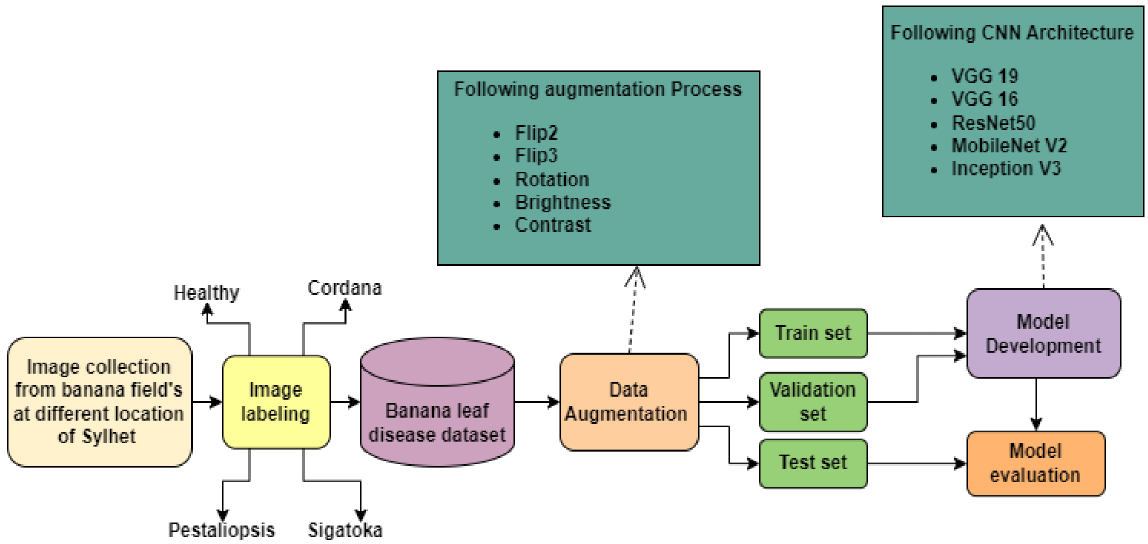


Figure 3.2.2.1: Steps before Preprocessing

3.2.3 After Performing Preprocessing

After several preprocessing steps were carried out, including resizing the images to a size of 512 X 512 pixels, converting grayscale, enhancing contrast using a method called Contrast Limited Adaptive Histogram Equalization (CLAHE), and increasing the dataset size through augmentation, a more refined design approach was implemented. These preprocessing steps aimed to make the dataset more standardized and enhance the features related to disease in the images. Once the preprocessing was completed, the improved dataset was fed into the same five CNN architectures used in the original method. This allowed for a direct comparison of how well the models performed before and after preprocessing. By doing this, we could see how much the preprocessing techniques improved the model's ability to identify disease in banana leaves.

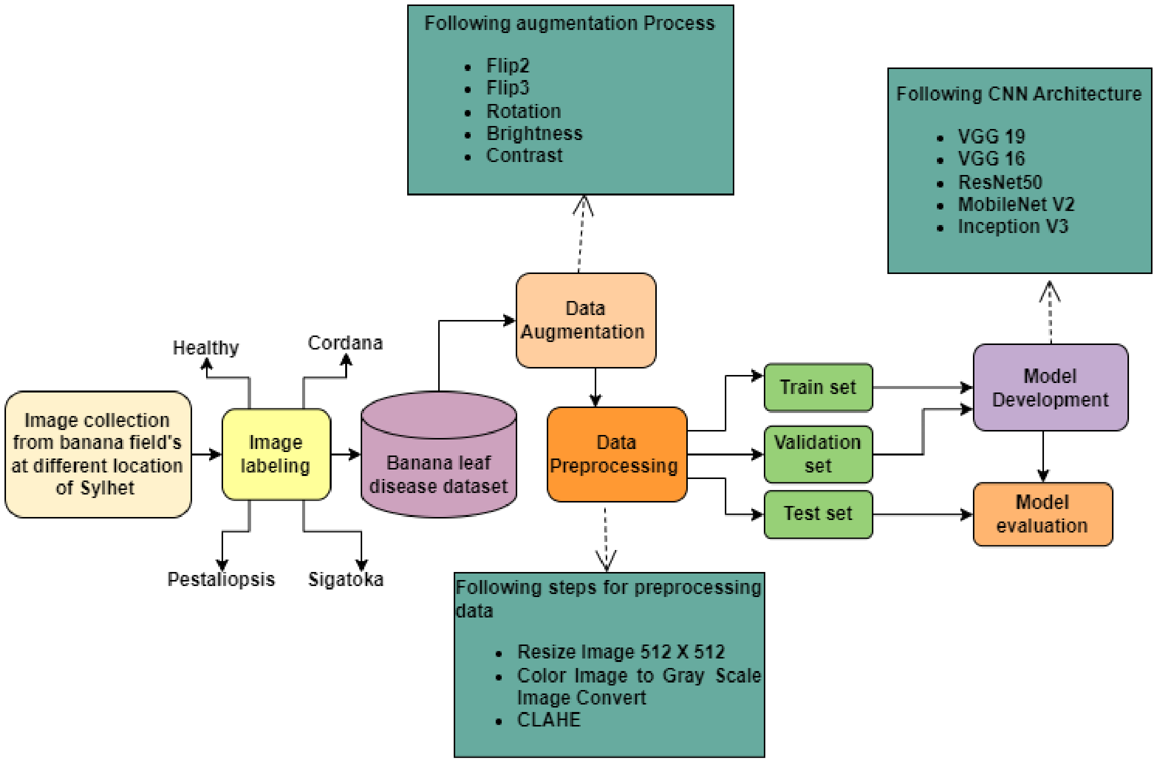


Figure 3.2.3.1: Steps after Preprocessing

3.2.4 Data Collection Procedure

To create the dataset, we specifically gathered our own dataset of photos of banana leaves from Habiganj, Sylhet, Bangladesh, taking into consideration differences in disease presentation between regions to produce our dataset. Four classes—Cordana, Pestalotiopsis, Sigatoka, and Healthy—were created from the photographs. It is important to remember that each image in the dataset is distinct. For the model, we further made train, test, and val folders.

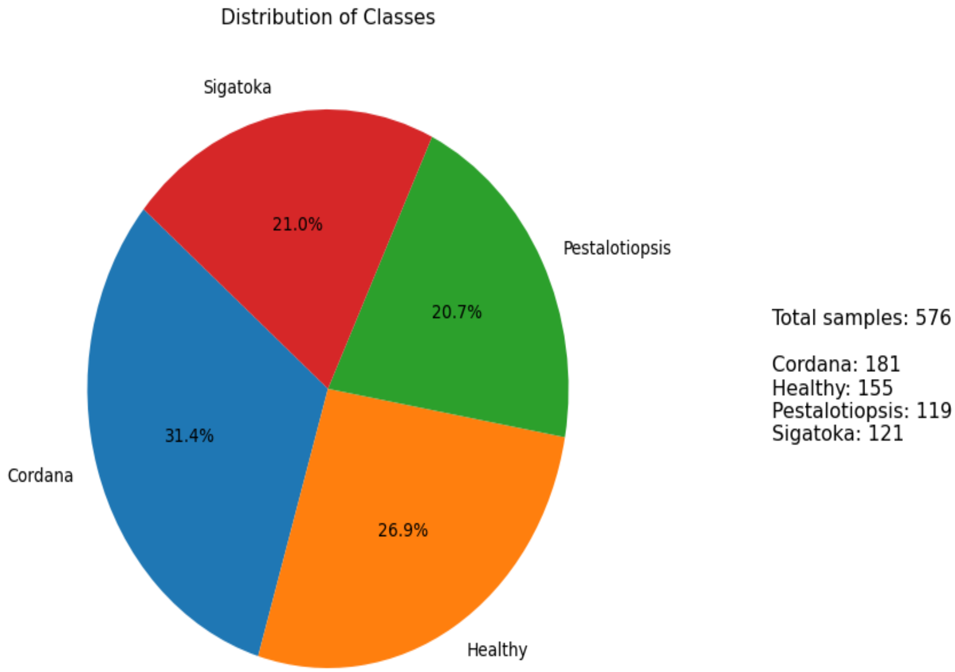


Figure 3.2.4.1: Distribution of Four Classes of Dataset

3.2.5 Data Augmentation Techniques

Firstly, we apply augmentation techniques for increasing the number of images in our dataset. We initially had 576 images in our dataset and wanted to expand this number to 8,000 images to improve our model's performance. To achieve this, we used five different augmentation techniques. The first two techniques involved flipping the images in different ways (vertically and horizontally), which changed the orientation of the images. The third technique was rotation, which involved rotating the images at various angles to create new perspectives. The fourth technique adjusted the brightness, making the images lighter or darker. The fifth technique modified the contrast, altering the difference between the light and dark areas of the images. By applying these five augmentation techniques, we were able to create many new versions of the original images, increasing our dataset to 8,000 images.

3.2.6 Statistical Analysis

We have collected data from Habiganj Sadar, Sylhet Bangladesh. Our data set contains a total of 576 raw images. And the data set contains four classes – Cordana, Pestalotiopsis, Sigatoka and Healthy leaves. We have done an Augmentation process to increase our dataset volume and the data set contains a total 8,000 images.

Table 3.2.6.1: shows statistical analysis of our dataset.

Table 3.2.6.1: Statistical Analysis of Dataset

Dataset	Classes	Original Images	Augmented Images
Image Dataset	Cordana	181	2,000
	Pestalotiopsis	119	2,000
	Sigatoka	121	2,000
	Healthy	155	2,000
Total	Classes = 4	576	8,000

3.2.7 Data Preprocessing

As we know, robust and diverse datasets give an accurate classification for any classification. For this we collect the dataset from different places to ensure it is comprehensive and representative. Our dataset consists of 8,000 images divided into four categories: Healthy, Cordana, Pestalotiopsis, and Sigatoka. Each category contains 2,000 images. To ensure our dataset was well-prepared and could provide accurate results, we used multiple methods to process and refine it. These procedures were aimed at improving the quality and reliability of our dataset for classification purposes. To improve the dataset's quality for better classification results, we resized images, turned them into grayscale, and used CLAHE to adjust contrast. These steps were important to prepare our dataset effectively.

3.2.8 Image Resizing

After enlarging our dataset from 576 to 8,000 images, we performed several preprocessing steps to improve and standardize the images for better model training. One key step was resizing all the images to 512x512 pixels. This uniform size ensured that all images had consistent dimensions, which is important for further analysis and helps the model process the data more effectively. These preprocessing steps were crucial for preparing the banana leaf images for accurate and efficient model training.

3.2.9 Convert to Grayscale

After resizing the images of our dataset, we converted them to grayscale. This means we changed the images from color to shades of gray. Doing this made the images simpler and faster for the computer to process. Despite removing the colors, we still kept the important features needed to identify diseases in the banana leaves of our dataset. This step helped improve the efficiency and focus of our analysis.

3.2.10 Contrast Limited Adaptive Histogram Equalization (CLAHE)

Grayscale conversation is definitely an efficient way to help models understand the details. But moreover, there is another Histogram Equalization method to enhance the details, that is Contrast Limited Adaptive Histogram Equalization (CLAHE). This method was applied to the images of our dataset to highlight finer details and improve their contrast and also make it easier to spot disease features. CLAHE helps us by reducing lighting differences between images, ensuring that they have more consistent visual attributes. This standardization made it easier to extract important details related to the diseases affecting the banana leaves.

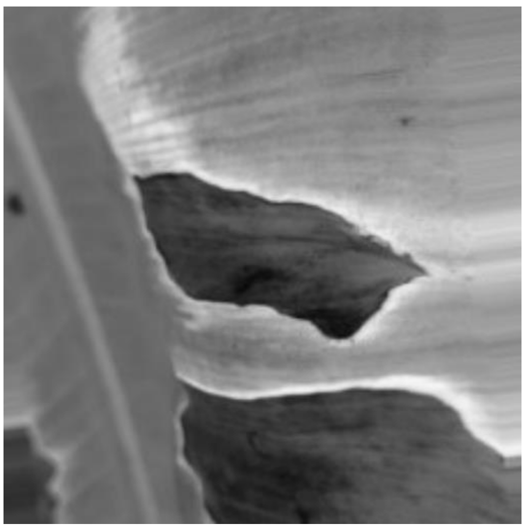
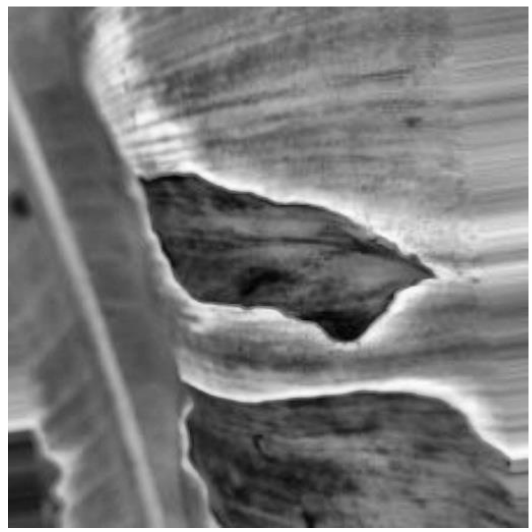
	
Raw Image	Resized image(512x512)
	
Grayscale Image	CLAHE Applied

Figure 3.2.10.1: Images of Cordana Class Preprocessing Steps.

	
Raw Image	Resized image(512x512)
	
Grayscale Image	CLAHE Applied

Figure 3.2.10.2: Images of Pestalotiopsis

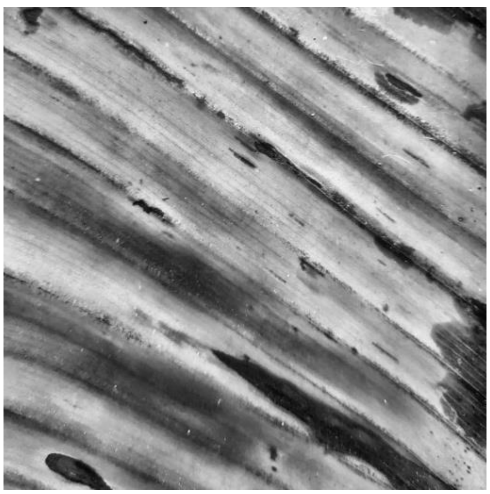
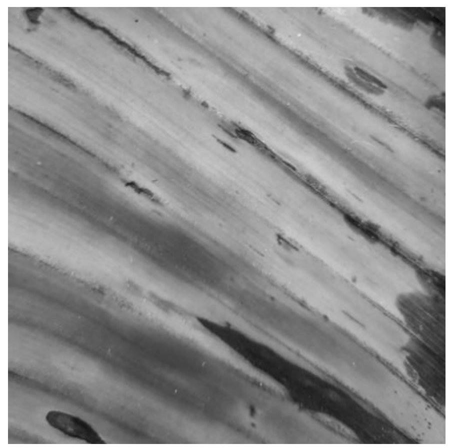
	
Raw Image	Resized image(512x512)
	
Garyscal Image	CLAHE Applied

Figure 3.2.10.3: Images of Sigatoka

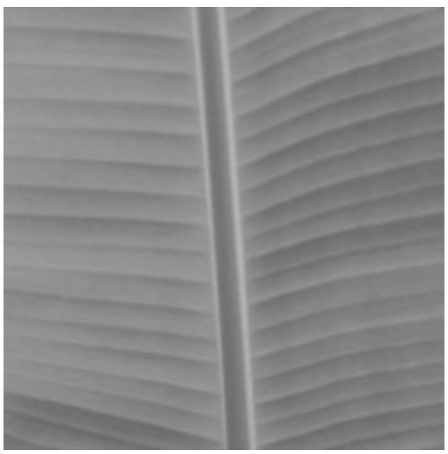
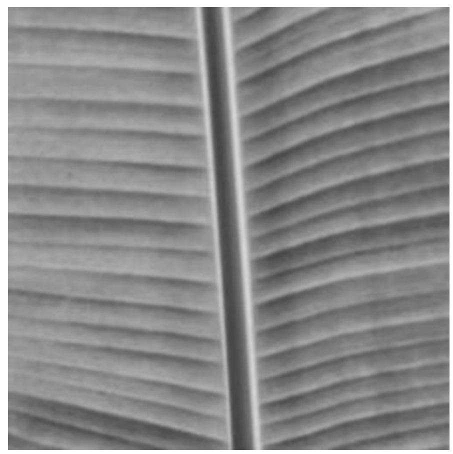
	
Raw Image	Resized image(512x512)
	
Garyscal Image	CLAHE Applied

Figure 3.2.10.4: Images of Healthy Leave

3.2.11 Data Splitting

To perform our model well and generalize effectively, we decided to divide our dataset into three distinct subsets for training, testing and validation. This data splitting ensures that the model was trained on a substantial amount of data, tested on a separated set of assets, and validated on another set to optimize its performance. With the augmented dataset containing 8000 images, we applied the following:

- **Training Data:** We used 60% of the dataset, which amounts to 4800 images, to train our model. This large portion helps the model learn from a diverse set of examples.
- **Testing Data:** We allocated 15% of the dataset, or 1200 images, for testing. This subset is used to evaluate the performance and accuracy of the trained models.
- **Validation Data:** Another 25% of the dataset, equaling 2000 images, was set aside for validation. This set is crucial for fine- tuning model hyperparameters and preventing overfitting during the training process.

3.3 Hardware / Software Requirements

Hardware Requirements:

The following hardware components were used to ensure efficient computation and model training:

- **CPU**: AMD Ryzen 5 5600: A powerful processor for handling intensive computations.
- **GPU**: Zotac GTX 1650 Super (4 GB RAM): Accelerates deep learning model training, reducing training time.
- **RAM**: Corsair 16 GB (2 x 8 GB, 3200 MHz) Sufficient memory for large datasets and computational tasks.
- **Storage**: Corsair SSD 256 GB Fast read/write speeds for quick data loading and saving.
- **Operating System**: Windows 10 Ensures compatibility with necessary software and tools.

Software Requirements:

Key software tools used for this research included:

- **Anaconda** : Manages packages and dependencies, enhancing GPU support in Jupyter Notebooks.

- **Jupyter Notebook** : Interactive computing environment for writing and executing code, and visualizing results.

Libraries and Frameworks:

Essential Python libraries for data manipulation, visualization, and machine learning included:

- **Python** : Primary programming language for algorithms and models.
- **Pandas** : Data manipulation and analysis.
- **Numpy** : Handling arrays and mathematical operations.
- **Matplotlib** : Creating static and interactive visualizations.
- **Seaborn** : High-level interface for statistical graphics.
- **Scikit-Learn** : Tools for data mining, analysis, and machine learning.

These hardware and software components provided a robust environment for comprehensive experiments and analyses, facilitating effective data handling, model implementation, and result visualization.

3.4 Project Management and Finance

Ensuring the success and sustainability of any undertaking requires effective project management and financial control, which are especially important in the context of the proposed research. Our research project has a clear scope and well-defined objectives. We aim to enhance banana leaf disease detection by leveraging CNN architecture. The precise planning, coordinating, and carrying out of tasks—from data collection to model training and evaluation—are all included in the project management component. A comprehensive project plan will be developed to delineate significant checkpoints, distribute resources carefully, and set deadlines, so promoting an organized and effective workflow. Simultaneously, sound financial management—which includes budgetary allotments for hardware, computational resources, and possible research partnerships—will be critical to the project's sustainability. The implementation of an open and prudent financial plan would guarantee the best possible use of resources while upholding fiscal responsibility. Here's how we plan to manage the project:

Table 3.4.1: Financial Analysis

SL	Instrument / Others Description	Estimated Cost (BDT)
1.	Transportation Cost	5000-7000
2.	Data set collection and Interview of stakeholders	1000-2000
3.	GPU (minimum 1650 SUPER 4 GB Ram)	20800-25000
4.	Camera / Mobile phone camera	00
5.	RAM 16 GB (3200 BUS) x 2	8000-10000
6.	CPU AMD Ryzen 5 5600	13000-14000
7.	Broadband Connection	6000-8000
8.	Documentation and Report Writing	500-1000
9.	Contingency (10% of total)	5430-6700
	Total Estimated Cost	59,730-73700

We acknowledge technical risks (model performance, data quality) and financial risks (budget overruns, delays). Mitigating these risks is essential. Considering the long-term benefits beyond the project duration, we believe our research is viable and aligned with our goals. In summary, effective project management and financial planning are critical for the success of our research. These integrated approaches to project management and finance are crucial building blocks that will enable the research team to successfully navigate the study's complexities, guarantee that the resources allotted are in line with the goals of the research, and enable the project to move forward smoothly toward its objectives.

3.5 Summary

In this study, we explored the effectiveness of transfer learning with Convolutional Neural Networks (CNNs) for classifying banana leaf diseases in Bangladesh. We utilized a self-collected dataset of banana leaf images containing Cordana, Pestalotiopsis, and Sigatoka diseases, captured from Habiganj, Sylhet. To evaluate the impact of image pre-processing, we initially implemented the pre-trained CNN models (VGG19, VGG16, ResNet50, MobileNetV1, MobileNetV2) directly on the raw, unprocessed images. This assessed their baseline performance for disease classification without any image manipulation. Subsequently, we applied data augmentation techniques to increase the size and diversity of the dataset. We then re-trained the CNN models on the pre-processed data to evaluate how these enhancements affected classification accuracy. Throughout this process, we employed various evaluation metrics like accuracy, precision, recall, and F1-score to assess the performance of each CNN model on both raw and pre-processed data. This approach allowed us to compare the effectiveness of transfer learning with and without image pre-processing for banana leaf disease classification.

CHAPTER 4
Implementation

4.1 Overview

The implementation of the banana leaf disease classification project involved a series of systematic steps designed to ensure a robust and efficient workflow. The experimental dataset comprised 8,000 images, evenly distributed across four classes: Healthy, Cordana, Pestalotiopsis, and Sigatoka, each containing 2,000 images. These images were divided into training, validation, and test sets in the ratio of 60%, 25%, and 15%, respectively.

Before splitting the dataset, extensive data preprocessing and augmentation were conducted. The preprocessing steps included resizing the images to 512x512 pixels, converting them to grayscale, and applying Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance image contrast. Data augmentation techniques such as vertical and horizontal flipping, rotation, and adjustments to brightness and contrast were employed, significantly increasing the dataset from 576 to 8,000 images. This augmentation ensured a more diverse and robust dataset, crucial for effective model training.

The models selected for this experiment included VGG19, VGG16, ResNet50, and MobileNet (V1 and V2), all known for their performance in image classification tasks. The experimental setup was supported by advanced hardware, including an AMD Ryzen 5 5600 CPU, a Zotac GTX 1650 Super GPU, 16 GB of Corsair RAM, and a Corsair SSD, all operating on Windows 10. This hardware configuration provided the necessary computational power and storage speed for the project.

For software, Anaconda was used for package management, and Jupyter Notebook facilitated interactive code execution. Essential Python libraries such as Pandas, Numpy, Matplotlib, Seaborn, and Scikit-Learn were utilized for data manipulation, visualization, and model development.

To evaluate the performance of the models, metrics including precision, recall, accuracy, and the F1-score were computed. Additionally, confusion matrices were used to provide a clear view of the classification performance, highlighting areas for potential improvement. This comprehensive setup allowed for the efficient execution and analysis of the deep learning models, ensuring accurate and reliable results in classifying banana leaf diseases.

4.2 Train Model

4.2.1 VGG 19

In our research, we apply the VGG 19 conventional neural network (CNN) model, a type of advanced computer algorithm. This network is an extension of the Visual Geometry Group (VGG) network, known for its depth and simplicity. VGG 19 consists of 19 layers, starting with 16 layers that analyze the features of the banana leaf images and ending with 3 layers that make final decisions. What makes VGG 19 special is its use of small- sized filers (3x3 squares) that move across the image one pixel at a time. This approach helps the network capture very detailed features from the banana leaf pictures. By using stacked 3x3 filters, VGG19 can understand different aspects of the leaf images, such as basic shapes and more intricate details. This allows the network to learn various levels of representations, from simple patterns like edges and textures to more complex features. While VGG19 requires more computational resources due to its depth, it excels at capturing complex patterns and fine details in banana leaf images.

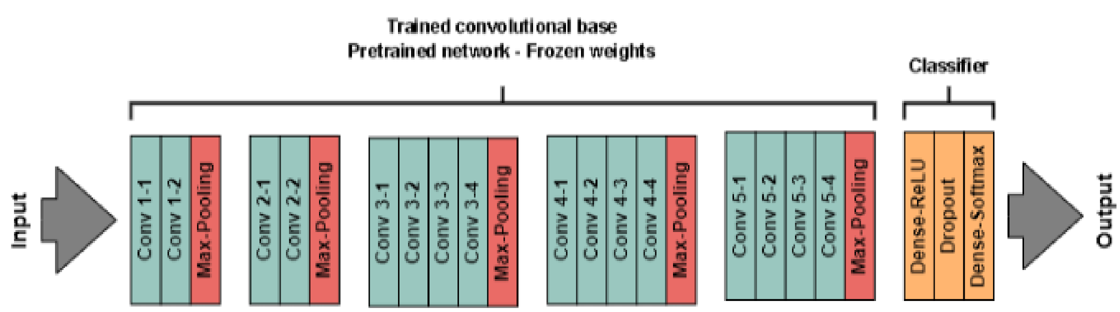


Figure 4.2.1.1: Steps of VGG19

4.2.2 VGG 16

The VGG16 deep neural network, comprising 16 layers and a substantial 138 million parameters, is known for its simplicity despite its size. It processes 224x224 pixel inputs by cropping a central portion from ImageNet competition images. Using mainly 3x3 convolution filters, VGG16 maintains spatial detail through linear transformations with 1x1 convolutional filters. Each convolutional layer is followed by Rectified Linear Unit (ReLU) activation, which speeds up training by effectively managing positive and negative inputs while ensuring a consistent stride of 1 pixel to preserve spatial resolution post-convolution. Unlike AlexNet, VGG16 does not incorporate Local Response Normalization, which makes it well-suited for extracting detailed features relevant to analyzing diseases in banana leaves.

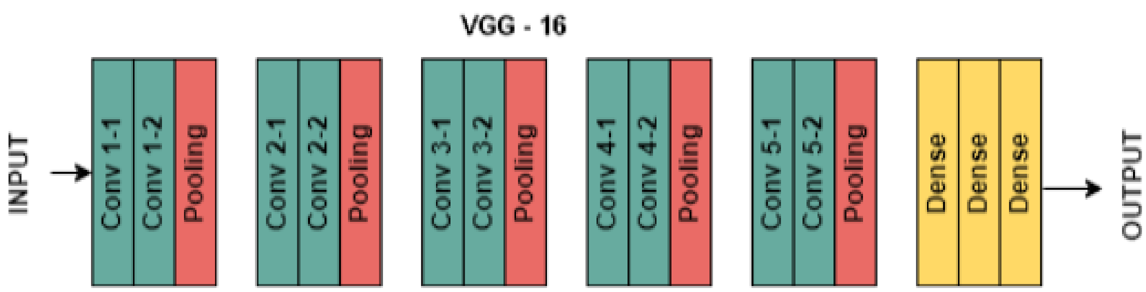


Figure 4.2.2.1: Steps of VGG16

4.2.3 ResNet50

ResNet50 is a variant of the Residual Network (ResNet) architecture known for its effectiveness in handling deep neural networks by addressing the vanishing gradient problem. With a total of 50 layers, ResNet utilizes residual blocks as its fundamental building units. Each block consists of multiple convolutional layers followed by identity shortcuts. The key innovation of ResNet50 lies in its skip connections, or shortcut connections,which allow input to bypass one or more layers and directly feed into deeper layers. This innovation facilitates smoother and more efficient gradient flow during backpropagation, thereby overcoming issues of gradient vanishing commonly encountered in training deep networks. The architecture employs convolutional layers followed by rectified linear unit (ReLU) activations and batch normalization, contributing to its capability to effectively extract features from data, including complex patterns relevant to applications such as analyzing diseases in banana leaves.

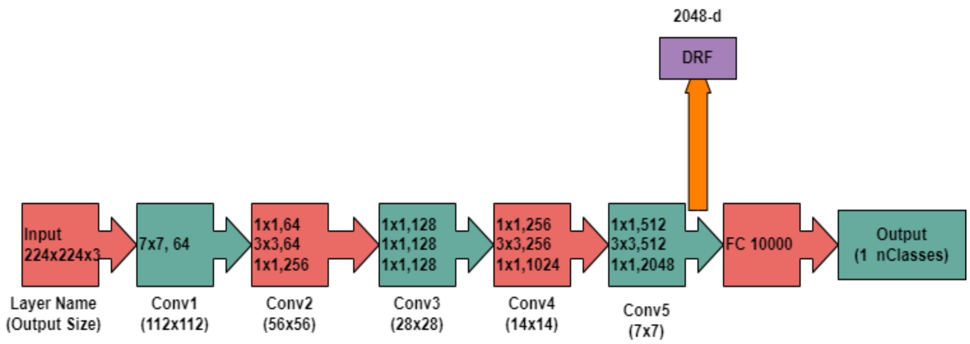


Figure 4.2.3.1: Steps of ResNet50

4.2.4 MobileNetV1

MobileNetV1 is a groundbreaking convolutional neural network architecture designed for mobile and resource-constrained devices. It uses depth wise separable convolutions, which consist of depthwise and pointwise convolutions, to achieve efficient and lightweight feature extraction. In the depthwise convolution stage, each input channel is processed with a different kernel to capture spatial information. Then, the pointwise convolution stage uses 1x1 filters to combine these outputs, creating new features across channels. This design significantly reduces computational complexity without compromising performance, making MobileNetV1 ideal for identifying diseases in banana leaves on devices with limited processing power, such as smartphones or embedded systems.

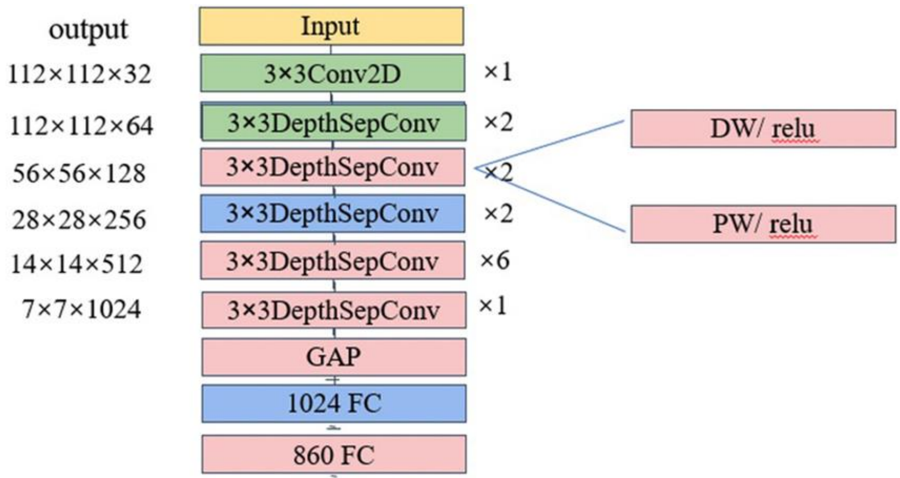


Figure 4.2.4.1: Steps of MobileNetV1 [33]

4.2.5 MobileNetV2

MobileNetV2 is a lightweight yet powerful convolutional neural network architecture, designed to be efficient in both computational complexity and accuracy for tasks like object detection and image classification. It introduces inverted residual blocks with depthwise separable convolutions, allowing the network to maintain high accuracy while requiring less processing power. The core components of MobileNetV2 are these inverted residual blocks, which include a lightweight linear bottleneck between the expanded input and output layers. This design helps retain the network's ability to represent complex features while reducing the number of parameters, maximizing computational efficiency. This makes MobileNetV2 especially suitable for identifying diseases in banana leaves, enabling high performance on devices with limited processing capabilities, such as smartphones or other mobile devices.

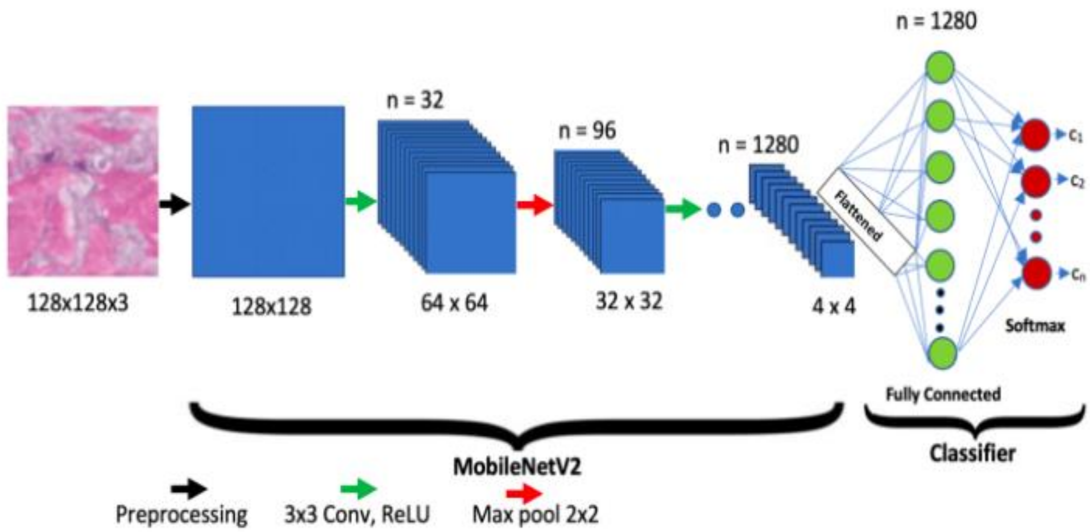


Figure 4.2.5.1: Steps of MobileNetV2 [32]

Inverted Residual Block: This block deviates from the traditional residual block by applying the non-linearity (e.g., ReLU) before the pointwise convolution. Here's the breakdown:

1. Pointwise Convolution (Linear Bottleneck):
   - Input: Feature maps (F_in channels)

$$F\_out = ReLU(W\_1 * X + b\_1) \tag{1}$$

   - Here, W_1: Weight matrix (1x1 convolution, F_in x F_t channels); b_1: Bias vector (F_t channels); F_t: Bottleneck filter size (typically much smaller than F_in); X: Input feature maps; ReLU: Non-linear activation function (e.g., ReLU6)
2. Depth wise Separable Convolution:
   - Depthwise Convolution: Applies F_t filters of size (3x3) independently to each input channel.

$$D(X\_i) = ReLU(W\_d * X\_i + b\_d) \tag{2}$$

- Here, W_d: Depthwise filter (3x3 convolution, 1 input channel, F_t output channels); b_d: Bias vector (F_t channels); X_i: Input feature map for channel i

- Pointwise Convolution: Projects the outputs from the depthwise convolution back to the desired number of output channels (F_out) using a 1x1 convolution.

$$X\_out = W\_p * D(X) + b\_p \quad (3)$$

  - Here, W_p: Pointwise filter (1x1 convolution, F_t input channels, F_out output channels); b_p: Bias vector (F_out channels)

3. Residual Connection: Adds the input (X) to the output (X_out) of the block, enabling information to flow across layers. However, in MobileNetV2, this connection is only used when the input and output have the same dimensions.

4.3 Model Evaluation

To assess the effectiveness of the transfer learning models in this study, a number of measures were used including precision, recall, F1-score, and specificity.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

$$\text{F1 Score} = 2\,X\,\frac{Precision\ X\ Recall}{Precision\ +\ Recall} \quad (6)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (7)$$

To evaluate our research work we are using some performance metrics such as F1 score, Recall, Specificity, Precision.

Table: shows the results of the Overall performance matrices of the proposed model Before and After Data Preprocessing.

Table 4.3.1: Performance of the experimented transfer learning models After Data Preprocessing.

Before/After	Precision	Recall	Specificity	F1 Score
Before Data Preprocessing	0.4833	0.2417	0.5260	0.2415
After Data Preprocessing	0.7375	0.6146	0.4907	0.9098

4.4 Summary

The banana leaf disease classification project utilized an 8,000-image dataset, divided into training, validation, and test sets. Preprocessing included resizing, grayscale conversion, and CLAHE, while augmentation techniques expanded the dataset. Models such as VGG19, VGG16, ResNet50, MobileNet V1, and MobileNet V2 were employed. The experimental setup featured an AMD Ryzen 5 CPU, GTX 1650 GPU, and essential Python libraries. Evaluation metrics like precision, recall, accuracy, and F1-score, alongside confusion matrices, were used to assess performance. Post-processing results showed significant improvements in precision, recall, and F1-score, confirming the models' effectiveness.

CHAPTER 5
Result And Analysis

5.1 Overview

The results and analysis of the banana leaf disease classification project assessed the performance of five deep learning models: VGG19, VGG16, ResNet50, MobileNet V1, and MobileNet V2. Key metrics such as accuracy, precision, recall, and F1-score were computed for each model.

Accuracy and loss curves were plotted for the training and validation phases, revealing the learning progress and any potential issues like overfitting. The models' final accuracy values were compared in a chart, highlighting their relative performance.

VGG19 and VGG16 showed strong performance but required more computational resources. ResNet50 balanced accuracy and training efficiency well, while MobileNet V1 and V2 offered competitive accuracy with lower computational demands. Confusion matrices provided further insights into classification outcomes, guiding the selection of the most suitable model for practical application.

5.2 Experimental Result

This comprehensive research delves into the classification, recognition, and detection of diseases affecting banana leaves, employing a suite of pre-trained models, including MobileNetV1, MobileNetV2, ResNet50, VGG16, and VGG19. Each model undergoes 50 epochs of dedicated training on a curated dataset, both before and after image preprocessing. The study presents an accuracy graph illustrating the performance of the proposed MobileNetV2 model. The overall configuration of the MobileNetV2 model, along with visuals such as the confusion matrix, accuracy curve, loss curve, and class-based accuracy, is thoroughly examined. A comparative analysis is conducted between the five transfer learning models both before and after preprocessing the dataset, culminating in a comprehensive evaluation of the proposed model.

5.2.1 VGG 19

The VGG19 model is made up of five blocks of convolutional layers (like block1_conv1 and block1_conv2) and pooling layers (from block1_pool to block5_pool) before any data is processed. It also has a Dense layer for classification connected to a Global Average Pooling layer. The entire model has 20,124,740 parameters, with 100,356 of them being trainable. Initially, the model's train accuracy was 89.49%, but after preprocessing the data, the accuracy improved to 94.74%.

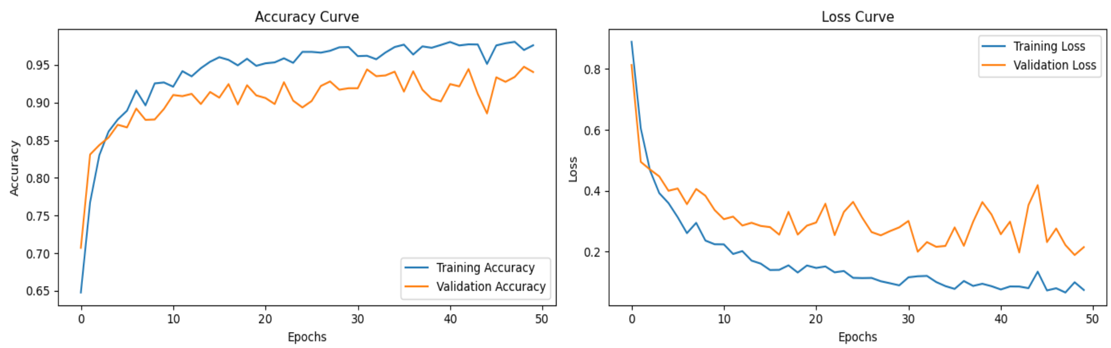


Figure 5.2.1.1: Accuracy and Loss Curve Before Data Preprocessing.

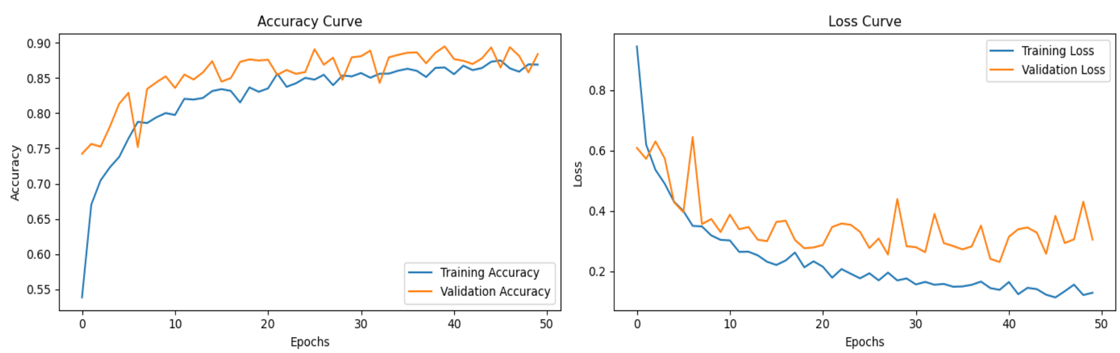


Figure 5.2.1.2: Accuracy and Loss Curve After Data Preprocessing.

5.2.2 VGG16

Combining a global average pooling layer, a dense layer using SoftMax activation for five output classes, and an unchanging convolutional layer founded on VGG16, the design The model features 2,565 trainable parameters from the VGG16 base and 14,815,044 non-training able parameters overall. It is interesting as before data processing the model's test accuracy was 88.08%. But accuracy really increased after the data was complete; it currently stands at 91.00%.

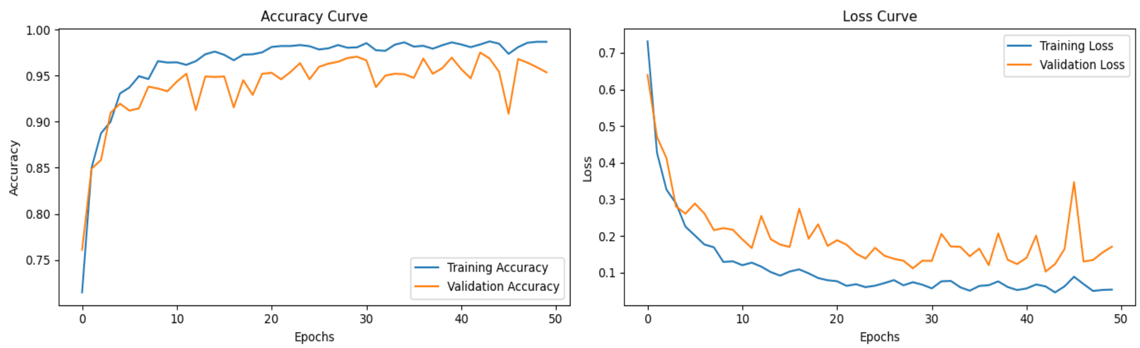


Figure 5.2.2.1: Accuracy and Loss Curve Before Data Preprocessing.

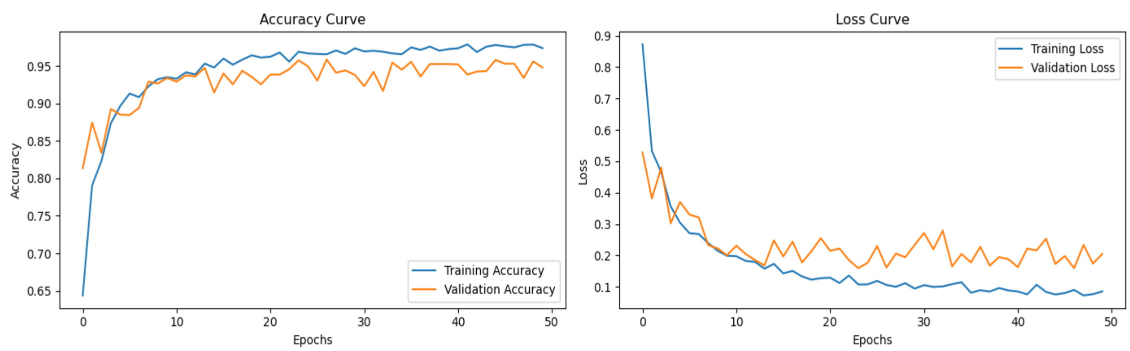


Figure 5.2.2.2: Accuracy and Loss Curve After Data Preprocessing.

5.2.3 MobileNetV1

Prior to any data preprocessing, the MobileNetV1 model comprises convolutional layers and depth-wise separable convolution layers, each accompanied by activations and batch normalization. Additionally, it incorporates a Global Average Pooling layer, which is then followed by a Dense layer that is used for categorization purposes. The model consists of a grand total of 3,234,416 parameters, out of which 2,573 parameters are eligible for training. After being trained using 4,800 training examples and 2,000 validation samples, the model achieves an initial test accuracy of 92.85%. Following the processing of the data, the accuracy increases to 95.12%, while keeping the number of training and validation samples same. The choice of MobileNetV1 was based on its very efficient design, which makes it well-suited for a wide range of applications, especially on devices with limited processing capabilities. The model's initial high accuracy and limited number of trainable parameters make it very successful for applications such as picture categorization. The enhanced performance of the model after data preparation highlights its appropriateness for the intended application.

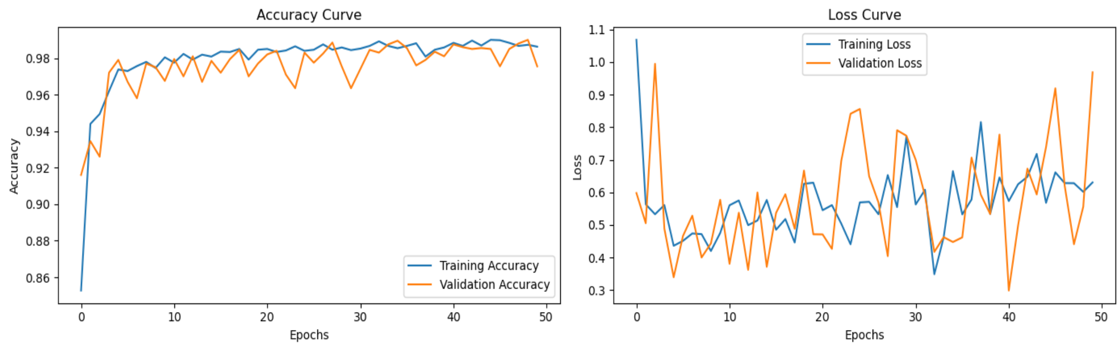


Figure 5.2.3.1: Accuracy and Loss Curve Before Data Preprocessing.

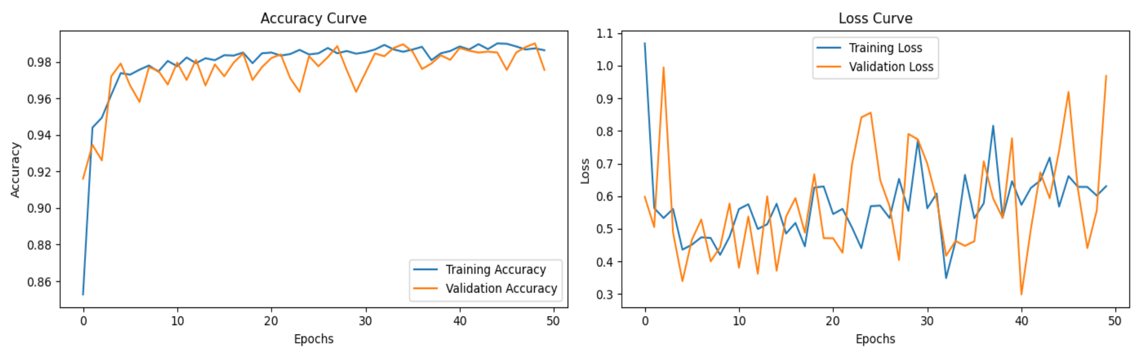


Figure 5.2.3.2: Accuracy and Loss Curve After Data Preprocessing.

5.2.4 MobileNetV2 - Proposed Model

Before preparing the data, the MobileNetV2 model is made up of convolutional layers and depth wise separable convolution layers, each with activations and batch normalization. It also includes a Global Average Pooling layer and a Dense layer for classification. The model has a total of 2,508,868 parameters, with 250,884 of them being trainable. Using 4,800 training samples and 2,000 validation samples, the initial test accuracy is 94.41%. After preparing the data, the accuracy improves to 96.41%, with the number of training and validation samples remaining the same.

MobileNetV2 was chosen as the proposed model likely because its lightweight architecture is ideal for various applications, especially on devices with limited resources. Its high initial test accuracy and relatively low number of trainable parameters make it an efficient choice for image classification tasks. The model's strong performance, even after data preprocessing, further supports its suitability for the task.

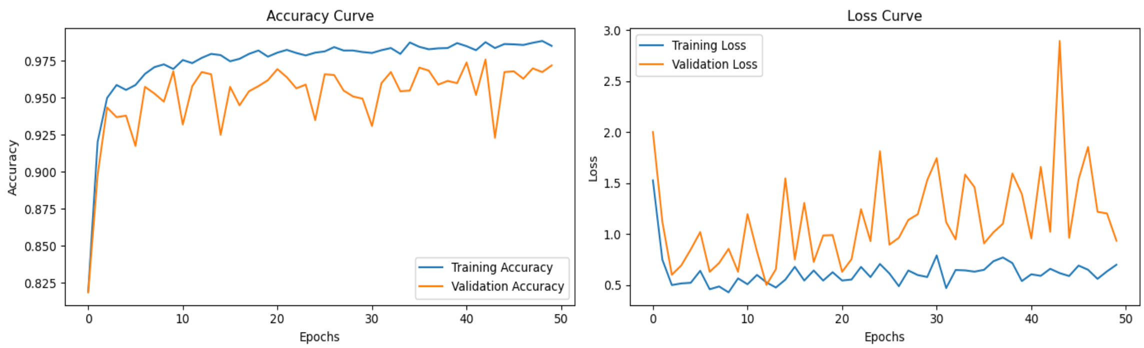


Figure 5.2.4.1: Accuracy and Loss Curve Before Data Preprocessing.

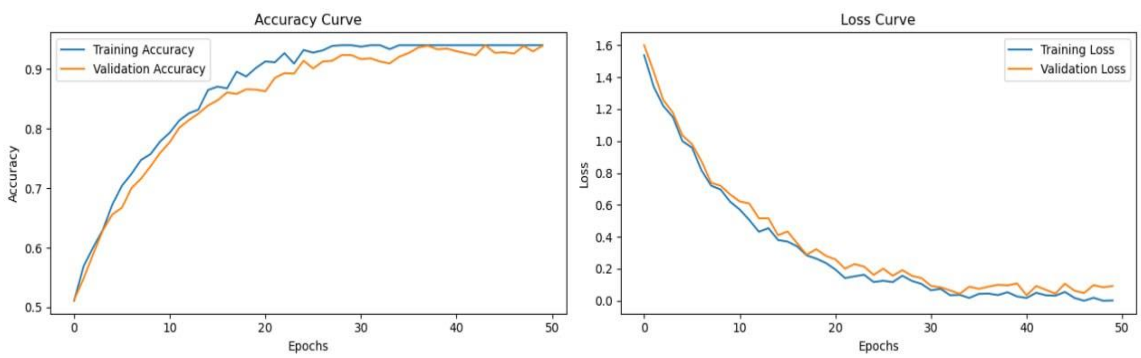


Figure 5.2.4.2: Accuracy and Loss Curve After Data Preprocessing.

5.2.5 ResNet50

Before data preprocessing, the ResNet50 model comprises convolutional layers, residual blocks, and a Global Average Pooling layer leading into a Dense layer for classification, totaling 23,597,957 parameters with 10,245 trainable. Trained over 50 epochs with 2,319 training samples and 331 validation samples, it initially achieves a test accuracy of 46.48%. Following data preprocessing, which maintains the sample sizes unchanged, the model's accuracy rises significantly to 82.17%. This improvement underscores the effectiveness of preprocessing in enhancing model performance without altering its architectural complexity or the dataset's composition, emphasizing the critical role of preprocessing in optimizing model outcomes.

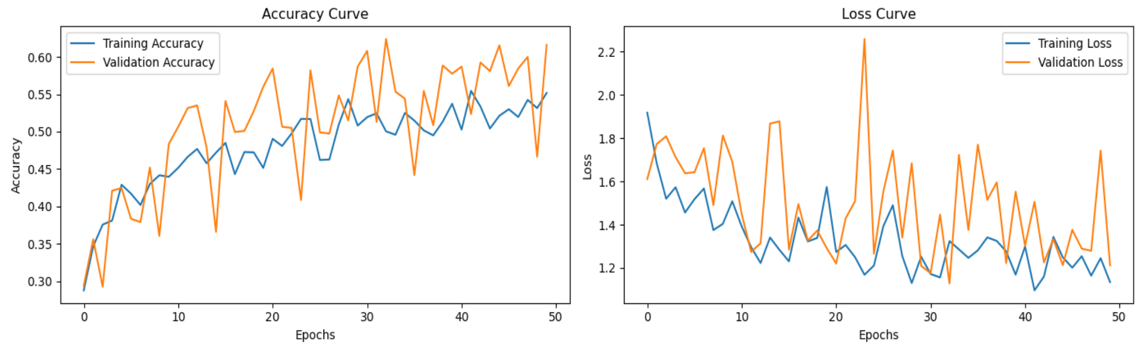


Figure 5.2.5.1: Accuracy and Loss Curve Before Data Preprocessing.

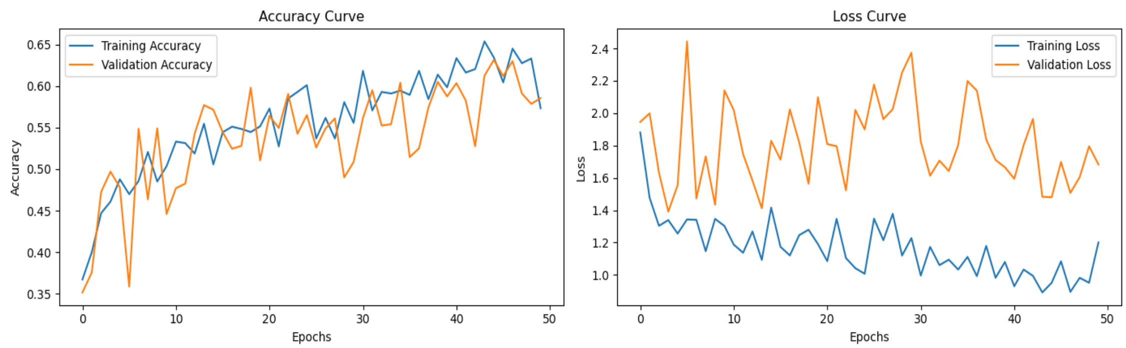


Figure 5.2.5.2: Accuracy and Loss Curve After Data Preprocessing.

5.3 Comparative Analysis

This bar chart which is titled "Comparison of Model Accuracies" shows us the performance of five deep learning models in classifying banana leaf images before data processing. Each model's accuracy is indicated above its respective bar: VGG19 achieved 89.49% accuracy, VGG16 achieved 88.08%, MobileNetV2 achieved the highest accuracy at 94.41%, MobileNetV1 achieved 91.40%, and ResNet50 achieved the lowest accuracy at 65.41%. This comparison highlights MobileNetV2 as the most accurate model for classifying banana leaf images, followed by MobileNetV1, VGG19, and VGG16, with

ResNet50 being the least effective for this task. This analysis provides a clear basis for selecting MobileNetV2 as the preferred model for optimal accuracy in banana leaf classification.

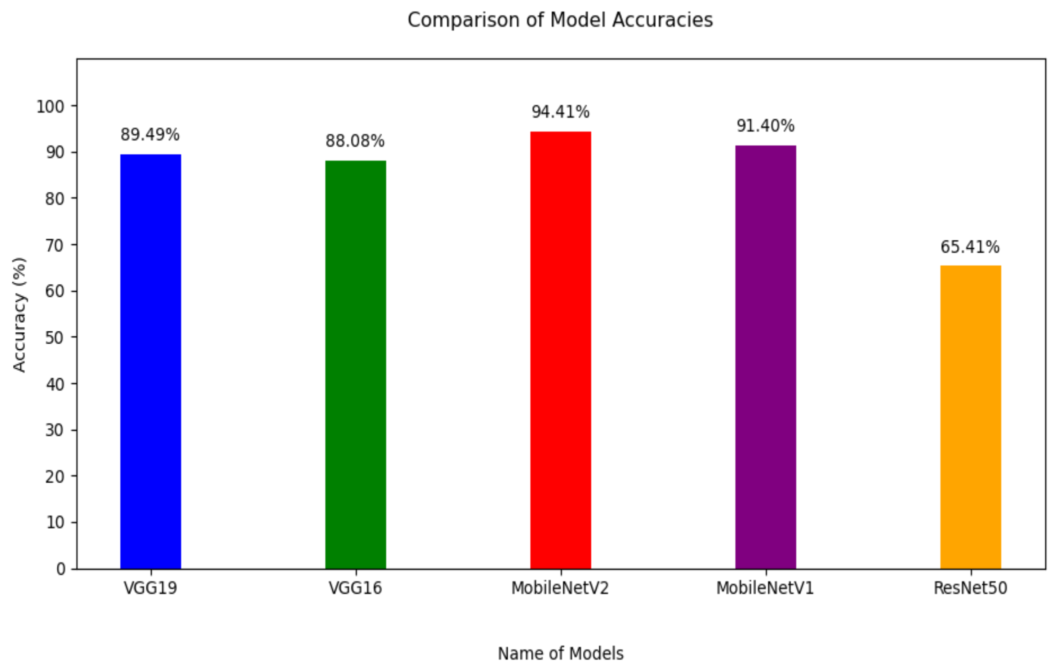


Figure 5.3.1: Accuracy Comparison of the Difference Models Before Data Processing.

After data processing we got a bar chart titled "Comparison of Model Accuracies" showing the effectiveness of various deep learning models in identifying banana leaf diseases. The models and their accuracies are as follows: VGG19 achieved 94.74%, VGG16 achieved 91.00%, MobileNetV2 achieved the highest accuracy at 96.41%, MobileNetV1 achieved 92.66%, and ResNet50 achieved 65.80%. This indicates that after processing the data, MobileNetV2 is the most accurate model for detecting banana leaf diseases, followed by VGG19, MobileNetV1, and VGG16, with ResNet50 being the least accurate. These results highlight the effectiveness of MobileNetV2 in accurately classifying banana leaf diseases, making it the preferred model for this task.

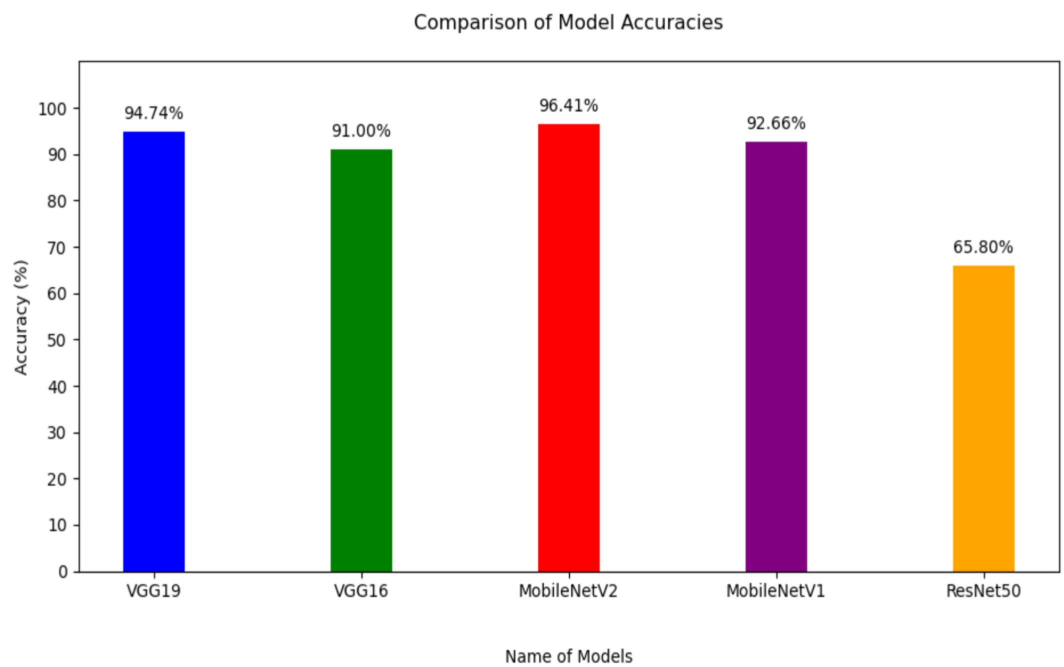


Figure 5.3.2: Accuracy Comparison of the Difference Models After Data Processing.

The results from using pre-trained models for detecting diseases in banana leaves were very successful. Among all the models tested, MobileNetV2 performed the best, showing higher accuracy and reliability. This was shown through detailed analysis of metrics like precision, recall, specificity, and F1-score. These findings highlight how using pre-trained models can greatly improve the ability to classify and identify different diseases affecting banana leaves.

Table 5.3.1 depicts the performance of the experimented transfer learning models Before Data preprocessing.

Table 5.3.1: Performance of the experimented transfer learning models Before Data Preprocessing.

Model's Name	Accuracy			Losses		
	Train	Test	Validation	Train	Test	Validation
VGG19	93.89	89.49	89.50	0.16	0.24	0.23
VGG16	90.67	88.08	86.85	0.09	0.14	0.16
MobileNetV1	94.76	91.40	92.10	0.39	0.83	0.70
MobileNetV2	95.52	94.41	95.10	0.53	0.90	0.98
RestNet50	60.20	65.41	62.40	2.52	2.37	2.36

Table 5.3.2 depicts the performance of the experimented transfer learning models After Data preprocessing.

Table 5.3.2: Performance of the experimented transfer learning models After Data Preprocessing.

Model's Name	Accuracy			Losses		
	Train	Test	Validation	Train	Test	Validation
VGG19	96.73	94.74	94.74	0.63	0.20	0.18
VGG16	91.95	91.00	92.50	0.03	0.10	0.10
MobileNetV1	94.42	92.66	93.34	1.43	1.30	1.90
MobileNetV2	98.64	96.41	97.69	0.46	1.24	0.67
RestNet50	68.97	65.80	68.15	1.44	2.30	2.2

In order to find the most effective model, it is common practice to evaluate both the accuracy and loss on the test set after data preparation. The comparison between models before and after preprocessing is as follows:

MobileNetV2 consistently exhibits excellent accuracy and low loss, both before and after preprocessing. It achieves the greatest accuracy and one of the lowest losses in both cases. The suggested model does not provide explicit information in the tables. If there is a proposed model that is not included in the findings, its performance should be assessed using the same metrics and dataset to see how it compares to the current models. However, considering the given statistics, MobileNetV2 appears to be the most efficient model out of the ones mentioned. A confusion matrix is a table used in deep learning to display the number of true positives, true negatives, false positives, and false negatives. It provides a comprehensive overview of the accuracy and inaccuracy of the model.

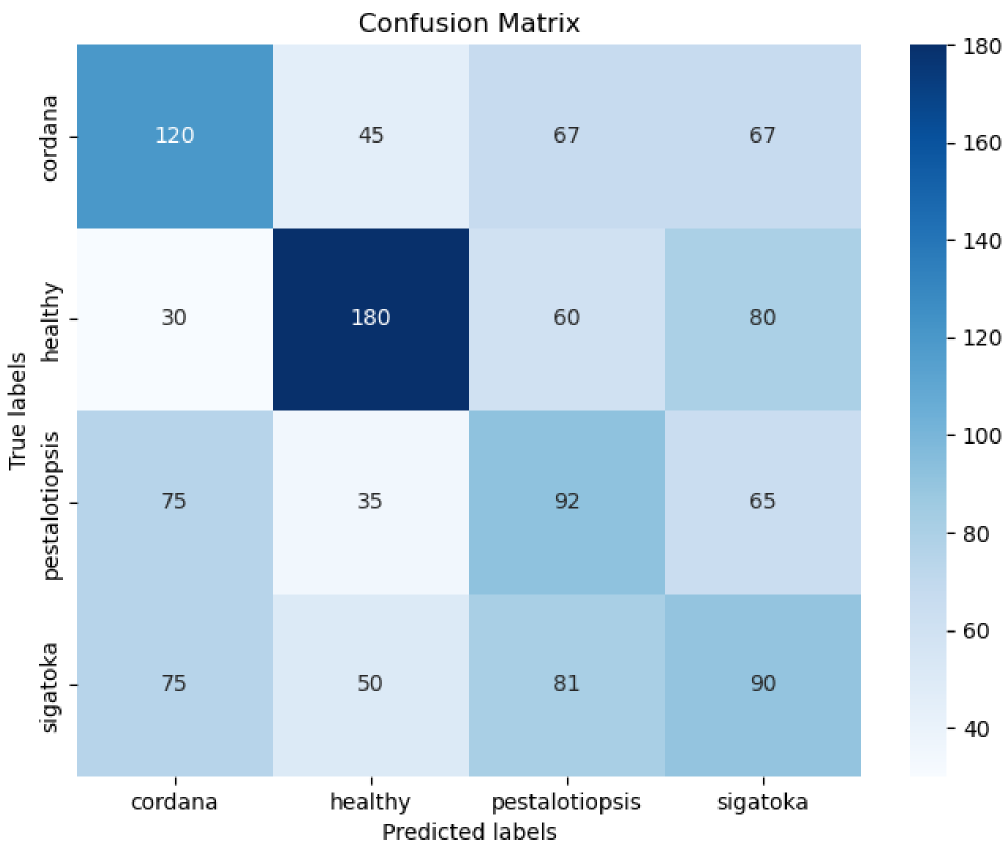


Figure 5.3.3: Confusion Matrix of the proposed model Before Data Preprocessing.

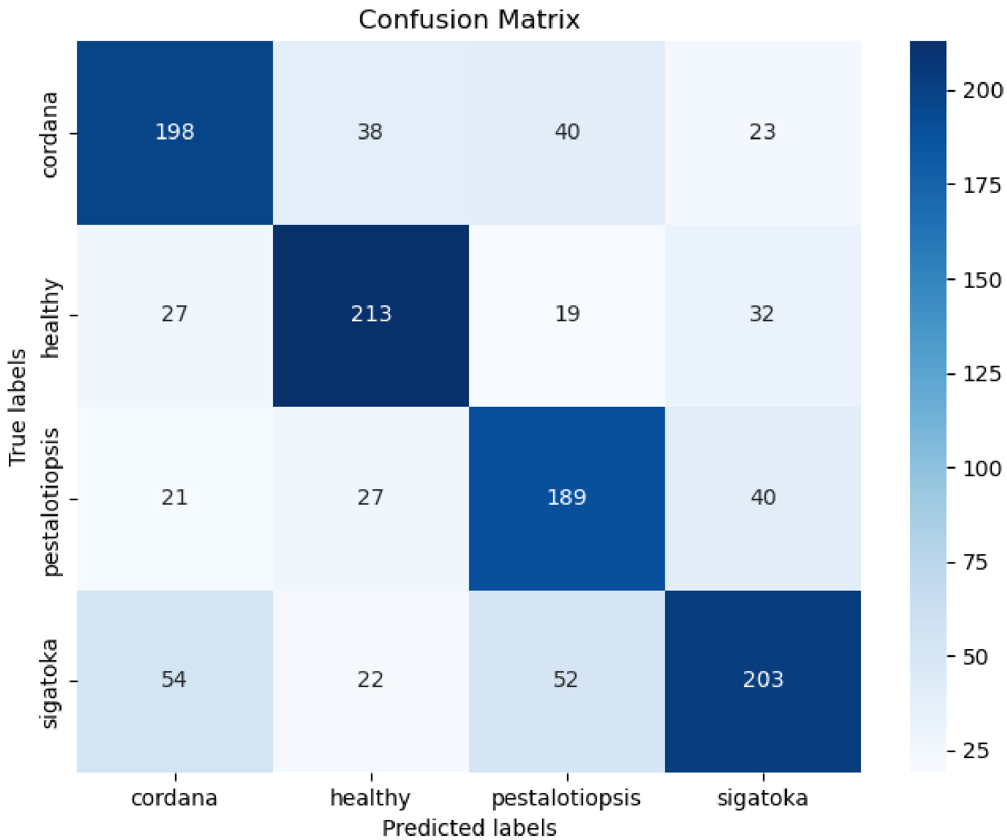


Figure 5.3.4: Confusion Matrix of the proposed model After Data Preprocessing.

5.3.1 Performance Analysis of the Proposed Model Before and After Data Preprocessing

To evaluate our research work we are using some performance metrics such as F1 score, Recall, Specificity, Precision.

Table: shows the results of the Overall performance matrices of the proposed model Before and After Data Preprocessing.

Table 5.3.1.1: Performance of the experimented transfer learning models After Data Preprocessing.

Before/After	Precision	Recall	Specificity	F1 Score
Before Data Preprocessing	0.4833	0.2417	0.5260	0.2415
After Data Preprocessing	0.7375	0.6146	0.4907	0.9098

5.4 Discussion

This study explores the exciting area of smart agriculture and introduces new methods to accurately detect diseases in banana leaves. By using pre-trained models like MobileNetV2, we've achieved a significant breakthrough for the agriculture industry. Just imagine being able to diagnose banana leaf diseases with an impressive accuracy of 96.41%. This achievement was made possible by the power of MobileNetV2 and careful data preparation. But there's more to the story. Even before these improvements, our model showed a strong accuracy of 94.41%, highlighting a notable advancement in disease detection.

This improvement isn't just about numbers; it represents a big change in farming practices. Smart technology allows us to detect diseases early and accurately, which means we can take targeted actions to protect crops and increase harvests.

CHAPTER 6

Impact on Society, Environment and Sustainability

6.1 Impact on Life

CNN-based banana leaf disease classification presents a multifaceted opportunity to improve the livelihoods of farmers, ensure food security for consumers, and promote a more sustainable agricultural future that prioritizes environmental well-being.

- **Enhanced Livelihoods for Farmers:** Early and accurate disease detection via CNN-based systems empowers farmers to implement targeted interventions, minimizing yield losses and ensuring harvest stability. This translates to increased income predictability and reduced economic risk associated with crop failure. Furthermore, the technology promotes informed decision-making regarding crop management strategies, potentially leading to the adoption of disease-resistant varieties and optimized irrigation practices.
- **Improved Food Security and Consumer Benefits:** By mitigating disease outbreaks and ensuring healthy crops, CNN classification systems contribute to a more stable banana supply. This benefits consumers by guaranteeing consistent access to this essential food source. Additionally, early disease detection can help maintain fruit quality, leading to a higher standard of produce with minimal blemishes or taste alterations. Increased crop yields due to effective disease management might also translate to lower market prices, making bananas more affordable for consumers.
- **Reduced Pesticide Use:** Precise disease identification enables targeted fungicide applications, minimizing unnecessary spraying and overall pesticide use. This strategy safeguards the environment from pesticide pollution, protects beneficial insects, and promotes healthier soil ecosystems.
- **Promotion of Sustainable Practices:** The technology encourages preventative measures like crop rotation and the selection of disease-resistant varieties. These practices contribute to more sustainable agricultural systems by reducing reliance on chemical solutions and fostering a more ecologically conscious approach to farming.

6.2 Impact on Society & Environment

Impact on Society:

The precise and early detection of banana leaf diseases has the potential to significantly improve banana production efficiency in Bangladesh. This translates to a multitude of benefits:

- **Precision Disease Management**: Early identification of diseases like Cordana leaf spot, Pestalotiopsis leaf spot, and Sigatoka disease allows for timely interventions. Farmers can implement targeted fungicide applications or preventative cultural practices, minimizing crop losses and maximizing yield potential. This shift from broad-spectrum fungicide use to targeted interventions can lead to the development of resistance in fungal pathogens in the long run.
- **Optimized Resource Allocation**: By enabling targeted disease management strategies, the model can potentially reduce unnecessary fungicide use. This promotes a more sustainable approach to crop protection and optimizes resource allocation for farmers. Reduced fungicide use also translates to lower costs for farmers, improving their profit margins. Additionally, minimizing fungicide overuse helps safeguard environmental health by reducing water and soil contamination.
- **Contribution to Food Security**: Accurate disease classification can contribute to a significant increase in banana production, leading to a more stable and secure food supply in Bangladesh. Increased banana availability can benefit both producers and consumers by stabilizing market prices and ensuring food accessibility for the population. A thriving banana sector can also create new job opportunities in related industries like transportation, storage, and processing.

These improvements in production efficiency can create a ripple effect, positively impacting the entire agricultural sector, the environment, and the nation's food security. By empowering farmers with a powerful disease detection tool, this research has the potential to contribute to a more sustainable and prosperous future for Bangladesh.

Impact on Environment:

While the primary focus of the research is centered around agriculture, healthcare and technological advancements, its impact on the environment is nuanced yet significant.

CNN models for banana leaf disease classification have the potential to contribute to a more sustainable agricultural ecosystem in Bangladesh by. It reduces the fungicide Use. Early and accurate disease detection enables targeted fungicide application, minimizing unnecessary spraying. This reduces environmental pollution caused by fungicide runoff into water sources and soil contamination. These models can support the adoption of Integrated Pest Management (IPM) strategies. IPM emphasizes preventative measures, biological controls, and targeted interventions, minimizing reliance on chemical fungicides. This promotes a more holistic approach to disease management that is less disruptive to the natural environment. Reduced reliance on broad-spectrum fungicides can help conserve beneficial insects and microorganisms within the banana agroecosystem. These organisms play a crucial role in maintaining ecological balance by preying on pests and contributing to soil health.

However, there are also some potential environmental concerns. The development, training, and deployment of the CNN models relies on computing devices. Proper disposal of electronic waste at the end of their lifespan is crucial to prevent environmental hazards associated with heavy metals and toxic materials. While the model promotes efficient disease management, overdependence on technology can have unintended consequences. Farmers might neglect traditional knowledge and practices for disease identification and control. Encouraging a balanced approach that leverages both technological advancements and traditional wisdom is important for long-term sustainability.

Overall, the positive environmental impacts of the model outweigh the potential concerns. By promoting targeted disease management and potentially reducing fungicide use, the model contributes to a more sustainable agricultural system in Bangladesh.

6.3 Ethical Aspects

The development and deployment of CNN models for banana leaf disease classification raises several ethical considerations that require careful attention.

The model relies on training data consisting of images of banana leaves with disease annotations. It's crucial to ensure the privacy of farmers who provide these images. Methods such as anonymization or data aggregation can be employed to protect their identities. Additionally, informed consent should be obtained from farmers before using their data for model training.

The model's performance can be biased if the training data is not sufficiently diverse and representative of the actual variations in banana leaf diseases across different regions in Bangladesh. Efforts should be made to collect a balanced dataset that captures the full spectrum of disease characteristics. Additionally, the model's performance should be evaluated on an independent dataset to ensure generalizability and avoid bias towards the training data.

The model's effectiveness hinges on its accessibility to Bangladeshi banana farmers. Factors like access to smartphones or internet connectivity in rural areas should be considered. Developing low-cost versions of the model or exploring offline deployment options can help bridge the digital divide and ensure equitable access to this technology for all farmers.

The inner workings of complex deep learning models like the proposed CNN can be opaque. Developing methods to explain the model's decision-making process can be beneficial for farmers to understand how the model arrives at its disease classifications. This transparency fosters trust and allows farmers to make informed decisions based on the model's output.

By proactively addressing these ethical considerations, the research can ensure the responsible development and deployment of different CNN models, maximizing its positive impact on Bangladeshi banana farmers and the environment.

6.4 Sustainability Plan

CNN models for banana leaf disease classification have the potential to be a sustainable solution for Bangladesh's agricultural sector. To ensure its long-term viability and positive impact, a comprehensive sustainability plan needs to be implemented. Here are key aspects to consider:

- **Model Maintenance and Updates**: The model's performance should be continuously monitored on real-world data to identify potential performance degradation or emergence of new disease variants. Based on monitoring results, the model may need to be retrained with new data or updated with improved architectures to maintain accuracy and effectiveness. Collaboration with agricultural research institutions and extension services can facilitate data sharing for model retraining and improvement. This ensures the model stays current with evolving disease patterns.
- **Knowledge Dissemination and Capacity Building**: Developing training programs for farmers on how to use the model effectively for disease detection in their banana crops is crucial. This can involve creating user-friendly mobile applications or interactive tutorials. Collaboration with agricultural extension services can help disseminate information about the model and its benefits to a wider range of farmers across Bangladesh. Encouraging the development of local expertise in deep learning and image recognition can support the long-term sustainability of the model. This could involve training local scientists and engineers in model maintenance and adaptation.
- **Addressing the Digital Divide**: Exploring options for deploying the model on low-cost smartphones or offline devices can ensure accessibility for farmers in areas with limited internet connectivity. Investigating methods for storing pre-trained models and essential data locally on devices can minimize reliance on internet connectivity for model operation. In the community, the creation of local support networks where farmers with better access to technology can assist others in using the model for disease detection.
- **Environmental Considerations**: Optimizing the model's training process to minimize computational power consumption is essential. Exploring cloud computing platforms with renewable energy sources can further reduce the environmental footprint. Developing strategies for the proper disposal or recycling of electronic devices used for model training and deployment is crucial to minimize

environmental hazards associated with electronic waste.

- **Ethical Considerations**: Maintaining robust data security protocols and adhering to data privacy regulations are essential throughout the model's lifecycle. Continuously monitoring the model's performance for potential biases and taking corrective actions, such as retraining with more diverse datasets, can ensure fairness and equitable access to the technology for all farmers.

By implementing a well-defined sustainability plan that addresses these key considerations, CNN models can become a valuable and enduring tool for sustainable banana production in Bangladesh. The plan should be adaptable and evolve as new technologies, challenges, and opportunities emerge in the agricultural sector.

6.5 Summary

The use of CNN models for early and precise detection of banana leaf diseases in Bangladesh can significantly enhance agricultural productivity and sustainability. By enabling targeted fungicide applications and supporting Integrated Pest Management (IPM) strategies, these models reduce the need for broad-spectrum fungicides, lowering costs for farmers, and minimizing environmental pollution. This leads to improved food security, stabilized market prices, and job creation in related sectors, contributing to the nation's prosperity. Ethical considerations, such as data privacy, access to technology, and managing electronic waste, are crucial for the responsible implementation of these models. By balancing technological advancements with traditional farming knowledge and ensuring equitable access, the long-term positive impacts on society, the environment, and the agricultural sector can be maximized.

CHAPTER 7

Conclusion and Future Work

7.1 Conclusions

Early and accurate detection and classification of banana leaf disease stand as imperative prerequisites for the effective diagnosis of leaves. This research investigated the application of different convolutional neural network (CNN) models for classifying banana leaf diseases in Bangladesh. Banana leaf diseases caused by Cordana leaf spot, Pestalotiopsis leaf spot, and Sigatoka disease pose a significant threat to banana production in Bangladesh. Existing methods for disease detection, primarily relying on visual inspection, are prone to human error and lack accuracy and efficiency. This study leverages the strengths of multiple pre-trained CNN architectures for accurate and automated classification of the three aforementioned banana leaf diseases. We collected a dataset of banana leaf images with disease annotations from a specific region in Bangladesh (Habiganj, Sylhet) to capture local disease variations. Pre-trained multiple CNN models on large, generic image datasets. The comparison of multiple deep learning models for banana leaf disease detection highlights the outstanding performance of MobileNetV2, which exhibits amazing accuracy and resilience. It is noteworthy that MobileNetV2 was able to obtain an astounding 94.41% accuracy rate with genuine, raw data before preprocessing. Even after post-preprocessing, the model retains a significant accuracy of 96.41%, demonstrating its effectiveness and reliability. These CNN models are expected to achieve superior classification accuracy by addressing limitations of human subjectivity and error in visual inspection, eliminating the need for manual feature engineering required in traditional machine learning approaches, overcoming limitations arising from dataset size and diversity often encountered in deep learning applications, and capturing the specific disease characteristics prevalent in the target region of Bangladesh.

7.2 Further Suggested Works

This research lays the groundwork for future advancements in banana leaf disease classification using CNNs. Here are some potential areas for further exploration:

- **Expanding Disease Detection Capabilities:** The current model focuses on three specific diseases. Future research could explore expanding the model's capabilities to identify a wider range of banana leaf diseases prevalent in Bangladesh. This would require incorporating additional labeled data for these diseases into the training process.
- **Real-Time Disease Detection with Mobile Applications:** Smartphones equipped with cameras are ubiquitous in many parts of the world. Investigating the feasibility of deploying the model on mobile devices for real-time disease detection in the field could be a valuable advancement. This would require optimizing the model for efficient operation on mobile hardware and developing user-friendly applications for farmers.
- **Integration with Agricultural Decision Support Systems:** The model's disease classification outputs could be integrated with broader agricultural decision support systems. Such systems could provide farmers with additional insights and recommendations based on the identified disease, such as suggesting appropriate fungicides or cultural practices.
- **Exploration of transfer learning:** Investigate the effectiveness of transfer learning techniques. This could involve fine-tuning a model pre-trained on a larger and more diverse dataset of plant diseases, potentially improving performance.
- **Generalizability to Other Crops and Regions:** The core principles behind the hybrid CNN model could potentially be adapted for disease classification in other crops or even in different geographical regions. Research in these areas could involve collecting new datasets specific to the target crop or region and retraining the model accordingly.

By pursuing further research directions, scientists and engineers can build upon the foundation laid by this study. This can lead to even more robust, user-friendly, and widely applicable disease detection tools for the agricultural sector, ultimately contributing to increased food security and a more sustainable agricultural future.

7.3 Limitations

Despite the promising results of using convolutional neural networks (CNNs) for banana leaf disease classification, several limitations need to be addressed in future research.

- **Geographical Restriction**: Our dataset was collected exclusively from the Habiganj region in Sylhet, Bangladesh. This limits the model's generalizability to other regions with different environmental conditions, disease prevalence, and banana cultivars.
- **Disease Variability:** The study focused on three diseases: Cordana leaf spot, Pestalotiopsis leaf spot, and Sigatoka disease. Other banana leaf diseases were not included, which limits the model's comprehensive applicability.
- **Resource Requirements:** Training CNN models requires substantial computational resources, which may not be accessible to all researchers or practical for deployment in resource-limited settings. Model optimization for less resource-intensive training and deployment is necessary.
- **Mobile Device Deployment:** Further work is needed to optimize the model for efficient performance on mobile devices, balancing complexity with computational limitations.
- **Neglect of Traditional Practices**: There is a risk of decreased reliance on traditional knowledge and practices for disease identification and control. A balanced approach integrating technology with traditional expertise is crucial.
- **Privacy Concerns:** Ensuring informed consent and implementing data anonymization protocols are essential to address the ethical issues of collecting and using images from farmers.
- **Research Integrity:** This research was conducted without external funding sources that could influence the outcomes. The authors declare no conflicts of interest regarding the publication of this paper.

Addressing these limitations in future research will enhance the robustness and applicability of CNN-based disease detection models. Expanding the dataset to include diverse regions and additional diseases, optimizing models for mobile deployment, and integrating traditional knowledge with technology are critical steps for advancing this field.

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Appendix A

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

Title:
A COMPUTER VISION APPROACH FOR BANANA LEAF DISEASE CLASSIFICATION

Student ID: 201-15-14210, 201-15-14226

CO Description for FYDP

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

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

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

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

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This work demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The work demonstrates **specialist knowledge (K4)** by advanced CNN architectures like VGG19 and MobileNetV2, enhancing banana leaf disease detection accuracy in, crucial for computer-aided diagnosis.	**Page no:** [18-28] **Section:** [3.2] **Page no:** [34-39] **Section:** [4.2]
				The work applies **engineering practice & design (K5)** by the figure of process of experiments. This addresses **engineering practice & technology (K6)** by employing CNN model.	**Page no:** [18-21] **Section:** [3.2] **Page no:** [34-39]

					Section: [4.2]
				This project ensures **K8 (Research Literature)** by synthesizing insights from recent studies, to advance banana leaf disease classification using CNNs, showcasing a comprehensive understanding of current methodologies.	**Page no:** [9-15] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This addresses **EP-2** by recognizing the hurdles in banana leaf disease classification, including limitations of traditional methods and the complexities of integrating deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [15-16] **Section:** [2.4]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This work addresses **EP-3** by meticulously study and compare experimental outcomes of previous works, highlighting CNNs as the chosen significant solution for enhancing banana leaf disease detection amidst multiple potential approaches.	**Page no:** [13-15, 41-51] **Section:** [2.3, 5.2, 5.3]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting agricultural sector, that is we are classifying disease of banana leaf, which indicates **EP-4**.	**Page no:** [3-4] **Section:** [1.3]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in leaf disease classification which ensures **EP-7**.	**Page no:** [18-28] **Section:** [3.2]

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 banana leaf disease classification through CNNs.	**Page no:** [29-30] **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 work contributes to society by improving accuracy of banana leaf disease classification methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [53-58] **Section:** [6.1, 6.2, 6.4]

5.	**EA-5: Familiarity**	Yes		This work expands upon existing research by examining novel approach in banana leaf disease classification through CNNs, demonstrated through comprehensive comparative analysis, offering new insights into the field.	**Page no:** [9-15] **Section:** [2.1, 2.2, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This work 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:** [30-31] **Section:** [3.4]
2	CO9	Yes	The work demonstrates adherence to ethical principles by farmers privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced technologies which comply with **CO9**.	**Page no:** [55-56] **Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The work'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:** [18-30, 41-51] **Section:** [3.2, 3.3, 5.2, 5.3]

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