Deep Learning Techniques for Automated Detection of Diseases in Guava Fruit and Leaves

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled **"Deep Learning Techniques for Automated Detection of Diseases in Guava Fruits and Leaves"**, submitted by **Md. Tanbir Hossain** and **Mirza Md. Abir** 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 July, 2024.

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We hereby declare that this project has been done by us under the supervision of **Mr.Md Assaduzzaman, Lecturer (Senior Scale), 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

The "Deep Learning Techniques for Automated Detection of Diseases in Guava Fruits and Leaves" research project aims to revolutionize guava farming by creating an automated system for early disease identification. By harnessing cutting-edge deep learning techniques, we strive to significantly improve agricultural production by accurately diagnosing plant illnesses. Our extensive collection of tagged guava plant images will lead to the training of advanced deep learning models, ultimately benefitting guava farmers worldwide. Our evaluation of various models, including ResNet50, VGG16, Inception V3, and DenseNet121, revealed that the ResNet50 model outperformed the rest with an impressive test accuracy of 92%. Its unparalleled accuracy and robustness make it an ideal choice for practical implementation in guava farming, promising substantial advancements in disease detection. Capturing and analyzing data, creating models, deploying solutions, and rigorous testing are pivotal project phases essential for success. Our meticulously planned project management includes a well-structured calendar, clear work allocations, and key milestones to ensure efficient and timely execution. A comprehensive financial analysis forecasts the project's total cost to be between 75,900 and 90,900 taka over a six-month period, encompassing field trips, personnel, software, hardware, cloud services, and other related expenses. This study aims to deliver a reliable solution for guava growers, enabling timely and accurate identification of plant diseases, ultimately leading to healthier crops and increased yields.

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CHAPTER 1

Introduction

1.1 Overview

In Bangladesh, guavas are a widely consumed tropical fruit in both urban and rural areas. This fruit, which is a member of the Myrtaceous family, was first brought to Portugal in the seventeenth century from the tropical regions of America. Guava is abundant in vital nutrients including calcium, iron, vitamin B6, magnesium, vitamin C, and nicotinic acid phosphorus, and it has a notable cholesterol-free content. The fruit is well-known for its health benefits. On a number of medical ailments, including as diabetes, blood pressure, diarrhea, and dysentery, and aid the immune system. [1][2]. Recognized as one of the world's leading producers of guavas, Bangladesh cultivates a substantial 0.3 million hectares of guavas annually, yielding roughly 3.7 million metric tons [2]. Essential elements like potassium, vitamin C, vitamin A, and dietary fiber are abundant in guavas. Regular guava consumption can support a healthy, well balanced diet. Guava is well-known for its therapeutic qualities. It is thought to possess antioxidant, antibacterial, and anti- inflammatory properties. In traditional medicine, guava leaves are frequently used to cure a variety of illnesses. Fruits from guava trees may become infected with different bacteria, viruses, and fungi. Guava fruits are frequently afflicted by anthracnose, guava wilt, fruit rot, and other diseases. Guava fruit output, quality, and appearance can all be impacted by these diseases. Many illnesses and bugs can also harm guava leaves. Fungal infections such as powdery mildew and leaf spot diseases are common problems. Guava leaves can also become infested by parasites and insects like mites and aphids. These illnesses not only raise production costs but also impede the availability of food on both domestic and international markets [3]. Based on farmers' experiences, the current approach used in Bangladesh to identify guava leaf illnesses involves manual labor and eye observation. This traditional method is costly, time-consuming, and unreliable. Furthermore, misdiagnosing an illness can result in interpreting the circumstances incorrectly [3].

Additionally, there are disease variances brought on by differences in plant species and climates, which can make it challenging for a specialist to accurately diagnose plant diseases. Plant disease diagnosis can be done more accurately by using computer vision and machine learning techniques. CNNs are built with the ability to automatically extract hierarchical features from pictures. Identifying patterns and structures in guava fruit and leaf photos that can point to the existence of illnesses is particularly advantageous. CNNs are appropriate for situations where prompt detection and reaction are essential since they can be tuned for real-time processing. CNN models have the ability to automatically identify illnesses in guava fruits and leaves once they have been trained. This can greatly expedite the process of identifying ailing plants, allowing for prompt management and intervention. For this reason, we proposed CNN based deep learning model that detect guava fruit and leaf disease.

1.2 Background and Present State

A popular tropical fruit in Bangladesh, guava is well known for providing essential minerals like calcium, iron, and vitamins B6 and C. Guava crops are vulnerable to multiple diseases, such as anthracnose and powdery mildew, which have a substantial impact on fruit quality and output, even if they are cholesterol-free, help with a number of medical disorders, such as diabetes, and support the immune system.

The present laborious, labor-intensive, and subjective approaches for identifying guava fruit and leaf diseases might result in inconsistent results and crop losses. The creation of more accurate and efficient diagnostic tools is required because these conventional approaches are not only expensive but also unreliable.

1.3 Problem Statement

The health of the crop depends on the timely and subjective diagnosis of illnesses in guava fruits and leaves, but the methods used today are labor-intensive, subjective, and manual, which could result in crop loss.

The objective of this research is to develop an automated deep learning system with accurate guava infection detection capabilities. Challenges encompass a scarcity of annotated datasets, intricate patterns, and diversity in symptoms. Eventually, increased productivity and decreased losses will result from conquering these challenges and providing farmers with a reliable tool for early disease identification.

1.4 Objectives

Guava Fruit and Leaf Disease Detection Using Deep Learning" research is driven by the need to improve farming methods. The key tropical fruit guava is threatened by a number of illnesses that can lower crop quality and productivity. Precision farming, early intervention, and a decrease in the need for physical inspection are some advantages of using deep learning for disease identification. The larger objectives of enhancing food security, sustainability, and the incorporation of cutting- edge technology into agriculture are all supported by this research.

To generate and refine deep learning models for properly recognizing and categorizing guava plant diseases. This include assuring real-time detection capabilities, extracting pertinent features, and building a diversified and annotated image library. The project intends to show scalability and generalizability, connect with precision agriculture techniques, and offer farmers an intuitive interface. In addition, the study will involve sharing open-source resources for cooperative breakthroughs in crop disease detection, doing comparison assessments with current approaches, and providing significant knowledge to the agricultural community.

1.5 Scope and Limitations

Deep learning will be used in this study to identify illnesses in guava fruits and leaves. Reviewing current approaches, creating a deep learning model, gathering and preparing data, and assessing the model's effectiveness are all part of it. Choosing programming tools and creating an intuitive user interface are part of the implementation. Future study directions will be offered, implications for managing guava disease will be examined, and results will be reviewed.

1.6 Report Organization

The study aims to systematically discuss the research and findings related to the use of deep learning algorithms for detecting illnesses in guava leaves. I will now provide detailed information on how I prepared the report.

Chapter 1: The overview, current situation, problem statement, goals, scope and constraints, report structure, and summary are all included in the introduction.

Chapter 2: The overview, relevant studies, comparison of the current body of work, unresolved concerns, and summary are all included in the literature review

Chapter 3: Methodology/Requirement Analysis & Design Specification includes the overview, proposed methodology/system design, hardware/software requirement, and project management and financial analysis.

Chapter 4: The system architecture, software tools utilized, and implementation specifics are all included in implementation.

Chapter 5: Results and Discussion comprises the analysis of the experiment's outcomes as well as a discussion of the conclusions.

Chapter 6: Future works and the conclusion are included in the conclusion.

Among the appendices are Appendix A: Course Outcome Mapping and Complex Engineering Activities/Problems

1.7 Summary

Guavas, widely consumed in Bangladesh, are nutrient-rich tropical fruits with health benefits. Bangladesh is a major guava producer. Guavas contain vital nutrients like calcium, iron, and vitamins B6 and C, and are cholesterol-free. They help with various medical conditions like diabetes and aid the immune system. However, guava plants are susceptible to diseases like anthracnose and powdery mildew, affecting fruit quality and production. Current disease identification methods are costly and unreliable. To address this, a deep learning model is proposed to accurately detect guava fruit and leaf diseases. Deep learning-based algorithms can efficiently identify patterns in images, enabling prompt management and intervention.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This study of the literature examines the work that has been done on the detection of illnesses in guava fruits and leaves as well as the application of deep learning to the detection of diseases in agriculture as a whole. It aids in our comprehension of the approaches that have been previously employed, the difficulties that researchers have encountered, and the solutions they have devised. This summary provides us with a solid foundation for determining how our project fits in and where we may make changes.

2.2 Related Works

M Mustak Un Nobi [4] said guava provides nutrition and food security for humans also it's a very demandable fruit in Asian countries. But due to various kind of diseases, farmers face unfortunate crop loss. That's why for solve this issue he proposed a transfer learning- based model named GLD-Det and also explained Grad-CAM technique and applied this model to different 2 datasets and got accuracy, precision, recall, and AUC score for the first dataset 0.98, 0.98, 0.97, 0.99 and f 0.97, 0.97, 0.96, 0.99 for the second dataset. According to Nikhil James [5], early detection of guava plant illnesses will aid in boosting output. His team is working to develop a CNN-based technique to detect guava plant illnesses early and administer the appropriate care. For this reason, they gathered a dataset from Kaggle and created an Android app using the CNN model, which resulted in an 84% rating. Here, the user inputs a photograph, and the applications identify the ailments on their own. However, Prof. Vikas Kadam [6] also developed a mobile app using deep learning and cloud computing. When a user uploads an image to the app, it transmits it to a server, which decodes it and provides the name of the illness and its treatment. The server's model yields an almost 95% accurate prediction. Working on bacterial blight and leaf brown spot, Abdur Nur Tusher

[7] developed a deep learning bass CNN model that can distinguish illnesses in guava, mango, rice, maize and peach plants with an accuracy of 95.26%. Rabindra Nath Nandi and Aminul Haque Palash[8] use the float16 and dynamic range two model quantization technique to present five state-of-the-art convolutional neural networks (CNNs). They use the dataset they have gathered to apply their model. On the GoogleNet model, they attained accuracy of over 97%. Mahesh T R , Vinoth Kumar [9] used mobilenetv2 architecture on their model with 53 layer and The first fully convolution layer has 32 filters, and there are then 19 additional bottleneck layers after that. With the help of mobilenetv2 the model give 95% accuracy. The methods now in use can only identify one disease from a single leaf. However, occasionally a single leaf will exhibit signs and symptoms of several different illnesses. This is a unique deep learning technique called Here (YOLO) for multiple item detection and localization. Numerous research on the detection of illnesses and other classifications have made use of this strategy.[10] A YOLOv5-based model developed by Javed Rashid can identify a number of diseases from guava leaves. Thus, using his suggested model, they created the Guava Patches Dataset and the Guava Leaf Diseases Dataset, and it achieved 73.3% precision, 73.1% recall, 71.0% mAP@0.5, and 50.3 mAP@0.5:0.95. Using YOLOv4, Roy and Bhaduri [6] developed a realtime deep learning model to identify two different apple leaf diseases (rust and scab) on a single leaf. The suggested approach produced 56.9 frames per second (FPS), 95.9% f1 score, and 92.2% mAP. To quicken TensorRT is the model that is used to maximise inference time. In 2023[11]Bella Dwi Mardiana and Wahyu Budi Utomo said that medicinal plants are widely used in medicine. That’s why they proposed a model using CNN with pretraiend VGG16 model that recognized species from 10 different classes. They use Image Data Generator for augmentation and get 97% accuracy. In 2023, V. Sathiya, M. S. Josephine,V. Jeyabalaraj [12] working on different types of diseases that occurred in Basil and Mint plants. And they introduce Inception V3 model on CNN for classification and get almost 77.55% for Basil leaves and an accuracy of 70.89% for mint leaves

2.3 Comparison between existing works

Table 2.3.1. Comparative analysis with previous work

SL NO.	Author Name	Used Algorithms	Best Accuracy
1.	Nikhil James. [4]	CNN	---
2.	Prof. Vikas Kadam [5]	Build a mobile app based on CNN	95%
3.	Abdur Nur Tusher [6]	CNN	95.26%
4.	Javed Rashid [3]	Hybrid deep learning-based framework, GLSM, GMLDD , GIP-MU-Net, YOLOv5 model	GIP-MU-Net model 92.41%
5.	Arunabha M. Roy [5]	The improved version of the YOLOv4 algorithm was used to develop a real-time high-performance disease detection model on a single GPU	F1-score of 95.9%
6.	Rabindra Nath Nandi [7]	Five state-of-the-art convolutional neural networks (CNN), GoogleNet, EfficientNet	EfficientNet model=99%
7.	Mahesh T R [8]	CNN, MobilnetV2, ResNet50V2, InceptionV3	MobilnetV2 architecture = 97.77%.
8.	Bella Dwi Mardiana [9]	VGG16	97%
9.	V. Sathiya [10]	CNN, InceptionV3 model	Basil leaves = 77.55% Mint leaves = 70.89%
10.	M Mustak Un Nobi [1]	Proposed GLD-Det model and Grad-CAM technique	---

2.4 **Open Issues**

- Limited Studies on Guava Diseases: Existing literature lacks research specifically focused on using deep learning for detecting diseases in guava fruits and leaves.
- Lack of Comprehensive Deep Learning Approaches: There's a gap in comprehensive deep learning methods tailored specifically for guava diseases, potentially overlooking unique challenges and characteristics
- Insufficient Focus on Leaf Diseases: Current studies tend to focus more on fruit diseases, leaving leaf diseases relatively unexplored despite their significant impact on guava yield and quality.
- Limited Utilization of Advanced Deep Learning Architectures: Many studies rely on conventional deep learning architectures, potentially missing out on the advantages of advanced models like CNNs or RNNs for guava disease detection.
- Scarcity of Benchmark Datasets: The availability of high-quality benchmark datasets specifically for guava diseases is limited, hindering the development of robust deep learning models.
- Limited Integration with Decision Support Systems: While some studies focus on disease detection, integration with decision support tools for farmers is lacking, limiting practical applicability in agricultural settings.

Addressing these issues can significantly advance the field of guava fruit and leaf disease detection using deep learning techniques, benefiting guava farmers and agricultural practices overall.

2.5 Summary

The application of deep learning to identify illnesses in guava leaves and fruit is highlighted in the literature study. Research has demonstrated that convolutional neural networks (CNNs) and transfer learning are effective methods for accurately classifying diseases. Additionally, some studies investigate the application of recurrent neural networks (RNNs) in illness prediction. Limited datasets and the requirement for real-world application in agricultural contexts provide challenges. Overall, deep learning seems to have promise for enhancing the identification of guava diseases; nevertheless, more study and real-world implementation are required.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS & DESIGN SPECIFICATION

3.1 Overview

The methodology for guava fruit and leaf disease detection using deep learning begins with the crucial step of data collection and preprocessing. This involves gathering a diverse array of images depicting guava fruit and leaves afflicted with various diseases. These images are then standardized in terms of size, format, and color to ensure consistency across the dataset. Next, the selection of appropriate pre-trained Convolutional Neural Network (CNN) models plays a pivotal role in the process. Four widely-used architectures, namely VGG16, Inception V3, ResNet101, and DenseNet121, are chosen for their proven effectiveness in image classification tasks. With the models selected, the methodology moves on to fine-tuning and transfer learning. Leveraging the pre-trained models, the classification layers are replaced, and the initial layers are frozen to retain the valuable features learned during the original training on large-scale datasets. This allows the models to adapt specifically to the task of guava disease detection while benefiting from the general knowledge encoded in the pre-trained weights. Subsequently, the dataset is divided into training, validation, and test sets. The models are then trained on the training data, validated using the validation set to monitor performance and prevent over fitting, and augmented with techniques like data augmentation to increase robustness and generalization capability. The effectiveness of the trained models is evaluated through rigorous assessment using metrics such as accuracy, precision, recall, and F1-score. This evaluation phase enables a comprehensive comparison of the performance of each architecture, providing valuable insights into their suitability for guava disease detection tasks. To further refine the models, hyper parameter tuning is conducted. Parameters such as learning rate and batch size are adjusted to optimize model performance, ensuring the most effective utilization of computational resources. Optionally, a model ensemble approach can be employed to combine predictions from multiple models, potentially leading to enhanced accuracy and reliability in disease detection.

Finally, the best-performing model is selected for deployment in real-world scenarios. User-friendly interfaces are developed to facilitate easy access to the disease detection system, ensuring practical utility and broad adoption among farmers and stakeholders involved in guava cultivation and management.

3.2 Proposed Methodology

The suggested approach entails obtaining a variety of photos of guava fruit and leaves, uniformity-checking them beforehand, and then classifying the images using the VGG16, Inception V3, ResNet101, and DenseNet121 models. By swapping out the categorization layers but keeping the learned features, transfer learning is implemented. Models are trained and assessed using metrics like accuracy and precision. The dataset is divided into segments for training, validation, and testing. For optimization, hyper parameters are adjusted, and for increased accuracy, ensemble approaches are a possibility. Ultimately, the most effective model is implemented with intuitive interfaces to detect guava sickness in the real world. I am eager to delve into a detailed discussion of my thesis process below.

Data Collection: In this study, we are utilizing the "Guava Disease Dataset (4 types)" dataset, which was obtained from Kaggle.[13] The dataset consists of a photo collection of guava leaves, encompassing both healthy and unhealthy samples. Specifically, it covers four types of diseases: Canker, Dot, Mummification, and Rust. The dataset contains a total of 2299 images, of which 2270 are in JPEG format and 29 are in JPG format.

Figure 3.2.1: Methodology

Standardization and Optimization: The photos are standardized to ensure consistency in size, format, color, and pixel values. This step helps maintain uniformity and improve the model's performance.

Data Augmentation: To bolster the resilience and adaptability of the models, data augmentation strategies are employed. This method involves creating variations of existing photos to enrich the dataset and improve the model's capacity to learn from diverse examples. The specific transformations I employed for data augmentation include rescaling (1./255), random height adjustments (0.2), random width adjustments (0.2), random zoom (0.2), and random rotation (0.2).

Feature Extraction:

When it comes to deep learning applications like guava plant disease detection, feature extraction is a crucial step in the data processing process. This process is taking raw data, like pictures of guava fruits and leaves, and determining which features or bits of information are most pertinent. In order to better comprehend and differentiate between healthy and diseased samples, the model might concentrate on the most discriminative parts of the data by extracting these characteristics. Feature extraction holds significant importance in improving the precision and efficacy of deep learning models for guava fruit and leaf disease detection. This is because feature extraction captures crucial patterns and attributes that are unique to certain disease types.

Classification:

In the field of deep learning, classification is a crucial problem that is used to detect diseases in guava fruit and leaves. It entails classifying guava fruit and leaf specimens according to their attributes and traits into various classes or categories. Classification in the context of disease detection seeks to differentiate between samples of guava that are healthy and those that are impacted by different diseases. Researchers can contribute to improved agricultural practices and crop productivity by offering useful insights into disease identification and management through the creation of deep learning models to reliably categorize guava samples. I meticulously assessed the performance of four distinct classification models, including:

1. **VGG16:** This 16-layer CNN is highly regarded for its simple design and use of small 3x3 filters. It was proposed by [20] Despite its demand for substantial processing power, it consistently delivers high classification accuracy for images.
2. **ResNet101:** ResNet50, a 50-layer deep residual network, circumvents the vanishing gradient issue through its use of shortcut connections.[21] This innovative approach enables deep networks to excel in complex image classification tasks.
3. **Inception V3:** Developed by [18], Inception V3 is a powerful CNN featuring a modular design with Inception modules. It effectively captures diverse spatial hierarchies in images, delivering outstanding classification accuracy and efficiency
4. **DenseNet121:** DenseNet121 is a 121-layer highly connected network that enhances feature reuse through dense connections, enabling cutting-edge performance in image classification and sophisticated pattern learning with fewer parameters.[19]

3.3 Hardware/ Software Requirement

Hardware Requirements:

The required hardware for our study is listed as follows:

Phase of Development and Training:

Workplace:

- CPU: AMD Ryzen 7 or higher, or Intel Core i7
- GPU: a minimum of 8GB of VRAM with an NVIDIA GeForce RTX 2070 or higher
- RAM: Minimum 16 GB; 32 GB recommended
- Storage: Minimum 1 TB SSD

Cloud Services (Advanced):

- Services: Azure VM, AWS EC2, Google Colab
- For instance: GPU-enabled devices (e.g., Google Colab Pro and AWS p2.xlarge)

Phase of Deployment:

Edge Device (Selective):

- Device: Raspberry Pi 4 with Coral USB Accelerator and NVIDIA Jetson Nano
- RAM: Minimum 4GB; Storage: 32GB on an SSD or microSD card

Software Requirements:

The following is a list of the software required for our study:

Development Environment:

- OS: Windows 10, macOS, or Linux (Ubuntu 18.04+)
- Language: Python 3.6+

Development Tools and Libraries:

- IDE: PyCharm, VS Code, Jupyter Notebook
- Frameworks: TensorFlow 2.x, PyTorch 1.7+
- Libraries: OpenCV, PIL, NumPy, pandas, Matplotlib, seaborn
- Annotation Tools: LabelImg, VGG Image Annotator (VIA)

Model Training and Evaluation:

- **Visualization:** Jupyter Notebook, TensorBoard

Deployment Tools:

- **API:** Flask or FastAPI
- **Edge Deployment:** ONNX Runtime
- **Containerization:** Docker

The following is a list of the software required for our study. These specifications provide a stable setting for creating, instructing, and implementing the guava fruit and leaf disease detection system.

3.4 Project Management and Financial Analysis

Our 18-week project is divided into distinct phases. The initial two weeks prioritize meticulous planning, goal-setting, material assembly, and comprehensive project scheduling. The subsequent four weeks are dedicated to data gathering and annotation, encompassing the acquisition and tagging of photos. The following six weeks focus on model development, involving data preparation, model training, and evaluation. The subsequent four weeks will involve model deployment, real-world testing, and user interface development. The final two weeks will be dedicated to compiling the conclusive report and finalizing the presentation.

Table 3.4.1 Financial Analysis

Expense Category	**Cost**
Hardware	60,000-70,000
Software	2,000-4,000
Cloud Services	150 per month
Field Visits	1,000
Personnel	10,000-12,000
Miscellaneous	2,000-3,000
Total Estimated Cost	75,900-90,900

An extensive summary of the project's anticipated costs is provided in Table 3.4.1. The total cost of the project over its six-month duration is estimated between 75,900 to 90,900 taka. This budget includes all project expenses such as hardware, software, cloud services, field trips, staff, and other costs.

3.5 Summary

Creating deep learning models (VGG16, InceptionV3, ResNet101, DenseNet121), setting project objectives, and gather dataset from kaggle, processing for guava fruit and leaf disease identification. Transfer learning and fine-tuning were used to train the models, which were then compared and their performance assessed. There was financial analysis and project management. The overall goal of the research was to use deep learning techniques for effective disease detection in guava crops.

CHAPTER 4

IMPLEMENTATION

4.2 Overview

In this chapter, we present a comprehensive analysis of the deep learning methods we employed to create our guava fruit and leaf disease detection system. The study utilized four convolutional neural network (CNN) models: VGG16, Inception V3, ResNet101, and DenseNet121. These models were chosen for their proven performance in various image classification tasks and their ability to capture detailed information necessary for accurate disease diagnosis.

4.2 Train Model

Four pre-trained convolutional neural network (CNN) models, namely VGG16, Inception V3, ResNet101, and DenseNet121, were utilized in our research. Detailed explanations of each model's architecture and features are provided here.

1. **VGG16:** The VGG16 model is well-known for its depth and simplicity. Its architecture consists of 16 weight layers, with 13 convolutional layers followed by 3 fully connected layers. The convolutional layers use 3x3 filters to capture left/right, up/down, and center concepts. To maintain spatial resolution, padding and a stride of 1 are utilized when applying these filters. Each block of convolutional layers is followed by a max-pooling layer (2x2) to reduce spatial dimensions by half. The network concludes with three fully connected layers, and a softmax classifier with 1000 nodes placed after the final layer, which in turn has 4096 nodes. VGG16's deep architecture enables it to effectively extract high-level features. It is a robust model for feature extraction, essential for diagnosing diseases in guava fruits and leaves, due to its consistent structure and use of small filters. VGG16 was chosen because of its simple and deep design, making it efficient for extracting high-level features from images. This is essential for accurately diagnosing illnesses in guava leaves and fruits.

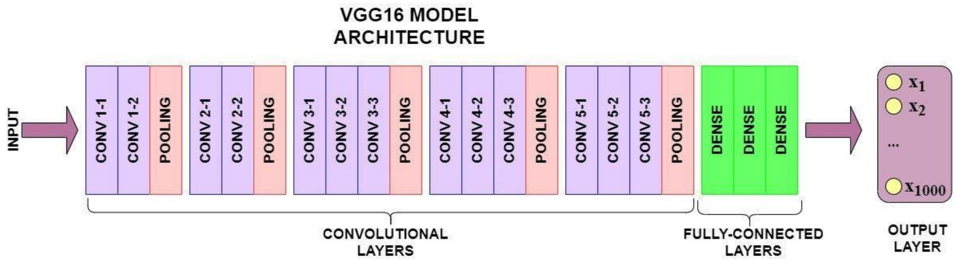


Figure 4.2.1: VGG16 Model Architecture [14]

2. **Inception V3:** The Inception V3 model utilizes a complex framework known as Inception modules. Each module consists of a 3 x 3 max-pooling layer and several convolutional layers with different filter sizes (1 x 1, 3 x 3, 5 x 5) concatenated along the depth dimension. This enables the network to capture features at various scales. The architecture reduces overfitting and increases training speed and accuracy by employing methods such as batch normalization, auxiliary classifiers, and label smoothing. Preceding the Inception modules in the architecture are several convolution and pooling layers, culminating in a fully connected layer and a softmax classifier. Inception V3 has the capability to extract features at different dimensions, making it suitable for recognizing complex patterns in images, which is essential for diagnosing various disease symptoms in guava plants. Because of its modular architecture and its capacity to collect features at various scales, Inception V3 was chosen. This is especially helpful for identifying intricate patterns and variances in the symptoms of diseases.

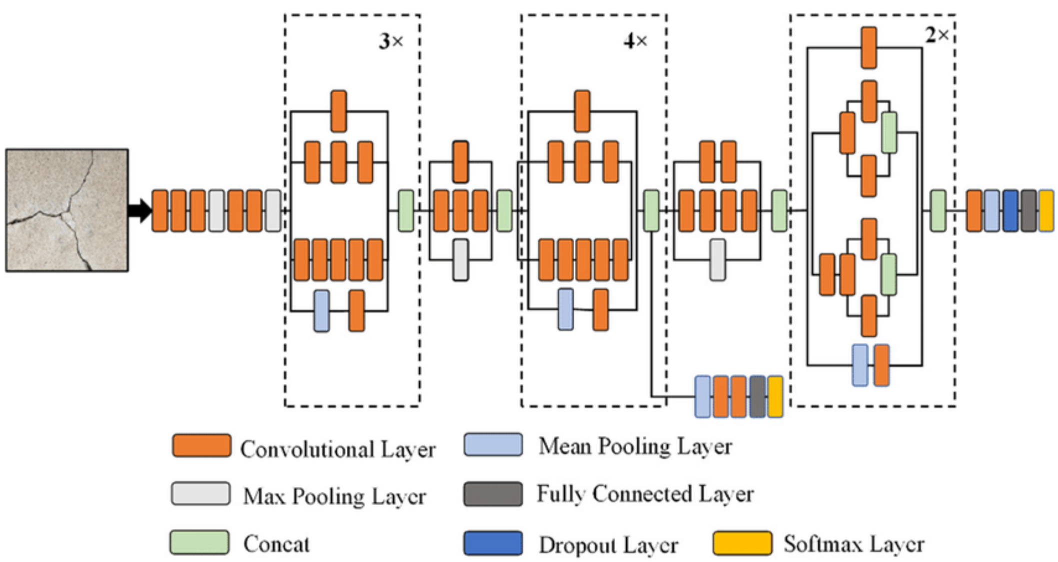


Figure 4.2.2: Inception V3 Model Architecture [15]

3. **ResNet101:** ResNet101 is a member of the Residual Networks family, and it addresses the problem of vanishing gradients in deep networks with its approach to residual learning. This network consists of 101 layers, primarily comprising residual blocks. Each block typically contains two or three convolutional layers activated by ReLU and batch normalization. The key innovation is the identity shortcut connection, which skips one or more layers. This allows the network to learn residual functions, making optimization simpler. The design starts with a single convolutional layer, followed by several residual blocks, a fully connected layer, and a softmax classifier. ResNet101 is extremely valuable for tasks related to disease identification due to its depth and residual connections. These features allow it to extract complex and detailed image features. The deep architecture and residual learning of ResNet101 facilitate accurate feature extraction and management of intricate patterns in the dataset. As a result, it is highly beneficial for tasks involving disease identification.

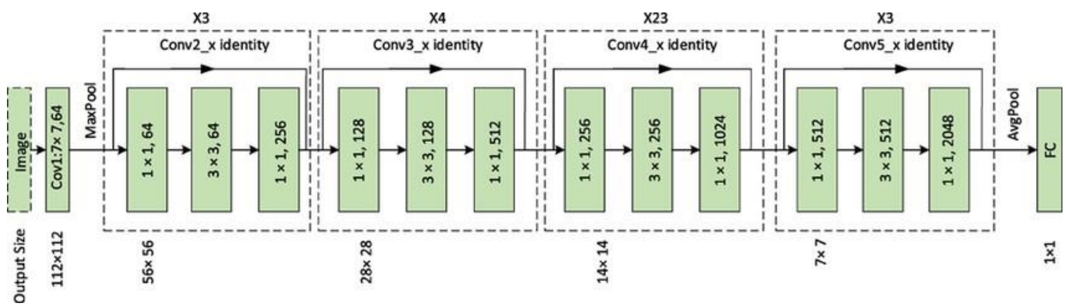


Figure 4.2.3: ResNet101 Model Architecture [16]

4. **DenseNet121:** Densely Connected Convolutional Network, also known as DenseNet121, utilizes dense connectivity to surpass traditional network topologies. In DenseNet121, each layer shares its feature maps with every other layer and receives input from all other layers as well. This creates a highly interconnected network that encourages feature reuse and reduces the necessary number of parameters. The innovative design of DenseNet121 features dense blocks, each comprising multiple convolutional layers, interspersed with transition layers enabled by 2x2 average pooling and 1x1 convolutions. The network culminates with a fully connected layer and a softmax

classifier. This dense connectivity ensures optimal gradient flow and feature reuse, ultimately enhancing learning and performance in intricate image classification tasks, including the detection of diseases in guava plants. DenseNet121's dense connection guarantees enhanced gradient flow and efficient feature reuse, resulting in superior learning and performance for intricate image classification challenges. This makes it exceptionally valuable for diagnosing diseases in guava leaves and fruits.

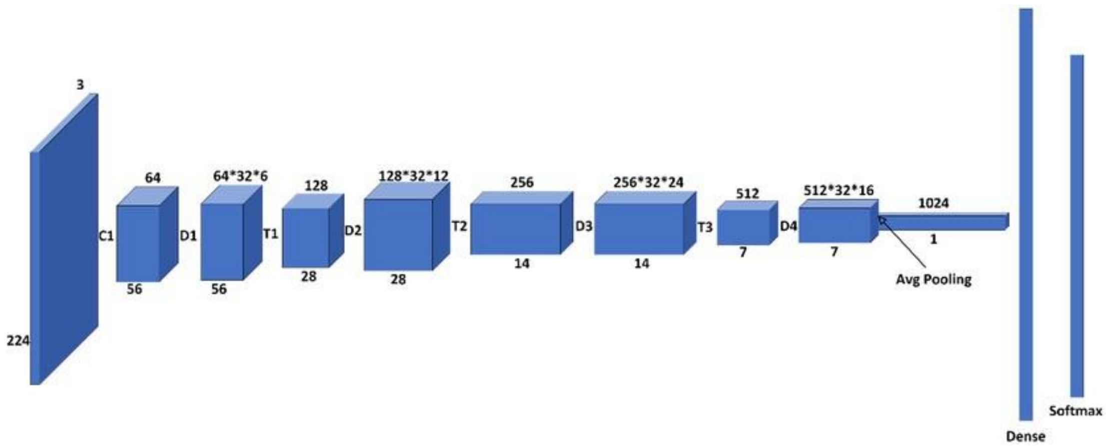


Figure 4.2.3: DenseNet121 Model Architecture [17]

The following models were selected for their unique designs and capabilities to ensure thorough and efficient detection of guava fruit and leaf diseases. VGG16 was chosen for its simple yet effective design, allowing for the extraction of high-level features from images, which is crucial for diagnosing illnesses in guava leaves and fruits. Inception V3 was selected for its modular architecture and ability to extract features at different scales. Identifying intricate patterns and variances in the symptoms of illnesses becomes especially helpful with the use of ResNet101. Its residual connections and deep architecture allow for accurate feature extraction and effective management of intricate patterns within the dataset. This makes it particularly useful for tasks related to illness identification. On the other hand, DenseNet121's dense connection ensures better gradient flow and facilitates effective feature reuse, leading to improved learning and performance on complex image classification problems. This feature makes it particularly useful for diagnosing illnesses in guava leaves and fruits.

4.3 Model Evaluation

4.3.1 Evaluation Metrics

Numerous crucial measures were incorporated in the study to comprehensively assess the effectiveness of the proposed ensemble-based transfer learning model. These measures included accuracy, F1 score, precision, and recall. Each metric provides valuable insights into various aspects of the model's performance.[17]

- **Accuracy:** Accuracy is the measure of correctly predicted occurrences compared to all instances in the dataset. While it offers a broad view of the model's performance, it can be misleading if the dataset is unbalanced

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \qquad \text{———————} \qquad (1)$$

- **Precision:** The concept of precision is crucial in evaluating the ratio of accurate positive predictions to all anticipated positives, including false positives. It serves as a powerful indicator of the real positive instances among the expected positive cases. A high precision level signifies an impressive accuracy and a reduced rate of false positives.

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \qquad \text{———————} \qquad (2)$$

- **Recall:** It is crucial to evaluate how effectively the model can identify all true positive cases. A high recall score signifies a minimal rate of false negatives.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \qquad \text{———————} \qquad (3)$$

- **F1 score:** Precision and recall are vital metrics in machine learning, with the F1 score offering a balanced measure that considers false positives and false negatives. This makes it an invaluable tool when dealing with imbalanced datasets. A high F1 score signifies a strong balance between recall and precision.

$$F1\ score = \frac{2 * \mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} * \mathrm{Recall}} \qquad \text{———————} \qquad (4)$$

Where TP = True Positive, TF = True Negative, FP = False Positive and FN = False Negative.

4.4 Summary

We developed a system for detecting diseases in guava fruit and leaves using four pre- trained CNN models: VGG16, Inception V3, ResNet101, and DenseNet121. To evaluate the models, we used accuracy, F1 score, precision, and recall as the main metrics. The F1 score provides a balanced assessment of recall and precision. Accuracy measures the overall correctness of predictions, precision indicates the accuracy of positive forecasts, and recall assesses the ability to recognize all positive examples. These metrics offer a comprehensive evaluation of the models' performance and demonstrate how effectively they identified guava plant diseases.

CHAPTER 5

RESULT AND ANALYSIS

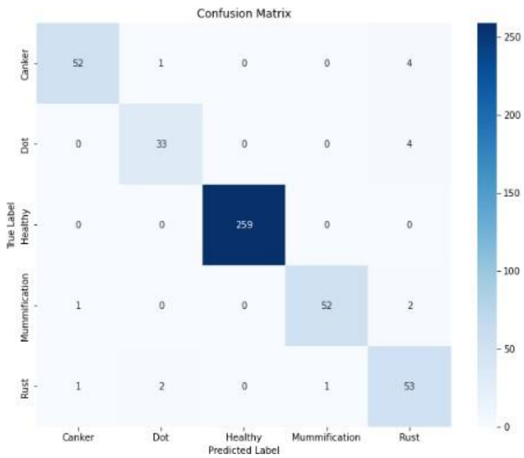
5.1 Overview

First of all here we collect a dataset from kaggle. Which has 5 different class of guava leafs and fruits image. After collecting the dataset we augmented our dataset from increase the volume of our data. Then shuffling and prefetching has done. We train some deep learning based models such as VGG16, Inception V3, ResNet-101 and DenseNet121 with various epochs. Here we train those models with 3 different epochs and that is 30, 60 and 100 to compare which particular model and epochs are suitable for this dataset. And finally we used some visualization tools it's the graphical representation of data.

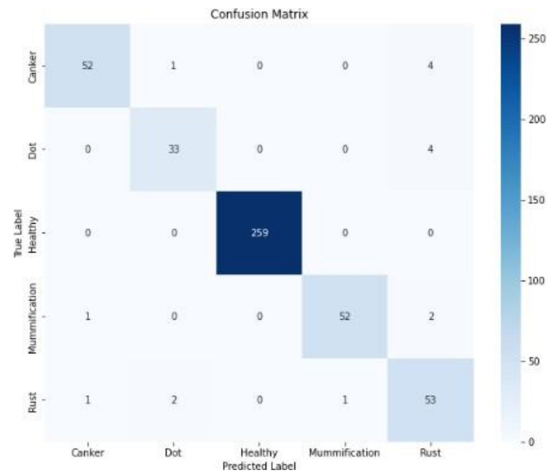
5.2 Experimental Result

In order to identify diseases in guava fruits and leaves, we created and assessed four different convolutional neural network (CNN) models in our study VGG16, Inception V3, ResNet-101, and DenseNet 121. In this section we want to describe the performance of those models that we applied to our study. For doing so we offer some illustration of models confusion matrix, validation, Training, accuracy and lose graph. To assess the performance of the models, we calculated evaluation metrics values, as well as the accuracy and loss of the final models during validation and training. Finally, we compared the performance of our final models with similar studies. [A real-time deep learning approach for classifying cervical spine fractures

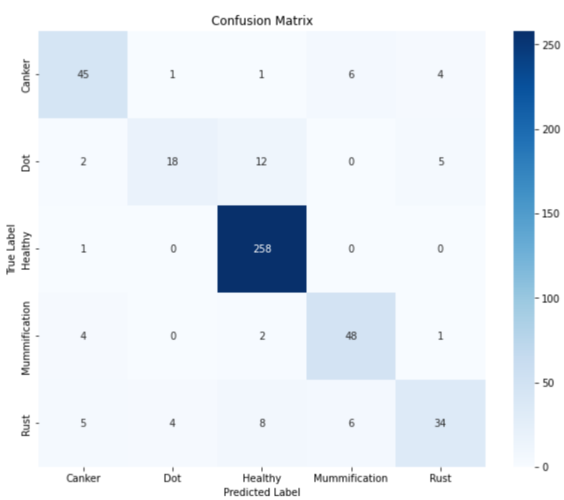
The confusion matrices for VGG16, Inception V3, ResNet-101, and DenseNet 121 are presented in Figure 5.2.1. Although all the models have some misclassifications, DenseNet 121 outperforms the others. VGG16 has moderate accuracy, Inception V3's complex design sets a high standard, and ResNet-101's residual connections result in significant improvements. However, due to its interconnected layers, DenseNet 121 surpasses them all, achieving higher accuracy and fewer misclassifications. Therefore, among the models examined, DenseNet 121 stands out as the most successful for classification tasks.



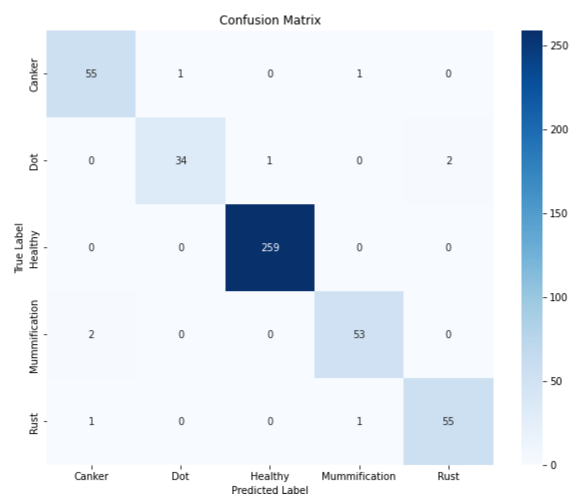
(a) VGG15 model's confusion matrix



(b) Inception V3 model's confusion matrix



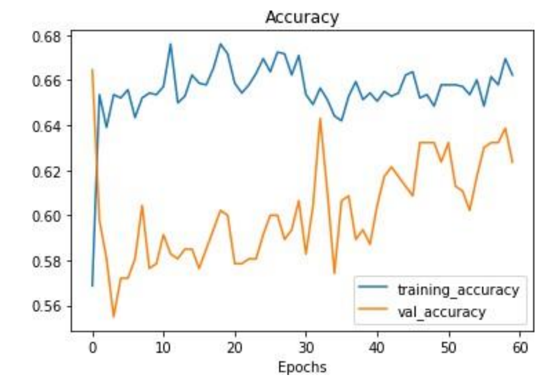
(c) ResNet-101model's confusion matrix



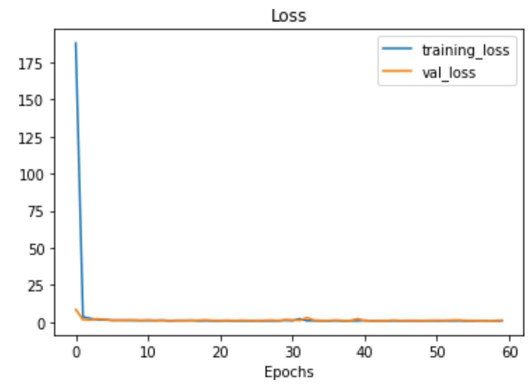
(d) DenseNet 121 model's confusion matrix

Figure 5.2.1 Confusion Matrix of VGG16, Inception V3, ResNet 101and DenseNet 121

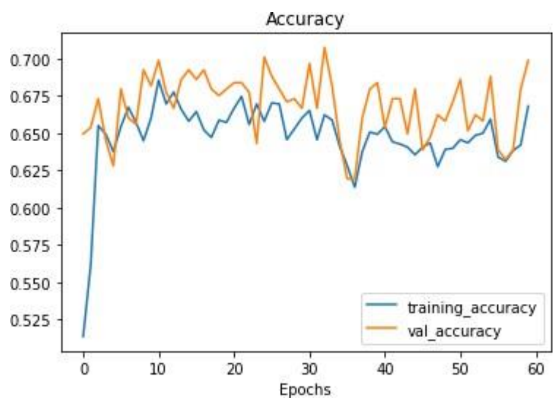
The accuracy and loss graphs in Figure 5.2.2 provide further information about how the models performed during the training epochs. These graphs show that, compared to the other models, DenseNet 121 not only reaches higher accuracy but also converges more quickly and retains a lower loss. The consistency of these measures highlights the superiority of DenseNet 121 in classification tasks. Therefore, among the models examined, DenseNet 121 stands out as the most useful for classification tasks.



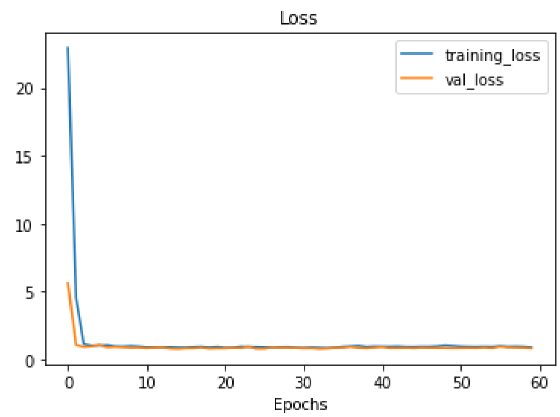
(a) VGG16 Accuracy



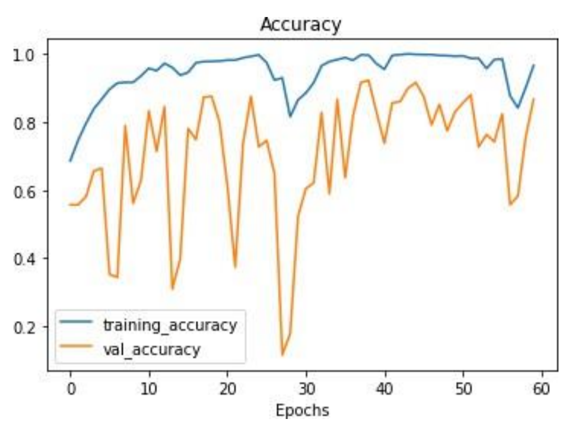
(b) VGG16 Loss



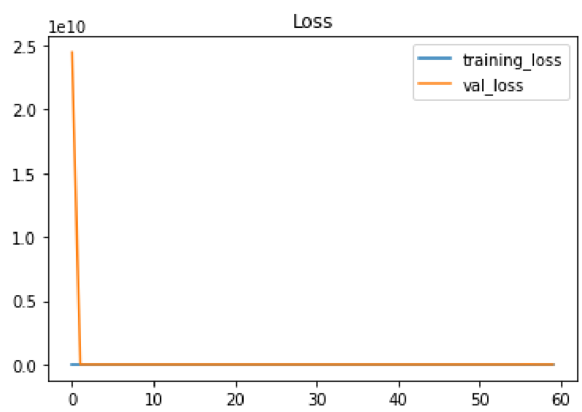
(c) Inception V3 Accuracy



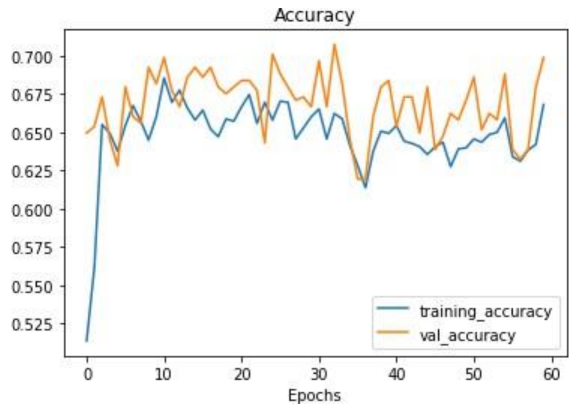
(d) Inception V3 Loss



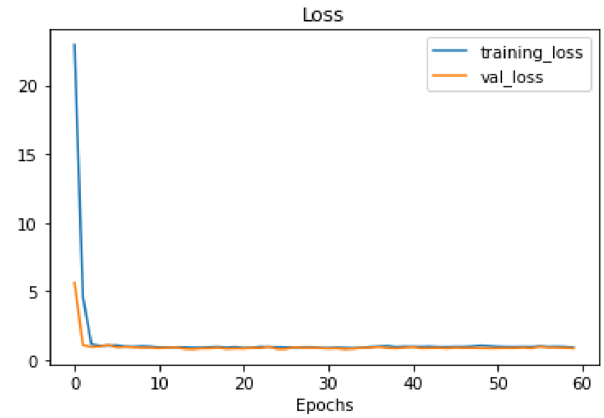
(e) ResNet 101 Accuracy



(f) ResNet 101 Loss



(g) DensNet 121 Accuracy



(h) DensNet 121 Loss

Figure 5.2.1 Accuracy and Loss Graph of VGG16, Inception V3, ResNet 101and DenseNet 121

5.3 Comparative Analysis

Table 5.3.1 Comparison of Model Performance

Model	Accuracy	Precision	Recall	F1-score
VGG16	17.20%	.55	.31	.31
Inception V3	69.89%	.31	.21	.16
ResNet 101	86.67%	.81	.75	.77
DenseNet 121	98.06%	.97	.96	.97

From Table 5.3.1, the Performance and Comparative study of VGG16, Inception V3, ResNet 101, and DenseNet 121:

Among the models evaluated, DenseNet 121 emerges as a standout performer, showcasing exceptional accuracy, precision, recall, and F1 score results. With an impressive accuracy of 98.06%, a high precision of 0.97, and a recall of 0.96, DenseNet 121 sets a high standard. Its balanced precision and recall, as evidenced by an F1-score of 0.97, underscore its exceptional reliability for classification tasks demanding high accuracy and consistency.ResNet 101 outperforms DenseNet 121, achieving an accuracy of 86.67%, a precision of 0.81, a recall of 0.75, and an F1-score of 0.77. This superior performance can be attributed to ResNet 101's use of residual connections, which help maintain accuracy despite its more profound architecture.

On the other hand, Inception V3 surpasses VGG16 with an accuracy of 69.89%. However, it lags in terms of precision (0.31), recall (0.21), and F1-score (0.16). This suggests that compared to DenseNet 121 and ResNet 101, Inception V3 needs help identifying instances and balancing precision and recall.

Out of all the models tested, VGG16 had the lowest accuracy (17.20%), precision (0.55), recall (0.31), and F1-score (0.31). It performed the worst overall, likely due to its deep design lacking dense or residual connections. On the other hand, DenseNet 121 showed superior performance in all assessed parameters and is recommended for applications requiring high classification accuracy and reliability. As an alternative, ResNet 101 also offers high performance, especially for applications prioritizing interpretability and computational efficiency.

5.5 Summary

DenseNet121 is the top-performing model for diagnosing diseases in guava fruits and leaves, according to the comparison analysis. Its continuously excellent test and validation accuracies throughout several epochs show that it has superior learning capacity and is resilient when applied to fresh data. ResNet-101 is not far behind, demonstrating good performance, especially in validation accuracy. While Inception V3 performs comparably to DenseNet121 and ResNet-101, it is less accurate. Accuracy measures show that VGG16 lags substantially, which may indicate architectural limits for this particular job.

CHAPTER 6:
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Detecting guava leaf and fruit diseases has a significant impact on life. Early and accurate disease identification improves farmers' livelihoods by reducing crop losses and increasing yield quality and quantity, enhancing food security and economic stability in farming communities. This leads to better-quality fruits for consumers, positively affecting public health.

Environmentally, precise disease detection reduces the need for excessive chemical pesticides, decreases soil and water pollution, and promotes ecosystem health. It also fosters innovation and skills development among farmers and researchers, encouraging modern, efficient, and sustainable agricultural practices. Overall, this technology supports economic stability, public health, environmental preservation, and the advancement of sustainable farming.

6.2 Impact on Society & Environment

Integrating deep learning techniques to identify diseases affecting guava leaves and fruits is a noteworthy development with significant implications for society. To improve agricultural production and food security, our study equips farmers with timely and actionable insights by deploying automated systems that can effectively identify disease indications in guava crops. In addition to streamlining disease control procedures, this technological advancement lessens the need for labor-intensive manual inspection techniques, giving farmers more time and resources to devote to other crucial duties. Furthermore, deep learning-based solutions' scalability and accessibility could help farmers in a variety of geographical areas, including neglected rural communities, by providing fair access to cutting-edge agricultural technologies. Ultimately, this research strengthens the socioeconomic well-being of farming communities, promotes sustainable agricultural practices for the benefit of society as a whole, and increases the resilience of farming systems by aiding in early disease identification and intervention.

Deep learning algorithms for the diagnosis of guava leaf and fruit diseases not only revolutionize agricultural operations but also have significant environmental implications. Our research leads to a decrease in the use of chemical pesticides, reducing pollution to the environment and maintaining the quality of the soil and water. As fewer harmful insects, soil microbes, and non-target species are harmed, the decrease in chemical inputs also promotes biodiversity and ecosystem health. Additionally, our strategy helps reduce the need for substantial land clearing and deforestation, thereby preserving ecosystems and storing carbon. This study enhances agricultural ecosystems' resilience and ensures the long-term profitability of guava agriculture while protecting the environment for coming generations.

6.3 Ethical Aspects

Sensitive data such as details about farmers, farming methods, and geographic areas—was cautiously handled to ensure security and privacy. Before analysis, all personally identifiable information was anonym zed, and data was stored in encrypted formats on secure servers with restricted access. Access controls and data encryption techniques were implemented to prevent unauthorized access and data breaches. Our efforts to ensure equal performance for all demographic groups were evident in our selection of a broad dataset. This dataset reflected a range of geographical locations, agricultural techniques, and socioeconomic statuses. We used balanced sampling, data augmentation, and fairness-aware training algorithms as part of our methods to reduce bias and ensure the model performed equally for all groups. We ensured that our research approach was transparent by thoroughly documenting every step of our methodology, from data collection to model evaluation. This included descriptions of data sources, preprocessing procedures, model architecture, hyper parameters, and assessment measures. To promote accountability and advance the body of scientific knowledge in the area, we encouraged examination and replication by making our code and datasets publicly available.

6.4 Sustainability Plan

Every facet of our study on guava leaf and fruit disease detection is infused with a commitment to sustainability. Our comprehensive sustainability plan is designed to minimize environmental impact, generate long-term benefits, and encourage collaboration and knowledge exchange. Among the tactics included in this plan are those that prioritize energy-efficient computing, reduce waste through digital documentation, implement sustainable laboratory procedures, collaborate with nearby farming communities, and provide public access to our research results. Our goal is to provide a reliable method for detecting guava leaf and fruit diseases while simultaneously making a significant contribution to a research environment that is more ecologically sensitive and sustainable through strict implementation and ongoing monitoring. Using a comprehensive approach, we guarantee that our research not only tackles current issues but also makes long-term positive contributions to agricultural methods, farmer welfare, and environmental sustainability.

6.5 Summary

Using deep learning, the study on guava leaf and fruit disease detection profoundly impacts life, society, the environment, ethics, and sustainability. Enabling early and accurate disease identification improves farmers' livelihoods, enhances food security, and provides better quality fruits for consumers, benefiting public health. From a societal and environmental perspective, the technology reduces the need for chemical pesticides, decreasing pollution and promoting biodiversity. It is through the efforts of agricultural researchers, policymakers, and stakeholders that these advanced agricultural technologies are made accessible to underserved rural communities, promoting fairness and equitable development.

Ethically, the study emphasizes data privacy and security, addresses bias and fairness with diverse datasets, and ensures transparency and accountability by publicly available research methodologies and data.

CHAPTER 7:

CONCLUSION AND FUTURE WORK

7.1 Conclusions

The research effectively demonstrated deep learning techniques, specifically DenseNet-121 and ResNet-101 models, for identifying diseases in guava leaves and fruit. This method enables early and accurate disease detection, improving crop quality and yield. The research contributes to environmental sustainability by reducing pollutants, preserving soil and water quality, and promoting biodiversity through decreased reliance on chemical pesticides. Farmers can benefit significantly from this technique, as it enhances crop yield and reduces losses due to disease. It also ensures the production of higher-quality fruits, promoting public health and food security. Prioritizing data security and privacy, anonym zing private information about farmers and farming methods, and ensuring the model's effectiveness across various demographic groups all address ethical considerations.

7.2 Further Suggested Works

To build on this research, several areas for future work are recommended. Advanced hyper parameter tuning, using techniques like grid search and Bayesian optimization, holds the potential to significantly enhance the performance of models like DenseNet-121. This improvement could mark a significant step forward in disease detection in agriculture. Incorporating diverse datasets and applying advanced data augmentation techniques can further bolster the model’s robustness and generalization. Exploring hybrid models and ensemble methods that combine features from multiple architectures can capture different aspects of the image data, leading to better accuracy.

Another promising area for future work is the development of a user-friendly mobile or web-based application for real-time disease diagnosis. Such an application could provide instant, actionable recommendations for farmers, significantly improving their ability to manage crop diseases. Leveraging pre-trained models through transfer learning and using domain adaptation techniques can further enhance the model's performance and adaptability to different environments or crops. Techniques like Grad-CAM can also be implemented to visualize model focus areas, thereby enhancing the models explain ability and building trust among users.

Integrating the detection system with IoT devices and precision agriculture techniques, such as drones and sensors, is a promising area for future work. Such integration can provide comprehensive real-time monitoring and enable timely interventions, significantly improving crop disease management. Testing the system in different geographic locations and environmental conditions through longitudinal studies and field trials can ensure its robustness and reliability in real-world applications. Working with agricultural experts can further refine the model, leveraging their expertise in dataset annotation, disease symptom identification, and prediction validation.

By addressing these areas, the effectiveness and applicability of deep learning techniques in guava disease detection can be significantly enhanced.

7.3 Limitations

1. **Dependence on Dataset Quality and Diversity**:

   The quality and diversity of the training dataset significantly impact the models' generalization and accuracy. It's possible that the dataset may not include all guava disease variants.

2. **Computational Requirements**:

   It requires significant computational power to train complex deep learning models such as DenseNet-121 and ResNet-101. The need for high-end GPUs and a considerable time investment makes this inaccessible to individuals with limited resources.

3. **Performance in Varied Conditions**:

   The performance of the models may vary depending on the location and environmental factors. This unpredictability affects the robustness of the models in real-world applications.

4. **Potential Conflicts of Interest**:

Research results may be influenced by partnerships with private funding sources or corporations developing agricultural technology. There can be issues with the technology's usability for all farmers.

5. **Ethical Considerations**:

It's important to carefully consider data privacy and the socioeconomic influence on traditional farming methods. Sustained adoption and equal benefits require balancing ethical and practical obstacles with technological advancements.

In order to direct future research towards more reliable, accessible, and socially responsible solutions for guava disease diagnosis using deep learning techniques, it is crucial to acknowledge these limitations and conflicts of interest.

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Appendix A

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

Title: Deep Learning Techniques for Automated Detection of Diseases in Guava Fruits and Leaves.
Student ID: 201-15-14174, 201-15-14050

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **Deep Learning Techniques for Automated Detection of Diseases in Guava Fruits and Leaves.** 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 project, which uses deep neural networks, data augmentation techniques, and a variety of CNN architectures for image processing and classification, significantly enhances Guava Fruit and Leaf Disease Detection. It serves as a powerful demonstration of **fundamental engineering (K3)** principles and showcases **specialist knowledge (K4)** in deep learning, employing advanced CNN architectures such as VGG16, InceptionV3, ResNet101, and DensNet121.	**Page no:** [10-12] **Section:** [3.2] **Page no:** [16-19] **Section:** [4.2]
				The project utilizes **engineering practices and design (K5)** to develop a comprehensive methodology for identifying diseases. This involves data collection, preprocessing, model training, and evaluation. The methodology integrates best practices in image processing, machine learning, and neural network construction to	**Page no:** [10] **Section:** [3.2] **Page no:** [22]

				provide reliable and accurate identification of guava leaf diseases. Additionally, the project addresses **engineering practices and technology (K6)** by employing CNN models, advanced deep learning frameworks, and approaches such as deep learning to enhance detection accuracy and efficiency.	**Section:** [5.2]
				Our research extensively investigates previous models with comparable objectives, obtaining information from various sources to improve our method for identifying guava leaf disease **K8 (Research Literature).**	**Page no:** [5-7] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project is dedicated to addressing EP-2 by identifying and overcoming the challenges involved in collecting data for guava leaf disease identification. These challenges include dealing with varying data formats and restricted access. Moreover, the project acknowledges the limitations of traditional methods and the complexities associated with integrating transfer learning and deep CNNs. Through rigorous comparative analysis, it endeavors to tackle the challenges in understanding various disease symptoms, while offering valuable insights for refining diagnostic methodologies.	**Page no:** [7-12] **Section:** [3.2, 2.3]

3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This study covered **EP-3**. A thorough analysis of experimental results demonstrates that Deep Learning stands out as the foremost approach for enhancing disease diagnosis among several viable methods.	**Page no:** [23-27] **Section:** [5.2,5.3]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach goes beyond computer science and engineering, influencing agricultural diagnostics in guava disease detection and contributing to advances in crop health and agricultural practices, as indicated by **EP-4.**	**Page no:** [5, 3] **Section:** [2.2, 1.5]
5.	**EP5: Extends of application**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	Our study addresses **Ep-7** by integrating data collecting, preprocessing, and classification components to provide a complete answer to the guava leaf disease detection difficulties while ensuring **EP-7**	**Page no:** [10-14] **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 aims to conduct systematic research and have a positive impact on the field of guava leaf disease detection through deep learning. To achieve this, we will utilize various resources such as GPUs, annotated datasets, deep learning frameworks, and ethical considerations.	**Page no:** [12-14, 16-20,29] **Section:** [3.3, 4.2,4.3.1 6.3]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This project aims to improve agricultural health by introducing new methods for detecting maize diseases. By identifying diseases accurately and promptly, we can mitigate crop loss and improve food security. The project also prioritizes environmental sustainability by utilizing efficient computational resources to reduce energy consumption and carbon footprint. Furthermore, ethical and equitable management of	**Page no:** [28-30] **Section:** [6.1-6.4]

				agricultural data is ensured through strict adherence to data usage guidelines.	

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	To effectively address **CO4,** this project seamlessly integrates efficient project management with precision financial control. Through detailed planning, strategic resource allocation, and accurate budget estimation, we can guarantee the optimal utilization of resources throughout the duration of the project.	**Page no:** [14] **Section:** [3.4]
2	CO9	Yes	By prioritizing data privacy, obtaining the necessary authorizations, and transparently reporting the research process, the project shows	**Page no:** [28-29] **Section:** [6.2,6.3]
			commitment to ethical principles. It also guarantees responsible sharing of knowledge and societal well-being by ethically applying advanced agricultural technologies that comply with **CO9.**	
3	CO10	No	N/A	N/A

4	CO12	No	The project demonstrates a strong commitment to adapting and continuously learning (CO12) in the rapidly changing technological environment. The project's extensive data collection efforts, detailed methodological development, and thorough experimental findings and analysis all highlight this commitment. The project's focus on staying current with the latest developments and continuously improving methods to effectively address contemporary challenges is evident through these rigorous approaches.	**Page no:** [10, 16-20] **Section:** [3.2, 4.2, 4.3]

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