Automated Detection of Banana Fruit Diseases Using Deep Learning

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FINAL YEAR DESIGN PROJECT REPORT

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

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Sep 17, 2025

APPROVAL

This Project titled "**Automated detection of Banana Fruit diseases Using Deep Learning**," submitted by **[Md Burhan Uddin; ID: 212-15-4187] and [Md Sujon Islam; ID: 212-15-4202]** 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 **Sep 17, 2025.**

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We hereby declare that this project has been done by us under the supervision of **Dr. Naznin Sultana, Associate Professor**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project (FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Dr. Naznin Sultana, Associate Professor**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of **Deep learning** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

The use of deep learning in the automation of banana fruit disease diagnosis is a new technique that has been used to deal with a major problem in agriculture and food safety. Little or poorly identified diseases can cause significant losses after harvest, low prices at the market, and dissatisfaction of customers. In this study, it is proposed to apply the most effective deep learning methods to banana fruit images to detect the various types of diseases and distinguish between diseased and healthy fruits. Various convolutional neural network (CNN) models were investigated, but the DenseNet121 model presented the most beneficial results. In this model the accuracy was impressive (99.12) on the first dataset and 98.42 on the second dataset in determining the disease types of banana fruits. The suggested method deals with the requirement of scalable, fast, and accurate solutions in agricultural supply chains, in particular, in the regions where human inspection is either unreliable or absent. Despite the existing shortcomings, including the fluctuating climate, disease presentation variations, and absence of data with annotations, the study demonstrates the prospective of AI-based systems to transform the assessment of agricultural illnesses. Our solution provides a cost effective and user friendly application with which farmers, retailers and consumers can make an informed decision. This study improves timely detection and management of disease as well as timely response thus reducing agricultural losses and increasing food distribution channels. The combination of AI-based technologies and mobile technology would enhance the diagnosis of diseases in isolated farmlands. This technology can be used to enhance food security throughout the world and in the long-term sustainable agricultural processes.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Introduction

Applications of deep learning in agricultural technology have garnered a lot of attention as a result of its capability to analyze complex visual information and give correct and automated solutions. Detection of diseases in banana fruits is crucial towards quality control and post harvest management but conventional methods like manual examination and visual evaluation is not always expedient, unreliable and uses a lot of labor. They cannot be used in large- scale operations because these conventional methods are prone to human error.

More recent surveys have examined the effectiveness of deep learning architectures, specifically convolutional neural networks (CNNs) in the automation and accuracy of the classification of fruit diseases. To differentiate between healthy and unhealthy fruits, these models apply advanced features extraction algorithms to recognize visual features, such as discoloration, blotch, lesion and texture abnormalities. Through transfer learning based on pre-trained models, researchers have been able to, based on a given set of agricultural tasks, enhance existing architectures, which enhances model generalization and higher detection accuracy.

This part of the paper explores the more recent developments in deep learning methods to identify banana crop diseases. As critical tactics, transfer learning, custom architecture, and data preparation and augmentation techniques are mentioned. Another aspect of the project is the problem of variability of the dataset, classes imbalance, and efficiency. ResNet50, InceptionV3, DenseNet121, and Light CNN are some of the models that we are currently testing. ResNet50 has been superior to its counterparts in many experiments.

The results of this research highlight the transformational potential of artificial intelligence in agriculture that can deliver scalable and accurate solutions in the classification of banana diseases that can greatly enhance efficiency, quality management, and decision-making throughout the supply chain.

1.2 Motivation

Due to the increased world demand of fresh and illness-free fruits, the need to provide proper cultivation, checking and distribution of bananas has never been as significant as it is today. Banana diseases are dangerous not only because of reducing and post-harvest losses but also because of ensuring consumer wellbeing, market standards, and economic returns. Early detection of the diseases will also aid in preventing massive destruction of crops and a consistent supply to the domestic and foreign markets.

The traditional manual inspection procedures are tedious, time consuming, and in most cases subjective because of human factors and errors. All these limitations underscore the fact that a high-speed, robust and scalable solution is not only necessary but will have to provide a consistent output irrespective of environmental and labor-related factors. Moreover, since it uses manual procedures, it is hard to develop an effective monitoring of large plantations, and thus, intervention is delayed and results into increased economic losses.

The impulse to conduct this study is in the fact that deep learning and computer vision technology provide prospects of revolutionizing the banana fruit disease detection process. Through the use of state-of-the-art visual recognition models, including DenseNet121, the detection process can be automated at a high degree of accuracy and little human supervision. These models can identify complicated patterns in images that a human being would otherwise have a hard time spotting and yield to the advantage of enabling early detection of even minor signs of an illness and assist in crop control.

An app or portable application on such technology would enable farmers, distributors and retailers both in developed and resource constrained areas. Such a tool would facilitate the real time data driven disease prevention and control decisions. Moreover, the system implemented in conjunction with cloud-based services or IoT systems may be used to expand the system and increase its accessibility, as well as enable around-the-clock monitoring to ensure that the stakeholders will have healthy crops and will be able to boost agricultural output overall.

1.3 Objectives

The main goal of the present study is to design and develop an automated system that would be able to detect banana fruit diseases with high accuracy with the help of DenseNet121. The ability of the proposed models to isolate various types of diseases and healthy fruits.

This study aims at making the most of a customized deep learning architecture in order to have a high accuracy with a low cost of computation. The custom model is tailored to both complex and speedy, which is why it may be used in real time detection of diseases in agricultural setting.

A low cost and user friendly application will be created to guarantee that there is a large access, and the application can be the one that is easily implemented by farmers, vendors and the agricultural stakeholders with the exception of those having limited resources and access to hi-tech applications especially in other regions where there is limited resource and access to technologies.

The main technical issues, including the imbalance of data sets, variable conditions of images, and inadequate training data are tackled with the help of such strategies as data augmentation, preprocessing and tuning of the model and make the system more robust and reliable.

The paper advances the study of AI in agriculture by providing a viable and scalable option of automated banana disease detection. The system is built to be sustainable, which addresses the international endeavors of developing efficient AI technologies that are environmentally friendly to address real world issues in agriculture.

1.4 Methodology

The paper offers a methodological solution to the problem of classifying banana fruit diseases with the help of advanced data preprocessing, data augmentation, and several deep learning models. The research design is aimed at creating an automated system that will be sure to achieve a high level of accuracy in determining various types of diseases using banana fruit images.

Banana Dataset was also resized to an average size of 224 x 224 pixels so that images could be used universally across model architectures and to make the calculations as simple as possible. The data augmentation methods used included rotation, zoom, flipping and contrast changes to increase the training dataset variability and robustness. The techniques also assisted in controlling overfitting besides balancing the classes which is important in predicting reliable model performance.

This study used and tested four deep learning architectures, namely Light

CNN, DenseNet121, InceptionV3, and Resnet50. The models have been fined tuned and made with customized settings of the batch normalization, dropout layers, and fully connected dense layers to enhance the performance of feature extraction and classifications.

The Banana Dataset was used in training and testing the models and a small percentage (10 percent) of the data was held out to test and evaluate the final results. During the training process, the accuracy and loss metrics were used to keep track of the performance of the models in terms of their learning efficiency and their generalization.

DenseNet121 was chosen as the best performing model among the tested models since it had high classification accuracy. It was more accurate and consistent when compared to other models, which proved its adequacy to the task of detecting banana diseases.

The present methodology can be used to emphasize the efficiency of the construction of an effective and accurate banana disease assessment system based on the custom designed deep learning model with the assistance of preprocessing strategies and a carefully crafted dataset.

1.5 Project Outcome

1.5.1 Classification Model

Our main purpose of study is to implement DenseNet121 in order to make an efficient and effective model that can be used to detect banana disease. The reason why the denseNet121 was selected was due to its excellent feature extraction and excellent visual classification. The model was discovered to have a 99.12 percent and 98.42 percent accuracy on the first and second dataset respectively and was in a position to differentiate between healthy and diseased banana fruit. The training and validation data was the Banana Dataset and was preprocessed, augmented and optimized to improve performance.

1.5.2 Comparative Architectures

Light CNN, DenseNet121, and InceptionV3, and ResNet50 are some of the deep learning models that we have looked at and compared. The models have been tested on the basis of accuracy, generalization and efficiency. DenseNet121 was more superior and sturdier compared to the rest of the models that offered guidance in selecting the model to be applied in the uses of banana disease detecting applications.

1.5.3 Contribution to Research Literature

The current paper is an addition to the research on AI controlled agriculture because it outlines the creation, training, and testing of a deep learning model to detect banana diseases. The article summarizes the results of the experiment and offers a structure of the further research in the field of computer vision and detection of agricultural diseases.

1.5.4 Agricultural Challenges

The paper addresses the broader question of agriculture by demonstrating the way AI is employed to enhance the efficiency, time, and precision of banana disease detection and the technical achievements. The results show that deep learning can be used to maximize productivity in terms of quality management and disease control through the reduction of human labor, the reduction of human error, and the reduction of the human error rate. The proposed solution can significantly contribute to the small-scale farmers and agricultural sectors by helping them in the provision of a stable and scalable tool of early detection of the diseases.

1.5.5 Educational and Training Resources

The results of this study can also be used as studies among students, researchers, and practitioners keen on application of AI in the agricultural sector. It helps to share knowledge and train skills in the ever-evolving sphere of precision agriculture and smart farming, especially in crop disease management, by demonstrating the development of deep-learning models, their training, and application to real-world problems.

1.6 Organization of the Report

Chapter 1: Introduction This chapter introduces the research problem and explains the motivation behind the study. It provides the background of the project, states the research objectives, and defines the overall scope of the investigation related to automated detection of banana fruit diseases using deep learning.

Chapter 2: Background This chapter presents an in-depth overview of key terminologies, concepts, and relevant literature in the field of banana disease detection using AI and deep learning. It discusses previous studies, identifies the limitations of traditional manual inspection methods, and highlights gaps that the current research aims to address.

Chapter 3: Research Methodology This chapter details the complete methodology adopted in the study. It outlines the data preprocessing steps, model architectures including Light CNN, DenseNet121, InceptionV3, and Deep CNN, along with training setups and evaluation metrics used to meet the research goals.

Chapter 4: Implementation and Results This chapter focus on the practical implementation of the proposed models and evaluates their performance. It presents comparative results, analyzes model effectiveness, and includes visual representations of metrics such as accuracy, precision, recall, and F1 score.

Chapter 5: Engineering Standards and Design Challenges This chapter discusses how the research aligns with relevant engineering standards and ethical considerations. It also addresses challenges faced during the project, such as limited dataset size, class imbalance, and computational limitations, along with the techniques used to overcome them.

Chapter 6: Conclusion This chapter summarizes the research findings, highlights the contributions made to the field of AI in agriculture, and provides suggestions for future work aimed at improving automated banana disease detection systems.

Chapter 2

Background

2.1 Introduction

Object detection is considered one of the most complicated issues in the sphere of computer vision since it involves localization and classification of objects in a scene [16]. Real time detection of objects is very essential in agriculture, especially in detecting the affected regions of the fruit by diseases, where minute morphological and textural changes are involved [4]. The object detection algorithm which is considered to be state-of-the-art, the YOLOv8, is known to be fast and efficient in its accuracy as the whole image is analyzed during a single pass [16]. YOLOv8 has various detection heads and anchor box to adjust to objects with different sizes, which is why it is appropriate in small lesion or spot detection on bananas [12,22]. It has a great flexibility, effective training and data insights, which make it better at real-time detection and more accurate in automated disease detection [16].

In the study, YOLOv8 was borrowed and fused with a classification network based on DenseNet121 to achieve proper detection and classification of banana fruit diseases [12]. YOLOv8 recognizes the area of interest (ROI) of the banana surface, and captures finer details of the banana like spots, discoloration or lesion areas which is then inputted to the DenseNet121 model to classify the illness [12,17]. In the recent years, deep learning has been applied to enhance object detection with a substantially faster pace. The one-stage detectors such as YOLOv8 are ideal detectors that can be used in a trade-off between speed and accuracy of detectors against two-stage detectors such as Faster R-CNN [23,25]. Integration with YOLOv8/DenseNet121 opens the chances to recognize the diseases with high precision and in real-time, eliminate false positives, and enhance the power of the classification process under different environmental conditions [16].

YOLOv8 is used to detect banana diseases, which enhances the speed and accuracy of detection; therefore, making the application suitable in real-time agriculture [19]. Improved functions, such as motion-adaptive inference and high-order feature extraction fine-tuning across network layers are important additions that enhance the performance of edge devices and lower computing costs [16,20]. The presented YOLOv8 DenseNet121 system is skillful in locating detailed and tricky visual patterns, which contributes to the proper classification of different types of banana diseases [12]. Further improvements could be the inclusion of additional models like InceptionV3 or EfficientNet to enhance feature extraction and real-world deployment of IoT to detect in the field in real-time [4,16]. The approach makes the study the whale of AI-powered agricultural innovations, improving effective, scalable, and accurate control over banana diseases [12,24].

2.2 Literature Review

Banana is another farm and a widely eaten fruit in many parts of the world making it a disease management vital to the agricultural output. Banana diseases can be described as the exact identification of the disease that is vital in the management and harvesting of banana plants, this is because of the irregular shaped banana that is green in color making it hard to detect in the natural environment [1]. Bananas are produced in more than 130 nations and have been a very important part of the world economy with an annual value of more than 52 billion and total production over 114 million tons. Fungal infections especially Fusarium wilt race 1 and Black Sigatoka are big challenges to banana production causing serious losses in plantations and thus significant losses in yield [19].

The rapid and precise detection of banana diseases is a pillar in the improved agricultural production. Recent changes in deep learning algorithms and computer vision methods have enabled automated disease classification at a significant level of accuracy. Modern approaches to the identification of multi-class illnesses are based on the latest models, such as Vision Transformers (ViT) and You Only Look Once (YOLO) networks. YOLO models and especially YOLOv8 are quite suitable to real-time applications because they have a high processing speed and accuracy on CPUs, which results in enhanced test accuracy and frames per second. Conversely, ViT models are efficient to train but slower to perform in real-time inference [2].

The process of disease detection requires high quality preprocessing and careful preparation of the datasets. The most crucial processes include obtaining the image, data augmentation and ensuring that a model is trained on a wide and representative sample [4]. The computer vision is also finding application in the agricultural field in automation of fruit diseases detection and classification through which vital tools are provided to see the condition of banana crops and to determine the quality of the fruit yield [6]. Early diagnosis of the diseases is important, which supports the timely interventions, spread of the infections, and loss of productivity.

Despite these developments, there are still problems. The difference in the colour, the texture, the environmental factors, and the visual similarity of the healthy and diseased fruits make it difficult to diagnose the disease through conventional methods, which often leads to inaccuracies. New recent innovations in image processing and machine learning provide effective alternatives to the fast and precise detection of the symptoms of banana diseases that outperform the traditional human inspection [12].

2.3 Gap Analysis

Despite significant advancements in deep learning and computer vision for agricultural disease detection, several research gaps remain in the context of banana disease identification.

Table 2.3: Research Gaps and Potential Solutions

S/N	Research Gap	Description / Implication	Potential Solution / Focus
1	Limited Disease Specific Datasets	Existing datasets are small or generalized, not covering all banana diseases, infection stages, or environmental variations. This limits model generalization and reduces detection accuracy in real-world scenarios.	Develop comprehensive, high-quality, and diverse datasets covering multiple diseases, stages, & conditions.
2	Real Time Detection Constraints	Models like YOLOv8 can run in realtime, but many approaches are computationally intensive, limiting deployment on smartphones or field-based IoT devices. ViT models, though accurate, are slow in real-time inference.	Optimize models for low resource deployment, use lightweight models, or compress models for mobile applications.
3	Variability in Environmental Conditions	Variations in lighting, background, and occlusion negatively impact model performance. Many studies do not handle these practical variations.	Implement robust preprocessing, data augmentation, and domain adaptation techniques to account for environmental variability.
4	Limited Multi Disease Detection	Most models detect only a single disease or a small subset. Systems capable of detecting multiple diseases simultaneously with high precision are lacking.	Develop multi class/multi disease detection frameworks with high accuracy and recall for simultaneous classification.
5	Lack of Integrated End to End Applications	Research often focuses on model accuracy, with few fully integrated systems combining real-time detection and user-friendly interfaces. Field	Create end to end applications that integrate detection models with intuitive interfaces for farmers

		deployment is limited.	and plantation managers.
6	Feature Extraction Challenges	Subtle morphological and textural changes, especially in early disease stages, are difficult to capture. Existing models may fail to extract high-order features.	Enhance feature extraction using advanced architectures, attention mechanisms, or hybrid models to capture subtle disease patterns.

2.4 Summary

In the recent studies, the field of AI and deep learning has been studied extensively regarding methods of analyzing banana diseases and determining their severity. Such models as YOLOv8, DenseNet, InceptionV3, and EfficientNet are among the approaches that are used to classify images of bananas according to visual symbols, like color changes, spots, lesions, and texture variations. Other studies have enhanced the accuracy of detection by employing ensemble learning or by employing image-based data with adding other features like spectral imaging, whereas others have incorporated sensor technology like hyperspectral cameras or the use of near-infrared sensors in order to further characterize the disease.

Besides single CNN architecture, hybrid and augmented architecture have been realized to enhance detection speed and accuracy. Lightweight network designs are presented so that they can be used in real-time in the field environment, increasing performance measures, including F1-score, mean Average Precision (mAP), and the speed of inference.

In general, these developments prove the great potential of AI driven methods in enhancing early disease and monitoring of banana diseases. Even then, more advancement has to be made so that it can be scaled down to make it cost effective and work well under different real world conditions in the plantations.

Chapter 3

Research Methodology

3.1 Methodology

3.1.1 Overview

Our study focuses on Automated Detection of Banana Fruit Diseases with an Application, which utilizes advanced deep learning methodologies to accurately detect and classify different disease types in banana fruits. The primary goal is to enhance agricultural practices and disease management processes through a reliable and intelligent system.

Our research employs a transfer learning based DenseNet121 model, enabling fine tuning and effective extraction of the most relevant features from banana fruit images. By integrating evaluation metrics and performance optimization techniques, the system ensures accurate classification of healthy and diseased fruits.

The paper is relevant to real-world agricultural issues like the inability to use manual inspection and losses at harvest by refining the accuracy of the disease detection process and providing a time-efficient and scalable solution. The bottom-line is to develop one of the most reliable and practical applications that assist farmers, vendors, and supply chain stakeholders who eventually help produce healthier crops, lower losses, and make more informed decisions in their agricultural practices.

3.1.2 Proposed Methodology

The one of the biggest issues with the agricultural AI studies is the lack of large and diverse data, particularly the banana disease detector. Transfer Learning (TL) can be applied to solve this problem through the use of the information about the pre trained models and applying this information to novel classification. This greatly helps in minimizing the reliance of large datasets and offers a strong basis on the extraction of features and classifying image of banana fruits.

In this study, a number of transfer learning-based deep learning models were used to classify the banana fruit images into healthy and diseased. The models selected are Light CNN, DenseNet121, Inception V3, and a Resnet 50. These models were optimized to fit the unique needs of banana disease detection and it is evident how transfer learning can eliminate constraints in a dataset and still achieve a high classification accuracy.

The entire methodology adopted in this work is presented in figure 1 and involves data augmentation techniques, fine tuning of various transfer learning models and evaluation of the most performing architecture. The input banana images were preprocessed in order to remove noise and balance the data, hence improving the quality of model training. Image augmentation methods like horizontal flipping and vertical flipping were used to balance the classes. All transfer learning models were then trained using the augmented dataset.

The model architectures were also optimized to improve the learning stability and the performance by incorporating the batch normalization, drop out layers and dense layers on each model architecture. Training and testing were performed using a banana fruit image dataset that is curated. The models were compared in terms of various measures, including accuracy, precision, and recall (sensitivity) and F1-score. In addition, the training performance was also pictorialized in the form of accuracy and loss graphs in order to measure learning behaviour of the models.

InceptionV3

The Inception V3 is a convolutional neural network architecture that is known to have high image classification performance, but has low computational complexity. The modules called inception are used in this architecture and utilize a combination of convolutional filters of varied sizes to extract multi scale characterization of space. These modules enable the network to obtain rich hierarchical representation of the input data besides making optimal use of the resources. The next significant feature of InceptionV3 is that the convolutions are factorized that could reduce the cost of the calculations due to the division of large convolutions into small and more effective convolutions. In addition, the architecture extensively uses the idea of batch normalization to improve training stability and convergence.

In the given research, the InceptionV3 model was trained on the fruit quality and the level of maturity. It was further extended to a batch normalization layer with size 2048 that was then followed with dense layer of size 256, dropout layer to reduce overfitting, and finally a dense output layer to do multi class classification. The InceptionV3 fine tuned model had 22,336,291 total parameters with 22,297,763 of them being trainable.

Light CNN

Light CNN architecture is an architecture of image classification, which is fast and efficient and can be used in real time applications and under resource limited conditions. It has fewer layers and fewer parameters, and therefore, results in a significant reduction of training time and memory consumption. Although the Light CNN is simple, it still has the ability to train discriminative features with the help of small-kernel convolutions, ReLU activations, and max-pooling layers.

The Light CNN constructed in this study had 4 convolutional layers, each being preceded by a batch normalization and ReLU activation and mixed with max pooling layers, which reduces the size of the image. The feature maps were flattened and then connected with a dense layer of 128 units, which was then followed by a dropout layer and an output unit. This architecture enables a light but efficient architecture that is applicable to categorize the stage of fruit maturity using less computation overhead.

DenseNet121

DenseNet, also known as Dense Convolutional Network, is known due to its excellent effectiveness in image classification. DenseNet alleviates the issue of the vanishing gradient, and enhances the use of specialized products, through dense connections between layers. This architecture has direct connections in the feedforward manner between each layer and the next layers, which enhances the flow of information efficiently and enhances propagation. DenseNet121 has shown excellent performance in many image classification tasks, beating many other state of the art architectures with a very low number of parameters.

This paper uses some additional layers in the DenseNet121 structure. These are a batch normalization layer consisting of 1664 units, a dense layer consisting of 256 neurons, a dropout layer, and a dense output layer to the end that has three neurons to perform the classification task. The fine tuned DenseNet121 model has 8,062,319 parameters out of which 7,890,731 parameters are trainable.

Resnet50

In this study, ResNet50 architecture was applied to gain high classification accuracy with the use of residual learning and greater network depth. ResNet50 has 50 layers and the block of residual layers which are made up of convolutional layers, batch normalization and ReLU activation. The major innovation of residual connections is that the model can address vanishing gradient problems, which is efficient in training very deep networks.

In order to achieve generalization, there was dropout in front of the fully connected layer, then there was a global average pooling layer and a final softmax activation to do multi-class classification. Being designed in a residual form and with a depth, ResNet50 is highly capable of capturing complex hierarchical features and hence it is highly applicable in the task of challenging fruit disease detection tasks where fine-grained distinctions are essential.

Advanced deep learning technologies were used to deploy automated detection of diseases of banana fruits to enhance precision, effectiveness and scalability in agricultural disease management. DenseNet121, InceptionV3, Light CNN, and ResNet50 models were trained as transfer learning models to classify banana images as healthy and diseased, and identify disease patterns that are commonly hard to identify using a human eye, which are accurately detected through transfer learning models. The process included preprocessing images to eliminate noise and class balancing to increase diversity; data augmentation to increase model diversity; and optimization with batch normalization, dropout, and dense layers to ensure a better learning stability and reduce overfitting. Measures of performance were determined based on accuracy, precision, recall, and F1-score, with DenseNet121 exhibiting the best results as the other models were utilized to offer competitive benchmarks.

This solution is scalable and practical, helping farmers, distributors and supply chain stakeholders to minimize losses on their crops, enhance their quality of yields and make smarter and data-driven decisions. The system enhances healthier crops, sustainability, and more productive use of the banana supply chain by integrating both traditional forms of manual inspection with new AI-based agriculture through the synergistic use of optimized deep learning models, effective training, and evaluation strategies.

3.2 Detailed Methodology and Design

Our research is aimed at coming up with a more effective and correct method of disease identification in banana fruits. We aim at creating an app that can detect diseases fast and accurately based on visual evidence and learned characteristics. To do so it takes well planned and systematic methodology. Figure 3.2.1 depicts the entire flow of the process and presents the workflow diagram of the proposed system based on the data collection and preprocessing through the disease classification and the output generating.

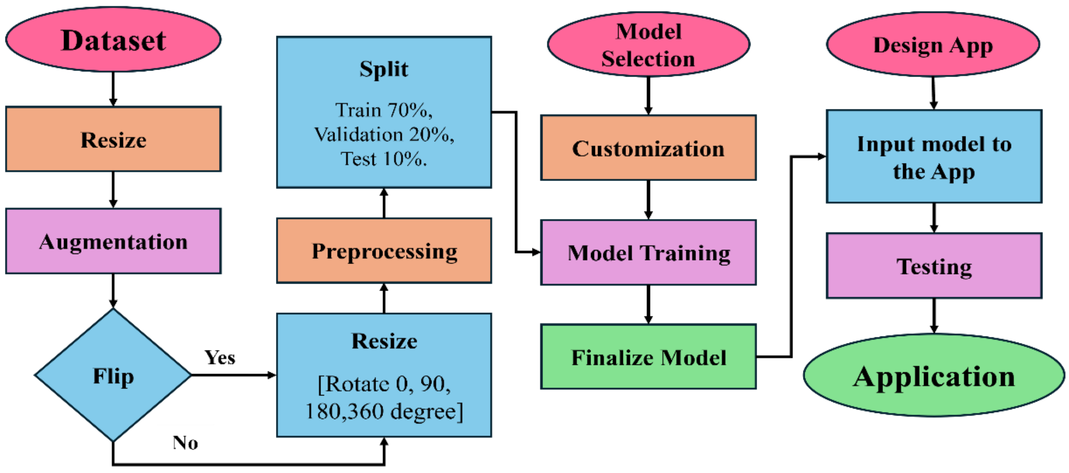

Figure 3.2.1: The workflow diagram for the proposed application.

To achieve proper classification, we have made use of the DenseNet121 architecture because it has high feature propagation properties and makes good use of parameters. The DenseNet121 is useful in extracting rich contents on the images of the banana fruit as well as being effective in learning complex patterns that characterize the relationship between healthy and diseased fruits. The architecture of the DenseNet121 model that we applied is described in detail in Figure 3.2.2.

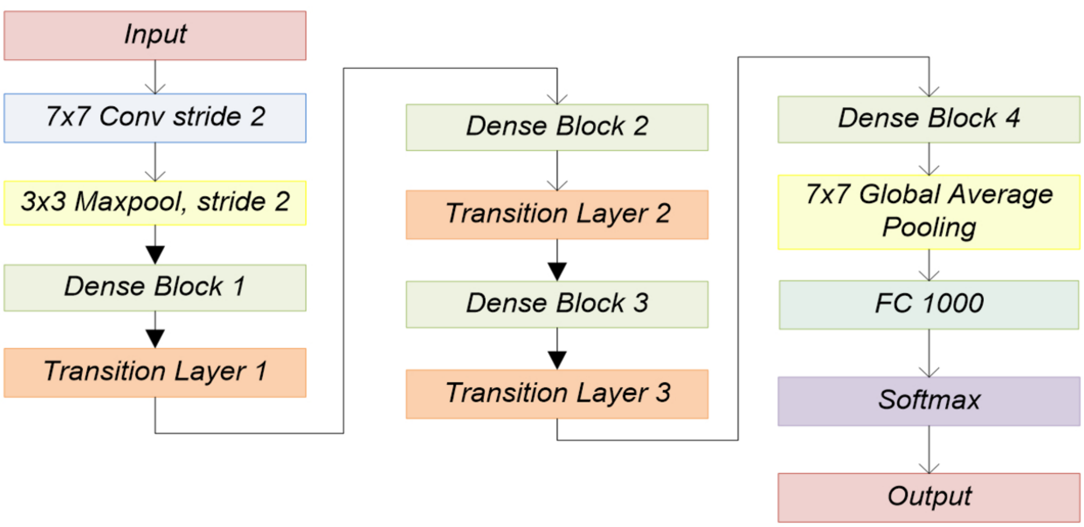

Figure 3.2.2: The workflow diagram for the proposed application.

The complete system formation involves several key steps: image acquisition, preprocessing (such as resizing and normalization), data augmentation, and feeding the data into the DenseNet121 model. The model is fine-tuned on our custom banana fruit disease dataset and outputs the predicted disease category for each fruit. The final output is then integrated into a user-friendly application interface that allows real-time disease assessment. This systematic design ensures both accuracy and usability for practical deployment.

3.3 Task Allocation

Our teamwork implemented in our research-based project was achieved with the help of a properly organized division of duties. We had structured ourselves into two teams where one was majorly coding team and the other documentation team but the teams frequently worked and assisted one another in all activities. This teamwork strategy helped us to keep a good communication process, efficient workflow, and deadlines without failure.

The individual team members were actively engaged in contributing their skills, be it in data preprocessing, model development or documentation. Our system is strong and effective as we were able to process the banana fruit disease data efficiently, tested various models, and attained high accuracy. Through regular reviews and monitoring, it kept us on track with the project objectives and to deal with any challenge in the project.

Along with the technical work, we read several research papers to acquire knowledge and information about the system design and writing of the report. We collaborated with one another in report writing, presentations and completing the system. Cohesion, time management, and supportiveness ensured that we successfully did the project on time and produced a system that can quickly and efficiently detect the diseases of banana fruits.

Table 3.4: Task Allocation

Tasks	Weeks																	
	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Improve an accuracy and F1 score																		
Finalize the model configuration																		
Develop a																		

Mobile application																		
Prepare detailed documentation																		

Estimated Work Period	
Actual Work Period	

3.4 Summary

This study explores the use of advanced deep learning techniques for automated banana fruit disease detection, focusing on models such as Light CNN, DenseNet121, Deep CNN, and InceptionV3. The methodology involves fine-tuning these models using custom layers and leveraging data augmentation techniques to address class imbalances in the banana fruit image dataset. Each model was evaluated based on metrics like accuracy, sensitivity (recall), precision, and F1-score, with performance further analyzed through accuracy and loss graphs. The research highlights the effectiveness of deep learning in handling variability in disease symptoms, aiming to enhance the accuracy of disease classification and provide a reliable, scalable solution for crop health monitoring and quality assurance applications.

Chapter 4

Implementation and Results

4.1 Environment Setup

4.1.1 Environment Specification

The laptop used in experiment to conduct the present study is ASUS TUF A15 RTX 4070 (2024) which comes with a powerful laptop GPU of NVIDIA GeForce RTX 4070 Laptop GPU 8GB GDDR6 Graphic with outstanding performance to perform the deep learning tasks. The laptop has an AMD Ryzen 9 8945HS Processor 5.2GHz, 8 Cores, 16 Threads and 16 GB of DDR5 5600Mhz RAM, which gives it good processing power to work with big datasets and execute computationally intensive models. The program was written with the Anaconda environment and the main tool to use in coding, visualization, and evaluation of the model was the Jupyter Notebook. In the deep learning tasks, Python, TensorFlow, and Keras were used to create and prepare the models effectively, taking the advantage of the ASUS TUF A15 being powered by a GPU to run the task faster.

4.1.2 Dataset

A custom dataset that was created during the research on banana fruit disease detection was used in this study. The data set is a total banana disease of 1000 plus high resolution images and 200 plus images of four different classes that represent the various types and levels of the banana diseases and the healthy sample.

Pictures were taken with precise conditions of lighting and background to keep noise to a minimum and uniformity of the entire dataset. The visual symptoms which were used to categorize each class in the dataset included spots, discoloration, lesions among other disease specific patterns on the banana surface.

All images were preprocessed and standardized to a uniform size to maintain consistency during model training and evaluation. To address class imbalance and enhance dataset diversity, data augmentation techniques such as flipping and rotation were applied. After applying augmentation techniques, we obtained 8 times the number of original images, resulting in a total of 6000+ images. This dataset served as both the training and testing source for the deep learning models used in this study.

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Hare is the figure 4.1.2 that show, some sample of images from dataset,

Figure 4.1.2: Sample images from dataset.

4.1.3 Data Preprocessing

Data preprocessing is a vital step to enhance model performance and reduce computational complexity. In this study, all images from the custom dataset were resized to a standard resolution of 224 × 224 pixels. This resolution was selected due to its compatibility with most modern deep learning classification architectures and to ensure uniformity across the dataset. Standardizing the image dimensions helped streamline the training process and reduce GPU memory consumption, thus improving computational efficiency.

To prepare the dataset for training and evaluation, 10% of the images were allocated as the validation set, allowing performance monitoring during training. Various data preparation techniques were applied, with a strong emphasis on data augmentation to enhance model generalization. Augmentation methods included flipping and rotation by (0, 90, 180, 270) degree, which introduced variability and reduced the risk of overfitting.

A series of ablation studies were performed to determine the impact of individual augmentation techniques on model accuracy and robustness. The selected augmentation pipeline significantly enriched the dataset by generating synthetic variations from existing images, ultimately contributing to a more reliable and accurate fruit classification system.

4.2 Results and Discussion

This part is the performance analysis of several deep learning models used in this work. The model was trained and tested with four different models with the custom dataset of 4 classes with 170 images each: Light CNN, DenseNet121, InceptionV3, and a Resnet50 architecture. The different models were fine-tuned to fit in the classification task of detecting and classifying banana disease.

To monitor the learning process and ensure optimal training, accuracy and loss graphs were generated for both the training and validation phases. These visualizations provided insight into model convergence, learning stability, and the avoidance of overfitting.

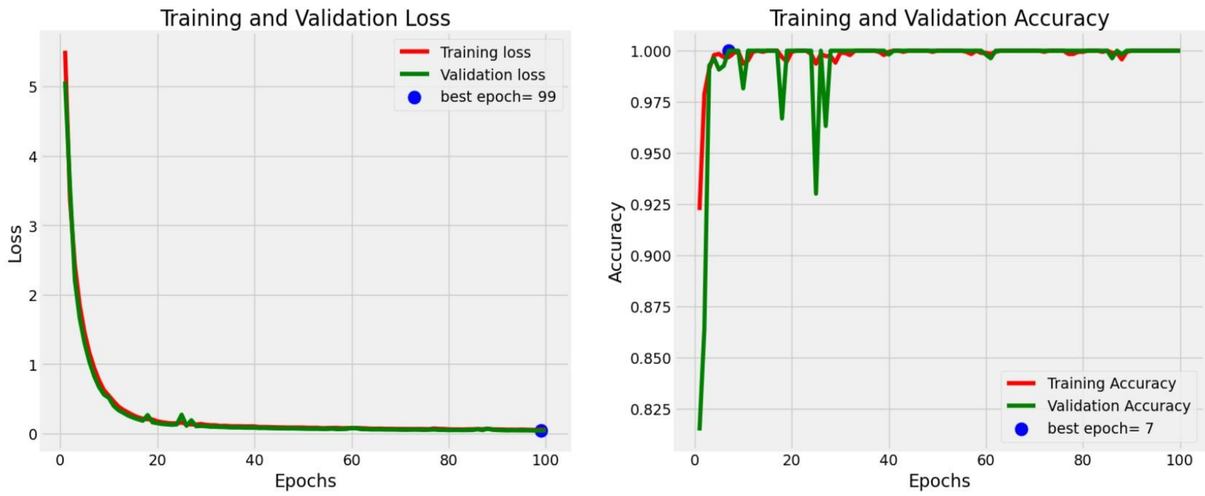

Figure 4.2.1: Accuracy, loss vs Epochs for Resnet50

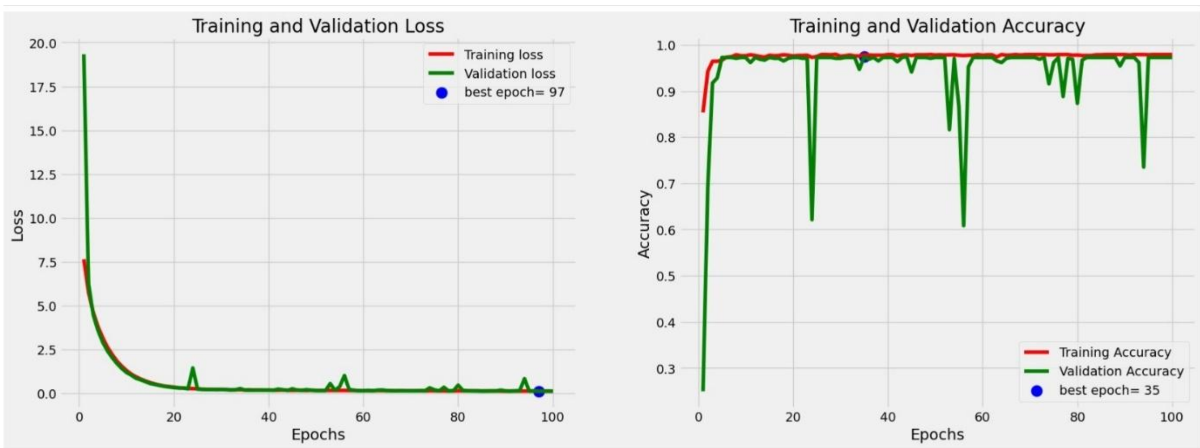

Figure 4.2.2: Accuracy, loss vs Epochs for InceptionV3

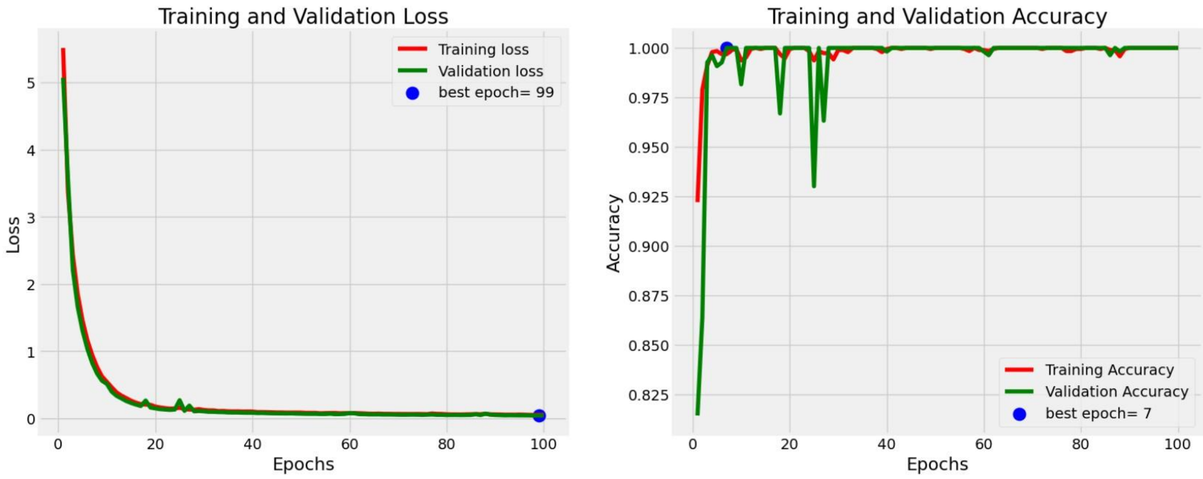

Figure 4.2.3: Accuracy, loss vs Epochs for Light CNN

Figure 4.2.4: Accuracy, loss vs Epochs for DenseNet121

Figure 4.2 Presents the accuracy and loss graphs for all four fine-tuned models, both primary and secondary datasets (with augmentation). The models were trained for 100 epochs, employing the Adamax optimizer with a batch size of 32. The accuracy versus epoch plots illustrates the training and validation accuracy following each epoch iteration. The loss against epoch plots is shown the training and validation losses. The red and green colors signify the training and validation curves, respectively, while the blue color indicates the optimal epoch.

The confusion matrix represents the best result obtained using DenseNet121 for classifying Banana Fruits conditions. The model shows outstanding performance, with nearly all predictions correctly classified across the four categories. Only a small misclassification occurred in the Bacterial class, where 3 samples were predicted as Healthy. Overall, DenseNet121 achieved highly reliable and accurate results, making it well suited for early disease detection. Figure 4.2.5 (A, B, C & D) shows Confusion Matrix of all the models.

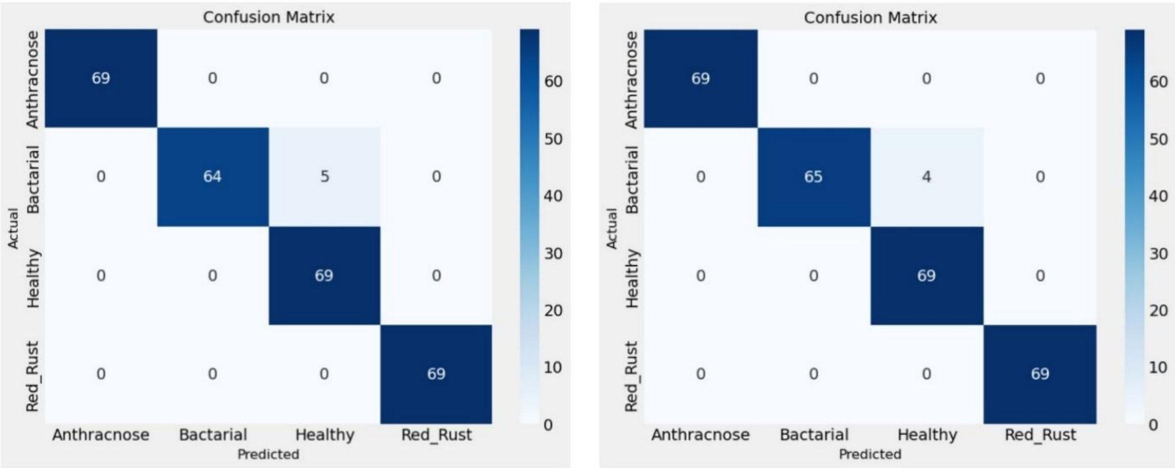

Figure 4.2.5 A&B: Confusion Matrix (InceptionV3 & Resnet50)

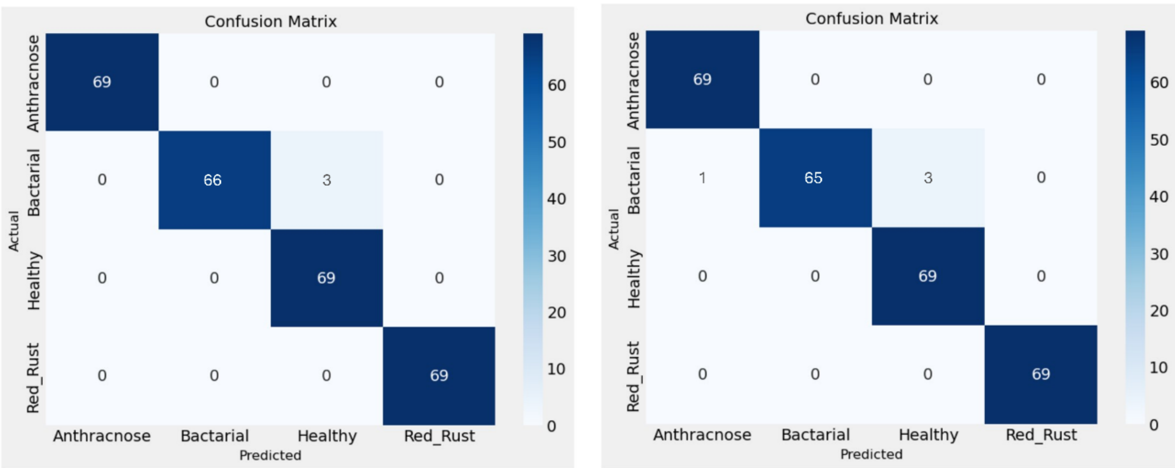

Figure 4.2.5 C&D: Confusion Matrix (DenseNet121 & Light CNN)

The model utilizing augmentation shows a little difference between the training and validation curves in contrast to the model without augmentation. Figure 4.2, demonstrates that the accuracy difference between training and validation is modest, suggesting that the model is well-fitted. Furthermore, in the loss against epoch plots, the loss values are significantly lower than the others. The graphs indicate that the DenseNet121 model, enhanced by data augmentation, has superior accuracy compared to the other models. Then the attention mechanism integrates with DenseNet121, as its outperforming.

Table 4.3.2: Models training and validation accuracy and loss.

		Accuracy		Loss	
Models	Accuracy	Training	Validation	Training	Validation
Resnet50 (secondary)	96.91%	0.9866	0.8074	0.1937	0.6513
Resnet50 (primary)	97.80%	0.9924	0.8735	0.1331	0.4694
DenseNet121 (secondary)	98.42%	0.9970	0.9186	0.0918	0.4591

DenseNet121 (primary)	99.12%	0.9994	0.9938	0.1234	0.4632
InceptionV3 (secondary)	96.04%	0.9917	0.8393	0.0632	0.5752
InceptionV3 (primary)	97.22%	0.9951	0.9026	0.1797	0.4114
Light CNN (secondary)	95.93%	0.9950	0.9277	0.0151	0.3162
Light CNN (primary)	97.77%	0.9945	0.9229	0.1192	0.3239

Table 4.3.2 compares the accuracy and losses of training and validation with augmentation and without augmentation. The comparison reveals a substantial disparity between the two. The implementation of augmentation approaches has resulted in the applied models attaining superior testing accuracy compared to models lacking such strategies.

The fine-tuned DenseNet121 model with attention mechanism, utilizing data augmentation approaches, has performed the best accuracy of 99.12% in primary and 98.42% in secondary dataset around the several applied models.

4.3 Summary

This chapter presents the experimental setup, dataset preparation, and evaluation metrics for the study on automated detection of banana fruit diseases using deep learning models. The custom banana disease dataset, containing 1000+ images across four classes, was preprocessed by resizing and enhanced using data augmentation techniques to improve model generalization. Four models, Light CNN, DenseNet121, InceptionV3, and Resnet50 were trained and evaluated with and without augmentation. The use of augmentation notably enhanced sensitivity, precision, and F1 scores. Among the tested models, DenseNet121 achieved the best overall performance in terms of classification accuracy, achieving 99.12% in the primary dataset and 98.42% in the secondary dataset. Comparative analysis confirmed that data augmentation played a key role in boosting model robustness and prediction reliability.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

5.1.1 Software Standards

It is seen that best practices in software development were harshly adhered to so that the fruit quality and maturity stage detection system could be stable, scalable, and usable. Preparation of the datasets, preprocessing, training of the models, evaluation and generation of results, were all well documented. The development environment was created and developed with Python programming language in the Anaconda distribution, with Jupyter Notebook being the main development environment. The fundamental deep learning operations were processed with the help of TensorFlow and Keras, whereas the image processing and data manipulation were performed with the help of OpenCV and NumPy. An optimized and custom pipeline was adopted in order to achieve the efficiency of the software.

5.1.2 Hardware Standards

This research employed an ASUS TUFE A15 as its gaming laptop that had an AMD Ryzen 7 processor, NVIDIA RTX 4070 with 8GB VRAM and 16GB RAM. This setup offered adequate computing power to process high-resolution images, train deep learning models, and run experiments using it. Local GPU enabled rapid processing without depending on the cloud GPU platforms, which provided a seamless and self-sufficient research experience. This hardware configuration allowed large scale model training and experimentation as well as being fast, reliable, and reproducible.

5.1.3 Communication Standards

All the development and training was done offline or locally in the Anaconda environment. But to share the results, provide backup and collaboration, the Wi-Fi network was used to synchronize files with the cloud storage (e.g. Google Drive). This allowed easy data handling, submission of reports and system updates. The local environment ensured real-time cooperation and access without relying on cloud GPUs such as Kaggle or Colab, so it is very convenient to implement in the real-world development.

5.2 Impact on Society, Environment and Sustainability

When the automated system is deployed to detect banana fruit disease, the potential of the system has immense possibilities of positive impact on the society, environment and sustainability. The technology will also reduce the use of manual inspection which is largely subjective, time consuming and liable to errors through providing a reliable and effective method of diagnosing banana diseases.

In the social meaning, the system allows the farmers, traders and consumers of bananas to possess data-driven information which enhances the decision-making both in agricultural and supply chain industries. It maintains fair prices, improves market transparency, and assists in eliminating frauds by marketing healthy bananas in the market. Small scale farmers are especially enjoined by the ease and affordability of AI solutions that will not only assist in the earlier detection of diseases, but also lessen the number of crops lost, increase the amount of time to harvest, and earn more income because of high quality assurance.

The solution will assist in reducing the waste produced in the environmental setting through disease infected bananas that are scrapped off. This leads to a good number of bananas wasting during the harvesting of bananas due to late or erroneous identification of the diseases. The system is able to minimize the postharvest losses, redundant use of pesticides and proper care of crops, because the early and precise diagnosis will become possible and will make the agricultural cycle more sustainable.

As far as sustainability is concerned, the project will promote accuracy agriculture and smart agriculture. The system also encourages proper management of resources, good with their long-term agricultural resilience, and the technology is aligned with the environmentally-friendly farming habits through deep learning technologies. Moreover, it reduces the superfluous chemical treatment that results in environmental and health gain of the consumers.

Overall, the research may be extensively deployed to bring new technology into the agricultural sector that would yield long-term benefits to bananas farming and result in a more sustainable and environmentally friendly food production system.

5.3 Project Management and Financial Analysis

This research was developed using publicly available datasets and free platforms such as Kaggle, Colab and many other presents, which helped to minimize costs and ensure accessibility. The implementation relied on personal computing hardware, with expenses limited to electricity and routine maintenance. The project was not financially motivated; rather, the main goal was to design a reliable and practical AI based diagnostic tool that could contribute to smarter agricultural practices.

Looking ahead, the system holds potential for monetization through a subscription-based model tailored for the agricultural sector, enabling even smaller institutions and individual farmers to access advanced diagnostic support at an affordable cost. In addition, licensing the technology to agri tech companies or related organizations could create sustainable revenue opportunities while simultaneously expanding its real-world impact. Such strategies would ensure both the long-term sustainability of the system and its role in supporting improved agricultural productivity and disease management.

Table 5.3: Financial Analysis table

SN	Components	Estimated Cost (BDT)
01.	Computer / Laptop (with GPU)	1,25,000-1,50,000
02.	Tools and Equipment	4,500-5,000
03.	Hardware, cards	12,000-15,000
04.	Documentation and Report Writing	1500-2000
Total Estimated Cost (Avg.)		1,65,000-1,85,000

The project is created using a small number of direct costs through the utilization of open-source resources, publicly available datasets, and personal computing infrastructure. Although the cost estimated is mainly the hardware, tools and documentation requirements, the research process carried out was very cost effective compared to the normal agricultural diagnostic solutions. In the future, the suggested subscription approach and the option of licensing might turn the system into a viable product not only in terms of small-scale farmers and institutions having access to it but also in the ability to generate revenue. This affordability, innovation, and scalability combination points to the practical usefulness of the system and its long-term prospects in the development of intelligent agriculture.

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.4.1: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of ApplicableCodes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓	✓		✓	

Mapping with Knowledge Profile for EP1

Table 5.4.2: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓	✓	✓

EP1: Depth of Knowledge

We solve this Engineering Problem 1. We achieve the Knowledge Profile **(K3-K8)**

K3 (Engineering Fundamentals): This research requires a fundamental knowledge of deep learning concepts and methodologies especially convolutional neural networks (CNNs) image processing, and machine learning.

K4 (Specialist Knowledge): This project requires specialized knowledge in agriculture image processing, specifically in understanding fruit images and their varying quality and maturity stages.

K5 (Engineering Design): This design of deep learning architecture, including the selection and optimization of models such as DenseNet121, requires solid expertise in model configuration and performance tuning.

K6 (Engineering Practice): To ensure that the model works effectively in real-world applications engineering practice knowledge is needed.

K8 (Research Literature): In the end K8 or knowledge of research literature is important for understanding the current record of work and improving it.

EP2: Range of Conflicting Requirements

We solve this Engineering Problem 2 we need the Knowledge Profile **(K3,K5,K6,K8)**

K3 (Engineering Fundamentals): Achieving a balance between computing efficiency and model accuracy requires an established basis in engineering concepts.

K5 (Engineering Design): Designing systems to satisfy performance and resource limitations requires ability in system optimization.

K6 (Engineering Practice): Implementing AI in environments with limited resources requires practical knowledge of its usage.

K8 (Research Literature): Insights of literature promote solutions to challenges in Agriculture systems improving performance and efficiency.

EP3: Depth of Analysis

We solve this Engineering Problem 3 we need the Knowledge Profile **(K3,K4,K5,K8)**

K3 (Engineering Fundamentals): Understanding deep learning techniques and data augmentation is necessary for full analysis.

K4 (Specialist Knowledge): Particular knowledge enables an accurate evaluation of model performance in oral cancer detection.

K5 (Engineering Design): Experience in model design and feature extraction improves performance and architectural selections.

K8 (Research Literature): Research findings guide and connect the project with best practices in the field.

EP4: Familiarity of Issues

We solve this Engineering Problem 4 we need the Knowledge Profile **(K4,K5,K6)**

K4 (Specialist Knowledge): Understanding the challenges in Automated Detection of Banana Fruit Diseases Using Deep Learning.

K5 (Engineering Design): The design of interfaces and workflows ensures the system's easy.

K6 (Engineering Practice): Understanding agriculture requirements helps the development of solutions that connect with the researchers and farmers.

EP6: Extent of Stakeholder Involvement

We solve this Engineering Problem 6 we need the Knowledge Profile (K6)

K6 (Engineering Practice): Using people ensures that solutions.

5.4.2 Engineering Activities

Table 5.4.2: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓		

EA1: Range of Resources

This project includes many tools, including computer infrastructure (CPUs and GPUs), histopathology imaging datasets, and deep learning frameworks such as TensorFlow or PyTorch. Effectively managing these resources is necessary for balancing computational capacity with model accuracy.

EA2: Level of Interaction

This system includes multi-tiered interaction among datasets, algorithms, healthcare professionals and end-users. Collaboration with pathologist is necessary for dataset annotation, engineers for artificial intelligence model design and clinicians for integrating systems into diagnostic procedures.

EA3: Innovation

This research applies innovation by utilizing advanced artificial intelligence methodologies such as transformers, DenseNet121 learning to solve the issues. Furthermore, it supports for the implementation of these solutions in areas with limited resources to address the agriculture connectivity gap.

5.5 Summary

In this chapter, we have already mentioned the particular requirements of the engineering challenge as well as the practical challenge and hurdles that we have faced in the course of development. This undertaking was done through the synthesis of a good-grounded research knowledge, application, and technical skills, backed by the information that is provided in the available literature. The structured approach helped us to discover the essential engineering issues and come up with efficient solutions balancing technical viability and real world implementation.

Another key element that has been highlighted in this research is the need to standardize engineering solutions to the wider societal and environmental values. Although the technical correctness and the performance of the system became the greatest goals, there was also equal focus on the fact that the results of the work should benefit the farming community, decrease the waste of resources, and foster the environmentally friendly philosophy of work. The combination of the deep learning approaches and the application to the agricultural problem is an indicator of how modern technologies should be modified to overcome the real-world issues in a sustainable manner.

On the whole, the research proves that such tasks as engineering can be successfully resolved in case technical innovation is used along with social consciousness and eco-awareness. The results do not only offer a viable solution to banana fruit disease detection using artificial intelligence but also offer a wider scope of advantage, including helping farmers, losses after harvesting, sustainability, as well as to the long-term sustainability of the farming industry. Therefore, the work represents a holistic style of research relating to practice and needs of society and creating an innovation to ensure sustainable development.

Chapter 6

Conclusion

6.1 Summary

Subsequently, we picked up a project of deep learning-based disease detection in banana fruits in this paper. The main goal was to create a sustainable and scalable system that would be useful in helping users detect the nature and intensity of the diseases in bananas by classifying the images. To this end, a tailor made Banana Dataset had been designed, which had more than 200+ images under four classes, which were specifically selected to aid training and evaluation.

A number of deep learning models were used and trained, such as Light CNN, DenseNet121, InceptionV3, and ResNet50. Training and fine-tuning of these models were done in the Anaconda environment with the help of high-performance hardware, namely ASUS TUF A15 laptop with an NVIDIA RTX 4070 graphics card, AMD Ryzen processor, and 16 GB RAM. Several preprocessing and data augmentation methods were used to enhance the robustness of the models, contributing to the minimization of overfitting, the elimination of class imbalance, and strengthening the generalization.

DenseNet121 had the best performance as compared to all other models that were tested as it provided high classification accuracy, and high evaluation metrics. A user-friendly application interface was also created to have usability in any setting, not limited to the research setting to facilitate actual use of the system. In general, the source shows the opportunities of AI-based solutions in agriculture and the food industry and how automated deep learning models can contribute to the efficient detection of early disease signs, loss prevention, and the development of intelligent farming.

6.2 Limitation

Although the results of this research are encouraging, there are certain weaknesses that should be taken into consideration:

Data Size, Diversity: The banana dataset is in a formatted format but contains only 1000 or more images and four categories. This is very narrow body of data which may not be able to extrapolate the model to different lighting, angles and fruit conditions that may be found in reality.

Environmental Dependency: The model can not work well in unsteady environments such as low light, cluttered background or noise of objects that can affect the quality of predictions.

Fruit Variety Coverage: The current plan has a limitation of four types of fruits. It lacks the favour of unfamiliar and hybrid varieties of fruits since this makes it less applicable in the broader agricultural practices.

Hardware Dependency: To train and run the models with a high level of accuracy, one will need a system with a dedicated GPU. This may not be possible to all users particularly those operating in rural or resource constrained environments.

6.3 Future Work

There is considerable potential for enhancing this system in the future. Several key areas of improvement and expansion are proposed:

Dataset Expansion: Increasing the size and diversity of the dataset by including more banana varieties, additional disease types, varying severity levels, and images captured under different lighting and background conditions can improve the robustness and generalization ability of the model.

Integration of Object Detection: Incorporating object detection techniques (e.g., YOLO or SSD models) would enable the system to identify multiple bananas in a single frame and detect disease symptoms on each fruit individually, which is particularly valuable for sorting, grading, and packaging processes.

Mobile and IoT Deployment: Transforming the current system into a mobile application or IoT-compatible device would allow farmers, traders, and agricultural inspectors to use the tool directly from smartphones or edge devices in the field for on-site diagnosis.

Multilingual Support and UI Enhancement: To reach a wider audience in banana-growing regions, the application could include multilingual support and an intuitive, user-friendly interface, ensuring ease of use for people with different technical backgrounds.

Cloud based Infrastructure: Deploying the model on a cloud server would make it accessible remotely without requiring high-end local hardware. This setup would also enable real-time predictions, centralized updates, and integration with agricultural management platforms.

Partnership and Commercialization: Future development could involve collaboration with agricultural research centers, banana exporters, or agri-tech startups to scale the system into a market-ready solution. A licensing or subscription-based model could ensure sustainable revenue generation and continuous technical support.

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Frequently Asked Questions

How should I interpret Turnitin's AI writing percentage and false positives?
The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI paraphrase tool or word spinner.

False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.

AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

The AI writing percentage should not be the sole basis to determine whether misconduct has occurred. The reviewer/instructor should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in accordance with their school's policies.

What does 'qualifying text' mean?
Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.