AN ADVANCED DEEP LEARNING APPROACH FOR DETECTING DRAGON FRUIT DISEASE

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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 "An Advanced Deep Learning Approach For Detecting Dragon Fruit Disease", submitted by **Md. Ariful Islam kushol & Tanjila Akter Remu** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15-07-2024.

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ABSTRACT

This area of cultivation is however faced with daunting challenges as the plants are prone to diseases that affect its health and production. To this end, we put forward an improved deep learning model for diagnosing dragon fruit disease based on CNN approach that better discriminates different categories of dragon fruit health conditions. Using a dataset comprising 2438 augmented images collected from a nearby dragon fruit nursery, annotated with four target attributes—Fresh, Brown Spot, Stem Rot, and Turning Yellow our study explores the effectiveness of five different CNN architectures: These include CNN, Xception, VGG16, DenseNet201, InceptionV3. Experimental analysis shows that DenseNet201 outperforms other networks, the best accuracy reaching 97. 23 % of all cases, whereas CNN and Xception networks detected it with accuracy of 92%. 62% and 92. 52%, respectively. However, it can be seen that VGG16 and InceptionV3 were able to produce slightly lower accuracy of about 86. 89% and 91. 80%, respectively. These findings also testify to the benefit of deep learning models especially DenseNet201 in diagnosing the diseases of dragon fruit. When applied, the proposed approach presents a viable strategy for the early detection of diseases in plants and efficient crop management to enhance productivity in the agricultural systems. More studies could focus on the ensemble and scale and transferability of deep learning approach for disease diagnostics to different agricultural environments making its utility superior and versatile in diagnosis of diseases in agriculture.

TABLE OF CONTENTS

CONTENTS	PAGE
Board of examiners	ii
Declaration	iii
Acknowledgements	iv
Abstract	v
Table of contents	vi-ix
List of Figures	x
List of Tables	xi
CHAPTER	
CHAPTER 1: INTRODUCTION	**1-5**
1.1 Overview	1
1.2 Background and Present State	2
1.3 Problem Statement	2
1.4 Objectives	3
1.5 Scope and Limitations	3
1.6 Report Organization	4
1.7 Summary	4

CHAPTER 2: LITERATURE REVIEW	**6-10**
2.1 Overview	6
2.2 Related Works	6
2.3 Comparison between existing works	8
2.4 Open Issues	9
2.5 Summary	10
CHAPTER 3: METHODOLOGY/ REQUIREMENT ANALYSIS & DESIGN SPECIFICATION	**11-15**
3.1 Overview	11
3.2 Proposed Methodology/ System Design	11
3.3 Hardware/ Software Requirement	13
3.4 Project Management and Financial Analysis	13
3.5 Summary	15
CHAPTER 4: IMPLEMENTATION	**16-20**
4.1 Overview	16
4.2 Train Model/ Prototype Design	16
4.3 System Testing/ Model Evaluation	18
4.4 Summary	20

CHAPTER 5: RESULT AND ANALYSIS	**21-32**
5.1 Overview	21
5.2 Experimental/ Simulation Result	21
5.3 Performance/ Comparative Analysis	31
5.4 Summary	32
CHAPTER 6: IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY	**33-35**
6.1 Impact on Life	33
6.2 Impact on Society & Environment	33
6.3 Ethical Aspects	34
6.4 Sustainability Plan	34
6.5 Summery	35
CHAPTER 7: CONCLUSION AND FUTUREWORK	**36-37**
7.1 Conclusions	36
7.2 Future Suggested Works	36
7.3 Limitations/ Conflict of Interest	37

REFERENCES **38-39**

APPENDIX A **40-45**

APPENDIX B (None)

LIST OF FIGURES

FIGURES	PAGE NO
Figure 3.1: Methodology Flowchart	13
Figure 4.1: Percentages of Target Attribute	18
Figure 4.2: Dataset Images	18
Figure 4.3: Number of Target attributes	19
Figure 4.4: CNN Model	20
Figure 5.1: Confusion Matrix CNN	24
Figure 5.2: Training loss and accuracy curve of (CNN)	25
Figure 5.3: Confusion Matrix (Xception)	26
Figure 5.4: Training loss and accuracy curve of (Xception)	26
Figure 5.5: Confusion Matrix (VGG16)	27
Figure 5.6: Training loss and accuracy curve of (VGG16)	28
Figure 5.7: Confusion Matrix (DenseNet201)	29
Figure 5.8: Training loss and accuracy curve of (DenseNet201)	29
Figure 5.9: Confusion Matrix (InceptionV3)	30
Figure 5.10: Training loss and accuracy curve of (InceptionV3)	31
Figure 5.11: Comparative Model Accuracy Bar Plot	32

LIST OF TABLES

TABLES	**PAGE NO**
Table 2.3. Comparative Analysis Table with Previous Work	9
Table 3.4: Project Management Table	15
Table 3.5: Estimated Cost	15

CHAPTER 1
INTRODUCTION

1.1 Overview

Dragon fruit, which can produce striking colors and has a peculiar external appearance, is a highly sought crop in the tropical and sub-tropical areas. But this is true for every type of agricultural production and dragon fruit is no exception as it may be affected by a variety of diseases that may cause a decrease in productivity and product quality. This is because management and control of the diseases depend on early and accurate identification and detection of these diseases to avoid crop loss and reduced productivity.[1] The conventional appearance-based approaches have many shortcomings, including longer analysis times, requiring skilled personnel, and potential errors. As the technology grows, especially the artificial intelligence concepts are embracing the world, automated and efficient solutions are on the rise. There are two types of machine learning; deep learning is one of them, and this is a perfect model for the recognition of diseases in agricultural applications.[2] This project aims at enhancing the Deep Learning approach to diagnose dragon fruit diseases using Convolutional Neural Networks (CNNs). Based on a dataset obtained from a nearby dragon fruit nursery, which has 2438 augmented images divided into four target attributes, the Fresh with 620 images, Brown Spot with 609 images, Stem Rot with 605 images, and Turning Yellow with 604 images, the model is expected to provide a correct health condition of the fruits.[3] Several state-of-the-art CNN architectures are explored in this study: Among the networks, we have Xception, VGG16, DenseNet201, and InceptionV3. There are certain benefits and advantages associated with each of these models in terms of the speed, precision and depth of analysis conducted. Xception uses depth wise separable convolution with high computational efficiency, VGG16 adopts the simplest and most effective approach in transfer learning, DenseNet201 optimizes feature reuse to address the vanishing gradient problem by using dense connections, and InceptionV3 uses inception modules to balance accuracy and computational time.[4] The use of these progressive CNN architectures will help the project establish an efficient and precise algorithm for early disease detection. This automated tool benefits farmers by providing timely appropriate actions and treatments as well as positively impacts sustainable farming by preventing crop losses and improving fruit quality. The adopted technologies in agriculture show great progress towards advancing practices in farming and eliminating food insecurity.

1.2 Background and Present State

As an initial step towards developing a direction for the formulation of this report, certain definitions of key concepts and terms that will be utilized in the course of the study should be outlined. This section contains brief definitions of major terms and concepts needed for further reading in the subsequent chapters. Included in this section is a brief on an introduction of the dragon fruit farming and its importance in agriculture, an insight on dragon fruit diseases, a brief understanding of deep learning and convolutional neural network for image classification tasks. Also, this section could discuss the necessity of early disease detection in crop management, the advantages of automated disease detection systems, and disadvantages of traditional disease diagnosis in agriculture. With the aid of these preliminaries, readers can easily appreciate the background and rationale for the study, before engaging in a deeper analysis of the research theme.

1.3 Problem Statement

The reason as to why this study was conducted lies in the fact that there is an increasing need for a proper identification of diseases affecting the dragon fruit crop. There are certain challenges associated with conventional visual inspection techniques These include the fact that the process is slow and that it is liable to human error. The adaptation of deep learning in its more sophisticated forms Convolutional Neural Networks (CNNs) provides an effective solution to this problem. Thus, the study is focuses on the development of an automated system which is aimed to identify the disease at the initial stage and with high accuracy using the best models such as Xception, VGG16, DenseNet201, InceptionV3. Besides, it optimizes crop management and generates cost-effective and environment-friendly technologies for mitigating crop losses and minimizing pesticide application. Recently developed technology for growing this crop can foster great results for the improved health and productivity of dragon fruit, which can benefit the farmers and society, enhance global food supply.

1.4 Objective

This research is motivated by the crucial need to improve disease detection techniques in dragon fruit agriculture. Existing manual inspection methods are prone to subjectivity and inefficiency, and they may fail to fulfill the critical need for timely action against diseases that threaten crop health and output. The growing prevalence and quick spread of illnesses in dragon fruit trees underlines the need for innovative, automated remedies. Deep learning, particularly convolutional neural networks (CNNs), has demonstrated efficacy in picture identification tasks, making it a promising method for detecting plant diseases. The fundamental goal of this research is to develop, implement, and evaluate an advanced deep learning approach that is specifically customized for identifying diseases in dragon fruit trees. Furthermore, the research wants to provide an accurate dataset that includes diverse illness phases and environmental variables, hence improving the suggested models' generalizability. The ultimate goal is to offer dragon fruit growers with an accurate, automated tool for early disease identification, enabling prompt intervention measures, and promoting sustainable production practices.

1.5 Scope and Limitations

The expected output of this study is, therefore, a state-of-art and accurate deep learning model on the detection and classification of dragon fruit diseases. Utilizing advanced CNN architectures such as Xception, VGG16, DenseNet201, and InceptionV3, the model should accurately distinguish between four specific conditions: Fresh, Brown Spot, Stem Rot and Turning Yellow. Performance is defined as accuracy, accuracy, precision, recall, and F1-score metrics, which demonstrate that deep learning works effectively for disease detection. Furthermore, the research shall avail a practical application of the technology to the farmers through the following areas of concern: Improved crop management, reducing possibility of manual inspection, Interventions to prevent disease transfer. It would be a great reference model if this model will be implemented in the real situation because it has a great impact on the agriculture and specifically to the yield and quality of the dragon fruit. This study could also open up avenues for the same kind of studies in other types of crops as well, and thus extend the use of deep learning models across agriculture.

1.6 Report Organization

The suggested report is organized in a thorough way that guides readers through the methodology, conclusions, and outcomes of the study. The distinct purposes of each chapter contribute to the overall structure and complexity of the document. Introduction chapter discuss before proceeding to make the literature review, it is imperative to introduce the research problem, objectives, and significance. Gives the reader an idea of the parameters of the study, the approach that will be used to undertake it, and the results that are expected from the study. Background chapter discussed previous studies and literature relating to diseases affecting dragon fruit crops, deep learning, and usage in agriculture. Aims to explain why disease identification is critical in crop context and the opportunity of deep learning in farming. Methodology chapter explains the data acquisition procedures, general features of the data set, and initial data preparations. Summarizes the architecture of a number of CNN configurations and other experimental information. Experimental Results displays the results of the experimented models and quantifiable measures of model performances. Introduces a new CNN based approach for the detection of diseases with the comparison of its performance to other similar CNN models. The Impact on Society focuses on evaluating societal, economical, and environmental implications for the developed technology. Explains how the farmers can be empowered through the automated disease detectable system and improve on crop production and sustainable use of farm produce. Chapter Conclusion and Implications for Future Research This last section is a brief conclusion of the entire study where main findings and contributions of the study are highlighted. It is concluded with the recommendation of future research directions and implications in the practical uses in the agriculture.

1.7 Summary

The first chapter provides background information on the detection of dragon fruit diseases in preparation to employing an advanced deep learning method. Of all the diseases in farming, dragon fruit is introduced by underlining the economic and agricultural importance of the fruit, with special focus put on the effects of diseases on production and quality. The post outlines a comparison between the conventional approaches that entail the identification of diseases, which may be slow, inadequate, and requiring human intervention, but deep learning is presented as a better solution to the problem. The chapter also defines the research aims and objectives, wherein an attempt is made to enhance the accuracy of the diseases' diagnosis using CNNs. It also explains the concept of using a large dataset and an annotated one with a connection to Xception, VGG16, DenseNet201 and InceptionV3 as the state-of-art pre-trained models. I chose to begin the introduction with the enumeration of the potential advantages of the use of deep learning in precision agriculture as such presentation creates the basis for the subsequent sections of the paper dedicated to the method and its application, as well as its implications on society.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

The second chapter of the research is the literature review that examines the state of the art and development in regards to predicting plant diseases based on deep learning models. The paper starts with the description of conventional approaches, which are not very effective in terms of precision and speed. The review then focuses on contemporary approaches under deep learning, more so the CNN that has demonstrated promising results in the identification of diseases from images in various crops. Some selected earlier works are elaborated and how pretrained models including Xception, VGG16, DenseNet201, and InceptionV3 can be used effectively in the identification of plant diseases is demonstrated. Likewise, the chapter also looks at issues concerning huge datasets that requires annotation process and appropriate preprocessing stages to improve the performance of the models. Finally, it discusses potential and development issues for this field, stating the importance of solving and improving issues that have an impact on such areas of precision agriculture and farming.

2.2 Related Works

Literature review focuses on previous studies that have been done regarding the detection of dragon fruit disease and the use of deep learning technologies in the agricultural field. Earlier works have described conventional approaches to disease diagnosis and its challenges, this urged for automation solutions. Several studies have been conducted in attempts to use deep learning methods, especially CNNs, for different tasks in the field of agriculture, one of which is crop disease detection. However, there is still a lack of publications that focus on dragon fruit disease detection through the use of advanced Deep Learning technique.

Malathy, S., et al. [5] used CNNs, this method seeks to use picture analysis to detect and diagnose fruit-related diseases, providing farmers with an invaluable tool for crop management. The suggested method, which focuses on using Python for implementation, demonstrates its potential to improve crop development and assist in disease management by achieving an impressive accuracy level of 97%. This accuracy level is the greatest that the study has documented, demonstrating how well the CNN-based method is in identifying fruit diseases.Hakim, Lutfi, et al. [7] presented three different kinds of dragon fruit stem situations using digital image processing, this study investigates feature extraction techniques such as color moments and gray level co-occurrence matrices. The use of the provided feature extraction strategies produces an ideal accuracy score of 87.5% in differentiating between insect stings, smallpox, and stem rot by using Support Vector Machine and k-NN methods for comparison. Additionally, this accuracy is the greatest that was attained during the investigation, demonstrating how well the suggested method works to identify various dragon fruit stem states. These outcomes highlight how well the suggested intelligent system can identify and predict diseases affecting dragon fruit. Trieu, Nguyen Minh,et al [9]presented an autonomous dragon fruit assessment and sorting system that uses a KNN and CNN combination to extract characteristics and categorize fruits into categories according to pre-established criteria. The system demonstrates its efficacy in automated fruit categorization with a high accuracy of 92.85% using data obtained from 2610 dragon fruits. In addition, the system provides notable increases in output, with an approximate productivity of five times that of manual categorization techniques. Shakil, Rashiduzzaman, et al. [10] Using extensive feature selection approaches on real-time photos, this research presents an autonomous system for diagnosing dragon illnesses. Important characteristics are prioritized according to mutual score through the use of analysis of variance (ANOVA) and least relative contraction and selection operator (LASSO) techniques, which improve the efficacy of machine learning algorithms. Interestingly, when used to the top-ranked feature sets derived from the LASSO feature ranking technique, AdaBoost and Random Forest classifiers attain the greatest accuracy of 96.29%, demonstrating the effectiveness of the system in disease detection. Wismadi, I. Made, et al. [12] used a deep learning application that uses the Smaller VGGNet-like Network approach to determine whether dragon fruit is ripe. Dragon fruits are classified as ripe or suitable for harvesting using CNN classification, with a high accuracy level of 91%. An AUROC value of 0.95 from testing over many epochs indicates the resilience and efficacy of the proposed method for determining the maturity of dragon fruit. Fu, Yuhang, et al. [13] applied deep learning and machine learning techniques to identify fruit infections early on in order to cure them promptly, taking into account any possible health hazards related to eating contaminated fruits. The greatest accuracy of 96.87% is attained using a suggested CNN model that has three convolution layers, highlighting the effectiveness of deep learning approaches in illness identification. Furthermore, CNN models are compressed by a Differential Evolution (DE)-based procedure. The VGG16 model achieves a maximum compression of 82.19% without a significant decrease in performance, showing the possibility of resource-efficient implementation.

2.3 Comparison between existing works

The work included in the studies takes advantage of different methodologies in deep learning and machine learning for fruit diseases identification and classification issues. The literature review also revealed that the CNN-based method by Malathy et al. and Mehta et al. outperform conventional techniques concerning accuracy. Mamat et al., for example, apply YOLO versions that demonstrate great accuracy in detecting the oil palm fruit and several fruits. Furthermore, feature extraction technique as presented by Hakim et al. highlighted the potential of feature extraction techniques when it comes to the distinction between various stem states of dragon fruit. Trieu et al. introduced accurate and fast independent systems for fruit categorization while Fu et al. focus on disease diagnosis with deep learning techniques. Altogether, these studies underscore the ability of the machine learning approaches in enhancing the way fruits are managed and food safety maintained.

TABLE 2.3 COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1	Malathy, S., et al.[5]	CNN	97%
2	Hakim, Lutfi, et al.[7]	Support Vector Machine (SVM), k-NN	87.5%
3	Trieu, Nguyen Minh,et al[9]	KNN, CNN	92.85%

4	Shakil, Rashiduzzaman, et al.[10]	AdaBoost, Random Forest	96.29%
5	Wismadi, I. Made, et al.[12]	CNN	91%
6	Fu, Yuhang, et al.[13]	CNN	96.87%

2.4 Open Issues

The area of interest in this study may be described as the introduction of a more efficient deep learning model to detect diseases in dragon fruit plants. More precisely, this research aims at using Convolutional Neural Network (CNNs) to predict the state of ten different types of dragon fruits, namely, Fresh, Brown Spot, Stem Rot, and Turning Yellow. This will involve data gathering and preparation of a dataset for dragon fruits' images, as well as training and optimization of the several CNN models with the goal of performance assessment in disease diagnosis. Although this concern is primarily methodological and revolves around the model and the available data, this paper also discusses the possibilities of automated disease detection in agriculture in general. These include possible gains in farming efficiency; decrease in losses resulting from pests and diseases; and adoption of 'sustainable agriculture'. Nonetheless, the study does not attempt to explore the areas of application or marketing of the emergent technology under analysis, investigating only the research and development phase. Consequently, this study intended to define the problem under investigation in an effort to showcase understandings of the feasibility and necessity of utilizing deep learning approaches for diagnosing diseases affecting dragon fruit farming.

2.5 Summary

In the literature review chapter, the current trend of deep learning for plant disease detection with an interest in dragon fruit is looked at. That is centered on conventional strategies as well as a comprehensive description of how it operates with the primary draw back that characterized this technique being a lack of precision together with low execution velocity. The review focuses on the improvement achieved in CNNs and demonstrates that these networks outperform other approaches when it comes to disease diagnosis based on images. A case of using pre-trained models that are Xception, VGG16, DenseNet201, and InceptionV3 is as follows, they are used in the following agricultural applications. This informs the significance of the use of vast number of annotated datasets and other preprocessing techniques in improving the accuracy of a given model. Thus, issues like scalability, building the infrastructure for large scale and highly reliable systems, or the problem of overfitting are discussed as well. Finally, the chapter points out the direction for the future studies in deep learning for precision agriculture with a particular focus on the creation of models for large-scale and high-performance agricultural applications.

CHAPTER 3
METHODOLOGY

3.1 Overview

The research subject is mainly about creating a new deep learning model that is to be used in disease detection in dragon fruit plants. This entails using convolutional neural network (CNN) which will help in examining the images of dragon fruits to categorize the fruits into five health conditions namely Fresh, Brown Spot, Stem Rot, and Turning Yellow. The main essential equipment for this study includes digital cameras or high-quality cameras to capture images, computers or other devices that can be efficiently used for model calculating, and TensorFlow, PyTorch, or other deep-learning frameworks that allow implementing CNN models. Moreover, there can also be the use of data annotation for creating labels for the given data set, and there will also be the use of version control systems like Git for the purpose of development. The use of instrumentation ensures the detailed assessment and advancement of the proposed deep learning solution to detect dragon fruit diseases.

3.2 Proposed Methodology

In the current paper, both the proposed methodology is presented in details in order to describe a sequential flow of the advanced Deep learning for dragon fruit disease detection.

Data Collection: Images at high resolution are obtained from an adjacent dragon fruit farm where diseased plants are grown under controlled conditions for profiling a wide range of disease status and growing environments.

Labeling: Each of these is labeled with one of four target attributes: Fresh, Brown Spot, Stem Rot, or Turning Yellow which tells about the health condition of the dragon fruit shown in the image.

Image Augmentation: Rotations, flips as well as scale augmentations are done so as to increase the range of data in the given set and thus improve recognition of patterns by the model.

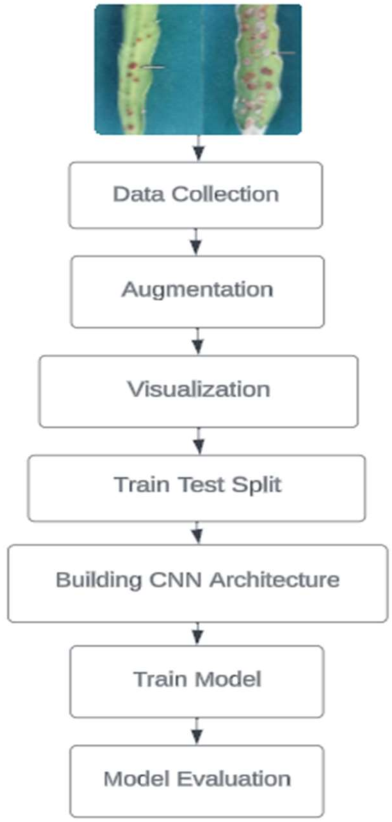

Figure 3.1 Methodology Flowchart

Model Selection: A number of existing advanced CNN models and also some Transfer Learning model such as Xception, VGG16, DenseNet201, and InceptionV3, is discussed based on its ability to work in the field of image recognition.

Model Training: They feed the selected model with the augmented dataset through transfer learning to fine-tune the pretrained weights of the model for dragon fruit disease detection.

Model Evaluation: Evaluating the performance of the trained model involves the use of a validation dataset through accuracy, Precision, Recall, and F1-score metrics.

Test Model: Last but not least, the final model with the highest accuracy is subjected, to a test data set to evaluate its suitability in real-life scenarios.

This approach enhances the effectiveness of addressing and finding a solution to the deep learning model in detecting dragon fruit diseases.

3.3 Hardware/ Software Requirement

Several requirements are important in order to achieve optimum outcome for the advancement of the proposed methodology. First, collecting a dataset of images of dragon fruit that is diverse and as much as possible representative of the problem, with corresponding labels indicating the disease, is necessary. To achieve good performance of the model, this dataset should comprise of a number of different diseases, and different environmental conditions in train data set. Furthermore, one needs computational infrastructure for creating models and training them, as well as to solve the tasks of verifying models. Supercomputing solutions consisting of GPUs are preferred to speed up training times and to manage the high computational requirements of deep learning techniques. In addition, to practice and adapt CNN architectures or try other approaches such as recurrent networks, having access to other deep learning frameworks such as TensorFlow or PyTorch is required. These frameworks offer extensive means and functionalities or Application Programming Interfaces, for developing, training and executing deep learning models efficiently. Lastly, knowledge of data preprocessing techniques, model selection strategies, hyper parameter optimization, and performance measures plays a vital role while tuning the model to a get high accuracy and thus better disease detection rates. Organization, multidisciplinary predicated from data scientists, agronomist, and software engineers might be needed to ensure the successful implementations.

3.4 Project Management and Financial Analysis

In addition to the above practices, the management of the project shall be based on agile methodologies for flexibility in responding to changes in requirements. The team would comprise data scientists, agronomists, and software engineers to plan and carry out the different stages effectively. Teleconferences and a scheduled review of project status will help manage communications and also make decision-making a smooth process. The financial requirements for this project will mainly include the expenses that will be necessary to gather data, to use computationally intensive tools and algorithms, to acquire necessary software tools, and to remunerate people resources needed for the realization of the present plan. It would help to seek support from headings such as agricultural research funding, avenues of funding, and agricultural research funding sources. The controlling process would cover the budget expiration to be utilized on the project to facilitate the delivery of the project requirements on time. Also, meaningful expenditure/revenue comparisons will be made in order to assist in determining the research's payback period, as well as the project's likelihood for replication and marketing. In given below Table 3.4 & 3.5 showing the Estimated cost and Project Management table.

TABLE 3.4: PROJECT MANAGEMENT TABLE

Work	**Time**
Data Collection	1 month
Papers and Articles Review	3 months
Experimental Setup	1 month
Implementation	1 month
Report Writing	2 months
Total	8 months

TABLE 3.5: ESTIMATED COST

SN	**Components**	**Estimated Cost (BDT)**
01.	Hardware	500-1500
02.	Software and Tools	500-1500
03.	Data Collection and Processing	5000-6000
04.	Documentation and Report Writing	500-1500
05.	Miscellaneous	500-1500
06.	Contingency	500-1500
Total Estimated Cost		7500-13,500

3.5 Summary

Understanding the approach of deep learning for identifying a disease in dragon fruit requires learning several phases: Firstly, a large amount of data of healthy and diseased image of dragon fruits are gathered and annotated. Since the images which represent data are large, some initial operations are performed such as resizing, normalization and data augmentation to enhance the model performance. It is a convolutional neural network (CNN) which architecture is frequently based on such networks as Xception, VGG16, DenseNet201 or InceptionV3 for extracting features. The model is then trained with the dragon fruit dataset, modifying the last few layers of the network, which depends on the number of disease categories. In training, such measures as early stopping and dropout are used in order to avoid overtraining. The trained model is then again evaluated by a calibration set and further tested on a previously unseen test data set to gauge the Model's accuracy, precision & recall. Moreover, the effectiveness of the model you present is evaluated to check its efficiency in the actual environment.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

The implementation entails setting up of the necessary software and hardware for model development and testing. Supercomputers with the incorporation of GPUs are used to train deep learning models effectively. Frameworks like TensorFlow or PyTorch are installed to help with the implementation and testing of the different models. The dataset is usually partitioned into the training set, validation set and the test set, in a 80:10:10 ratio. Augmentation is used as a way to expand datasets and augment training data by rotating, flipping, and scaling the images. For comparison, several modern architectures of CNNs are chosen, namely, Xception, VGG16, DenseNet201, and InceptionV3. The models are learned based on the training dataset, checked using the validation dataset, and lastly tested on the test dataset to assess their accuracy in classifying dragon fruit diseases.

4.2 Train Model

This data set was obtained from a nearby dragon fruit nursery, being careful to obtain different environmental conditions affecting the plant as well as the disease afflicting the plant. Digital photographs were taken by portable cameras with personal-quality resolution, comprising various aspects of dragon fruit health, to include a total of 2438 images. These images were extracted and augmented for the purpose of improving the variety of the dataset. They include hot probe, move, blackspot, curve, rust, mildew, and temp attributes, which are associated with seven different diseases or health conditions of dragon fruits that can be used to train and test the deep learning models for disease identification.

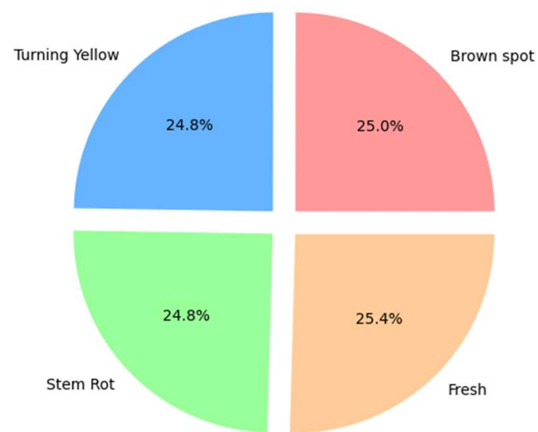

Figure 4.1: Percentages of Target Attribute

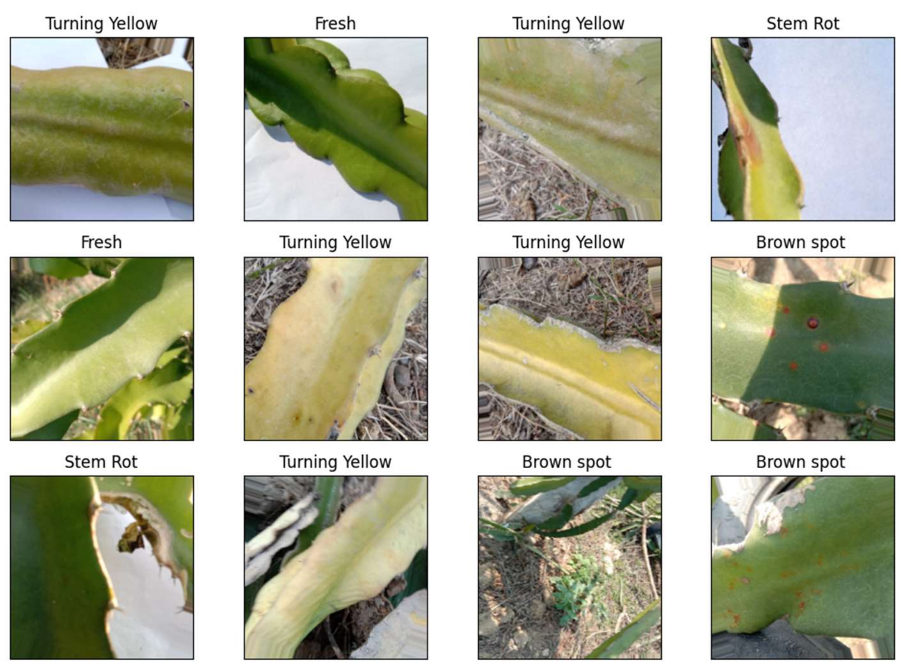

Figure 4.2: Dataset Images

Figure 4.3 shows the number of target attributes I included in my research.

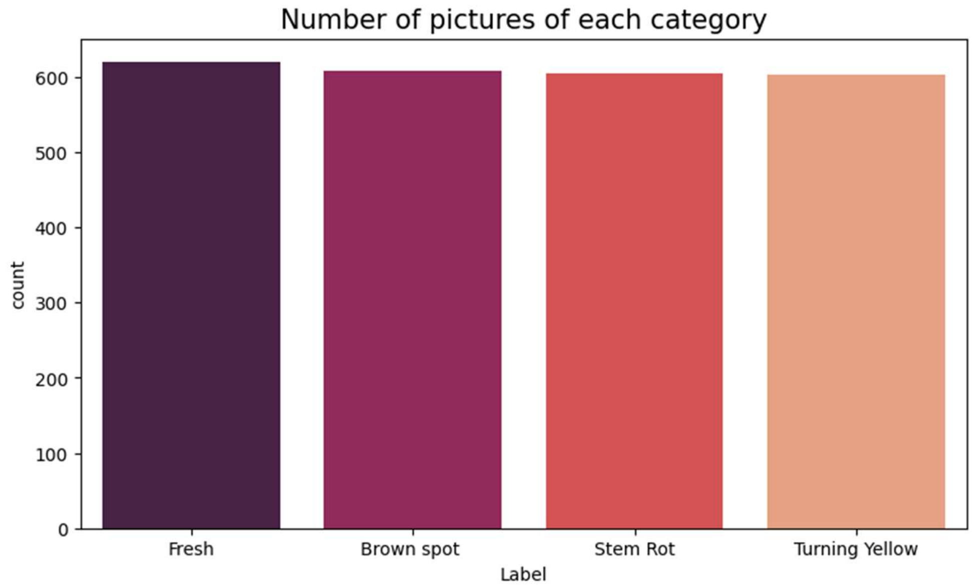

Figure 4.3: Number of Target attributes

In Figure 4.3, dataset is categorized into four target attributes: In the remaining 4 categories, Fresh (620 images), Brown Spot (609) images, Stem Rot (605 images), and Turning Yellow (604 images).

4.3 Model Evaluation

Several requirements are important in order to achieve optimum outcome for the advancement of the proposed methodology. First, collecting a dataset of images of dragon fruit that is diverse and as much as possible representative of the problem, with corresponding labels indicating the disease, is necessary. To achieve good performance of the model, this dataset should comprise of a number of different diseases, and different environmental conditions in train data set. Furthermore, one needs computational infrastructure for creating models and training them, as well as to solve the tasks of verifying models. Supercomputing solutions consisting of GPUs are preferred to speed up training times and to manage the high computational requirements of deep learning techniques. In addition, to practice and adapt CNN architectures or try other approaches such as recurrent networks, having access to other deep learning frameworks such as TensorFlow or PyTorch is required. These frameworks offer extensive means and functionalities or Application Programming Interfaces, for developing, training and executing deep learning models efficiently. Lastly, knowledge of data preprocessing techniques, model selection strategies, hyper parameter optimization, and performance measures plays a vital role while tuning the model to a get high accuracy and thus better disease detection rates. Organization, multidisciplinary predicated from data scientists, agronomist, and software engineers might be needed to ensure the successful implementations. The custom CNN model comprises several Conv2D and MaxPooling2D layers, Flatten, Dense, Dropout, and Batch Normalization layers for processing input images to obtain the features and classify them. Some of the pretrained models are Xception, VGG16, DenseNet201, and InceptionV3. Xception mostly utilizes depth wise separable convolutions, VGG16 has 13 convolutional layers and 3 fully connected Dor point-wise layers, DenseNet201 has 201 layers, and InceptionV3 apply factorized convolutions and several auxiliary classifiers to focus on scales. Operating processes consist of loading & initializing the model by linking various libraries such as TensorFlow/pytorch & having pretrained weights. Intermediate layers are used for feature extraction, and generally, new datasets are fine-tuned using the TFL replacing the last layers and training it with a small learning rate. Input images are always preprocessed while the output can be either class probabilities or some other relevant parameters.

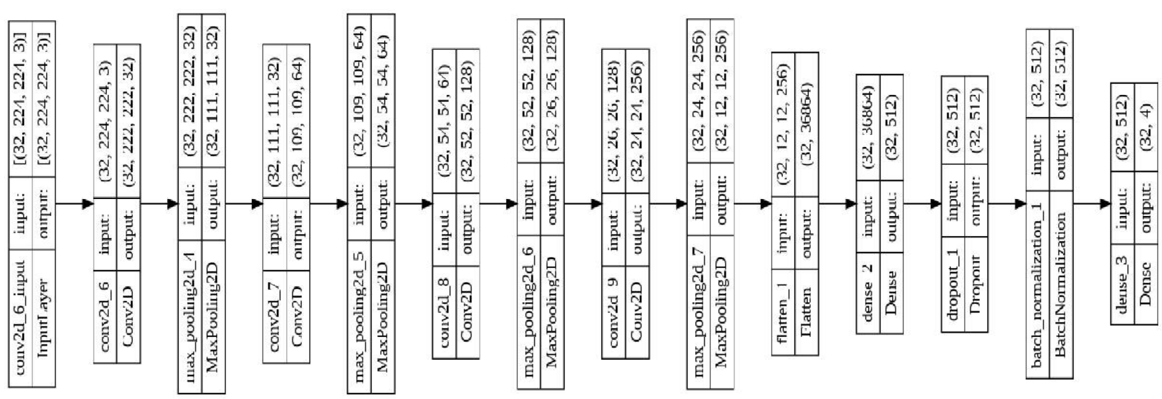

Figure 4.4: CNN Model

4.4 Summary

When it comes to the practical application of an advanced deep learning method for the detection of diseases of dragon fruits, several crucial stages can be identified. First, a large number of healthy and diseased dragon fruit images are gathered and labeled. Second, the images necessitate preprocessing, and augmentation to improve the model on compositions. A convolutional neural network (CNN) structure is then trained possibly on large databases, and fine-tuned on this database. Thus, the developed model is validated and fine-tuned for the finest accuracy in practice-oriented detection of diseases.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

Several requirements are important in order to achieve optimum outcome for the advancement of the proposed methodology. First, collecting a dataset of images of dragon fruit that is diverse and as much as possible representative of the problem, with corresponding labels indicating the disease, is necessary. To achieve good performance of the model, this dataset should comprise of a number of different diseases, and different environmental conditions in train data set. Furthermore, one needs computational infrastructure for creating models and training them, as well as to solve the tasks of verifying models. Supercomputing solutions consisting of GPUs are preferred to speed up training times and to manage the high computational requirements of deep learning techniques. In addition, to practice and adapt CNN architectures or try other approaches such as recurrent networks, having access to other deep learning frameworks such as TensorFlow or PyTorch is required. These frameworks offer extensive means and functionalities or Application Programming Interfaces, for developing, training and executing deep learning models efficiently. Lastly, knowledge of data preprocessing techniques, model selection strategies, hyper parameter optimization, and performance measures plays a vital role while tuning the model to a get high accuracy and thus better disease detection rates. Organization, multidisciplinary predicated from data scientists, agronomist, and software engineers might be needed to ensure the successful implementations.

5.2 Experimental Result

findings of this research show the efficiency of using five various CNN architectures, namely CNN, Xception, VGG16, DenseNet201, and InceptionV3, for dragon fruit, disease detection. The visualization of the proposed layers shows that DenseNet201 has the highest accuracy of 97. 23%, and this can be cited as the reason why it outperforms the other models. This research indicates that DenseNet201 has numerous dense connections that enhance the feature reuse and gradient flow to higher layers so that it yields better performance. On the other hand, accuracy results in an application of VGG16 were lower compared with other architectures proving that depth of networks and their representational capabilities for this task is somewhat limited. In conclusion, the experiments presented in this study emphasize the validity of model selection and architecture design as factors that can determine the efficiency of disease detection in dragon fruit plants. These results indicate that there are certain issues attached to certain parts of the project that need to be looked at in relation to the specific aspect in question so as to comprehend why one particular pattern has been highlighted out of all the possible patterns that have been result from the samples numerically.

I am evaluated the Accuracy, Precision, Recall, and F-1 Score of the Confusion Matrices for our proposed methods.

Accuracy:

Accuracy determines how accurate the model's predictions are as a whole, accomplished by dividing the total number of samples by the successfully classified samples. They give the overall idea of the performance of a model but may not necessarily give a comprehensive picture.

Accuracy: (TP+TN)/(TP+TN+FP+FN)……………………………………………(i)

Precision:

Accuracy is focused on the percentage of the correctly predicted positive cases from all those positive cases predicted by the model.

Precision = TP/(TP+FP)……………………………………………………….(ii)

Recall:

Recall is the ratio of correctly predicted positive among all the actual positives. It is alternatively called sensitivity, or the true positive rate.

Specificity is calculated as TP / (TP + FN)………………………………………(iii)

F1 Score:

The F1 score is developed from the harmonic mean of the precision and the recall. It provides a reasonable measure that considers the precision and recall factors. Specifically, the F1 score is useful in cases where class distribution is uneven because it measures the harmonic mean between false positive rate and false negative rate. This is an optimal measure that shows how the F1 score balances between precision and recall.

*F-1 score = (2*Precision*Recall) / (Precision + Recall)……………………(iv)*

In given below we are describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

CNN

Achieving Test Accuracy of CNN is 92.62%. In below Figure 5:1 describing the confusion matrix of CNN

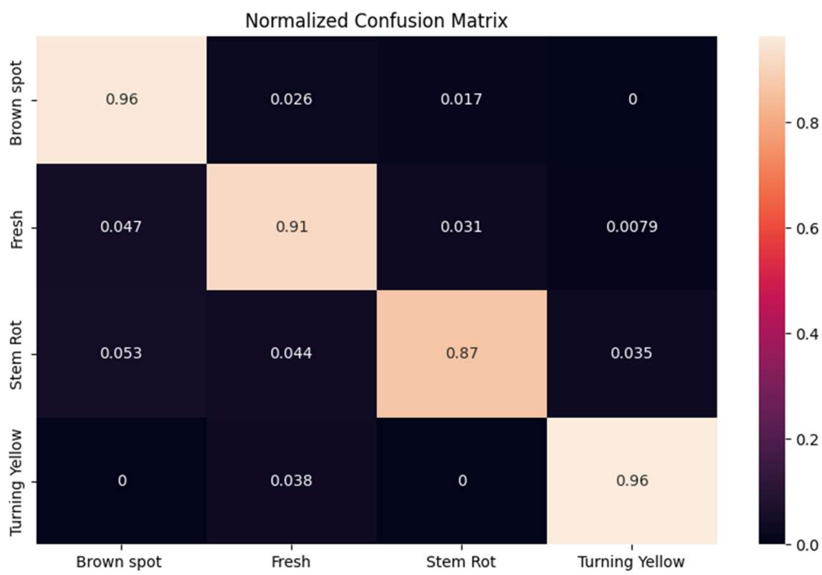

Figure 5.1: Confusion Matrix (CNN)

Figure 5.1 shows the CNN model confusion matrix breaks down classification performance into four categories: Among them, the vivid titles include: Brown Spot, Fresh, Stem Rot, and Turning Yellow. It demonstrates that the model is quite effective in identifying Turning Yellow when compared with the attributes and metrics, precision and recall are at 0.96. Similar to the trends described above, our results also indicate that the Brown Spot category is highly accurate with a recall of 0. A value of 0.96, which means that most of the Brown Spot occurrences are accurately mentioned, illustrates the Brown Spot model. As for the Stem Rot category, it has a slightly lower recall with the value of 0.87; however, the given precision equals to 0.94 which means that there are still some mistakes done by the algorithm, yet good number of the given results are accurate.

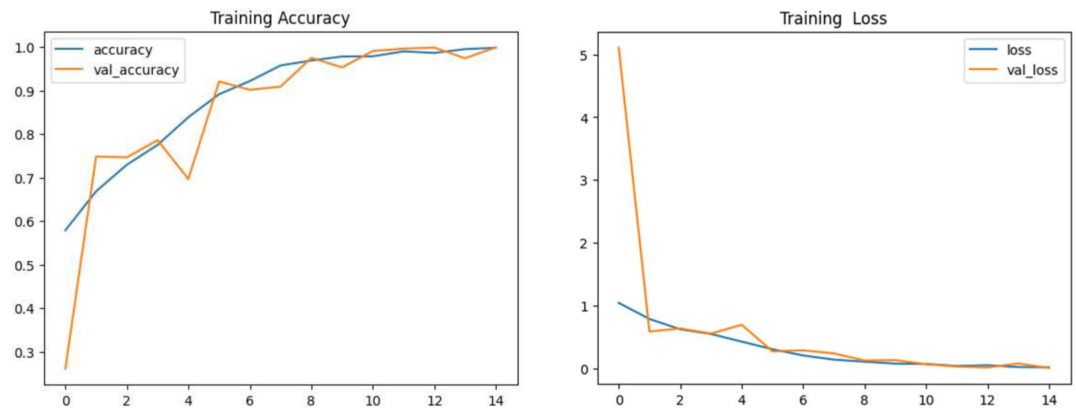

Figure 5.2: Training loss and accuracy curve of (CNN)

Figure 5.2 shows the training accuracy and loss plots for the CNN model derived from the training dataset depict that as the number of epochs increases, training accuracy increases while training loss decreases. This also implies that the proposed model is able to capture features from the training datasets. However, such type of ideal curves would have a trend where accuracy progressively increases as it approaches one. and a decrease in the amount lost towards 0. This optimal value is zero, which is difficult to achieve in real life applications.

Xception

Achieving Test Accuracy of Xception is 92.52%. In below Figure 5:3 describing the confusion matrix of Xception: In given Figure 5.3 shows the confusion matrix for the Xception model reveals high performance across the four categories: Symptoms include; Brown Spot, Fresh, Stem Rot and Turning Yellow. Brown Spot and Fresh categories, for instance, have high levels of precision and recall, which are both over 0. 90, which means that there is a high accuracy when identifying and classifying these components automatically. Stem Rot, on the other hand, is somewhat less accurate, having a recall of 0. 85, its precision remains equally high at 0. 92, which indicates that there may be some subjectivity with the identified typology, however the predictions are quite precise. From the table above it is clear that Turning Yellow setup show the best performance in terms of both precision and recall that are both around 0. 95-0. 96. Specifically, accuracy of this model is 0. 93 meaning all the categories were well as balanced and the classes appropriately grouped.

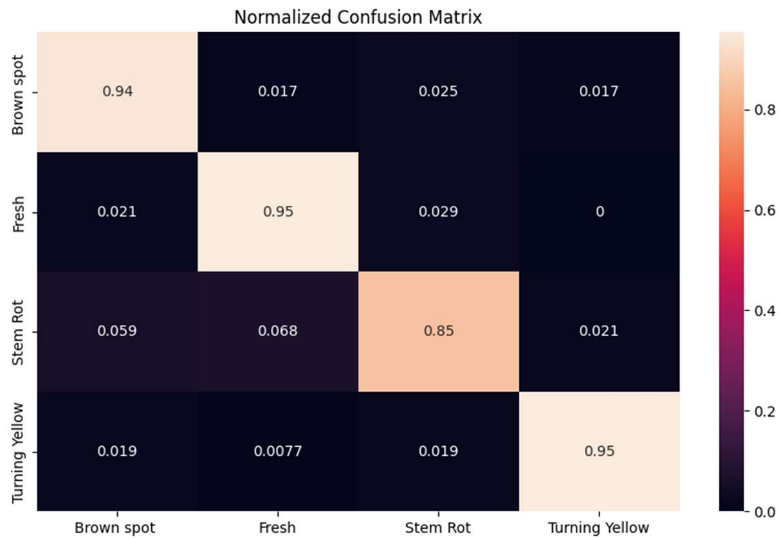

Figure 5.3: Confusion Matrix (Xception)

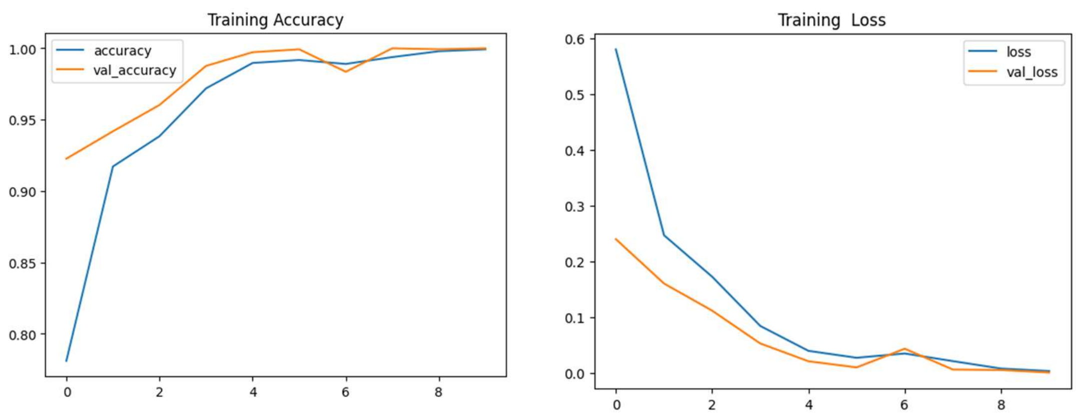

Figure 5.4: Training loss and accuracy curve of (Xception)

Figure 5.4 shows the following figures represent the training loss and accuracy for the Xception model; From the graphs, it can be seen that as epochs increase, training accuracy increases from approximately 0. 5 to nearly 1. 0 which proves severe learning and hence better classification accuracy is achieved. Similarly, the training loss reduces from approximately 1, at the start of the test phase: From 0 to nearly 0, which shows the substantial learning over time to reduce the mistake. In an ideal world, such curves would ideally reach up to 1. An appropriate score of 0 has been chosen for both accuracy and precision. 0 for loss and while this sounds theoretically feasible, it can hardly be a practical reality in many fields. The observed trends are hence evidential of a good learning process, yet the validation metrics need to be regularly checked about generalization and overfitting.

VGG16

Achieving Test Accuracy of VGG16 is 86.89%. In below Figure 5:5 describing the confusion matrix of VGG16

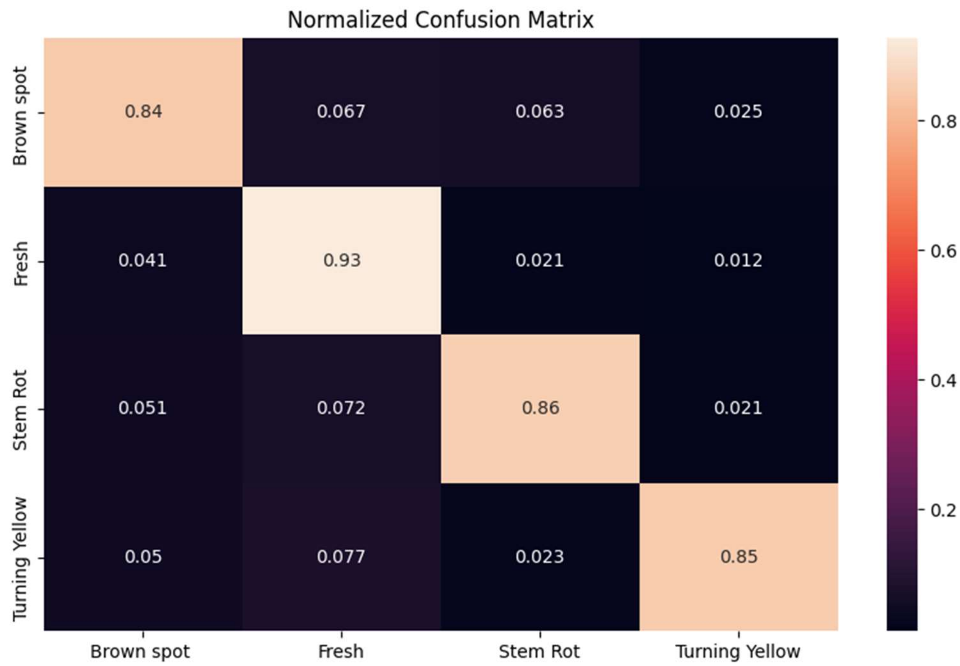

Figure 5.5: Confusion Matrix (VGG16)

Figure 5.5 shows the confusion matrix for the VGG16 model indicates varying performance across the categories: Some of the titles include: Brown Spot, Fresh, Stem Rot, and Turning Yellow. For Brown Spot, precision and recall rates are approximate that are 0. 85, suggesting that it has some errors but it is mostly slotting well. Fresh shows a higher recall at 0 percent while stale shows a lower mean recall of 0. 85 but a lower precision at 0. 81, indicating that this algorithm is expected to generate more false positives. Stem Rot retains high performance metrics consistently with precision and recall remaining close to 0. 86-0. 89. Turning Yellow has medium accuracy of 0. 94 but a lower recall at 0. 85, which means there were some occurrences that were not captured. In general, the model proposes an accuracy of 0. 87 which can be seen as a good, but not great overall performance on all the criteria.

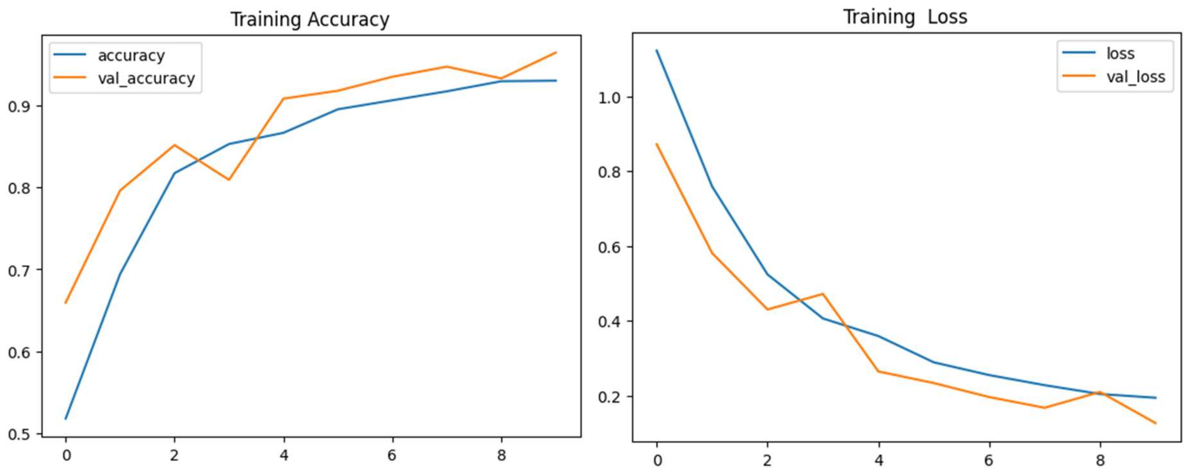

Figure 5.6: Training loss and accuracy curve of (VGG16)

Figure 5.6 shows the Training and validation loss and accuracy of VGG16 The initial training accuracy of VGG16 is very low however as the no of epochs increases the training accuracy rises inferring that the model is indeed learning with time how to classify the training data. At the same time, the training loss drops from a relatively high value, showing that the error rate decreases during the training process. Ideally, accuracy would move up to a value of 1 indefinitely as can be seen from the graph below. , which means that increase would rise to 0 and loss would fall to 0. The ideal value is thus 0, although this is hardly ever attained in real-life practice. It is equally important to watch out both curves of training and validation and differentiate between a situation where the model gives a high accuracy on training data but low accuracy on validation data this is known as overfitting and a case whereby, the model is unable to learn adequately the data patterns this one is called underfitting. This feature means that the model will have good ability to generalize to other data.

DenseNet201

Achieving Test Accuracy of DenseNet201 is 97.23%. In below Figure 5:7 describing the confusion matrix of DenseNet201.

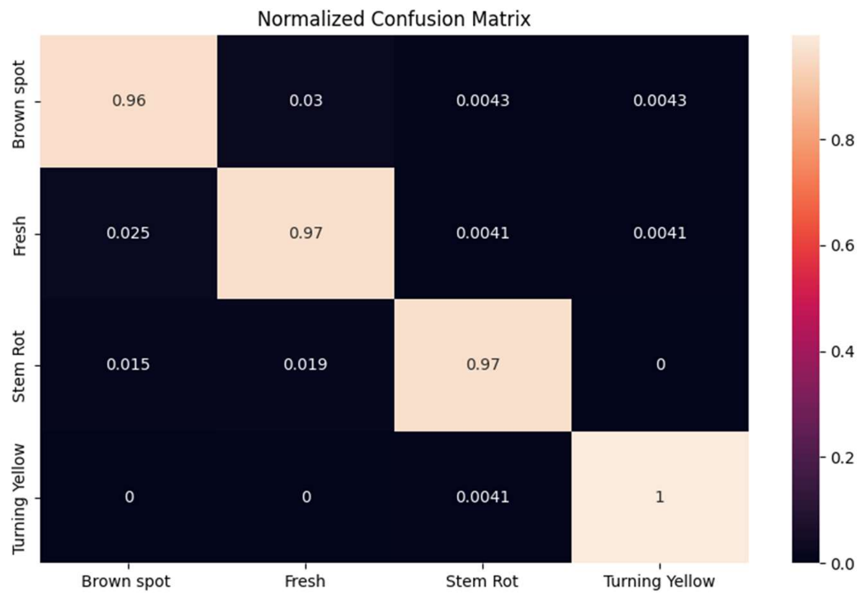

Figure 5.7: Confusion Matrix (DenseNet201)

Figure 5.7 shows All of the four categories: Brown Spot, Fresh, Stem Rot, and Turning Yellow are improved in DenseNet201 models confusion matrices. Brown Spot and Fresh both provide a high level of precision and recall that varies between 0. 95-0. Another result obtained was 0. 97 meaning that most instances were classified correctly with little misclassification. In the case of Stem Rot, the information retrieval measures of precision and recall are almost perfect, being higher than 0. 97.

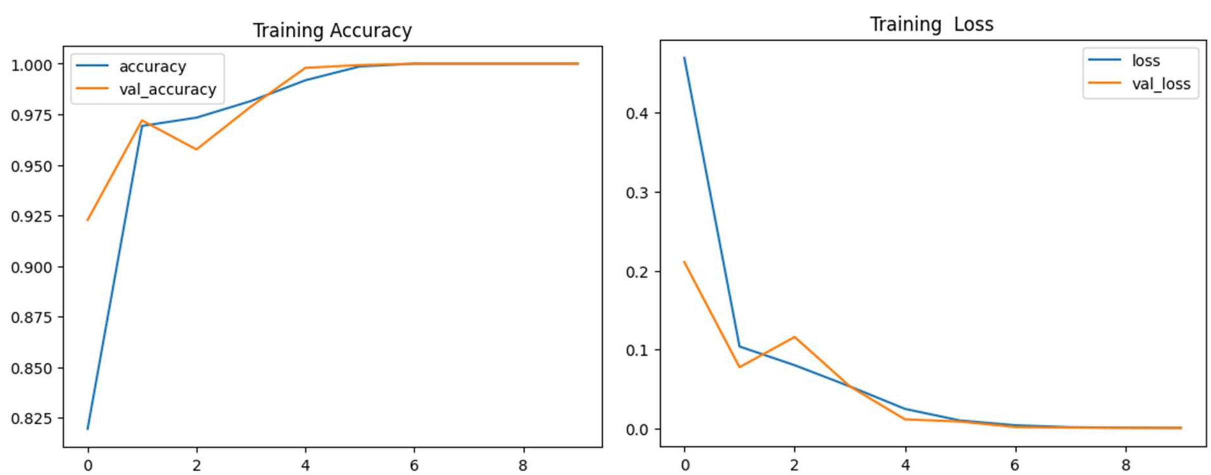

Figure 5.8: Training loss and accuracy curve of (DenseNet201)

Figure 5.8 The training curves of DenseNet201 model illustrate that training loss and accuracy are respectively increasing with the increase number of epochs from about 0. 825 to nearly 1. It is equal to 0, which suggests great learning and progressive enhancement of the classification of the pictures over time. Furthermore, the value of the training loss decreases from approximately 0. 35 to near 0. It has an average value of 0 which shows that there is large improvement in error correction. It is possible that perfect curves will see accuracy attain the value of 1. 0 while loss reduces to 0. 0, this idea of a perfect setting is hardly ever seen. However, it is crucial to evaluate different validation metrics in order to identify overfitting which is when the model does well with training data but poorly with new data and underfitting where the model does not efficiently learn the relations in given data. It also serves to guarantee that the model is capable of better learning from new data.

InceptionV3

Achieving Test Accuracy of InceptionV3 is 91.80%. In below Figure 5:9 describing the confusion matrix of InceptionV3.

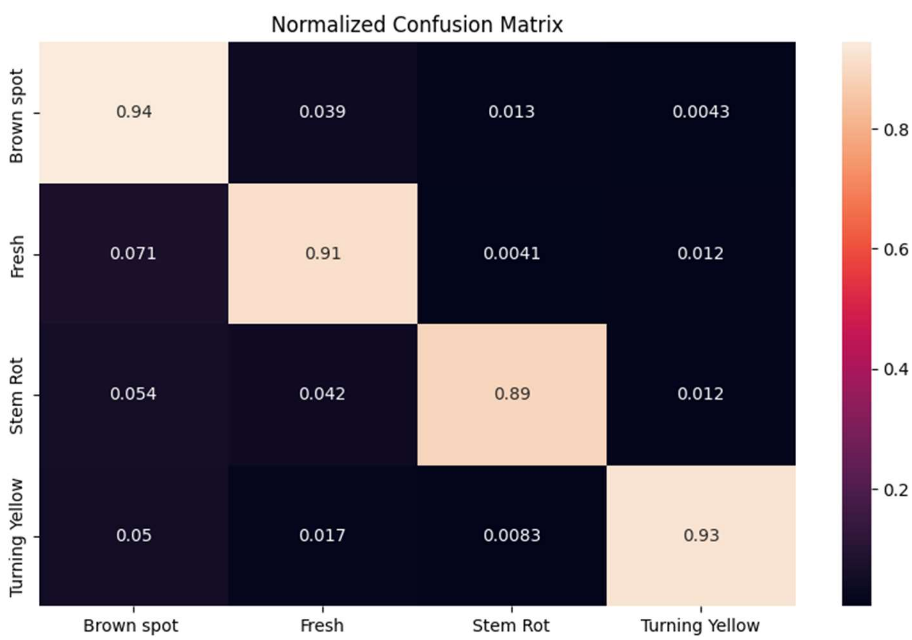

Figure 5.9: Confusion Matrix (InceptionV3)

Figure 5.9 shows the confusion matrix for the InceptionV3 model reveals strong classification performance across the categories: Brown Spot, Fresh, Stem Rot, and Turning Yellow are the major diseases affecting the yield of rice production. Looking at

Brown Spot, it has a better recall which stands at 0. Estimated overall accuracy is 94 percent, which suggests that most cases are correctly classified; however, the precision of 0. 84. Fresh holds a good accuracy and nearly equal numbers for both precision and recall in around 0. 90-0. 91, reflecting reliable performance. Stem Rot, gives very accurate results at 0. 97 but lower recall at 0. 89, which means there are some false negatives exist in the guide. According to the evaluation, Turning Yellow has a high precision and recall, which is more than 0. 90, showing robust classification. In conclusion, the model achieves an average of 0. 92 thus ensuring that there is a good balance in all the areas of performance showcased in the index.

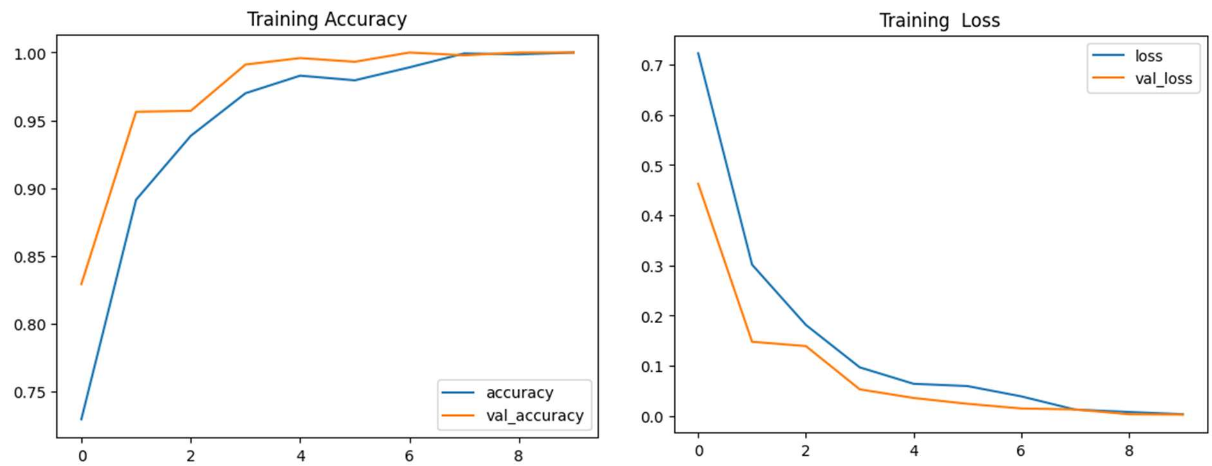

Figure 5.10: Training loss and accuracy curve of (InceptionV3)

Figure 5.10 shows the training loss and accuracy curves of InceptionV3 indicates that training accuracy starts off low but gradually increases, which suggests that the model is gradually improving its ability in classifying the training data set with increasing epochs. At the same time the training loss increases from a high initial value and declines, which approximates a decrease in classification error. Ideally, accuracy would be equal to or greater than 1. 0 and loss would come down to 0. 0, although such a state is hardly ever reached in reality. One must track and analyze both training and validation metrics to understand the overfitting and underfitting where training accuracy is high while validation accuracy is low or vice versa. This makes sure that the model works well on unseen data that are still distinct from the training data set.

In given below I am showing Comparative Model Accuracy Bar Plot

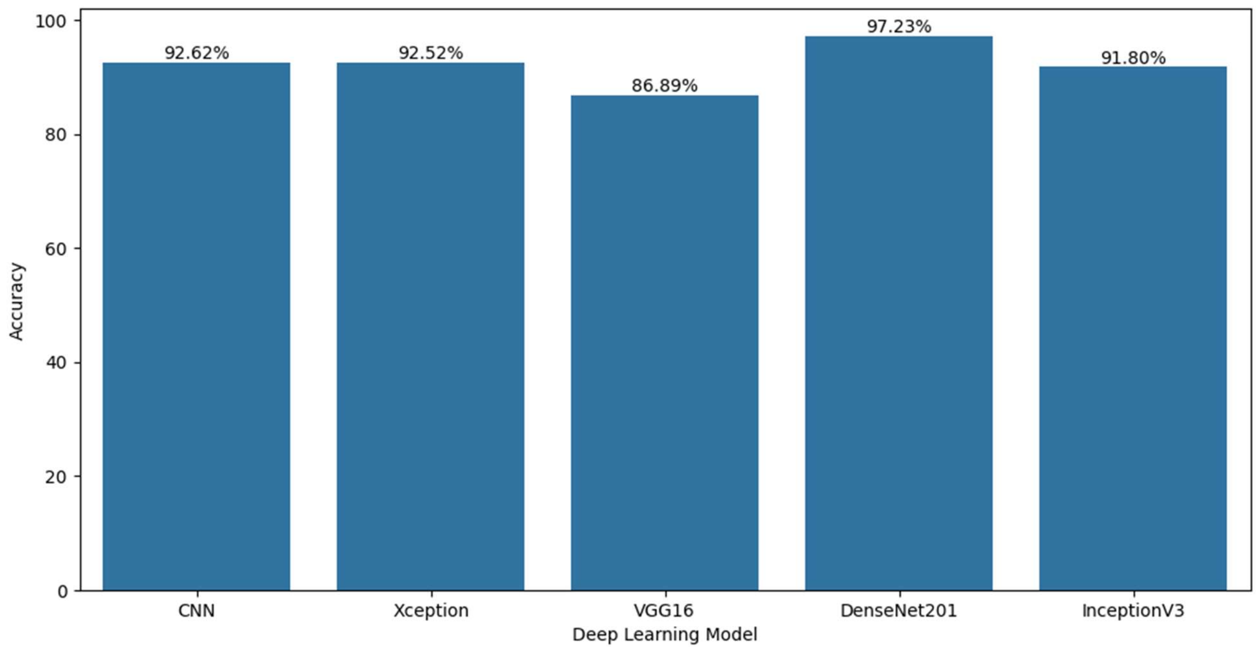

Figure 5.11: Comparative Model Accuracy Bar Plot

Figure 5.11 shows the accuracy of each model is evaluated on a test dataset, with the following results: CNN source says: 92. 62%, Xception: 92. 52%, VGG16: 86. 89%, DenseNet201: 97. 23%, InceptionV3: 91. 80% According to his research paper, DenseNet201 has high density connection and thus it enhances better features reuse and Gradient flow leading to better performance of about 80%. On the other side, VGG16 demonstrated a low level of accuracy in comparison with other architectures, this can be attributed to several factors; namely the depth and representational power of the architecture for this task.

5.3 Performance and Comparative Analysis

Analyzing the performances of various CNN architectures for the detection of dragon fruit disease resulted in the following findings: DenseNet201 unveils the highest accuracy, which confirms the efficiency of utilizing the dense connections to capture the detailed features. On the other hand, VGG16 was slightly slower and less accurate, which could be attributed to their rather simple structure. These considerations highlight the importance of choosing the right CNN architectures that will suit the nature of the given dataset and problem. Furthermore, the findings indicate potential directions for future research, including the attempts to combine the architectures within a single approach or to perform transfer learning to use the existing models with better results. In summary, this discussion highlights the importance of architectural design for improving the effectiveness of DL models in agricultural settings to foster improved disease diagnosis in dragon fruit farming.

5.4 Summary

The purpose of this research was established as follows: To devise and test a new deep learning model for identification of diseases in dragon fruit plants. In this regard, the study used CNNs, and through the dataset acquired from a neighboring dragon fruit nursery, compared different CNN architectures for disease diagnosis. The results reveal DenseNet201 as the model with the highest accuracy Compared to other models, DenseNet201 features high accuracy levels proving the efficiency of dense connectivity when it comes to learning feature interactions. Furthermore, central to the study was the specification of architectural design that determines the efficiency of disease detection outcomes. In general, the research provides avenues for further understanding of new advances in the use of technology in identifying diseases affecting the agriculture and implemented better forms of protecting the dragon fruits.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

It can be asserted that the potential of developing an improved deep learning model for the diagnosis of diseases in dragon fruit will be highly beneficial to society. When farmers are equipped with a reliable diagnostic tool, the technology can improve the farming practices, saving money and minimizing losses due to disease outbreaks, all of which contributes positively to food security. Furthermore, the use of such technology enhances sustainable agricultural operations because it reduces the use of pesticides and efficiently utilize resources. Additionally, timely detection of diseases in dragon fruit crops means that yields and quality increase, positively impacting the farmers and local economy. In conclusion, the presented technology benefits the society in terms of productivity not only in agriculture but also in economy, conservation of the environment, and the general well-being of communities in farming regions.

6.2 Impact on Society & Environment

In this case, the use of an enhanced deep learning technique applied in the identification of the dragon fruit disease is of paramount importance to the environment. Since it can facilitate early and accurate diagnostics of the diseases, the application of the technology reduces the usage of chemical pesticides and fungicides which, in turn, has a positive impact on the environment and ecosystems. Also, through the enhancement of some crop practices as well as rational use of inputs, the technology enhances sustainable farming, and has a reduced impact on the environment as compared to traditional farming practices. The reduction in pesticide use concurrently decreases the risks of threat posed to non-target organisms and increases the bio-diversity in agriculture systems. In conclusion, the implementation of this technology leads to a better solution of environmental preservation in protecting the crops and hence influence the sustainable prosperity of farming systems.

6.3 Ethical Aspects

All in all, the use of advanced deep learning technology for the identification of dragon fruit's disease brings a lot of advantages however the main ethical concerns must not be ignored. It is equally important to establish its availability for usage preferably to the small holder's farmers and other disadvantaged unit. Also, preserving data confidentiality and integrity will play a significant role in preserving farmers' limited rights when collecting, storing, and disseminating agricultural data. Also, the mechanisms of creating the algorithms and using them for decision-making should be transparent to ensure that the artificial intelligence system is trusted and responsible. Furthermore, this shift from conventional farming systems and human resource solutions should be regulated well in order to reduce negative socio impacts emanating there from yet harness the benefits of such developments. In the end, ethical standards should inform the proper application and use of deep learning technology in the field of agriculture to the common good of stakeholders.

6.4 Sustainability Plan

This research work therefore has the following sustainability plan of development in line with the overall sustainability vision for this research project that focuses on the development of sustainable technology: To begin with, the key strategy is to enhance awareness and enable the agricultural stakeholders or the farmers to utilize the disease detection mechanism based on deep learning effectively. This includes programs that provide support for farming practices in the form of training, technical support and facilitating access to materials that promote the practice of sustainable farming. Moreover, assessment of the efficiency and effectiveness of the technology as well as the effects on agricultural yields, environment and other socio-economic aspects will be made now and then in order to establish the possibility of enhancing on the use and implementation of the technology. In total, the sustainability plan helps to promote the reliability and integration in Agri-tech advancements so that the impact of the technology is fully realized for all parties, as well as the resourcefulness of the biomaterials and societies for current or future usage.

6.5 Summary

To a large extent, the society benefits from the application of an enhanced deep learning technique for diagnosing dragon fruit diseases in agriculture production to improve its yield. The identification of diseases in the initial stages and their diagnosis also helps in decreasing crop losses and makes availability of food more predictable and increases the farmers' income. This technology also reduces the use of chemical pesticides hence enhancing environmental health and safety of the produce that consumer to eat. Besides, it promotes the further development of precision agriculture, which creates the foundation for new approaches to farming and may be used in relation to different crops. In a nutshell, the above-discussed approach leads towards realizing a more efficiency, sustainability, and profitability of the agricultural output.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

In conclusion therefore, this research project has upon revealed the capability, the possibility of deploying advanced deep learning techniques in the advancement of disease detection in dragon fruit plants. Utilizing convolutional neural networks and a multiclass dataset, the study revealed DenseNet201 as an efficient model to perform this classification with a notable accuracy rate in disease differentiation. The presented results are of great concern and importance to agriculture practices, it provides farmers an accurate and intelligent system to assist in diagnosing and mitigating diseases. Besides, the study suggests that research and development should be sustained and more focus should be placed in utilizing new techniques in solving problems within the agricultural sector. In summary, the study benefits the progress of sustainable agriculture and food security; it demonstrates potential application of deep learning in the protection and management of crops.

7.2 Future Suggested Works

However, there are several areas that need further investigation in following up this study on the use of deep learning approach for disease detection in dragon fruit. To begin with, establishing how to assemble various CNN architectures for the better disease identification performance and resilience could be effective. In the same regard, expanding the applicability of the developed technology to several geographical regions and crop species would be useful to the research. Therefore, it is necessary to carry out experiments in the field and tracking studies in order to evaluate the effectiveness and socio-economic impact of the technology in agriculture. However, expanding the feature set with other variables like environmental conditions and past disease rates could enhance regular deep learning models and help to create preventive measures in healthcare systems. All in all, development of these areas will enhance agricultural technology and support sustainable agricultural practices among crop producers in the future.

7.3 Limitations

The following are some of the issues which need to be overcome as the formulation of an improved deep learning technique for the detection of the disease disaster on the dragon fruit: Firstly, acquisition of a dataset of images of the fruit containing corrupted or healthy instances of the fruit from different geographic locations is a major task. Moreover, the labelling of the annotated data needs to be done with great precision and may take considerable amount of time due to its complexity. In addition, training deep learning models and especially with complicated structures. The model complexity/complexity of the system needs to be well balanced so as to enhance the possibility of deployment on the field given the environmental conditions that prevail in agricultural production. In addition, the training of the models into generalizable forms, which can easily be deployed in different geographic regions and varying climatic conditions forms another challenge to this research. Finally, the implementation of the developed technology in the current practices requires operational integration in the field coupled with various social and economic factors that may pose a stumbling block to the innovation in traditional farming practices.

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Appendix A

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

Title:
AN ADVANCED DEEP LEARNING APPROACH FOR DETECTING DRAGON FRUIT DISEASE

Student ID: 201-15-14162 & 201-15-14143

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Teach the newly acquired and the previous learned knowledge in the Detecting dragon fruit disease problem for the Final Year Design Project (FYDP).	**PO1**
CO2	Considering the goals in the context of this FYDP, it will be necessary to consider various aspects of the goals in developing a corresponding solution to this problem.	**PO2**
CO3	Discover multiple problem domains within the literature, define the problem, and set up these objectives for the FYDP	**PO4**
CO4	Carry out economic appraisal and cost control and use appropriate project management techniques at every phase of the development of the FYDP	**PO11**
	Phase -II	
CO5	Design and build technical solution related to technical specifications and system parts or processes to fulfill the given standards and regulation of public health and safety; also, cultural and socio-economic and environmental factor in this FYDP	**PO3**
CO6	Select and implement proper techniques, tools, and modern engineering and IT tools for handling sophisticated engineering activities, which entail prediction and modeling during the implementation of this FYDP, constrained by existing policies.	**PO5**
CO7	Identify various social, health, safety, legal, cultural factors, and their related responsibilities in relation to civil engineering practice and the solution of this problem using formal deductive approach coinciding with understanding of context.	**PO6**
CO8	Understand and assess the historical sustainability and effectiveness of professional engineering activities in solving complex engineering problems in the context of social and environmental systems.	**PO7**
CO9	This FYDP shall incorporate the principles of ethics and practice principles and guidelines of the profession.	**PO8**
CO10	Competent in performing efficiently in the context of a single worker and as part of a team or a team leader within this FYDP, in relation to the different types of groups and in an interdisciplinary manner.	**PO9**

CO11	Maintain and create clear communication with the engineering community and the society in general about various intricate engineering activities to include comprehending and preparing comprehensive reports and design documentation, as well as the ability of giving and receiving clear instructions in this FYDP.	**PO10**
CO12	Recognize, the value of self-motivated and throughout the life continuing education within the context of technological advancement and have the preparedness and capacity to undertake life-long learning pursuits.	**PO12**

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

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

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	The engineering signifies and complies with the fundamental engineering (K3) hence why there is the usage of deep neural networks, data augmentation techniques and different types of CNN architectures for image processing and classification. The project fulfills the K4 specialist knowledge by doing deep learning with CNN, and transfers learning for enhancing Detecting dragon fruit disease.	**Page no:** [32-33] **Section:** [3.2] **Page no:** [12-17] **Section:** [1.1]
				The engineering practice & design (K5) is applied in this project through the figure of process of experiments. The project relates to the knowledge area of engineering practice and technology (K6) by using Deep Learning Model.	**Page no:** [32] **Section:** [3.2] **Page no:** [34-35]

					Section: [3.4]
				This project guarantees to K8 (Research Literature) because it uses a review of recent studies such as Detecting dragon fruit disease using deep and Transfer learning, which demonstrates awareness of contemporary approaches present in the literature.	**Page no:** [23-30] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This paper responds to EP-2 because it identifies the barriers in Detecting dragon fruit disease, such as disadvantages of earlier techniques and difficulties in implementation utilizing deep learning. It puts forward difficulties in interpretative procedures involved in the spatial distributions; it contains suggestions on how to improve the diagnostic techniques.	**Page no:** [30-31] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	The present project contributes to the response of EP-3 wherein careful demonstration of the tangibility of the outcomes of the experiment is established and stressed the utilization of deep and transfer learning as the chosen significant solution for the improvement of Detecting dragon fruit disease approaches.	**Page no:** [37-48] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's fields of application are not just confined to computer science and engineering; it has affected Detecting dragon fruit disease correctly EP-4.	**Page no:** [23-31] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	The work done in this project entails a holistic solution bearing in mind that high levels of problems require an integration of different components done in data collection from local farm and nursery, statistical analysis and proposed methodology to EP-7 in the solution of complex issues in data collection.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	The resources of the study include High-Performance Computing infrastructure, GPUs, deep & Transfer learning frameworks, annotated datasets, and ethical consideration for systematic research for the progression Detecting dragon fruit disease.	**Page no:** [33-35] **Section:** [3.5]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This project benefits the society by enhancing Detecting dragon fruit disease, yet, it also respects environmentally friendly principle with blended optimization computational resources and ethical standard on local farming data data.	**Page no:** [50-51] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		In the present research work, the author has extend the earlier existing research by exploring a different approach in Detecting dragon fruit disease via deep and deeper learning model exemplified with preliminary terminologies and backed by systematic comparative analysis on the overall results attained from this research work thereby proposing something new.	**Page no:** [23-29] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	The current project tackles CO4 in terms of aligning project management comprehensively with financial control, which including strict distinctive project planning, resource leveraging, and budgetary estimates for the most efficient resource use in every phase of the research activity.	**Page no:** [20] **Section:** [1.6]
2	CO9	Yes	This indicates that the project meets the ethical standards focusing on privacy of data, informed consent, and clear documentation of the research process that will serve the public good and enhance the responsible use of classification technologies that are in line with the outlined CO9.	**Page no:** [51] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	In terms of the project's responsibility to constantly learn and adapt within the context of a constantly shifting technological environment (CO12), the project has carried out comprehensive data collection, performed robust statistical analyses, designed detailed methodologies, reported significant experimental results, and provided extensive analysis, demonstrating the project's awareness of current issues and its efforts to refine the necessary technologies and strategies to better fit the current climate.	**Page no:** [32-36, 37-48] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

AN ADVANCED DEEP LEARNING APPROACH FOR DETECTING DRAGON FRUIT DISEASE

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