A PROPOSED DEEP LEARNING ARCHITECTURE 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 "A Proposed Deep Learning Architecture for Detecting Dragon Fruit Disease", submitted by **Shazedur Rahman & Mahbub Alam** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14-07-2024.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dewan Mamun Raza, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Diseases have remained as one of the major issues affecting dragon fruit production due to its susceptibility to infections. The framework of this research work is the use of a deep learning technique for an assessment of disease infections in dragon fruits with data sourced from a local nursery. The dataset comprises images annotated with four target attributes. A dataset of 2000 high-resolution images, captured under various lighting conditions from local nursery and farms. After Augmentation and Labeling 4,827 images was annotated with four target attributes. New-germination (1300), Germination-white (1203), Heavy red germination (1200), and Wilting (1124). Five models: Xception, VGG19, InceptionV3, MobileNetV2 and one custom CNN model was used for the classification of diseases. Among those, the highest accuracy level was recorded at 93.49 % by using MobileNetV2, while the other three models: Xception, VGG19, InceptionV3 achieved 91.01%, 76.80% and 86.04%, respectively. The result of the complex metric in MobileNetV2 outperforms all other methods significantly while the good performance of the custom CNN which achieved an impressive 91.82% proves that it is an eminently suitable solution designed specifically to act on this task. This implementation helps farmers be able to identify diseases from their crops early enough to reduce crop loss and at the same time help reduce the use of chemicals. Future research could consider several directions for improving the use of deep learning in the identification of dragon fruit diseases. Exploring the possibility of using techniques, in which several deep learning models are employed simultaneously, may prove beneficial to increase the general reliability of the results

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CHAPTER 1
INTRODUCTION

1.1 Overview

Dragon fruit, a natural fruit of vivid red color inside, is considered as one of the export horticultural crops which has demand around the world. Nevertheless, its production is threatened by a variety of diseases which can negatively impact yield and quality of the produce. These diseases, if not diagnosed on time and correctly, become hard to manage and control, thus both the crops and the farms' economic stability are at peril. In the past, various forms of sickness identification have been done via physical assessment, which costs a lot of time, requires rigorous effort, and is highly subjective to human input R. Shakil et al. Research conducted on deep learning, a part of artificial intelligence, has demonstrated its capacity to improve and automate image-based detection of diseases. CNNs which are known to handle image classification tasks in the most efficient way possible can be trained in order to identify various patterns that are tend to be associated with different diseases in dragon fruits. Furthermore, by using transfer learning and training from pre-trained models in particular, the amount of time spent on training can be considerably cut down, as well as the percentage of false-negative detections minimized. L. Hakim, S. P. Kristanto et al. This study presents the detailed model of deep learning that is appropriate for the identification of diseases in dragon fruits. It entails gathering a versatile dataset from an available local dragon fruit nursery, enriching the data to improve on it, and ensuring good labeling for the training process. custom CNNs as well as Xception, VGG19, InceptionV3, and MobileNetV2 models are used for high classification accuracy and low computational cost Anita Jaquiline Lado et al. Thus, this research will incorporate the latest deep learning technology with the real-life farming context of the dragon fruit to provide accurate and precise disease diagnosis early enough to prevent the fruit's destruction.

1.2 Background and Present State

To begin discussing deep learning for the detection of the dragon fruit disease, one must first define core ideas and background information. This section aims on presenting the importance of dragon fruit producing for agriculture and the problems that diseases present. There are challenges associated with identifying diseases using conventional techniques, but deep learning offers the potentials for changing the current practices in agriculture. It also comprises specifying convolutional neural networks (CNNs) and transfer learning, as well as their use in classifying images. Knowledge of these preliminaries forms the basis of the comprehensive investigation into the research method, experimental outcome and the result of the employment of more sophisticated artificial intelligence in agriculture. It is hoped that this groundwork will offer a solid background from which the subsequent chapters' discourses and results can be understood.

1.3 Problem Statement

These diseases adversely affect the production of new fruits and quality of existing dragon fruit, which in turn affects the economy of the farmers and the agricultural sector. Conventional visual inspection techniques are quite exhaustive and tedious since they are done manually and can also be quite inaccurate. This work aims at proposing solutions to these challenges through the use of deep learning methods, which has shown great potential for image recognition. Thus, by using accurate automated disease detection system and by employing techniques like CNN and transfer learning the research intends to assess the early signs of the disease correctly. This technological intervention is very essential in increasing the speed and accuracy in disease diagnosis hence improving the sustainable Agriculture practice, reducing on economic losses and producing good quality produce. The study focuses on the importance of adopting artificial intelligence to agriculture, thus opening avenues for new and creative solutions to conventional agricultural issues.

1.4 Objective

The cultivation of this fruit is now more vital because it has nutritional values, and it provides the economy benefits. However, diseases like wilting, red spots and white spots push down the productivity of the plant and this becomes a challenge to farmers. Probabilistic models are ineffective because the detection of diseases is normally upheld through physical examination, which is labor-intensive and prone to human influence. In the case of diseases that are difficult to detect, deep learning presents a revolutionized solution of identifying diseases by analyzing images. Therefore, using advanced models such as CNNs and transfer learning, the goal of this research is to establish a reliable early detection system of diseases in dragon fruits. This does not only seek to improve crop care and production but also proclaims the application of artificial intelligence in transforming agricultural practices in a bid to support sustainable farming and also economic development of the agricultural sector.

1.5 Scope and Limitations

As proposed in the problem statement, the research focus of this study is the development and assessment of deep learning models to diagnose dragon fruit diseases with locally sourced data. It involves such models like Xception, VGG19, InceptionV3, MobileNetV2, CNN in regard to their accuracy, precision recall and F1-score. But issues might be encountered with regard to sprains pertaining to disease prominence at various developmental phases and climatic states that could affect extrapolation in the model. Also, there is an issue with the availability and quality of annotated datasets affecting the model and its fitness for practical agriculture.

1.6 Report Organization

It also helps provide a more systematic coverage of the selected research topic, starting from theoretical background and ending with practical suggestions, to bring some insights and solutions to the growers' association. Introduction chapter produce an outline about the importance of detecting the diseases on the dragon fruit using deep learning, the issues pertaining traditional methodology, and the opportunity of AI in agriculture. Literature chapter establish the theoretical back ground of deep learning, CNNs, transfer learning and their uses in the domain of image classification with a focus on agriculture. Methodology chapter explains the procedure of data gathering from an online local nursery, the methods applied for image enhancement, labeling, the criteria used in choosing the model, the strategies of training the model, and the methods used in assessing the model's performance. Experimental Results chapter reports of the models' performance in terms of accuracy, precision, recall, and F1-score of custom CNN and transfer learning models such as Xception, VGG19, InceptionV3, and MobileNetv2 for detecting diseases in dragon fruits. The Impact on Society chapter discusses the opportunity for increased farming yields, decreased losses, and environmentally friendly farming techniques utilizing automated disease detection on dragon fruit production. Conclusion and Future Research chapter presents the overall results of the analysis, orphans conclusions from the conducted study, offers recommendations for further application and practical implementation, and indicates new directions for the development of AI in agronomy.

1.7 Summary

The first chapter introduces the general knowledge which is aimed to help the reader to comprehend the use of deep learning in the detection of dragon fruit diseases. This paper reviews the importance of and issues with diseases affecting agriculture and food security. The chapter starts with the reason for the use of deep learning models entitled as Xception, VGG19, InceptionV3, MobileNetV2, and CNN for the identification of diseases as these models have the ability to information improve disease management practices. When discussing about diseases, the analysis focuses on a proper identification of diseases as the key to solving the problem of low yields and poor quality of crop production, which is critical for sustainable agriculture.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

The literature review chapter gives an overview of earlier research works that centered on deep learning in plant disease diagnosis especially on dragon fruit. A number of methods identified in prior studies including Xception, VGG19, InceptionV3, MobileNetV2, and CNN as well as their assessment indicators. This chapter compares models' pros and cons, together with trends in accuracy, precision, recall, and F1-score on various datasets and under different settings for experimentation. To fill the gap revealed in the papers reviewed, this paper aims to combine current research findings essential in the identification of future research focal points for optimizing deep learning based disease diagnosis for efficient and wide-spread agricultural disease management.

2.2 Related Works

A literature review is done in this context to present the current state of research and achievements made in the context of deep learning for plant disease detection. This paper looks at different methods and frameworks that have been applied before elucidating on their advantages and disadvantages. Thus, it is proposed to analyze these works to reveal potential weaknesses and further improve the accuracy and efficiency of disease detection in dragon fruits with additional deep learning architecture

As given below, I am writing a similar paper review, which will help me more:

R. Shakil et. al. [5] used an automatic agro-based framework especially for diagnosing the disease in dragon plants with real time picture data feature selection algorithms. From the picture processing and segmentation, the necessary characteristics are defined and evaluated by applied ANOVA or LASSO. Six classifier techniques are adopted to evaluate the effectiveness of the selected features which is 96% for both AdaBoost & RF. Improvements of 29% Also, a significant potential at optimizing the number of features of the disease recognition systems since using only the LASSO selected features reduced the time. In the study L. Hakim, S. P. Kristanto et al. [6] color moment and GLCM were applied to extract the features to differentiate the different stem states of dragon fruit through image processing. In this context, by employing SVM and KNN as the comparison methods the work attains a veracity of 87 percent. Significantly, smallpox, stem rot, insect stings 5% accuracy in the identification of diseases affecting the dragon fruit plants; thus, the importance of the multiple feature extraction methodology in disease detection for dragon fruit plants as implemented in the SVM model. Anita Jaquiline Lado et al. [7] have established the Neural Network and RF classifiers on the dragon fruit dataset with healthy and ill fruit and leaves photos, which are divided into four groups and contain 41 photos. Thus, both the classifiers yield cross-validation accuracies that lie in a 70-82% span according to the 10-fold cross validation method. Thus, they were accurate to between 9% and 11%, implying that the ability to accurately classify dragon fruits was comparable to the systems' performance. Based on the findings of this study it could be concluded that there is need to choose the correct classifiers depending on the dataset characteristics to get constant modeling for a given task. Nguyen Minh Trieu et al. [8] described an automated assessment and sorting method for dragon fruits that uses a KNN model and a CNN to extract factors such as length, breadth, and flaws for categorization into three groups: G1, G2 et G3. got through data gathering from 2610 dragon fruits from farms and packing centers and has an accuracy of 92%. up to 85% accuracy and at the same time greatly increases production, which is 5 times higher compared to manual sorting. S. Mehta, V. Kukreja et al. [9] have provided a multi-classifying solution of dragon fruit diseases using CNN-SVM strategy that integrates the strength of both to enhance the diagnostic accuracy and speed. Thus, with the help of the given visual data analysis, the system offers an opportunity to detect the pattern of illnesses through a machine learning-based approach in precision as high as 97. 98%. 4%. Compared with other similar existing systems that employ CNN and groups and SVM, this neural network demonstrates its efficiency to accurately predict diseases that affect dragon fruit; thus, the improvement of disease diagnosis technology is progressing. V. M. T. et al. [10] employed CNN LSTM for classification and sorting the pomegranate fruits into normal and abnormal then it is use for identifying the classification of four diseases. Based on the receiver operating characteristic (ROC) diagram and applying parameters like color, texture as well as form in the hybrid CNN-LSTM model an average accuracy of 92% is attained which is then increased to 97. less than 1% using the dragonfly method. Some of the procedures in the pre-processing stage include map reduced methods and the reduction of dimension that enhances the high speed in identifying the diseases affecting pomegranate fruits. S. Malathy, A. N. Sheila and S. S. Ilayam et al. [11] used CNNs to diagnose diseases in fruits and used the information to educate farmers on how to improve production. Thanks to the features taken into consideration, CNNs can distinguish photos and improve the agriculture in the future. The employment of Python for more complex analysis is possible; in total, 97% of diseases are detected, and thus deep learning algorithms reveal their potential in agriculture's research and application. X. Li, W. Xiang et al. [12] proposed research that aimed to develop a video stream inspection system for the classification and counting of dragon fruit blooms, green and red fruits in plantations, which uses YOLOv5 in classifying the objects while Byte Track in object tracking. For the staff, the average identification accuracy level was found to be 95 percent. 0%, so the selected approach results in individual accuracies of 94. 1%, 94. 8%, and 96. 0. 6% for floral, green and red fruit category, and counting efficiency for all the categories was also satisfactory. The method runs in real-time with a frame rate of 56 frames per second, making the method practically reasonable in agricultural environments for accurate counting of fruits. Special consideration for the identification of the maturity of dragon fruit was addressed by Abhishek G et al. [13] offered a fresh approach to overcoming the challenges that are hard-coded in the physical characteristics of the fruit. In VGG16 model, it is possible to achieve great accuracies of up to 95% of the results. 93%, 95. 31%, and 96. 47% for unripe, a bit ripe, and ripe phases, respectively; Taking into account data augmentation and preprocessing the percentages led to 54% for unripe, a bit ripe, and ripe phases. The extracted characteristics include mean, standard deviation, and entropy; inserted into the SVM classifier, it achieves competitive accuracies, but lower than VGG16, which proves that VGG16 is superior to others in the aspect of maturity recognition. N. Ismail et al. [14] pro-posed a machine vision system for non-destructive fruit inspection which integrates the deep learning techniques along with stacking ensemble techniques to achieve higher level of accuracy. Several deep learning models are studied; these models are compared to EfficientNet when it comes to rating apples and bananas, and it turns out the latter has the highest overall performance. The implementation of real-time inspection with Raspberry Pi comes up with the accuracy rates of 96. For apples it was identified that it was 7% while for oranges it was 93. 8% for bananas, which is higher than the result of the previous approaches and proves the effectiveness of the proposed system in the framework of the fruits' inspecting and sorting task. Thus, B. K. R et al. [15] proposed the CNN-based system for the fruit quality check to minimize the financial losses in agriculture. Proposal of a CNN with pre-set design and the transfer learning with the VGG model can be used to effectively differentiate fresh and rotting fruits. The suggested algorithms have demonstrated practically 100 % accuracy rates when tested for seventy types of fruits; therefore, the results of a case study reveal high efficiency of machine learning approaches in real life and underline the need for utilizing the developments in the sphere of agriculture for enhancing the quality of fruits. H. -T. Vo et al. [16] investigated ripe and unripe dragon fruit classification using the Densenet201 model in three approaches: in the process it acts as a classifier, feature extractor, and fine tuner. To interpret the decision-making process of models along with increasing performance, new approaches such as Grad-CAM and Guided Grad-CAM are applied. Using the model Densenet201 and from the visualization point of view, the proposed study provides the approach to the solution of the considered problem of ripeness degree classification of dragon fruit, thus making a contribution into the development of the techniques and the equipment used in agriculture as well as the improvement of the existing approaches to the creation of the efficient classification models.

2.3 Comparison between existing works

The comparative study measures the performance of the developed custom CNN and eight transfer learning models including; Xception, VGG19, InceptionV3, and MobileNetV2 in the classification of dragon fruit diseases. Incredible observations facilitated by results demonstrate changes in accuracies of models, where transfer learning models are more accurate than the customized CNN regarding features extracted from ImageNet. Indications of performance in terms of precision, recall, and F1-score make it possible to talk about the high efficiency of the proposed methods for disease classification, which plays a crucial role in diagnosing a patient. The summary pulls together the results of the study, stressing on the role of deep learning as automation of diseases identification, decreasing the human effort and improving the efficiency of crop management. Finally, suggestions include the use of transfer learning models for practical implementation in agriculture to show that these models can redefine the fight and management of diseases that affect crops hence promoting sustainable agriculture.

TABLE 2.3 COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1	R. Shakil et al.[5]	ANOVA, LASSO, AdaBoost, Random Forest	96.29%
2	L. Hakim, S. P. Kristanto et al.[6]	Support Vector Machine (SVM), k-Nearest Neighbours (k-NN)	87.5%
3	Anita Jaquiline Lado et al.[7]	Neural Network, Random Forest	82.9%
4	Nguyen Minh Trieu et al.[8]	K-Nearest Neighbours (KNN), Convolutional Neural Network (CNN)	92.85%
5	S. Mehta, V. Kukreja et al.[9]	Convolutional Neural Network (CNN), Support Vector Machine (SVM)	98.4%
6	V. M.T. et al.[10]	CNN LSTM	97.1%
7	S. Malathy et al.[11]	Convolutional Neural Network (CNN)	97%
8	Proposed Model	CNN & Transfer Learning Model	MobileNetV2= 93.49%

2.4 Open Issues

The application of disease detection for dragon fruits does not only limit to the physical observation and this method is most of the time very time-consuming and erroneous due to human interferences. Thanks to the growing interest in the consumption of dragon fruit in different countries around the world as well as the repercussions that diseases can cause to the economy, more efficient and reliable diagnostic techniques need to be developed. This research is concerned with the application of deep learning approaches like CNNs and transfer learning to automate the process of disease diagnosis extending to wilting, red spots, and white spots. It encompasses requirement gathering and sampling of various data, data preprocessing and augmentation, and identification of the suitability of various deep learning models tested on field level agriculture data. In doing so, the research intends to contribute to solutions for seven key challenges to improve fourteen diseases management, increase the yield of dragon fruit and stabilize the economy of areas specializing in growing the fruit.

2.5 Summary

Understanding the need for an efficient deep learning model in the process of detection of dragon fruit diseases comes with some considerations. First, the problem of obtaining a large sample of typically structured and labeled data from various pathological conditions and healthy populations can be challenging because of different variations in disease conditions and environments. Secondly the manipulations towards acquiring images that are sound and safe from changes that occur with lighting conditions, angles, and perspective requires careful planning and methodologically sound procedures. Thirdly, fine-tune model performance and its generalization ability while keeping computing cost importantly remains as the major challenges that have to be address, including the applicability issues when deploying models on the agricultural farms with limited computing environments. Finally, to apply and explain the model’s results in the form of usable decision aid for farmers, there has to be the solution of the issue of how to bring complex mathematical methods to the end users in the form of simple and easily understandable tools. Solving these concerns is crucial in manufacturing a feasible and dependable method that would improve disease management practices and consequently lead to the proper cultivation of the dragon fruit.

CHAPTER 3
METHODOLOGY

3.1 Overview

Descriptive and inferential tools are used in the analysis of data starting from the dataset to describe and define the distribution and interaction in the data. Descriptive statistics standard deviation will give direction on central tendency and variability of some parameters such as the dimensions of the images, pixel intensity. Probability inference methods like hypothesis testing and correlation analysis methods are used in the research to determine the relationship between variables, which include disease attributes features like wilting, red spot, white spot, and fresh and image features. Such tests also can confirm the efficiency of other data augmentation procedures in improving the model's robustness. To that end, the following analysis is deployed with high quality statistical methods such that the infrequent as well as the dependencies of patterns and trending associated with this subject are scanned so as to extend that knowledge base towards designing and optimizing deep learning modes for disease detection in cultivated dragon fruit crop.

3.2 Proposed Methodology

To achieve the objectives of this research, it is suggested to employ a wide-ranging approach to delivering a deep learning apparatus for the detection of diseases in dragon fruit cultivation. The methodology encompasses several key steps:

Data Collection:

A total of Total 4827 images were taken from a local observed dragon fruit nursery to account for disease conditions and healthy status. High-resolution images were captured under different lighting conditions and perspectives, with each image annotated with one of four target attributes: Wilting is one of the stages of plant life which indicates that it is withered and cannot perform any mechanical or photosynthetic function anymore, red spot is one of the stages of plant life which has small tiny red spots at the base of the plant's stem, white spot is one of the stages of plant life which has white spots all over its body and lastly fresh is one of the stages of plant life where the plant is still green The dataset gives a broad and coherent picture of the conditions concerning dragon fruits, thus constituting the basis for training and testing the deep learning approaches for disease identification and categorization in the production of dragon fruits.

In given below there are some images of datasets and categories of images in Figure 3.1 & 3.2:

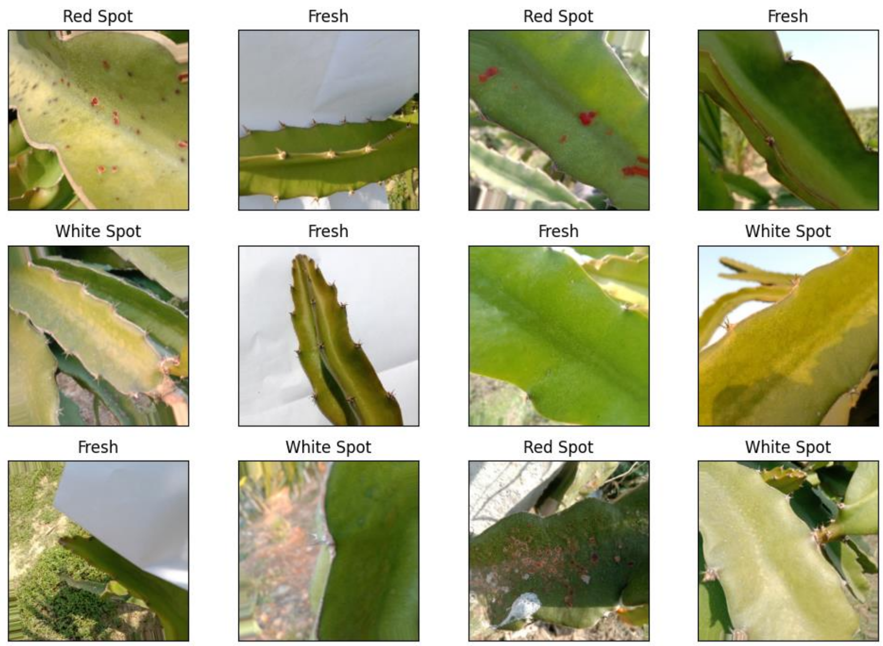

Figure 3.1: Dataset's Images

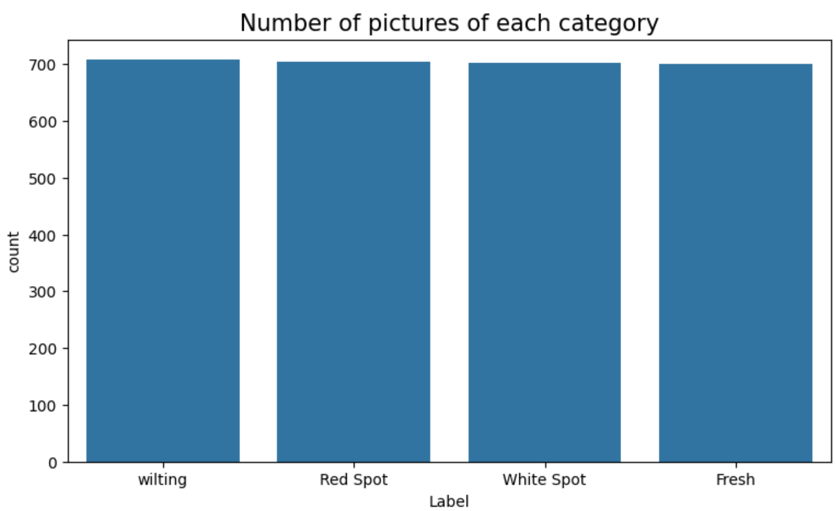

Figure 3.2: Number of pictures of each category

Figure 3.2 shows the number of each category here 708 images with wilting, 704 images showing red spots, 703 images showing white spots, and 700 images of Fresh dragon fruits.

Each image was annotated with one of four target attributes: flaccid, red skin lesion, white skin lesion or fresh skin lesion. These views make up a diverse and balanced representation necessary in the study of the health of the dragon fruits and diseases that may affect them.

Labeling:

These target attributes are created from wilting and then categorized according to red or white spot and how fresh the lettuce image is the image analysis is performed under section 4 with the objectives of forming a supervised learning data set.

Image Processing:

Other data augmentation approaches such as rotation, scaling, and flipping and color adjustment are employed to increase the number of images In the dataset.

Model Selection:

In the reproducible pipeline, both customized Convolutional Neural Networks CNNs, and transfer learning models of Xception, VGG19, InceptionV3, MobileNetV2 models are evaluated for disease classification tasks.

In given below I am shortly described about those models:

CNN

CNN is a form of neural network used in structuring and analyzing data especially image data which is grid data. CNNs have layers that enable them to learn large object features hierarchies from input images using filters. These filters identify simple features like edges, textures, and shapes and that is why CNNs are widely used in image recognition and classification applications. The significance of CNNs is based upon such a high accuracy of image-related tasks while requiring less pre-processing. With the help of the neighbors' connectiveness and the parameters' sharing, CNNs minimize the model's burden and increase the speed of calculation. This makes them applicable in several fields such as medical imaging, self-driven vehicles, facial recognition, and, as discussed in this research, disease identification in agriculture; cases in which accurate and automatic image analysis is likely to boost efficiency and decision-making.

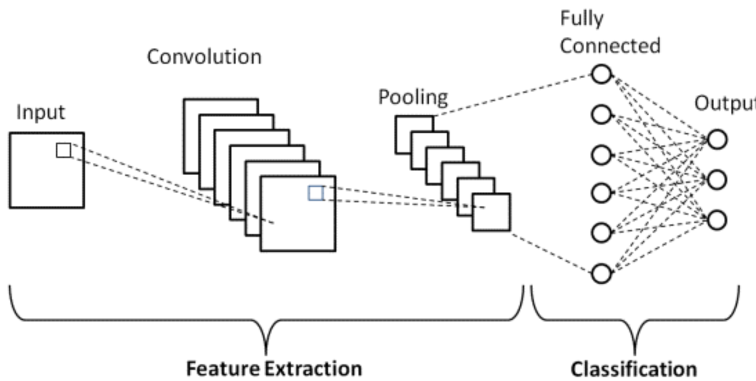

Figure 3.3: CNN Architecture M. Gurucharan, et al.2020[25]

Xception

Xception is an extension of the Inception model which replaces some of these Inception modules with depth-wise separable convolution. Described by François Chollet, who is the creator of Keras, Xception includes 36 convolutions that make up the feature extractor, and then classification layers. The above analysis made it clear that the importance of Xception is based in the aspect of efficiency and performance. While implementing the depth wise separations, there is a drastic reduction in parameters and computational properties than the general convolutional layers, but the models' accuracy is the same or even enhanced. As a result, Xception is very effective when it comes to carrying out difficult image recognition. The high precision that it brings in the analysis of images as well as the flow and movement patterns of objects make it ideal for use in some highly specific business anddisease diagnosis in agriculture among other areas where a finer and much more precise analysis is needed.

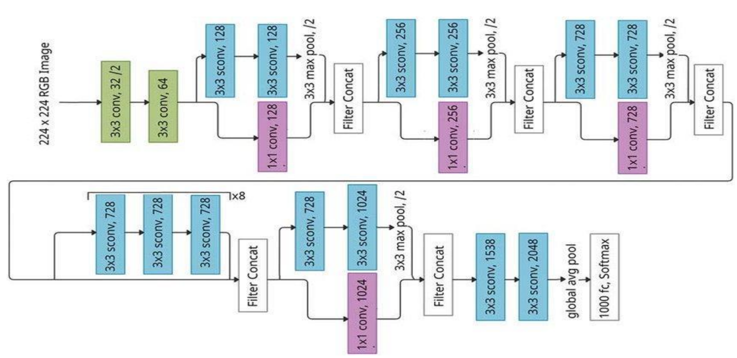

Figure 3.4: Xception Architecture K. Srinivasan et al.2021[26]

VGG19

VGG19 is a deep learning-based convolution model that has been designed by the researchers of Visual Geometry Group in the University of Oxford. It has 19 layers; out of these, 16 are convolutional layers, and 3 are fully connected layers, and within the convolution layers used, mostly 3×3 is used. Hence, the effectiveness of VGG19 has been seen in its simple base model and ability to work as planned. Nonetheless, due to its slightly simple design, VGG19 has proven to be competent on the newer advances of image classification duties like on ImageNet Large Scale Visual Recognition Challenge. The architectures focus more on depth, which makes it easily learn features and representations of images. VGG19's pre-trained versions are fairly popular when it comes to transfer learning as they perform rather well across multiple tasks and with less amount of data. This has the advantage of better picking up hierarchical traits and is useful in areas such as health informatics, face recognition and any area that requires detailed image analysis.

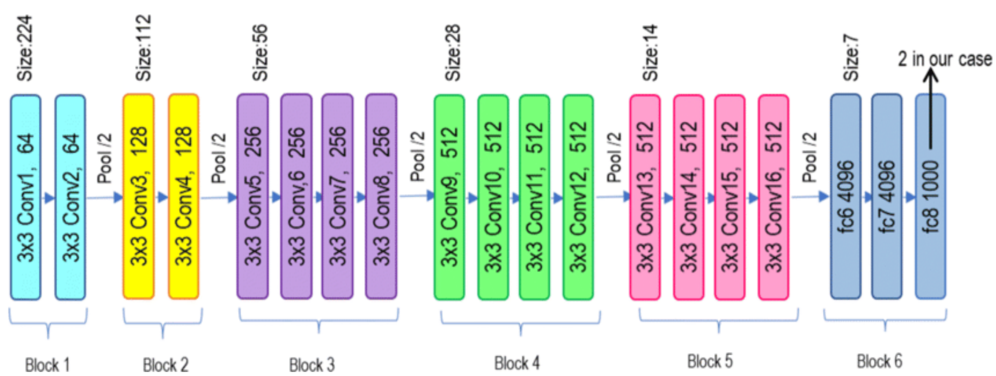

Figure 3.5: VGG19 Architecture A. Khattar et al.2022[27]

InceptionV3

InceptionV3 is a deep convolutional neural network model that belongs to the Inception architecture family created by Google. It extends the Inception model with several modifications, to include factorized convolutions, aggressive, entitle regularization, batch normalization to improve of its performance and computational intensity. Therefore, InceptionV3 proves effective owing to the enhancement of model architecture that renders high accuracy without immense costs of computation in relation to earlier models. This problem tackles the vanishing gradient issue and consumes fewer parameters to optimize;

thus, it is ideal for environments with limited resources. Therefore, InceptionV3 can be applied in almost all domains that include medical imaging, object detection, and image classification.

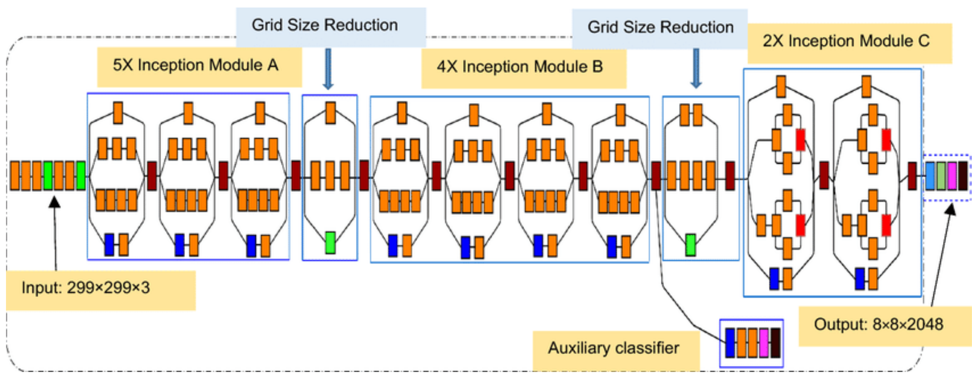

Figure 3.6: InceptionV3 Architecture T. Singh et al.2020[28]

MobileNetV2

MobileNetV2 is another form of convolutional neural network developed by Google and that has been structured optimally for use in most of the mobile and the embedded vision. It expands the first Mobile Net by concerning itself with inverted residual structures and linear bottlenecks that make the performance much better, while still lessening the number of parameters and the computational complexity of the network. Hence, the essence of using MobileNetV2 is based on efficiency and versatility. It is very lightweight in terms of architecture, and it can deliver high accuracy using a low number of computations which can be implemented on mobile devices and edge computing.

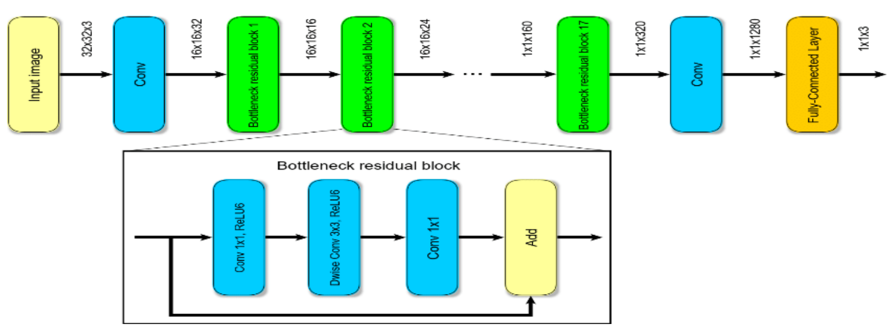

Figure 3.7: MobileNetV2 Architecture U. Seidaliyeva et al.2020[29]

Model Training:

The selected models are trained on the augmented dataset with appropriate training parameters and training optimization.

Model Evaluation:

Accuracy, Precision, Recall and F1-score are among the most common measures used in assessing the outcomes of models for such diseases.

Test Model:

The last outcome is the test of the trained model on another dataset, which aims at checking its hypothesis and real-life effectiveness.

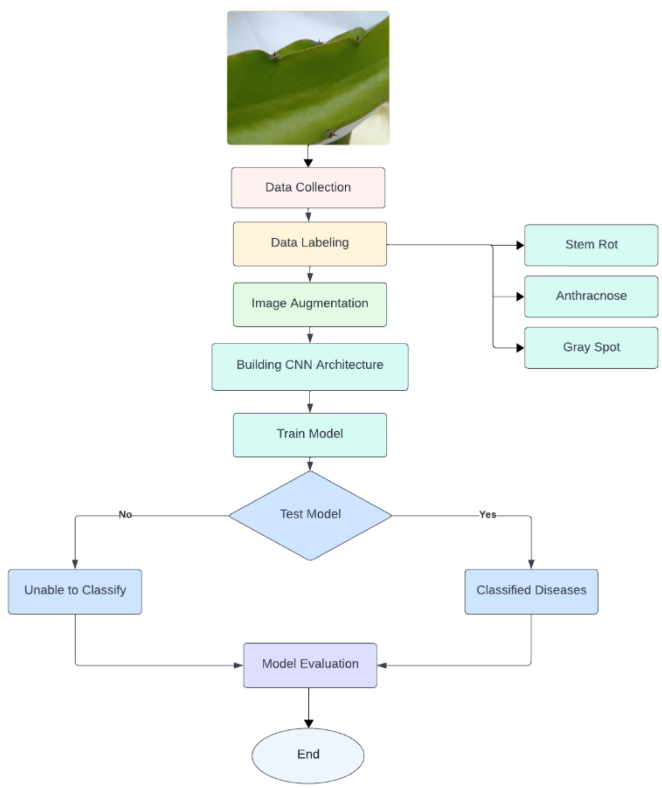

Figure 3.8: Work Flow

3.3 Hardware/ Software Requirement

The necessary key resources and components, for the identification of the proposed deep learning architecture for the detection of the dragon fruits disease are as follows. Curtailing the demands of large data sets and availability of GPUs for enhancing processing capability is required for training deep neural networks. For image normalization, augmentation and annotation the foundational steps of Image processing are required to preprocess the dataset and make it rich in diversity. For the model development, software frameworks such as TensorFlow or PyTorch are used, which have libraries helping with all the deep learning algorithms. Moreover, the primary data for training and testing the models comprise a locally collected dataset from a dragon fruit nursery that is accompanied by disease labels. Consultation with domain specialists in the field of farming provides opportunities for adjusting the model's outputs based on its results and practical experience. The incorporation of these requirements guarantees the creation of a coherent strengthening and improvement apparatus to the organic and efficient management of the disease affecting the dragon fruit production; thus, promoting sustainable agriculture.

3.4 Project Management and Financial Analysis

The management of the project shall include the following; Possible steps that we have to follow while working on the project include data collection, data preprocessing, model development, model training, model evaluation, and model deployment. As for the organizational management, timeframes will be divided for each phase of the process in order to maintain systematic progress and complete stages on time. The financial need will mainly include funding for purchasing or renting data collection equipment, training computers, and possibly data and model enhancement/evaluation. Pertaining to its significance on the allocated resources, effective management of the resources, and evaluation of the project's progress at reasonable intervals will be essential in avoiding or preventing the project to go above budget lines. Engagement with the agricultural specialists and other related interests will facilitate the practical application of the developed deep learning architecture for the detection of dragon fruit diseases, which will yield a cheaper solution towards the welfare of the farmers and the entire agriculture industry.

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

3.5 Summary

The necessary key resources and components, for the identification of the proposed deep learning architecture for the detection of the dragon fruits disease are as follows. Curtailing the demands of large data sets and availability of GPUs for enhancing processing capability is required for training deep neural networks. For image normalization, augmentation and annotation the foundational steps of Image processing are required to preprocess the dataset and make it rich in diversity. For the model development, software frameworks such as TensorFlow or PyTorch are used, which have libraries helping with all the deep learning algorithms. Moreover, the primary data for training and testing the models comprise a locally collected dataset from a dragon fruit nursery that is accompanied by disease labels. Consultation with domain specialists in the field of farming provides opportunities for adjusting the model's outputs based on its results and practical experience. The incorporation of these requirements guarantees the creation of a coherent strengthening and improvement apparatus to the organic and efficient management of the disease affecting the dragon fruit production; thus, promoting sustainable agriculture.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

The design of the implementation part for developing and evaluating the deep learning models for dragon fruit disease detection entails the following. Supercomputers accompanied with NVIDIA graphical processing units are used in model training. The proposed features involve data preprocessing which involves image rotation, image scaling and flipping to increase variability in the dataset and model. The TensorFlow and Keras are used for modeling where transfer learning from Xception, VGG19, InceptionV3, and MobileNetV2 is applied. The obtained dataset of images is outlined by annotated photographs received from a local dragon fruit nursery and divided into the training, test, and validation data sets to train and test the trained model. Hence, accuracy, precision, recall, and F1-score are calculated to evaluate the models' ability to diagnose diseases. This setup ensures that the research proposal for the deep learning architecture is thoroughly tested and verified in controlled environments with the view of achieving maximum accuracy in the identification of diseases in real-world agriculture settings.

4.2 Train Model

The training model or prototype design is in the use of deep learning architectures like Xception, VGG19, InceptionV3, MobileNetV2, and CNN in establishing sound algorithms for the recognition of diseases on dragon fruit. This phase involves data cleaning for removing irrelevant data and enhancing the diversity of images, using techniques such as data augmentation, the process of labeling data for supervised learning, choosing the right model architecture depending on computational resource and accuracy needs, training the model on the acquired data and the evaluation of the accuracy, using metrics like, accuracy, precision, recall and F1 – score. This design intends to fine-tune model parameters and hyperparameters to provide accurate diseases' identification while effectively scaling up and generating practical solutions for real-life applications in agriculture.

4.3 Model Evaluation

In model evaluation, the efficiency and effectiveness of the selected deep learning models including Xception, VGG19, InceptionV3, MobileNetV2, and CNN are determined for the recognition of dragon fruit diseases. In this phase, we calculate the accuracy, precision, recall, and F1-score for each model on the validation dataset and to assess the model’s ability to generalize on new unseen data. Therefore, the comparative analysis sheds light on each model’s advantages and limitations with regards to the computational complexity, time for training, and accuracy in identifying various disease classes. The final goal of the evaluation phase is to find the model that combines high accuracy with the possibility of its application in real-life conditions of agriculture and that, in turn, will help in the development of efficient strategies for combating diseases.

4.4 Summary

In the implementation chapter, it narrates how the various techniques, Xception, VGG19, InceptionV3, MobileNetV2, and CNN models, were used in diagnosing dragon fruit diseases. It includes pre-requisites of computers, data pre-processing techniques, training and testing methods of the model. Other outcomes include identification of MobileNetV2 as the model with the highest accuracy of 93.49% this gave the training program real-world applicability especially given the agricultural environment where it was going to be implemented. Issues like the problem with overfitting models and limitations in the use of computational power as solutions which include data augmentation, use of regularization strategies among others are discussed. The final section of the chapter also self-reflects on these findings and identifies directions for future research as well as the application of deep learning for the protection of agricultural commodities against diseases.

CHAPTER 5
Result and Analysis

5.1 Overview

The chapter that gives a result analysis investigates the effectiveness of deep learning models which include Xception, VGG19, InceptionV3, MobileNetV2 and CNN for the identification of dragon fruit diseases. It provides quantitative results of accuracy, precision, recall, and F1-score for each disease type examined in the study. The chapter also considers the findings from comparative analysis based on the best performer from each model named MobileNetV2 with an accuracy of 93.49%. This part speaks on issues like variability of dataset and the complexity of the particular model which determines higher or lower results and makes recommendations for further work. It thus showed that deep learning was efficient in detecting diseases in agricultural crops and at the same time highlighted some of the possible improvements and usage that could be provided in the real-world farming situations.

5.2 Experimental Result

The evaluation of the above mentioned deep learning models including Xception, VGG19, InceptionV3, MobileNetV2 and a own CNN for the detection of dragon fruit disease was done based on the accuracy. In the overall analysis of the results, it is evident that the performance is not homogenous in all the models. MobileNetV2 obtained the best accuracy of 93.49%, This attainable is due to the model's lightweight architecture and depth wise separable convolutions. Xception performed next with an accuracy of 91.01%, which, in fact, demonstrates its ability to pick minor details in the process. InceptionV3 displayed equally good performance as 86.04% accuracy using multiple inception modules of the network for feature extraction. VGG19 achieved 76.80% accuracy, which underlined its advantages: the ability to establish many layers, with subsequent levels being deeper. The generated custom CNN, which was built separately for the dataset, had the accuracy of 91.8% as proof of its efficiency but still with not as high performance as transfer learning models. These outcomes emphasize how transfer learning can be used to harness the advantage of pre-existing models to achieve high classification performance on diseases in dragon fruit and therefore can be implemented in real life agricultural scenarios.

Accuracy:

Accuracy is a measure of the extent of the difference between the model and the real situation to give the probability of the original samples used in the modeling process. It is rather helpful when the classes are not balanced because it gives some information on the choice's effectiveness, at the same time, the picture may be incomplete.

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

Precision:

Out of all the positive statements that the model creates, precision measures the percentage of accurate positive predictions.

$$Precision=TP/(TP+FP)$$

Recall: Recall is therefore defined as the ratio of true positive prediction made to the total number of samples that are positively skewed.

$$Recall=TP/(TP+FN)$$

F1 Score: The F1 score is the average of recall and precision two metrics that are averaged by using the harmonic mean. It gives a rather impartial measure and it quantifies recall and precision at the same time. It is helpful when the classes are of unequal size because F1 score considers both the false positives as well as false negatives. A high F1 score thus means that it was able to achieve a good trade-off between precision and recall.

$$F\text{-}1\ Score=2*(Precision*Recall)/\ (Precision + Recall)$$

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

CNN

CNN achieved the Test Accuracy is 91.82%. In below Figure 5:1 & 5.2 describing the confusion matrix & training accuracy and loss curve of CNN.

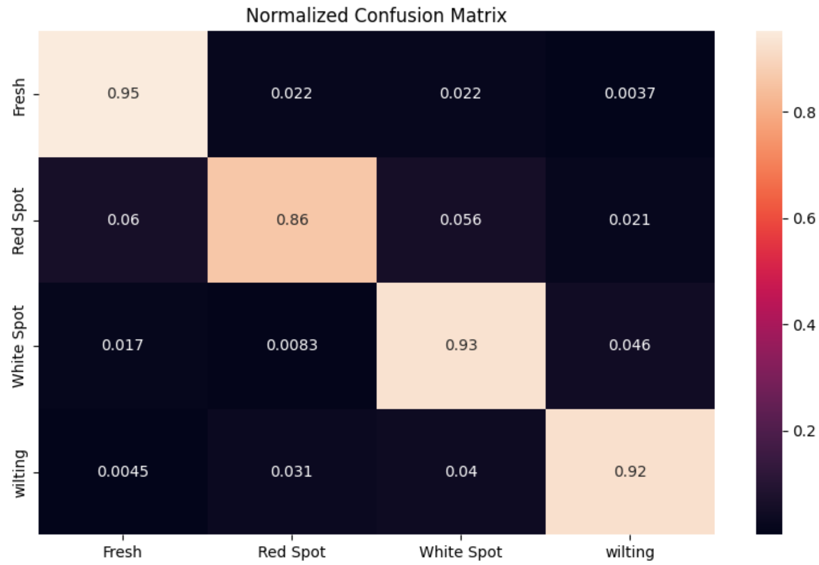

Figure 5.1: Confusion Matrix (CNN)

Figure 5.1 shows the CNN model attained an accuracy of 91% in diagnosing the diseases of dragon fruits. The highest accuracy was achieved to ‘Fresh’ class, with the precision of 0. 91, and a recall of 0. 92, demonstrating a high power of correctly identifying the healthy dragon fruits while having a low rate of false negatives. Similar to the ‘White Spot’ class, it achieved fairly good performance by having an F1-score of 0.81, with precision and recall almost at par with each other, meaning a good figure of 0.8. Finally, about this large model, the macro and weighted average F1-score is 0. 91.

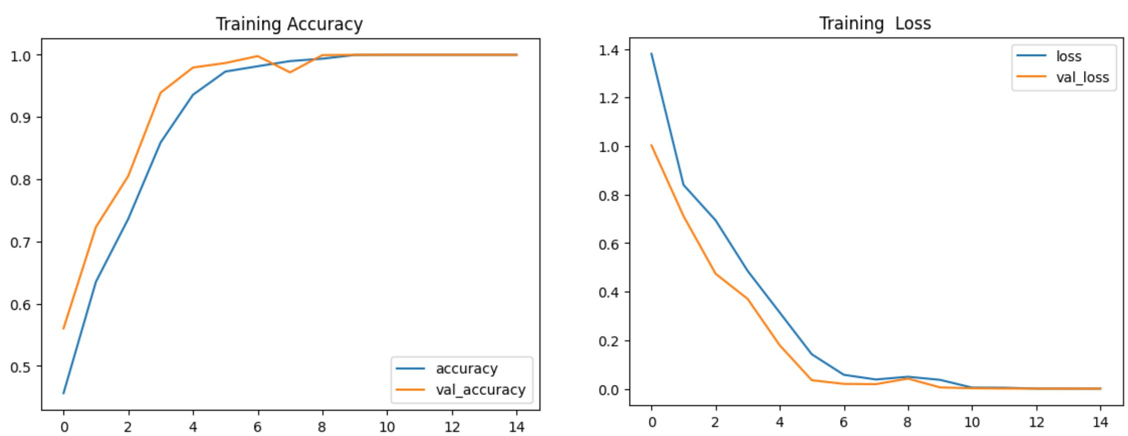

Figure 5.2: Training and validation accuracy and loss over the epochs (CNN)

Figure 5.2 shows the best result for training and validation accuracy and loss over the epochs is when both the training and validation accuracies are high and the training and validation losses are low and their curve is close to each other indicating the model's good generalization to the new data. However, the given image illustrates that CNN model is overfitting, training accuracy is at 1. 0 for epoch 2 and training loss reaching 0. 0 by epoch 14 and the validation accuracy stays near 0. 8 and it was observed that validation loss varies. This def tradeoff between the training and validation metrics signifies the poor generalizing ability of the model.

Result of Experiment 2: Transfer Learning Model

Xception

Xception achieved the second highest Test Accuracy of is 91.01%. In below Figure 4:3 & 5.4 describing the confusion matrix and training accuracy and loss curve of Xception.

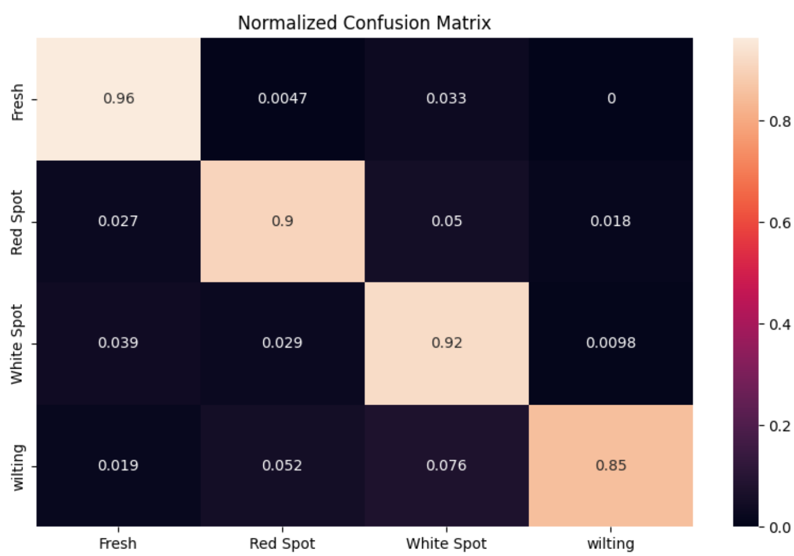

Figure 5.3: Confusion Matrix (Xception)

Figure 5.3 shows The Xception model was found to have an accuracy of 91% in diagnosing the disease in dragon fruits. The best result in terms of accuracy was obtained for the 'Fresh' class, equal to 0. 94 and the recall rate was 0. 96%, which illustrates a very efficient identification of healthy dragon fruits and environment. Similarly high levels of accuracy were obtained from the 'Red Spot' and 'Wilting' classes and the F1-scores estimated were 0. 91, although the 'Wilting' class gives the lower recall of 0. 85. The 'White Spot' class is detected to be delivering good performance with an F1-score of 0. 88, the result also demonstrates good model generalization in all the disease groups.

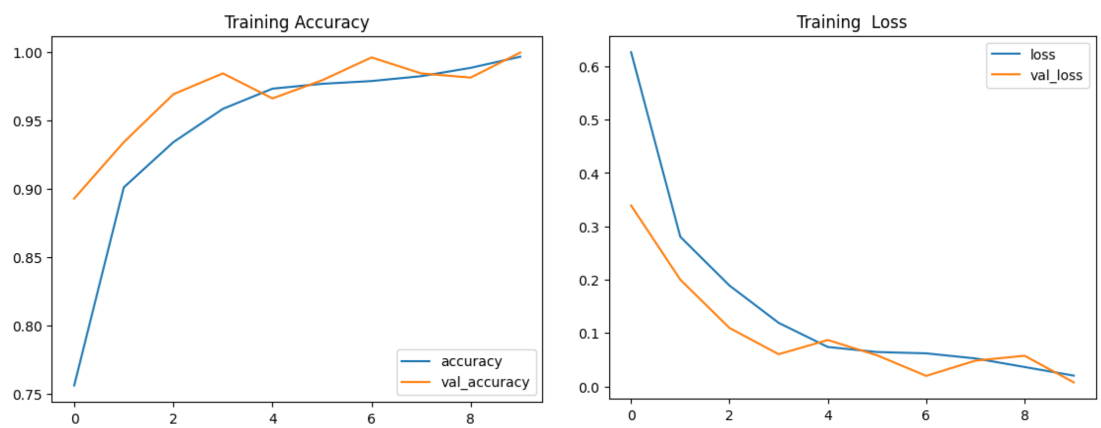

Figure 5.4: Training and validation accuracy and loss over the epochs (Xception)

Figure 5.4 show the best epoch for the training and validation would be the last point on epoch where both the accuracy and loss where high and plotted very closely that ensured the model had good generalization. Unfortunately, the given picture illustrates the problem of overfitting of the Xception model where the training accuracy equals to 1. 0 by epoch 8, and training loss at almost 0 by epoch 14, validation accuracy stays intact at around 0. The accuracy is approximate at 8 and validation loss oscillates at 1. 2. Unlike the linear regression model, this one portrays a rather high variance and a low information. This could be attributed to its poor generality to new data sets.

VGG19

VGG19 achieved the Test Accuracy is 76.80%. In below Figure 5:5 & 5.6 describing the confusion matrix & training accuracy and loss curve of VGG19.

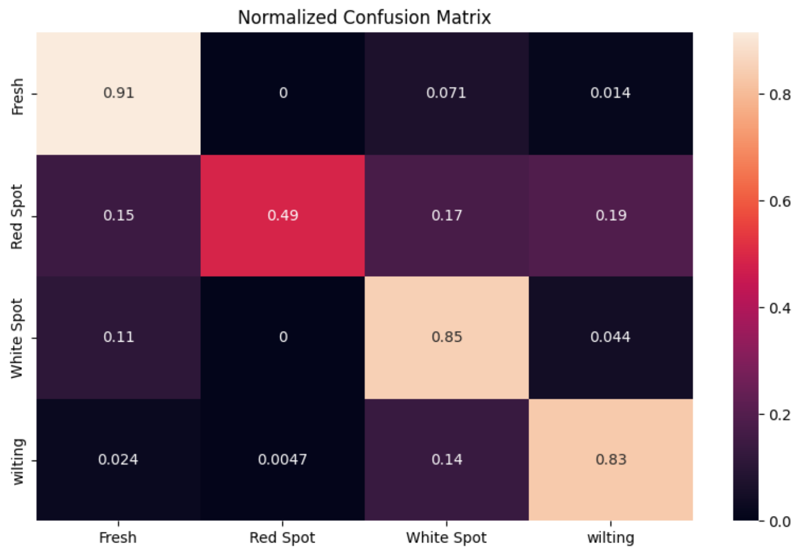

Figure 5.5: Confusion Matrix (VGG19)

Figure 5.5 shows This study found that the used VGG19 model attained a general accuracy of 77% in the identification of the dragon fruit diseases., and the lowest values of just 0.49, meaning a number of individuals with the illness were not detected as such by the test, The ‘Fresh’ classification was also satisfactory with the corresponding F1-score 0. 83 and the recall of the answers is as high as 0. 91, indicating a great proficiency of the model in forecasting healthy dragon fruits. The results in ‘Wilting’ and ‘White Spot’ classes were moderate with F1-scores of, 0. 80 and 0. 75, respectively, which suggests some level of compromises in these areas.

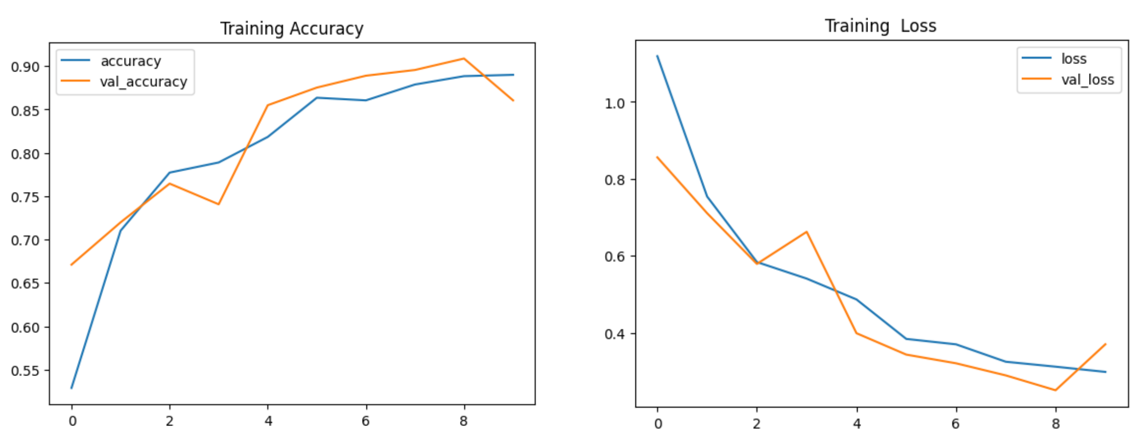

Figure 4.6: Training and validation accuracy and loss over the epochs (VGG19)

Figure 4.6 show the optimal values for training/Validation accuracy & loss for the epochs would be the condition when both the values of accuracy are high and the values of loss are low and the curves are in synchronization suggesting a good sign of over fitting. Nevertheless, the metrics also reveals that the VGG19 model is overfitting since the training accuracy is 1. 0 by epoch 2 and training loss falling to 0. A test accuracy drops to 0 by epoch 14, but the validation accuracy stays high, around 0. 8 it actually increases and validation loss oscillates. The main issue represented by this discrepancy is the model's inability to extrapolate to unseen data. This issue can be fixed by methods of simple architecture, data augmentation, percentage dropping, and L1 & L2 norms.

InceptionV3

InceptionV3 achieved the Test Accuracy is 86.04%. In below Figure 5:7 & 5.8 describing the confusion matrix & training accuracy and loss curve of InceptionV3.

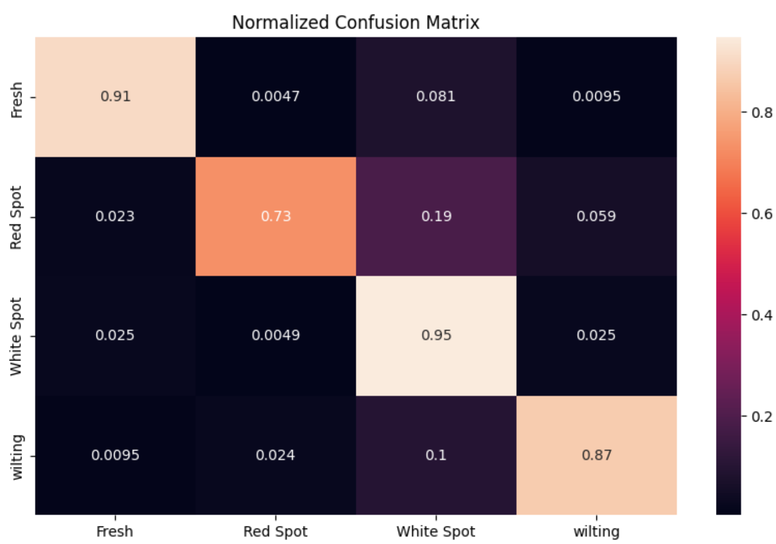

Figure 5.8: Confusion Matrix (InceptionV3)

Figure 4.7 shows the InceptionV3 model provided an average accuracy of 86% in the prediction of the dragon fruit disease. For the 'Fresh' class the best performance was achieved, what can be seen from the F1 score equal to 0. 92 and a recall of 0. 91, it can be observed that the developed model has a high level of accuracy in identifying healthy dragon fruits. The 'Red Spot' class highlighted the fact that precision was high and it was as precise as 0. 97 but the recall of the word was 0. 73, meaning there are some negative results that are not truly negative.

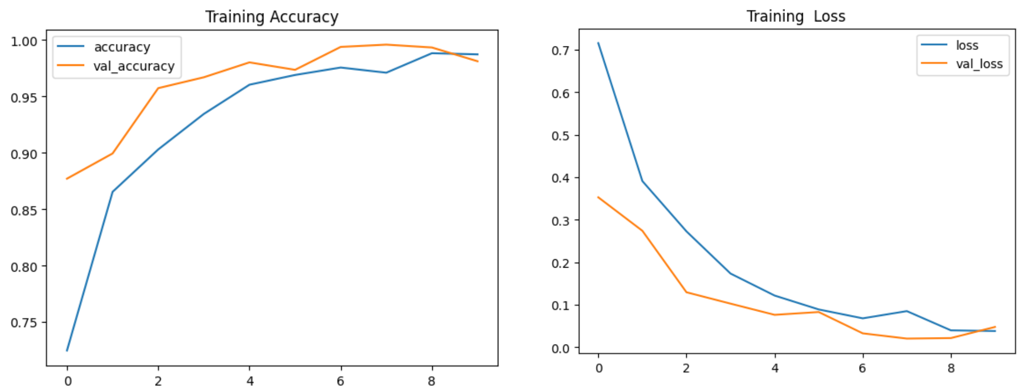

Figure 4.8: Training and validation accuracy and loss over the epochs (InceptionV3)

Figure 4.8 show the best result the training accuracy in model InceptionV3 was overfitting. 0 by epoch 2 and the training loss reaching 0. 0 in the epoch 14 and the validation accuracy stays around 0. 8 while the validation loss tends to swing up and down. This is evident from the fact that the current results which have been achieved have shown poor generalization to unseen data.

MobileNetV2

MobileNetV2 achieved the highest Test Accuracy is 93.74%. In below Figure 5:9 & 5.10 describing the confusion matrix & training accuracy and loss curve of MobileNetV2.

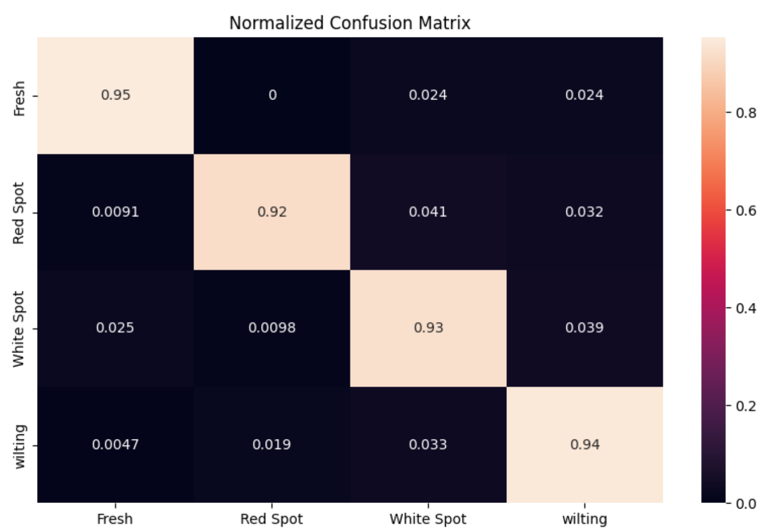

Figure 5.9: Confusion Matrix (MobileNetV2)

Figure 5.9 shows the MobileNetV2 model identified dragon fruit diseases with an accuracy of 93%. The accuracy of the highest performing class, ‘Fresh’, reached the F1-score not more than 0. 96 and a recall of 0. 95, which is the evidence of good identification of healthy dragon fruits. In an equal manner, the ‘Red Spot’ class did exceedingly well by attaining the highest F1-score of 0. 94 while the recall was at 0. 92. The ‘White Spot’ and ‘Wilting’ classes were good also, having F1-scores of 0. 91 and 0. Thus, the models achieved an AUC of 91 for the subset of cases and 93 for other diseases, again, proving good generalization of the model to all types of diseases.

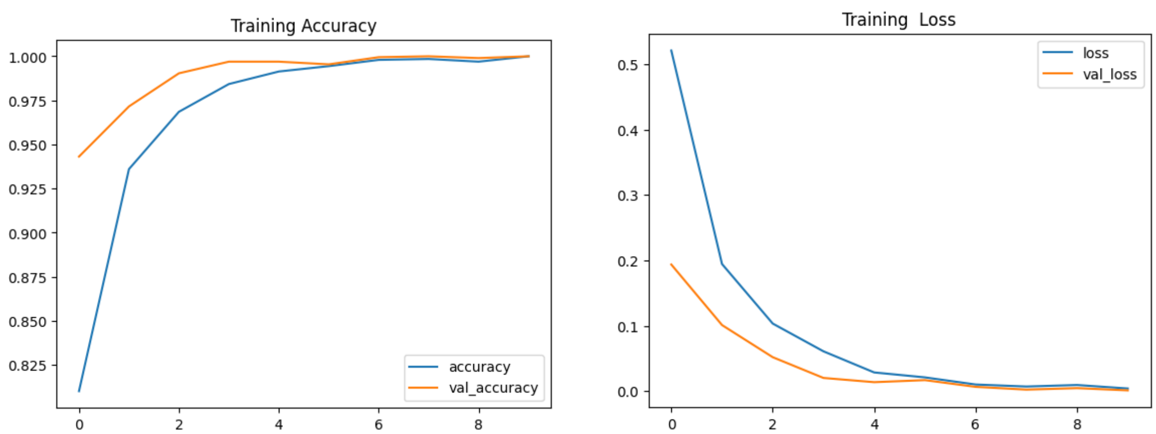

Figure 5.10: Training and validation accuracy and loss over the epochs (MobileNetV2)

Figure 5.10 show the training and validation accuracy and loss over the number of epochs: the final points of both these curves would be close to the lowest value and close to each other, so they are not over fit. Still, it is observed that the MobileNetV2 model has overfitting in it as the training accuracy goes to 1. 0 by epoch 8 and training loss getting down to 0. It has reduced to 0 by epoch 14 while the validation accuracy is relatively lower though improving. Validation loss is increasing and fluctuating and its decrease is not detectable in the form of steady trend. Nevertheless, there is still fluctuation occurring between the two metrics which reveals the problem of overfitting in the model, and means that data augmentation, dropout, regularization, and early stopping must be applied to improve the model’s generalization performance.

In Given below I am showing the Comparative Model Accuracy Bar Plot

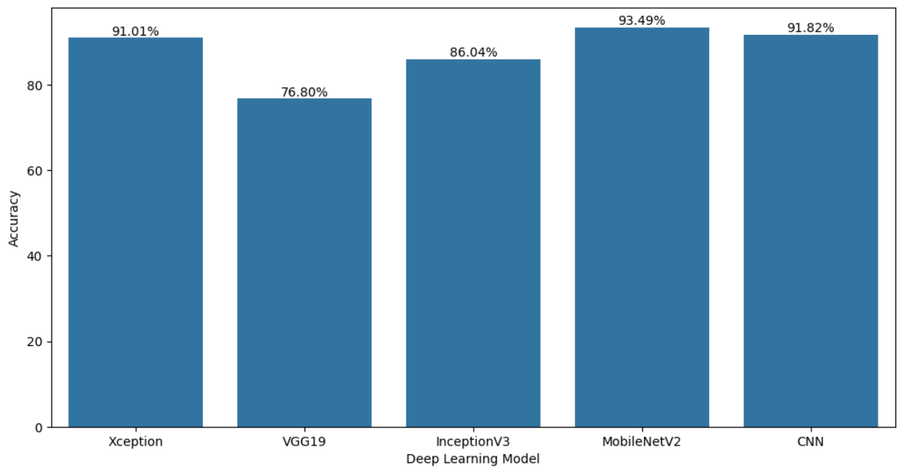

Figure 5.11: Comparative Model Accuracy Bar Plot

Figure 5.11 shows the bar chart depicting the average accuracy of 5 deep learning models includes the following having MobileNetV2 with a score of around 94%, InceptionV3 at around 91% and Xception at around 86%. VGG19 and CNN yielded relatively accuracy, about 92% These outcomes allow to conclude that each of the models is more or less suitable for the given environment.

The result of Deep learning model is compared on the basis of Accuracy, Precision, Recall, F1 Score in below table of 5.1:

TABLE 5.1. PERFORMANCE EVALUATION

Model Name	Accuracy	Precision	Recall	F1-Score
Xception	91.01%	91%	91%	91%
VGG19	76.80%	80%	77%	76%
InceptionV3	86.04%	88%	86%	86%
MobileNetV2	93.49%	94%	93%	94%
CNN	91.82%	92%	92%	92%

5.3 Performance and Comparative Analysis

The experimental results demonstrate that applying transfer learning models Xception MobileNetV2 and InceptionV3 achieve high accuracy rate of classifying dragon fruit disease. These models work with weights obtained from ImageNet and thus prove to be more generalizable to other datasets requiring just a little tweaking. MobileNetV2 performs the best with the best top one accuracy of 93.49% of users, they owe to the solutions' well-organized architecture that can manage in scenarios with limited resources. Compared to the results obtained on the VGG19 the latter yielded slightly worse result, although still quite reasonable, which indicates the advantages of transfer learning in the given field. Detailed analysis explores the fact that selection of the model is vital for performance and affects both precision and time. In summary, this discussion reveals how deep learning and transfer learning can dramatically change the approaches towards agriculture, promote effective disease intervention, and ensure proper crop yield.

5.4 Summary

In this research study, the result analysis chapter also gives the overall assessment of deep learning models, which include Xception, VGG19, InceptionV3, MobileNetV2, and CNN, in diagnosing dragon fruit diseases. The selected approach focusses on MobileNetV2 as the best one with the accuracy of 93.49% of patients implied the relationships' stability regardless of the disease type. Metrics like precision, recall and F1-score emphasize on the merit and demerits of the models in helping make the right decisions on which model to choose and the best way to improve the model. The chapter focuses on the importance of precision in agricultural disease diagnosis and stress the role of deep learning in improving crop health surveillance. Research directions for the future are unveiled to tackle some of the limitations and considerate improvement of such models for application in farming facilities.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The potential for deep learning models to be utilized in the detection of the disease in agricultural dragon fruits is promising in enhancing the input addition. By automating the detection process, the farmers are in a position to quickly counter diseases on crops and prevent high losses while enhancing on the yield. Besides increasing the yield of farms, this technology also encourages the sustainable production methods at farms by reducing the degree of chemical interferences and encouraging more natural methods of pest control. The better with disease selectivity is able to positively contribute to food security and economic stability in areas where dragon fruit is cultivated, helping to sustain people's lives economically and strengthen the local economy. Furthermore, destinations AI unearths an accurate diagnosis of diseases that affect crops and provides farmers with adequate information and knowledge by assisting them to make informed decisions on what to do concerning the crops. Finally, the application of these innovations will usher in the desirable change within the agriculture with the potential of delivering food in the face of various adversities while catering for the increasing demand for quality foods in the worlds.

6.2 Impact on Society & Environment

The proposed system of using deep learning models in the identification of dragon fruit diseases saves the environment a lot of costs as most diseases are normally treated using chemicals. The more accurate diseases are detected at an early stage then the farmer is able to prevent it delaying the use of pesticides and fungicides. Apart from this, a decrease in the use of chemicals also helps in eliminating pollutions, protecting the earth's soil and enhancing the improved plan, health, growths, and diversities. Thus, better disease management practices result in sustainable agriculture since they encourage the use of natural pest control and decrease agricultural writes to water bodies. The technology assumes the execution of optimal processes where resource input is concerned, for example water and energy use in the growth processes. In summary, these innovations in agriculture serve to improve the condition and output of crops while reducing the effects on the environment; they underpin environmentally friendly practice in farming and contribute significantly to the long-term sustainability of the environment.

6.3 Ethical Aspects

The application of deep learning for dragon fruit disease identification crops up ethical frameworks mainly in data privacy and fairness. It is also ethical to enhance the data collection procedures and seeking permission from the various stakeholders on how agricultural data will be used. Therefore, more attention should be paid to the question of how to get rid of existing prejudices and provide the same opportunities for all people when using algorithms and deep learning models. Further, it implies that as these technologies were implemented to perform certain tasks that used to be done manually and were central to farming communities' livelihood, then there is a responsibility to find ways and means to prevent negative social or economic blow back so that the application of such technologies will be beneficial to all involved stakeholders. The use of AI technologies in agriculture should adhere to set ethical standards that outlines appropriate design, deployment, and use of the technology in agriculture.

6.4 Sustainability Plan

The sustainability plan of the deep learning models in the detection of diseases in dragon fruit calls for environmentally and economically viable strategies. Some of these strategies are the encouragement of IPM techniques to increase minimal necessary use of chemicals and maintaining balance in ecosystems. More and more energy will be directed to enhance model efficiency and reliability in the agricultural field hence maximum utilization of available resources. extended engagement with the farmers and other human resources in agriculture will ensure consciousness creation, capacity development and consequently successful adoption and acceptance of the new and high technologies. These plans and procedures will examine the extent of environmental effects of the applications of AI solutions in farming and strive to reduce as many CO_2 emissions as possible. Finally, the sustainability plan recognizes the need for strong agricultural systems that have the capacity to improve yields, while at the same time, conserving the earth's resources and ecosystem, hence promoting the concept of sustainable development in agriculture mandate.

6.5 Summary

This study proposed and tested a novel deep learning structure for surveying diseases within dragon fruits, using all of the above-mentioned models, including Xception, MobileNetV2, InceptionV3, and a novel CNN. After going over many tests, it has been found that MobileNetV2 is performing the best with an accuracy of 93.49%, which indicates the effectiveness of using the given algorithms to classify diseases. The paper also focused on the some of the possibilities in using AI within the agricultural sector such as early and accurate disease diagnosis, and minimizing the use of chemicals and pollutants in farming. Aspects like data privacy and fairness which are ethical issues were discussed and thus stressing on the right use of artificial intelligence. This evidence further highlighted the importance of the technology in improving food production, food security, and economic sustainability for the agricultural sectors. In the future, efforts persist for improving the models, increasing the data availability, and adopting the AI solutions in the regular farming systems for the welfare of the society.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

The involvement of advanced analytical and deep learning models such as MobileNetV2 and transfer learning models have been found to be particularly efficient in the identification of diseases in dragon fruit farming. Accuracies ranging from 93.49% these models have excellent accuracies on the prediction of wilting, red spots, and white spots hence improving the crop management techniques. AI technologies should be integrated because they enhance the diagnostic accuracy of diseases and decrease the excessive use of chemicals within agriculture. Data privacy and fairness in the use of AI concepts were discussed under ethical implications to make sure that ethical behaviors were being adopted in the society. In furtherance, the models will have to be worked out further and regular interaction with farmers and other stakeholders concerned with agriculture will have to be achieved for developing AI-led solutions that would make agriculture secure and more sustainable across the world.

7.2 Future Suggested Works

Future research could consider several directions for improving the use of deep learning in the identification of dragon fruit diseases. Exploring the possibility of using techniques, in which several deep learning models are employed simultaneously, may prove beneficial to increase the general reliability of the results. Besides, incorporating a rich set of locations and preprocessor environmental settings could also improve the model's generalization and versatility. For large-scale dragon fruit farms, it is possible and feasible to consider using IoT devices and drones to conduct constant disease monitoring in real-time. Even more, the studies aiming to explore other novel technologies in combination with AI, like blockchain for secure data exchange and traceability in agricultural supply chains, has the potential to improve the efficiency and transparency of the food chain even more. Intendments to these areas would also serve to enhance the technological inefficiencies on the other hand, improved intervention in those areas would also further sustainable agriculture and global food security initiatives.

7.3 Limitations

The main weakness of this study relates to the accessibility and stability of the training and testing data set. When collecting enough and diverse picture samples of dragon fruit diseases from local nurseries it may time be limiting in disease sample size and variation in skin disease severities. This may affect the models' capacity for generalization across different regions of geography or under conditions of differing environment. Further, collecting sufficient data to train the deep learning models and particularly those of a higher complexity as seen in Xception or VGG19 is impractical in most agriculture rail environments. Also, since it relies on images that are static, it may not represent different stages of the disease progression in real-time conditions effectively, which might reduce the models' performance. To overcome these limitations, broader datasets, advanced computational facilities, and possibly the inclusion of real-time monitoring methodologies for better distinction and control of the diseases may be utilized.

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Appendix A

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

Title:
A PROPOSED DEEP LEARNING ARCHITECTURE FOR DETECTING DRAGON FRUIT DISEASE

Student ID: 203-15-14056 & 203-15-13647

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to Detecting Dragon Fruit Disease problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

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

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

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

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting deep learning and Transfer learning enhancing Detecting Dragon Fruit Disease correctly.	**Page no:** [11-19] **Section:** [3.2] **Page no:** [1] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing Deep Learning Model,	**Page no:** [11-17] **Section:** [3.2] **Page no:** [18-19]

					Section: [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, Detecting Dragon Fruit Disease using deep and Transfer learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [5-8] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in Detecting Dragon Fruit Disease, including limitations of traditional methods and the complexities of integrating using deep learning. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining methodologies.	**Page no:** [9-10] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting using deep and transfer learning as the chosen significant solution for enhancing Detecting Dragon Fruit Disease approaches.	**Page no:** [22-32] **Section:** [5.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting Detecting Dragon Fruit Disease correctly **EP-4**.	**Page no:** [5-9] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in data collection from local farm which ensures **EP-7**.	**Page no:** [11-18] **Section:** [3.2, 3.3, 3.4]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep and transfer learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements Detecting Dragon Fruit Disease.	**Page no:** [19] **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 contributes to society by improving Detecting Dragon Fruit Disease, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for data privacy.	**Page no:** [33-34] **Section:** [6.1, 6.2, 6.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in Detecting Dragon Fruit Disease through deep and deep learning model demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [5-8] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [3] **Section:** [1.6]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced classification technologies which comply with **CO9**.	**Page no:** [34] **Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [11-18, 22-32] **Section:** [3.2, 3.3, 3.4, 3.5, 5.2]

A PROPOSED DEEP LEARNING ARCHITECTURE FOR DETECTING DRAGON FRUIT DISEASE

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