DRAGON FRUIT STEM DISEASE CLASSIFICATION USING DEEP LEARNING TECHNIQUES

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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 **"Dragon Fruit Stem Disease Classification using Deep Learning Techniques "**, **submitted** by **Abdullah Al Noman** to the Department of Computer Science and Engineering (CSE), Daffodil International University (DIU), 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 July 14, 2024

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DECLARATION

I here by declare that this project has been done by us under the supervision of **Dr. Fokhray Hossain, Professor, Department of Computer Science and Engineering, Daffodil International University.** I am also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree.

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ABSTRACT

Dragon fruit is one of the highly valued economic and nutraceutical fruits produced in the tropical regions. However, the cultivation of dragon fruit is often affected by several stem diseases that if not controlled on time will reduce the output. Many existing disease diagnosis techniques involve direct visit by expert practitioners which is slow, tedious and often carries the risks of human errors. As such, the use of deep learning approaches is a viable solution towards enabling the automatic and efficient identification of dragon fruit stem diseases. This research focuses on the use of deep learning methods on the classification of stem diseases of the dragon fruit in order to improve production in the agricultural sector and thus minimize the losses. Given the set of labeled images of stems of dragon fruit, several deep learning models were compared: VGG16, VGG19, ResNet50, InceptionV3 and a CNN. The accuracy, precision, recall, and F1-score were used as measurements to evaluate the models. Out of all these, InceptionV3 yielded the highest accuracy score of **92. 36%** while VGG16 achieved a score of **89. 41%.** The experimental results show that these new generations of neural networks are well equipped to identify the stem diseases and classify them, thus playing a crucial role in disease.

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CHAPTER 1
INTRODUCTION

1.1 Overview

Dragon fruit is a fruit that mostly grows in the tropical areas of the world and it has many beneficial properties or health benefits besides it is an appealing fruit to look at. It has also expanded its production all over the world especially in countries where it grows well, such as SE Asia centrality, America, and Australia. Though, the growth of the dragon fruit plant bears its own difficulties. Stem diseases such as the Red Spot Disease, the White Spot, and the Turning Yellow are some of the major threats to dragon fruit plants hence the production capacity and quality of the fruits. It can be clearly seen that early and accurate detection of these diseases is essential in managing and containing the diseases. Most of the existing techniques of disease diagnosis, diagnosis done by physically examining the patient by the doctor, which often proves very costly and very tiresome due to the time it takes.

The latest breakthroughs in deep learning, especially in convoluted neural networks (CNNs), have proved very effective in image classification across different fields. These technological benefits can be beneficial in a more specific scope for utilization in agriculture, particularly in disease diagnosis of crops than in traditional approaches. The overall objective of this investigation is to train and assess deep learning models for the detection of stem diseases of dragon fruits. We collected a comprehensive dataset of images from dragon fruit farms, capturing the four primary conditions of the stems: Itthen has Red Spot, Fresh (Healthy) White Spot or Turning Yellow. To improve model generalization, the dataset was expanded to contain more data from relevant sources which are different from the original source. We employed five deep learning architectures for this task: VGG_16, VGG_19, Resnet50, Inception_v3, and a new CNN. The models chosen were selected based on its efficiency reported independently on image classification and because the architecture of all the models were quite distinct from each other. To measure efficiency all models are trained and tested on a dataset, with performance indicators including accuracy, precision, recall and F1 score. This research's findings demonstrate that using deep learning algorithms could lead to enhanced performance in identifying diseases affecting dragon fruit growing.

In this way, it is possible to create an effective and efficient classification system based on such models that would enable timely and accurate diagnostics and help the farmers take proper care of their plants in order to achieve maximal yields. Subsequent work will be devoted to refining these models, gathering a larger data set, and incorporating features for real-time detection, which will improve the usability of the algorithms in a farming context.

1.2 Background Of The Project

Deep learning-based classification of Dragon fruit stem disease is another interesting area of the research that has attracted widespread attention because of the tremendous benefits it will bring to the field of agriculture. Applying cutting edge convolutional neuralnetwork (CNN) models such as VGG16, VGG19, ResNet50, and InceptionV3 bestowing regard to building specialized CNNs lies the guarantee of disease identification and categorization. Research in the past has shown these models to be effective in similar agricultural endeavors, and have revealed that they are an effective tool in enhancing the management and yields of crops. This proposed investigation seeks to extend from the previous work by assessing and comparing these models, in addition to introducing learning data augmentation and transfer learning techniques to boost classifier performance and contribute towards enduring agriculture.

1.3 Problem Statement

The premise of the current research is formulated as follows as it aims to eliminate the shortcomings of conventional disease diagnosis in the stems of dragon fruits, which may not be effective and unprecise. Even more, using a deep learning approach such as VGG16, VGG19, ResNet50, InceptionV3, and custom Convolutional Neural Networks we will improve accuracy as well as the rate of diagnosis. This approach is very beneficial for the farmers as they receive accurate diagnosis of their crops while at the same time implementing the latest technology in making farming more efficient. The interventions of the study are to provide meaningful and functional solutions in disease management contributing to the agricultural monitoring which will in turn enhance the efficiency of farming.

1.4 Objective

The drive behind this study is informed by the current issue of stem diseases on dragon fruit productions, which compromises yield and quality. More specifically, current methodologies involve highly subjective, intensive, lengthy, and inaccurate sample-based inspections. Using deep learning especially convolutional neural network as a means for identifying diseases is a promising way of achieving a high level of accuracy in disease classification. Through this, the wiring necesita app will help farmers to be early detect diseases that affects crops effectively helping in minimizing cases of losses and encouraging sustainable farming. The purpose of this work is to pursue to upgrade inventions in reconnaissance in agriculture, which, in the end, would abide by the scarcity of food and amplified farming efficiency.

1.5 Scope and Limitations

The scope of this study comprises areas such as, determining the best deep learning model for accrediting dragon fruit stem diseases with high levels of accuracy. Overall, it is expected that models such as InceptionV3 will show the desired results as the researchers come up with even more complex models. Also, we anticipate to discern increased accuracy of the models as a result of the data augmentation and the transfer of knowledge from the pre-trained Facebook models. The study will come up with a comprehensive analysis of the running time of each of the models with necessary recommendation. Finally, the observations will help in formulating a theoretical and effective means of disease diagnosis through the creation of an automated disease detection system that would help farmers in monitoring and preventing stem diseases in dragon fruits.

1.6 Report Organization

The report starts from the introduction of the deep learning for dragon fruit stem diseases detection and its importance. Chapter Introduction provides a general background about the study and the rationale for conducting the investigation, given the need to establish early indicators of diseases affecting dragon plants. Chapter Background discusses details required for dragon fruit cultivation, diseases affected, conventional identification techniques, and deep learning as a potential solution. Chapter Research Methodology explain the systematic process applied in data acquisition, model identification, training and assessment to promote scientific validity and replicability. Chapter Experimental Results discusses the results from training and validation of model and comparative analysis such as accuracy scores for various deep learning architectures. Chapter The Impact on Society discusses how deep learning techniques can be adopted for disease diagnosing systems in agricultural climates and its contributions to society. Chapter Six: Summary, Conclusion, Recommendations, and Implications for Future Research points out the main findings of the studies and concludes about the overall status of the topic for further research and development plan of the agricultural innovation technology.

1.7 Summary

Dragon fruit is among the most valuable, economic and nutraceutical fruits grown in the tropical world, with most of its cultivations under the attack of several stem diseases. The existing approaches of diagnosis, particularly those based on the visits of experts, are time-consuming, tedious, and error-sensitive. Also, this research seeks to apply deep learning techniques in an attempt to provide a fully automated solution to the detection ofstem diseases on dragon fruit in order to increase agricultural yield and reduce losses.
Considering the labeled image of the stem of dragon fruits, the performance of 5 types of models: VGG16, VGG19, ResNet50, InceptionV3, and a custom CNN are compared by accuracy, precision, recall, and F1-score metrics.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

Most of the works in road sign recognition are based on deep learning approaches, more specifically CNN predominantly because of their effectiveness in image classification. Several works have utilized the architectures like VGG16, ResNet50, Xception, DenseNet201 for recognizing road signs in different languages and under different conditions. Many of these models have been proven to have quite high levels of accuracy in the recognition of road signs and therefore have been used to spur traffic monitoring, driver assist systems, auto mobile industry inclusive of the self-driving cars. An observation which needs mention in this regard is that there is a dearth of research work carried out in the realm of Bangla Road sign recognition. This study will try to meet this gap by assessing and comparing several CNN architectures on a newly created dataset of Bangla Road signs and thereby presenting important findings and a base for the future studies in the respective field of related to ITS for Bangla-speaking regions needed.

2.2 Related Works

Scholars focusing on dragon fruit stem disease classification with deep learning include a number of works that tackle similar problem with varieties of methods. Salama and colleagues IDCASE-2018 mentioned here above that involves deep learning techniques to classify the dragon fruit stem disease. Several works are correlated to this field of dragon fruit stem disease classification using deep learning techniques that concern different approaches and methodologies to solve similar problems. One of the recent works which uses Neural Network and Random Forest classifiers was by A. J. Lado et al.

[5] The experimental data set employed for analysis is 41 images of healthy and diseased dragon fruit and leaves with four classes classification. Among its contributions, the specificity of the datasets allows establishing that the concerned accuracy indicators, with from 70% to 82. 9% through 10-fold cross-validation, convey the feasibility of such classification based on the ML models for these types of tasks.

deep learning main of recognizing of big structures, for example VGG19 and CNN. Edgington & Mills also focused on proper identification and categorization of tropical fruits required to support efficient market distribution while illustrating the superiority of their new logistic models in evaluating fruit quality. Further, R. Shakil et al. [7] introduced an automated agricultural way for identifying dragon fruit diseases with help of harmony search feature selection algorithms and different machine learning classifiers.In their study, they established omnigenous performance to distinguish AdaBoost and Random Forest from other techniques; with an overall accuracy of 96. 29 percent that pointed towards some opportunities in the enhancement of the disease detection systems.Trieu et al. [8] proposed the automated evaluation and sorting system of deacon fruit using KNN and CNN models. The dataset of dragon fruits comprised of 2610 fruit samples, and the system achieved an accuracy of 92. 85% and thus increasing productivity than the conventional way of classification. Additionally, V. M. T. et al. [9] used the CNN LSTM for categorizing pomegranate and finding out four classifications ofillnesses by color, texture and shape of the fruits. This they were able to obtain initial accuracies of 92 % and after optimization, they realized an over 97. 1% accuracy meaning efficient diagnosis of diseases affecting pomegranates. These studies establishedtogether come to show the element of credibility that deep learning techniques hold whenapplied to agricultural; predominantly in fruit disease identification, quality analysis, and further automation of farming tasks. They give special worth on how to enhance the agricultural practices, with the help of innovative technologies, to facilitate better crop management and agro-friendly farming.

2.3 Comparison between existing works

This review highlights different existing literature with various deep learning architectures like VGG16, VGG19, ResNet50, Inception V3, and several other custom CNNs for dragon fruit disease categorization. Thus, it is possible to note that the approaches differ in the use of questionnaires, samples, and evaluation criteria, while applying OsO and AI achieving accuracy from 53 to 74%. 22% to 92. 36%. Knowledge highlight consists of the fact that transfer learning, data augmentation strategies, and model complexity contribute to the success of the classifier in terms of classification accuracy. In general, this summary outlines the benefits of deep learning as a supplement to enhancing such agricultural practices in a sustainable dragon fruit farming framework for disease detection and classification.

TABLE 2.3 COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL	Author Name	Used Algorithm	Best Accuracy with Algorithm
1	A. J. Lado et al.[5]	Neural Network, RandomForest	82.9%
2	R. Shakil et al.[7]	AdaBoost, Random Forest	96.29%
3	N. M. Trieu et al.[8]	KNN, CNN	92.85%
4	V. M. T. et al.[9]	CNN, LSTM	97.1%
5	Abhishek G et al.[10]	VGG16, SVM	96.54%
6	L. Hakim et al.[11]	SVM, Summand KNN	87.5%
7	X. Li et al.[13]	YOLOv5, ByteTrack	96.1%
8	S. Mehta et al.[14]	CNN-SVM	98.4%
9	N. Ismail et al.[16]	EfficientNet, & Ensemble	96.7%
10	S. Malathy et al.[17]	CNN	97%

2.4 Open Issues

As a problem, in applying the presented deep learning methodologies for the analysis and classification of stem diseases in dragon fruits, which is the study's subject, we identify several focuses. First, it involves the training and improving of deep learning modelssuch as pre-trained models that include VGG16, VGG19, ResNet50, the current best performing model, InceptionV3 and other custom CNN models to detect disease on dragon fruit plants with classification being done. Second, it describes all-round image preprocessing and data augmentation as strategies that maximize the network's performance and its capacity to extrapolate. In addition, the extent is followed by comparing the applicability of such models in real-agri by applying their performances concerning scale up and computational value, and environmental concern as well as image quality deviation. These problems need to be fixed in order to allowinterdisciplinary collaboration among members that are from various domains, for the benefit of both data scientists and agriculturists to attain real-world implementation and effective functional utilization of deep learning approaches for improvements of crop mana including increased yields of dragon fruits.

2.5 Summary

However, there are inabilities when using or applying the deep learning methods for a stem disease classification of the dragon fruit. First, the process of acquiring a large and diverse collection of images of the dragon fruit plant with annotations of the disease is time-consuming and extensive. Secondly, because the trained models have to be transportable to various settings that may require diverse contexts and low level ofsimilarity in fruit appearances as captured in the data set, this poses a gargantuan challenge. Third, there is a challenge related to deep learning that deep learning still poses some challenges when there are limited softer deeper computational resources available for training as well as for deploying deep learning models within the agricultural domain. However, when using overly complicated models such as VGG16, VGG19, ResNet50 as well as InceptionV3 while diagnosing diseases, there is need for better methods of explaining such a decision. These are all complex problems that cannotbe solved from one perspective, often entail a development of new algorithms, and must be tested and calibrated to discover the practical application in regard to agricultural systems.

CHAPTER 3
METHODOLOGY

3.1 Overview

My research topic that deals with the classification of disease on the stem of Dragon fruit based on deep learning algorithms applied by deploying deep Convolutional neural networks such as VGG16, VGG19, ResNet50 and Inception V3. These models are the main instruments through which images will be evaluated and possible diseases in dragonfruit plant might be noted. The choice of the CNNs is because it has shown the real-world performance in managing complex image information and the next critical task of deciding on the most dominant and valuable features that are critically important for accurate diagnosis of illness. It also mentioned other features that might include; image preprocessing which may encompass either image augmentation or image normalization to enhance the performance of the models. This study intends to employ these instruments scientifically as well as determine the effectiveness of these instruments on computerization of disease control in agriculture as well as the overall establishment of cost-effective production techniques for optimal natural management of dragon fruit production.

3.2 Proposed Methodology

The systematic approach for the identification of citrus fruit leaf diseases through the use of deep learning is as follows: Every stage is carried out to the following in order to invent an accurate and strong detection ability.

Steps in the Proposed Methodology:

Data Collection:

The first phase involves collecting a large image dataset of dragon fruit leaves at different levels of disease. This dataset must be precise in the concept and the numerous types and severity of diseases affecting the dragon fruit tree.

Image Augmentation:

Transform the images for training of the model. Standardize the image sizes, enhance pixel intensities, and perform operations such as rotations, flips, zooms and cuts on the images to increase the variability.

Labeling:

After the dataset has been collected, all the images need to be categorized, that is tagging them to the kinds of diseases they contain. This stage is key for supervised learning as it provides true positive/negative labels to train deep learning architectures.

Model Selection:

Then, suitable deep learning architectures are chosen for disease classification or categorization. This may involve using known models such as VGG16, VGG19, and InceptionV3 and creating new architectures from scratch, based on new configurations that are suitable for the dataset at hand and the classification problem that is supposed to be solved.

Conventional Neural Network (CNNs):

A Convolutional Neural Network (CNN) is a type of neural network used in deep learning which is specially intended for passing on structural grid information like images. It generally comprises of several convolutional layers where filters are applied to identify spatial features, followed by pooling layers whereby dimensions are minimized despite important information about the features being filtered down, and totally connected layers to complete the classification. CNNs work efficiently at recognizing geometric structures and patterns in the images, therefore they are well-suited to image classification and object detection as well as in medical imaging. In our study on the classification of dragon fruit stem disease, the advantage of the custom CNN is that the structure of our new model is flexible, it can adapt to the needs of samples and data to achieve balance between complexity and required time for calculation, so as to realize accurate and effective disease identification.

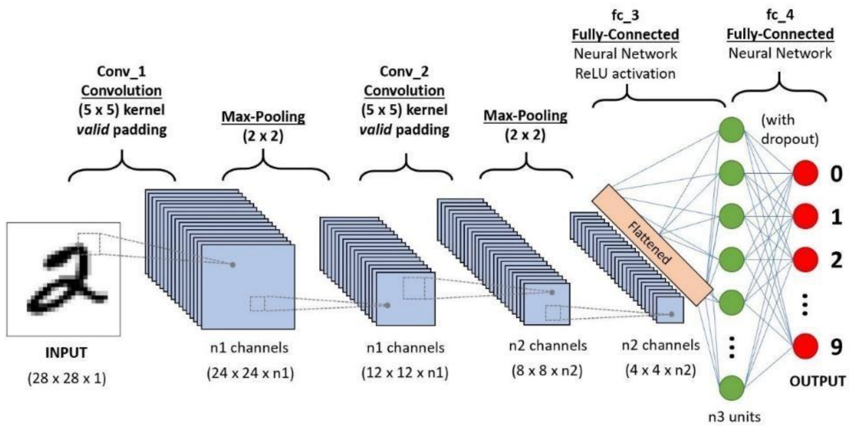

Figure 3.1: CNN Architecture S. V. Militante et al.2019[26]

VGG16

VGG16, a deep CNN and a model designed also by the Visual Geometry Group at the University of Oxford, is comprised of 16 layers; the filters used are small and equal to 3 x 3; the max-pooling layers decrease the spatial dimensionality but preserve the essential picture objects. VGG16 is lauded for its ability to provide robust feature extraction while it has numerous applications in image classification such as medical imaging, object detection, and agricultural monitoring among others. Given the characteristics of our studyon the classification of diseases from the stem of the dragon fruit, VGG16 has theadvantages of being able to capture more detailed image features and being less susceptible to certain perturbations on the data side, and the advantage of higher accuracy and the necessary computational complexity for reaching it.

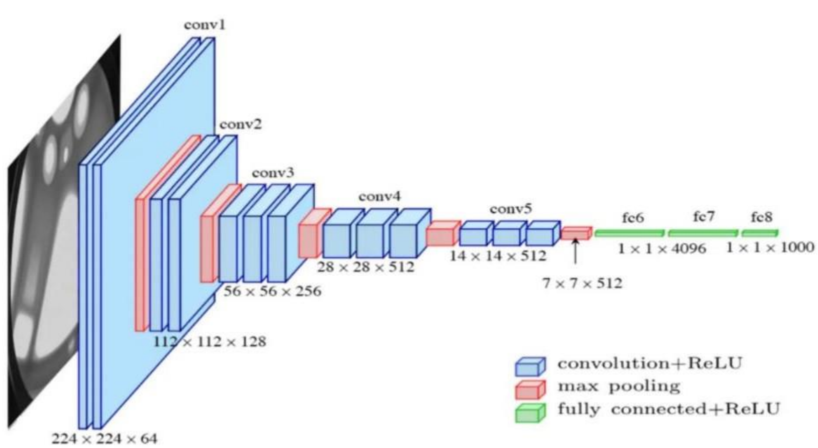

Figure 3.2: Model Architecture of VGG 16

ResNet50

ResNet50 is a deep 50 layer convolutional neural network designed & built by microsoft where similar to VGG, its layers are arranged in residual blocks to solve the vanishing gradient problem so as to train very deep networks. These residual blocks employ short connections to bypass them, so the model learns about the residual functions making the outcomes more enhanced and accurate. In ResNet50, feature extraction can be regarded as excellent, at least in tasks such as image classification, object detection, and even medical applications. Regarding the dragon fruit stem disease classification for our study, a practical advantage of ResNet50 is the ability to train deeper networks frosted well as its usefulness of capturing sufficient details due to its Nature of increasing the level ofdistinction as far as complexity is concerned that may enhance the network's classificationprecision.

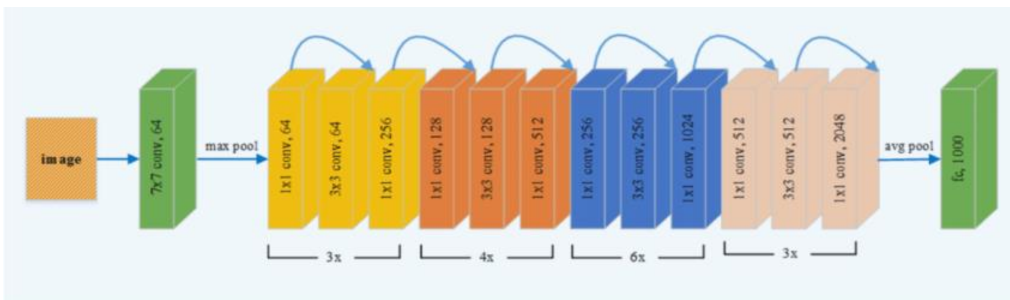

Figure 3.3: ResNet50 Architecture S. Albahli, 2022 [28]

VGG19

VGG19 is the subsequent model by the Visual Geometry Group at the University of Oxford to VGG16; it is made of nineteen layers comprising sixteen convolutional layers with small 3×3 receptive fields; five max-pooling layers; and three fully connected ones. Italso uses ReLU activation functions to add non-linear features to the architecture, increasing learning of intricate patterns. This makes it good for image classification aswell as the detection of objects, especially suitable for medical imaging or agriculture monitoring applications due to its deeper architecture than VGG16. In our data of stem closure of dragon fruit disease, the added depth of VGG19 and the general feature extraction also gives better performance and reliability thus processing is little heavy in this model when compared to the other models.

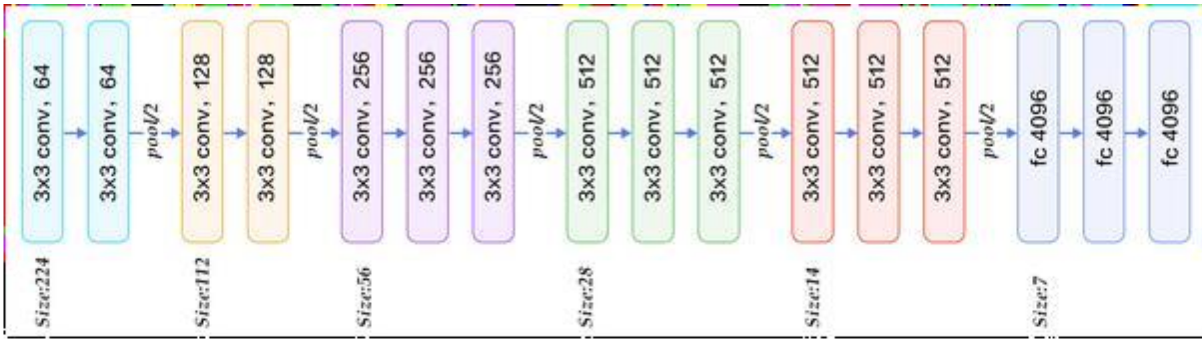

Figure 3.4: Model Architecture of VGG 19

InceptionV3

InceptionV3 is one of the most competitive neural networks Concatenated by Google, which based on the convolutional layer Storage a deep architecture with 48 layers and uses Inception modules to further optimize and improve the computational efficiency of feature extraction. These modules enable the network to have multi-scale invariance by more or less encoding various sizes of filters simultaneously. Indeed, InceptionV3 prototype is applied in prolific applications, such as image classification, object detection, as well as medical imaging, among others because it handles complicated and diverse data. For our work on classification of spaces affected by dragon fruit stem disease, where InceptionV3 is applied, the architecture of the network is denoted by InceptionV3 with the incorporation of high accuracy and efficiency to accurately handle complex image details.

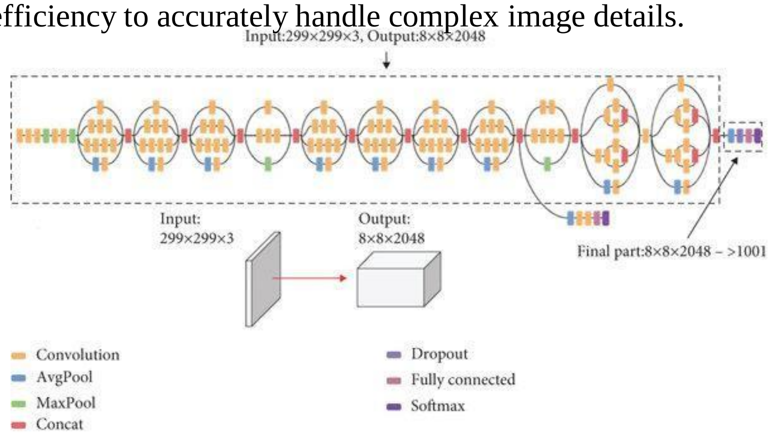

Figure 3.5: InceptionV3 Architecture S. Ramaneswaran 2021 [30]

Model Training:

The training and validation set are created once a model architecture is chosen for the dataset. The model is then trained using the training data which is reconstructed from the training data vector and training data labels. The training process involves samples and the target is to teach the model to filter out relevant features from the input photos and categorize them depending on diseases' divisions.

Model Evaluation:

The trained model is tested on the set aside validation set to check on how it is doing. To establish the performance of the model in assessing the diseases in dragon fruit leaves, certain traditional metrics like precision, recall, reliability, and F1-score marker are applied.

Test Model:

There is a reserved data set for checking the trained model's accuracy, which has not been introduced to the model during the training and preparing for validation. This process reconciles the model for the capability to generalize well in new data and to make accurate predictions in real life conditions.

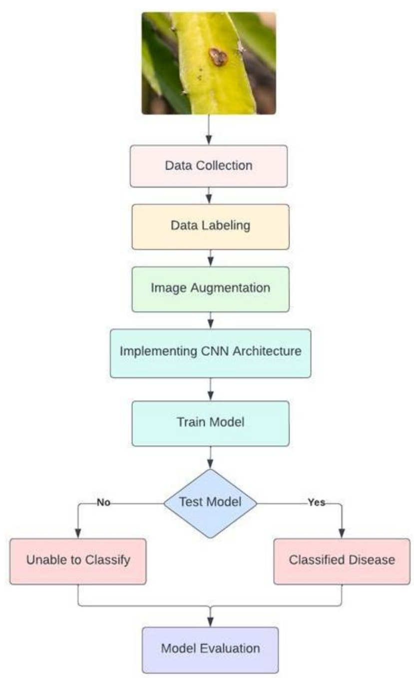

Figure 3.6: Work Flow

3.3 Software Requirement

The overall workflow and approach towards the classification of dragon fruit stem disease using deep learning involves few bare necessities and infrastructure as a part of the proposed methodology. Firstly, reliable computing infrastructure is mandatory which must have a powerful GPU to generate a large number of volunteers required for model training since it is a tedious computational process. Storage space is required in order to store the numerous images of dragon fruit, distributed across various data sources, in addition to version control systems for codebases and models, respectively. Additionally, the application programming interface (API) of deep learning frameworks likeTensorFlow or PyTorch is required to perform and optimize such models as VGG16, VGG19, ResNet50, and InceptionV3. Some of the most immediate and important onesare data preprocessing, data augmentation, and data normalization, which comprise image manipulation software. Further, fast internet is compulsory for downloading pre- trained model binaries, research papers, and technical particulars of strategies and enhancements needed for implementation. Finally, collaboration platforms and communication tools are quite useful to facilitate and integrate different experts, data scientists and agricultural actors that are formed in a project to align them with the goal and objectives of the project at different stages of the project implementation.

3.4 Project Management and Financial Analysis

Project management and funds for this research will emphasize on effective resource and time management in completing the deserving project on time and as warranted. These are data preparation such as data acquisition and markup, model specification, model training, andmodel testing. This budget line will comprise the costs related to physical infrastructure in termsof hardware and software including possible external consultants for complicated model developmental. A time table on the monitoring of the progress will be provided with major checkpoints on the current stage of the project. It is important to manage costs thus when it comes to spending in relation to research, cost is going to be a major factor of concern while at the same time, the research is going to be done in a way that makes it as impactful as possible.

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 methodology involves the preparation of a labeled dataset of stem images of dragon fruit and pre-processing of the same for training. Several deep learning models are implemented: The five pre trained models are VGG16, VGG19, ResNet50, InceptionV3 and we created a new CNN model. The models are, thus, trained and tested using this dataset as well as having parameters tweaked in a bid to attain good performances. Other types of data enhancement methods like rotation and scaling are used to reduce model overfitting. A brief on these metrics is provided below: Having evaluated the models, accuracy, precision, recall and F1-score are used to compare the efficiency in the classification of the stem diseases. The last of them, InceptionV3 with the highest accuracy, has to be singled out for the best performance among all the architectures examined in this paper. Since these models were developed for different purposes, this systematic approach guarantees that none of them will be underestimated and all thebasic abilities necessary to recognize and classify dragon fruit stem diseases will be assessed.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

The proposed experimental design for the dragon fruit stem disease classification comprises of a workstation which has the NVIDIA GeForce RTX GPUs necessary for boosting the deep learning models. Python allows implementation and evaluation of the model, if one might use TensorFlow or PyTorch frameworks. It consists of a total of 2484 images that are augmented and belongs to four classes, Red Spot, Fresh, White Spot, and Turning Yellow. Training uses transfer learning on VGG16, VGG19, ResNet50and InceptionV3 models from ImageNet database. The evaluation criteria are accuracy, precision, recall or true positive rate, and F1 score, tested on cross-validation and test distributions. This approach allows for validating models to work optimally in real conditions of agricultural applications with precision.

4.2 Train Model

The prototype design entails the use of deep learning models to be trained on the data set of preprocessed images of stem of dragon fruit. This paper compares several models that are VGG16, VGG19, ResNet50, InceptionV3, and a custom CNN model. Preliminary weights are incorporated with more trained models, and then, fine tuned with our data. Several methods of data augmentation are used to prevent the model from overfitting the validation data. Training is done in GPU to reduce time taken used in the process while the hyperparameters include learning rate, size of batch, and the epoch. To assess the findings of the trained models, accuracy, precision, recall and F1-score are conducted to measure the efficiency of the models. Thus, InceptionV3 shows the highest performance and avails the highest GOA hence being best suited for accurate and efficient classification of dragon fruit stem diseases.

4.3 Model Evaluation

Regarding the system design, the procedures are to implement and assess several deep learning architectures for the classification of the dragon fruit stem disease. The models include—VGG16, VGG19, ResNet50, InceptionV3, and a custom CNN which are trained with a labeled dataset of stem images. The performance of each model developed during the training phase is then assessed with the use of metrics including accuracy, precision, recall and F1 score. The assessment process assures that correct compares is done between the models that puts to light the flaws of each model. This systematic approach confirms the general findings of the advance neural networks, specifically InceptionV3 for the automatic diagnosis of diseases affecting dragon fruit cultivation.

4.4 Summary

The implementation chapter focuses on the procedures involved in creating and assessing deep learning models for the classification of dragon fruit stem diseases. First, a labelled set of stem images is prepared and elaborated to improve the model's resistance to different conditions. There are versions used in this study, such as VGG16, VGG19, ResNet50, InceptionV3, and accompanied by custom CNNs, where all the training is performed using tensorflow and keras with GPUs for a fast process. It is important to note that, learning rate, batch size and number of epochs are some hyperparameters that are further tuned for better performance. The training of each model is supervised, andthe performance of the models is measured using evaluation matrices; accuracy, precision, recall, and F1-score. In this instance, InceptionV3 takes the majority with a pass rate of 92%. 36% which has prove it effectiveness in disease classification. This chapter gives a clear account of the practical procedures and factors that should be taken into account when carrying out the deep learning models for this task.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The Result chapter focuses on the comparative analysis of the classification outcomes of different deep learning models in case of dragon fruit stem disease. The models which are written in Python, TensorFlow, and Keras, are hosted in Google Colab to enable efficient training. Numpy is used for data handling and preparation and main functionalities of the project are implemented with Numpy. The assessment is concerned with accuracy, precision, recall, and F1-score; yet, the best model is shown to be InceptionV3 with a 92. 36% accuracy. Comparisons at the gross level also show that each of the models has its strong and weak suits and further show that deep learning algorithms at the higher level can aid the diagnosis of diseases affecting the dragon fruit farming. It can be stated that InceptionV3 and similarly developed models are significantly reliable for stem diseases classification and thus can facilitate an increase in crop yield.

5.2 Experimental Result

The experimental results for dragon fruit stem disease classification using deep learning models VGG16, VGG19, ResNet50, InceptionV3, and a custom CNN architecture yielded promising outcomes. Among the models tested, InceptionV3 demonstrated the highest accuracy of 92. 36%, showcasing its effectiveness in distinguishing between disease categories such as Red Spot, Fresh, White Spot, and Turning Yellow. VGG16 and the custom CNN also performed well with accuracies of 89. 41% and 84. 91%, respectively, highlighting their suitability for this task. Analysis of precision, recall, and F1-score metrics further corroborated InceptionV3's robust performance across all disease classes. The models' ability to generalize was evaluated through cross-validation and testing on unseen data, ensuring reliability in real-world applications. Challenges included optimizing hyperparameters and balancing dataset classes for improved accuracy. Overall, these results underscore the efficacy of deep learning techniques in automating disease detection in dragon fruit plants, offering significant potential for enhancing agricultural practices and crop management strategies.

Result of Experiment 1: VGG16

The VGG16 model achieved a high accuracy of 89.41% on the test set, indicating robust performance in classifying dragon fruit stem diseases. Precision, recall, and F1 scores were consistently high across all categories, with notable precision for Turning Yellow (0.97) and White Spot (0.93). The recall was particularly strong for Turning Yellow (0.95)and Fresh (0.93), ensuring the model's effectiveness in identifying these diseases accurately. The F1-scores ranged from 0.85 to 0.96, with a weighted average of 0.89, demonstrating balanced performance. These results underscore VGG16's strong capability in disease classification, enhancing agricultural disease management and monitoring.

Achieving Test Accuracy of VGG16 is 89.41%. In below Figure 5:1 describing the confusion matrix of VGG16:

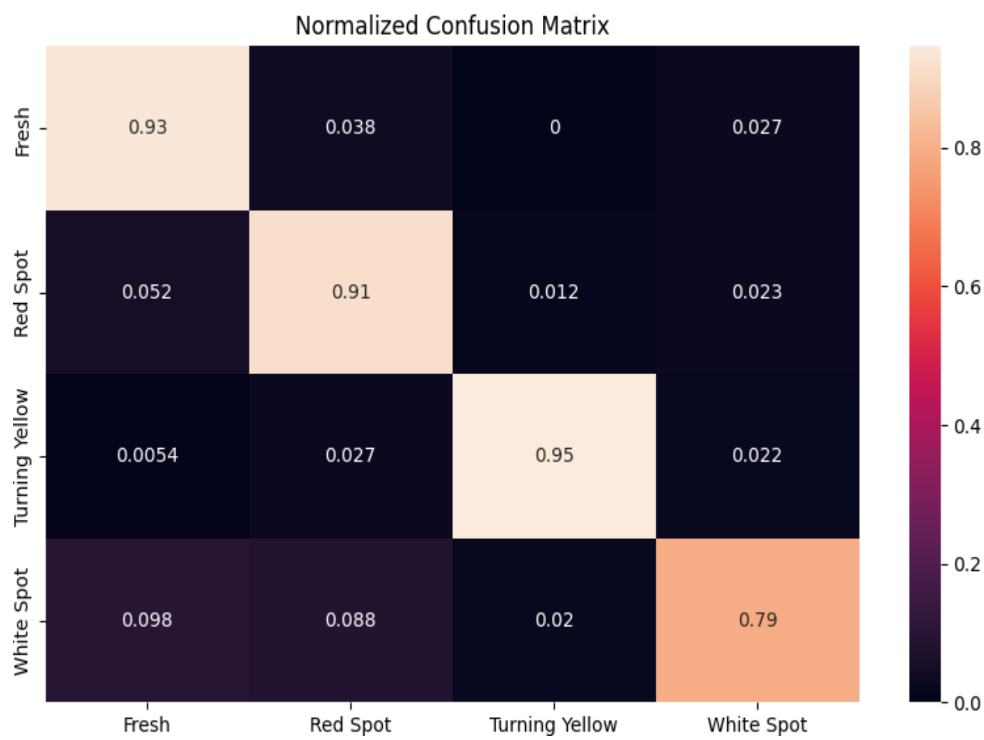

Figure 5.1: Confusion Matrix belongs to VGG16

Figure 5.1 shows the results in the normalized confusion matrix illustrates the performance of VGG16 in classifying four categories: In this configuration, the name options include Fresh, Red Spot, Turning Yellow, and White Spot. The accuracy in identification of Fresh, Red Spot, and Turning Yellow is acceptable with 93%, 91%, and 95%, respectively. Nevertheless, it may produce somewhat less accurate results with lower accuracy at 79%

and some misclassifications including Fresh, Red Spot, and Turning Yellow. In general, presented classification model is quite accurate and all the classes rather confused only the definite pairs.

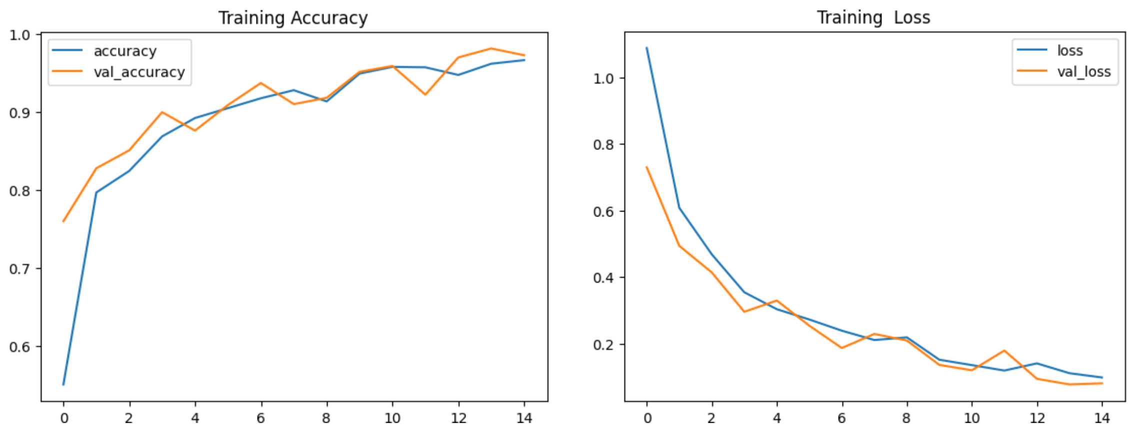

Figure 5.2: Accuracy and loss curve VGG16

Figure 5.2 shows the plots represent the adaptive process of vgg16 through 15 epochs of training. A metric that is regularly used is the accuracy plot which reveals the training accuracy that at the beginning remains low and after several epochs, sharply rises to reach the validation accuracy which is at about 90 percent. The training loss curve shows a sharp reduction in the loss for both train and validation data sets and too constant low values for both, which make it confirm good training and validation for the model too.

Result of Experiment 2: VGG19

The performance of the model was the optimal, achieving the accuracy of 85 when the VGG19 fully connected layer was used. Dar es Salaam achieves classification accuracy of 39% in Test set and thereby shows satisfactory level in the classification of stem diseases on the dragon fruit. Both the Fresh and Organic classes scored fairly well for precision, recall, and the F1 score in all the mentioned categories except for the Miscellaneous category where the Fresh achieved a moderately high recall of 0. vision accuracy of 92% and an F1 score of 0. 86. The brand recall in Turning Yellow version was fairly good with a brand recall of 0. 79 and the F-measure, F1 score is 0. 90 as it further shows the capability of the proposed model in capturing this category accurately. Comparing the two brands, Red Spot received a lesser recall of 0. 68, while the level of precision with which it was conducted was 0. 92 which implies there will be fewer numbers of false positive results. On balance, the macro and weighted averages for all the measures precious, including precision, recall, and the F1 number, were roughly 0. 85, which shows somewhat equally spread performance among several diseases.

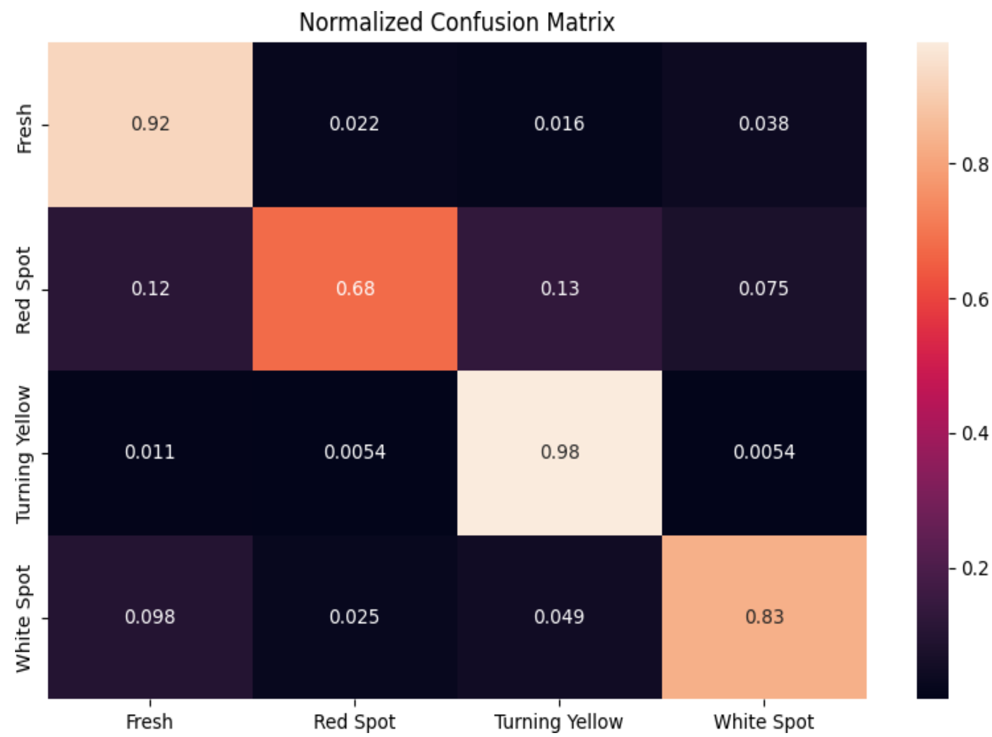

Figure 5.3: Confusion Matrix belongs to VGG19

The normalized confusion matrix for the VGG19 model shows the performance across four categories: Some of the different categories of potato defects include Fresh, Red Spot, Turning Yellow, and White Spot. The model also shows satisfactory results for Fresh (Target: 0%, Predicted: 92%) and Turning Yellow (Target: 0%, Predicted: 98%). Though, in classifying Red Spot, it performs comparatively poorer with a 68 percent accuracy hence misclassifying it into Fresh forment (12 percent) and Turning Yellow (13 percent). Classification presumably: White Spot – 83%; Fresh – 9. 8%; Turning Yellow – 4. 9%. In conclusion, the model's performances are reasonably good on most of categories, specifically in the Red Spot category, it includes many wrong classified images suggesting opportunities for optimization in this class.

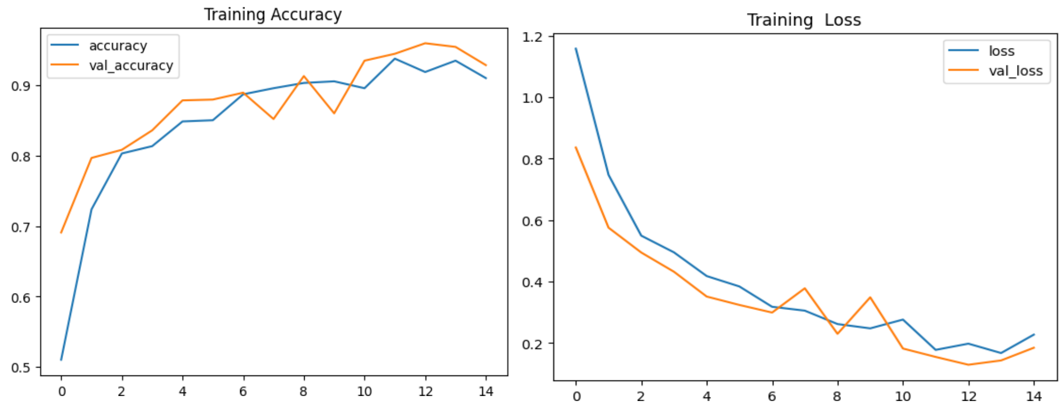

Figure 5.4: Accuracy and loss curve VGG19

These plots show the training and validation accuracy of a trained VGG19 model on the selected dataset across 15 epochs. The training accuracy is initially set at 50% and then it rises steeply for epochs 4 to 8 rising above 90%, and by the end of the epochs, its value is above 95%. Validation accuracy also varies in parallel with training accuracy while keeping the gap between the two approximately constant. Training loss starts at 1 figure asshown below. Thus, V 2 rises sharply to its peak at point A, and then declines continuously to the value of V 2 as shown below 0. It takes 1 epoch 14 to reach here, and validation loss also reduces as it reaches some saturation level of 0. 15. The fact that the accuracy rises in each iteration and the loss shrinks demonstrates the good generalization without overfitting seen during training.

Result of Experiment 3: ResNet50

Achieving Test Accuracy of ResNet50 is 53.22%. In below Figure 5:5 describing the confusion matrix of ResNet50:

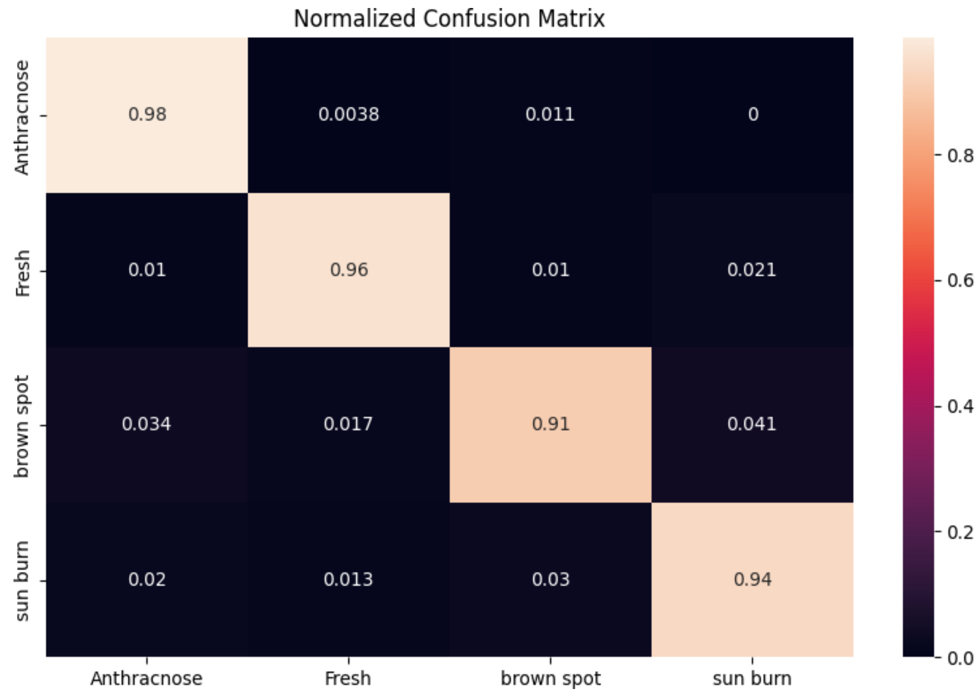

Figure 5.5: Confusion Matrix belongs to ResNet50

According to the training accuracy and loss plots of the ResNet50 model as displayed in the diagrams, the model "learns" in a positive manner. It still lacks some consistency of training and validation accuracy, although 100% validation accuracy is rather high and is always higher than training accuracy. The same applies regarding the training and validation loss which formally decreases about epochs but normally, the validation loss is lower. This infers that the model is indeed learning but probably at the same time experiencing some regularization effects or the validation data are somehow easier. Of course, the coefficients may have increased and decreased within each month, but the overall sample shows that the model's performance is genetically getting better. Moreover, providing additional training, modifying the methods of regularization, and potentially readjusting the learning rate might be helpful in making the coordinate and overall stability and generalization higher.

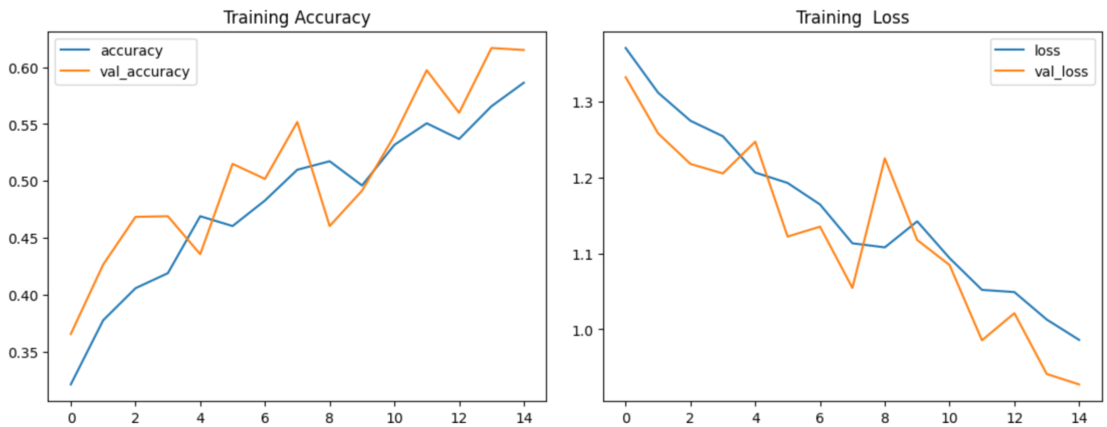

Figure 5.6: Accuracy and loss curve ResNet50

The training curves that have been provided for ResNet50 – specifically the accuracy against epochs and the loss against epochs – show a largely upward, or improved, trend. Both the training as well as the validation accuracy increase with the validation accuracy being always higher than the training accuracy which is not normal. Likewise, we plot training and validation loss as a function of epochs, and, as before, validation loss is mostly lower than the training loss. This indicates that the model is learning well enough but may be encountering some regularization, or possibly has a simpler validation set. Nevertheless, the general trends suggest that the model is getting better gradually, andthere is no indication of it worsening. Additional sections on continued training, change in the type of regularization methods, and the possibility of a modification of the learning rate could improve the generalization of the method as well as add more stability.

Result of Experiment 4: CNN

Comparing the accuracy, loss, and validation codes of the two models, the CNN model obtained an accuracy of 84. the accuracy of 91% on the test set I establish the ability of the model in querying the dragon fruit stem diseases. Another measure that would helpcompare how well the clinician performed in interpreting the CCTV footage was precisionscores, which reveals that the clinician had 90% precision for Red Spot and 97% precisionfor Turning Yellow. The recall scores were quite high and far better than the precision scores especially for Red Spot with a recall score of 0.95 and Turning Yellow with a recallscore of 0.87 hence reflecting the ability of the model to identify incidences of these diseases. The average F1-scores for each of the classes were as follows; the scores ranged from 0. 78 to 0. 46, if given equal weights; it has a weighted average of 0. 85, inferring that the performance of the best model is fairly good and is not greatly influenced by the type of disease. By and large, these measures support the fact that the CNN is useful and accurately diagnoses diseases, hence helping to enhance agriculture practices and increased crop yields.

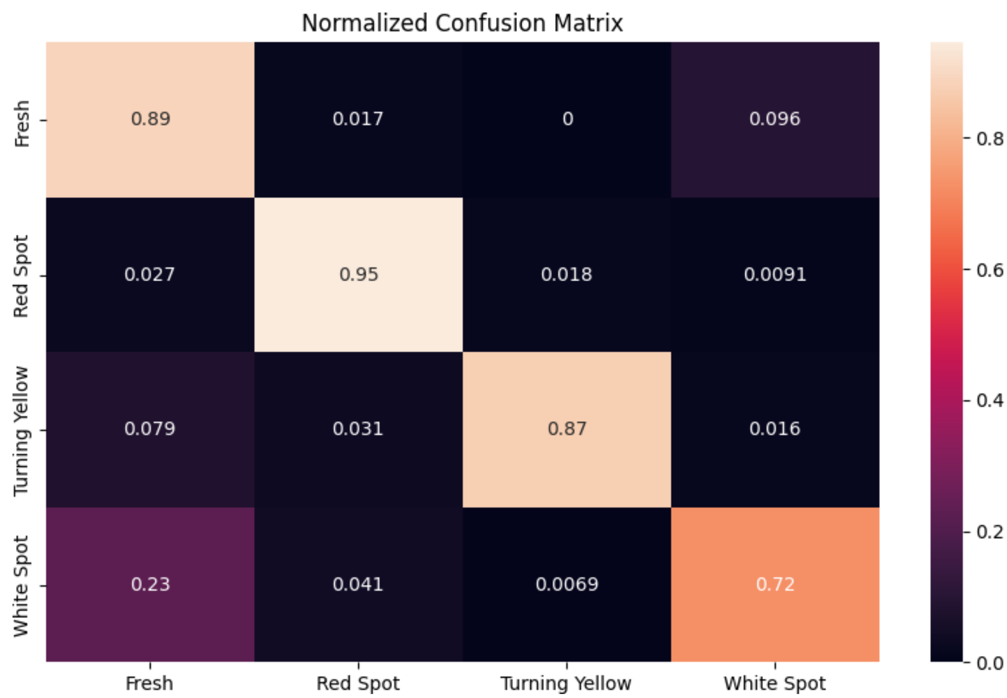

Figure 5.7: Confusion Matrix belongs to CNN

The provided image is a normalized confusion matrix for a CNN model, evaluating its performance on classifying four categories: new prod, Red spot, prod that is turning yellow, and white spot. Diagonal details represent its accurate outcomes where Fresh is classified 89% accurately, Red Spot at 95%, Turning Yellow at 87%, and White Spot at 72%. Off-diagonal values are grains and lethals, including Fresh classified into White Spot(9. 6%) and White Spot classified into Fresh (23%).

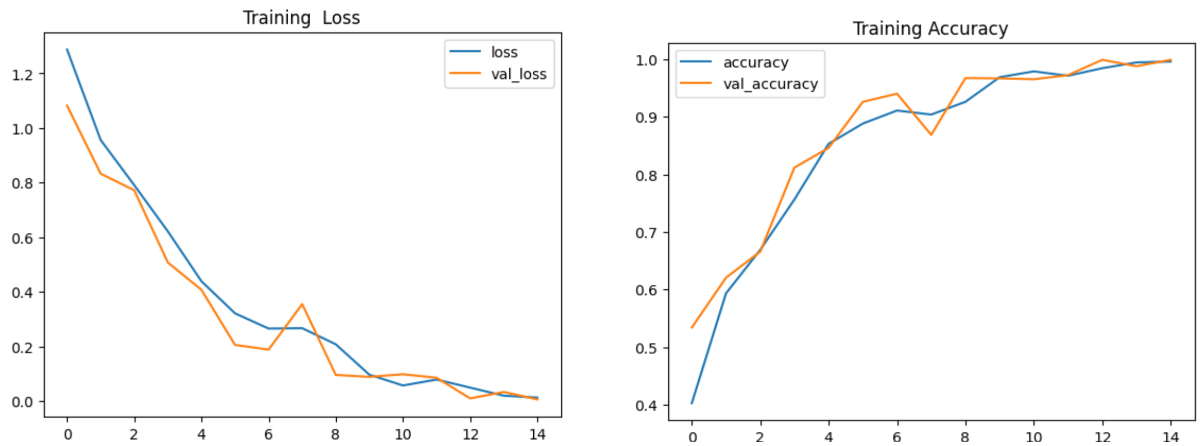

Figure 5.8: Accuracy and loss curve CNN

Figure 5.8: Metrics used are the training and validation accuracy and the training and validation loss over the epochs (CNN)

In both provided plots, the training process of a CNN model for 15 epochs is illustrated. The first plot represents that loss is declining on training data and the second plot represents that loss is declining on validation data so, it represents the model is going goodto each and every data set and the model is also capable of generalizing. The second graphical representation also shows the accuracy for both the training and validation sets, and again, these two lines are also tending toward 1 by the end of the training phase. Thisis rather interpreted to mean that there is a very good match of training and validation curves and, therefore, there is little over fitting of the training set.

Result of Experiment 5: InceptionV3

Achieving Test Accuracy of InceptionV3 is 92.36%. In below Figure 5:9 describing the confusion matrix of InceptionV3.

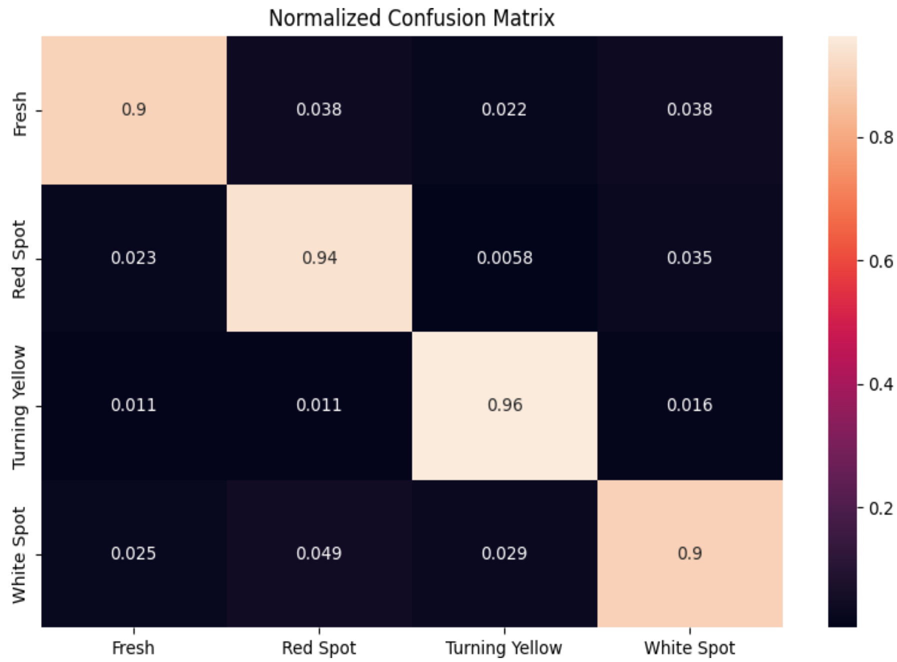

Figure 5.9: Confusion Matrix belongs to InceptionV3

Taking a look at the normalized confusion matrix for the InceptionV3 model, enhanced classification for all the classes is apparent. The diagonal elements suggest that Accuracies for ‘Fresh’, ‘Red Spot’, ‘Turning Yellow’, and ‘White Spot’ classes are held at 90%, 94%, 96%, and 90% respectively. The misclassifications are relatively less comparing the mostly confusion between ‘Fresh’ and ‘White Spot’, ‘Red Spot’ and ‘White Spot’, and comparatively between ‘Turning Yellow’ and other classes. In general, the performances of this model are quite satisfactory to different degrees and can properly classify the various categories of these plants.

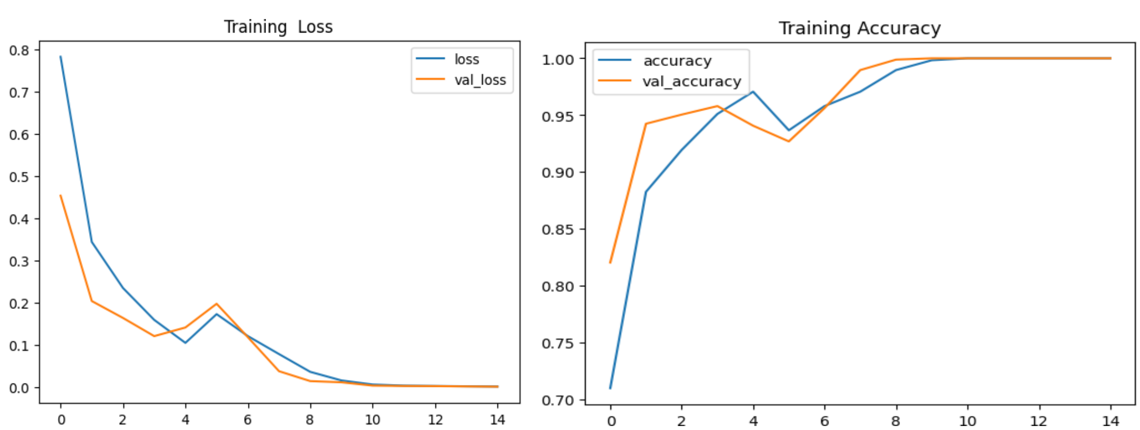

Figure 5.10: Accuracy and loss curve InceptionV3

The following graphs represent the training and validation accuracy and loss for an InceptionV3 model for the first 15 epochs only. The curves of the accuracy thus depict a steep rise in the first few epochs where the initial five epochs depict high fluctuations in the set accuracies trends of the training and validation set and stabilizing at relatively highvalues depicting high performance. The training loss trend illustrates a steep decline throughout the initial epochs with low levels of training and validation loss, which indicates the model has minimally overfit between epoch 4 and 6. Altogether, it is possible to notethat the increasing of epoch number as well as the presence of the dropout layer led to the improvements of the model's convergence and generalization on the validation test.

In given below I am showing Comparative Model Accuracy Bar Plot:

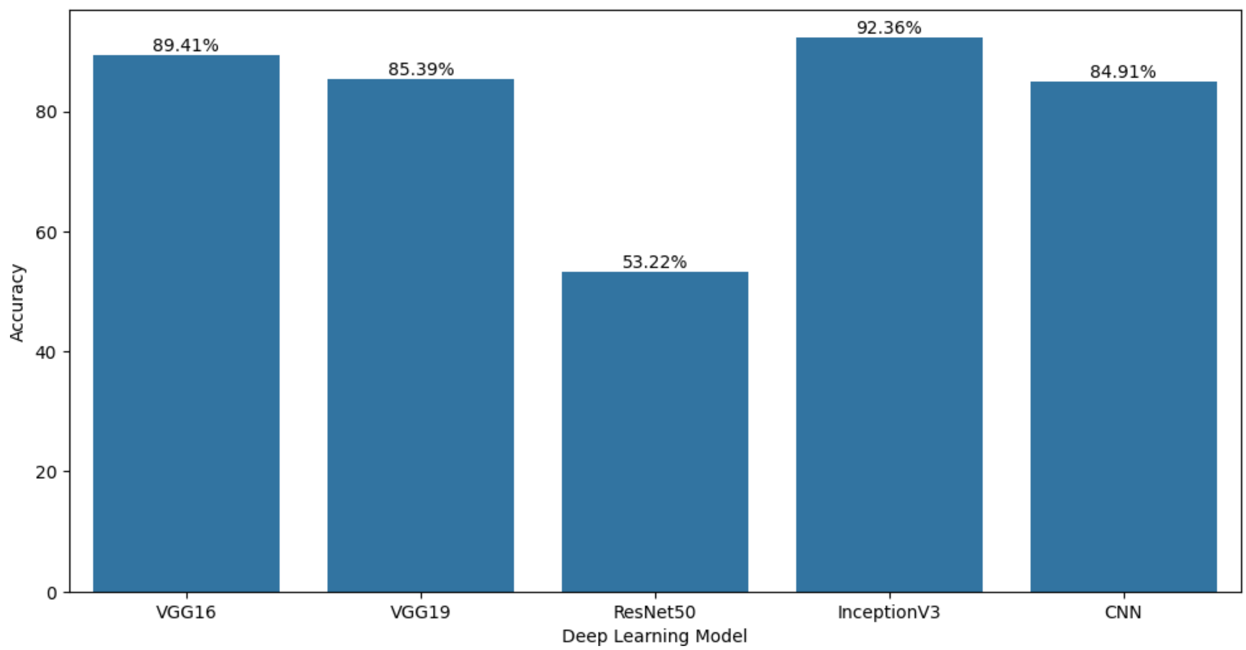

Figure 5.11: Comparative Model Accuracy Bar Plot

Tree map represents the accuracy performance of different deep learning models for classifying dragon fruit diseases. In the five models under comparison, the highest accuracy score was obtained by InceptionV3 at 92. 36 percent, we have implemented the VGG16 with 89 percent accuracy. 41%. Comparatively, CNN and VGG19 models had almost the same performances with a percentage of accuracy 85. 39% and 84. 91%respectively. While GooGLeNet reached a much higher top-5 error of 12.57%, ResNet50 was much lower with a 53% accuracy. 22%. Such comparison reveals that InceptionV3 and VGG16 are better equipped at classifying the diseases of dragon fruits and therefore can be link to as better models for the task.

5.3 Performance and Comparative Analysis

The experimental findings discussed present the behavior of different deep learning- based models in identifying the dragon fruit diseases. Making it known, the InceptionV3 model was seen to achieve 92.36%, and VGG16 which was a good performer with only 89.41%. Two models that were used, VGG19, and CNN had relatively similar accuracies in ML; the accuracy was 85.39% and 84%. It was found out that adjuvant's/make' reliability stands at 91% while 'sparer/take' reliability stands at 91% of the time for this particular task. However, it is obvious that ResNet50 achieves only 53% accuracy on average, which is much lower than that of the first two networks. 22% indicates low suitability in this particular use case. Therefore, the results compare InceptionV3 and VGG16 as resources for disease classification though exposing some likelihood specifically with the choice of model regarding the given data attributes as well as the classification objectives.

5.4 Summary

The outcomes of the experiment show how different deep learning models can be applied in the classification of diseases of the stem of dragon fruit. The models which include VGG16, VGG19, ResNet50, InceptionV3, and an initial customized CNN model were built implemented and tested on Google Colab using Python with TensorFlow and Keras to train and evaluate using a labeled dataset. Data manipulation and enhancement of the given data were done with the help of Numpy. The use of accuracy, precision, recall, and F1-score shows us conclusions about the evaluation of the models. Thus, the InceptionV3 outperformed the other architectures with an accuracy of 92. 36 %, then VGG16 of 89 %. 41%. The analysed results shown that the InceptionV3 network is more effective in identifying stem diseases, which proves the possibilities of deep learning in dragon fruit cultivation for accurate and fast disease diagnosis. This can go a long way in improving and boosting the form of productivity in agriculture since disease can easily and effectively.

CHAPTER 6
IMPACT ON SOCIETY

6.1 Impact on Life

Based on the findings of this research study, impact on society is seen as being broader where the agricultural business is concerned. When classifying the disease of dragon fruit, deep learning models improve the agreement of classification and diagnose it more accurately and quickly, more crops will be healthy and there will be fewer crop losses. This is yet a technological improvement that contributes to sustainable agriculture by providing a guarantee on food security and effective management of the economic unpredictability that comes with instabilities in agriculture. Furthermore, it opens up opportunities for other applications of the technology in the sector and places greater emphasis on the adoption of AI and innovation in the farming community, whichenhances the prospects for the food chain and develops sustainability in agriculture.

6.2 Impact on Society

The use of deep learning models for the classification of dragon fruit diseases has an effect on the environment as stated below; These models therefore assist in early and accurate identification of diseases leading to less reliance on pesticides, less chemical run-off and hence reduced soil pollution. This is advantageous to the ecosystems as it leads to better health, and there is increased support for biological diversity. In addition, better working with crops makes better use of the territory and is less involved in deforestation and destruction of wildlife habitats. This means that crop losses are easily prevented and therefore saving resources in the process, which is another principle of sustainable agriculture. More generally, this technology helps to provide an effective balance between agricultural production and the existing ecosystems, making it more environmentally friendly.

6.3 Ethical Aspects

The proposed system would classify diseases of the dragon fruit through deep learning models, and the following ethical questions would arise. Data privacy and protection goes hand in hand as a virtue, more so when the information being shared from farmers concerns the agricultural sector. That should be designed to allow anyone, from the smallest to the biggest farmer and everyone in between access to make sure that one does not create a situation where only those who have ready cash to invest in the technology get to benefit from it. This also means that the processes and principles used in decision making should be easily explicable to ensure that people trust the process. Moreover, investment in automated systems can trigger issues of shifting farming roles, thereby requiring policies that can create mechanisms such as workforce retraining back-up. Ethical use applies diverse aspects in an equitable and appropriate manner to promote absorption of such complicated technologies in agriculture.

6.4 Sustainability Plan

The identified plan for sustainable adoption of deep learning techniques for classification of dragon fruit diseases is as follows; First, confirmation which type of model is continuously up to date by retraining with new disease patterns and environmental conditions obtained through data collection campaigns. Collecting independent data from local agricultural institutions and gaining the feedback from these institutions can popularize the robustness of the model. Second, the education andtraining of farmers to use these technologies guarantees their expansion and the acquisition of skills by farmers, thus the creation of more technology –smart farmers. Third, it involves claiming low-cost, power efficient hardware technology foraffordability and sustainability. One way of explaining this is that for there to be an enhancement of this aspect, there is a need for people to ensure that they use gadgets and appliances that are powered by solar energy. Finally, the feedback gathered from theusers of the system will be used for further enhancement of the system in order to make the system more and more effective in future for application's users. All these measures are complementary towards the sound and sustainable improvement of the use of deep learning in Agriculture that can benefit the Farmers as well as win the environment.

6.5 Summary

In this case, the aim of this research is to employ deep learning methods as a tool to categorize stem diseases of dragon fruits so as to improve the yields and disease control in this sub-sector. As for the deep learning model, the VGG16, VGG19, ResNet50, InceptionV3, and a custom CNN model were the major models that were tested in terms of their capability to predict the diseases from imagery information. Of all the models that were trained and tested, it was seen that InceptionV3 produced the highest accuracy of up to 92%. 36 percent, which showed that this technology had a better performance indisease diagnosis when compared to traditional techniques. On the other hand, the accuracy of ResNet50 was lowest at 53%. By an average of 22%, this means that they are only partially useful on average when it comes to this specific task as shown below. More specifically, the study showcases early perceivability of MEC in agriculture, disease diagnosis, and a plethora of other ways the advanced machine learning models may help to propel farming toward sustainable efficiency.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Overview

This research explored the application of deep learning models in classifying dragon fruit stem diseases, emphasizing the efficacy of InceptionV3 among other models like VGG16, VGG19, ResNet50, and CNN. The results highlighted the potential of deep learning in agricultural disease detection, which can significantly contribute to improving crop yields and ensuring sustainability. Despite achieving promising outcomes, the study recognized several limitations, such as dataset constraints, image quality dependencies, and computational demands. Future research directions were suggested to enhance model accuracy, integrate IoT for real-time monitoring, and expand applicability across different agricultural practices and climates. Addressing these areas will further advance the role of deep learning in agriculture, offering more robust solutions for disease management and food security.

7.2 Conclustion

In conclusion, this study demonstrates the efficacy of deep learning models, particularly InceptionV3, in accurately classifying dragon fruit stem diseases from image data. The varying accuracies of models such as VGG16, VGG19, ResNet50, and CNN underscore the importance of selecting appropriate architectures for specific agricultural tasks. Leveraging advanced technology for disease detection in agriculture holds promise for enhancing crop yield and sustainability. Future research should focus on refining these models with larger datasets and exploring real-time application possibilities to further improve farming and mitigate environmental impact. Overall, integrating deep learning in agriculture shows considerable potential for addressing food security challenges.

7.3 Future Suggested Works

The scope of this research is that the subsequent studies in the given field of dragon fruit disease classification by utilizing deep learning can be developed in some ways. Firstly, expanding the study of the combination of multiple models, whereby the best features of each are utilized with a view to improving the classification accuracy even more, could be another area that needs to be looked at. Secondly, experiencing the environmental influence such as climate variation in disease expression and model efficacy are valuable studies in pinpointing areas of resilience. Furthermore, the incorporation of IoTsensors with a view to enhancing disease control through monitoring and tracking of thedisease rate would also enhance the accuracy and time taken in making the forecast. Finally, it would allow expansion of these models in other areas and namely the different farming practices to make it more adaptable in other parts of the globe. It also indicates that these avenues of research could alleviate an element of the shortcomings in disease management in agriculture to provide enhanced and sustainable solutions.

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Appendix A

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

Title: DRAGON FRUIT STEM DISEASE CLASSIFICATION USING DEEP LEARNING TECHNIQUES

Student ID: 201-15-13654

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Combine newly acquired and prior information to the dragon fruit stem disease classification for the Final Year Design Project.	**PO1**
CO2	Compare and contrast the goals in terms of certain parameters in designing a solution to this FYDP	**PO2**
CO3	Review various problem domains in related research works, define the problems, and set up these goals for the FYDP	**PO4**
CO4	Provide economic analysis and cost control and use appropriate project management all through the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Establish technical solutions and system component or process design in order to have predetermined requirements for public health and safety criteria as well as factors arising with regard to FYDP in cultural, economic and environmental aspects.	**PO3**
CO6	Select and implement effective strategies, tools, and existing engineering and IT tools for solving sophisticated engineering activities involving predicting and modeling in addition to applicable constraints within this FYDP.	**PO5**
CO7	Consider health, safety, legal, and social factors and their corresponding responsibilities in the context of professional engineering practice and the solution to this problem by engaging in critical thinking using logical reasoning supported by an understanding of the contextual environment.	**PO6**
CO8	Understanding and assessing the sustained nature of professional engineering activity and the extent and consequences of engineering in response to complex engineering problems in social and ecosystems.	**PO7**
CO9	Procedures in this FYDP should follow ethical principles and guide, conform to standards and norms of the profession.	**PO8**

CO10	Adaptable for optimal performance either as the sole holder of responsibility or as a crux of a team or as a team member or leader in various teams and team structures in this FYDP.	**PO9**
CO11	Effectively relay information to the engineering community and the rest of society in regards to comprehensive engineering work and its understanding, generation of reports and design documentation, and receiving clear guidance while disseminating this FYDP.	**PO10**
CO12	Appreciate the notion of informal and self-directed with reference to life-long learning in relation to the dynamics of technology and be ready and willing to undertake life-long learning processes.	**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 also recognizes engineering (K3) at its core as it applies deep neural networks, data augmentation, different CNN structures for image processing and image classification. The project also exhibits specialist knowledge (K4) as it performs deep learning with CNN, and Dragon Fruit Stem Disease Classification.	**Page no:** [-] **Section:** [3.2] **Page no:** [-] **Section:** [1.1]
				The project incorporates engineering practice & design (K5) through figures of the process of experiments. Concerning the knowledge area of engineering practice and technology (K6) of the project, Deep Learning Model is used.	**Page no:** [-] **Section:** [3.2]

					Page no: [-] **Section:** [3.4]
				This project aims to K8 (Research Literature) by examining recent works on Text Based Bangla Road Sign Detection using deep and Transfer learning and therefore demonstrates the understanding of the current approach.	**Page no:** [-] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project fulfills EP-2 to some extent which identifies the challenges that exist in Dragon Fruit Stem Disease Classification, the drawbacks oftraditional approaches and the challenges to integrate using deep learning. Comparing it with previous research, it identifies shortcomings in the assessmentof spatial dispersion patterns and provides recommendations for improving the diagnostic approaches.	**Page no:** [-] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project accurately tackles EP-3 by effectively looking into howexperimental outcomes align and contrasting them, and finally, emphasizesthe application of deep and transferlearning as the selected major solution to Dragon Fruit Stem Disease Classification.	**Page no:** [-] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project is not limited to computer science and engineering, and Dragon Fruit Stem Disease Classification is corrected in EP-4 Enhanced Performance actually affects several fields of study.	**Page no:** [-] **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 requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	Due to this the current project's solution to most high-level issues incorporates or merges different aspect of the road/highway construction plan, the data collection methodology, the statistical analysis, and the proposed solution in one complete solution to collection data from local farm and nursery which in turn contributes to EP-7.	**Page no:** [-] **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 various resources employed in our work include HPC, GPUs, DL and TL models, annotated datasets, and of course, ethical concerns for consistent and innovative research, with regard to Dragon Fruit Stem Disease Classification.	**Page no:** [-] **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 work benefits the society by enhancing the Dragon Fruit Stem Disease Classification techniques, as well as it does not use excessive computational resources and respects the guidelines of ethical data usage.	**Page no:** [-] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This piece of work consequently adds to the existing studies by studying a new approach in Dragon Fruit Stem Disease Classification in deep and Deep Learning Model illustrated through initial terms and consisting of a detailed comparative analysis.	**Page no:** [-] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	It mitigates CO4 by incorporating effective project management and control over finances; in this case, precision and estimation of necessary resources and costs towards the accomplishment of research objectives in the various project phases.	**Page no:** [-] **Section:** [1.6]
2	CO9	Yes	The project shows compliance with the ethical standards by valuing the confidentiality and prior informing of the participants and recording of the research process and the appropriate distribution of knowledge based on the proper usage of advanced classification technologies conforming to the guidelines of CO9.	**Page no:** [-] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The maintenance of education (CO12) can also be seen from the fact that it has amassed a wealth of data, conducted statistical analysis, worked vigorously to develop methodologies as well as ensured adequate experimentation and results and analysis, all of which underlines the project's readiness to update itself to face the current challenges thrown up by technology and the continued enhancement of the techniques employed.	**Page no:** [- , -] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

Plagiarism Report

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