DRAGON FRUITS STEM DISEASE CLASSIFICATION USING DEEP LEARNING

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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"**, submitted by **Mst Mohsina Akter** and **Sakin Jahan Mumu** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **15 July 2024**

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Abdus Sattar Assistant Professor Department of Computer Science and Engineering (CSE), Daffodil International University** (DIU). We 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 Fruits Stem Disease Classification is a critical task in agriculture to ensure the health and productivity of dragon fruit crops. Utilizing deep learning techniques, this study aims to accurately classify various stem diseases affecting dragon fruits, including Fresh, Maroon Spot, Sun Burn, and Wilting. We collected and labeled a diverse dataset of dragon fruit stem images from different farms and applied image processing and augmentation techniques to enhance the dataset. Several Convolutional Neural Network (CNN) architectures were implemented and evaluated, including Xception, VGG19, a custom CNN, InceptionV3, and MobileNetV2. The results demonstrated that MobileNetV2 achieved the highest accuracy of 96.17%, followed by Xception with 92.17%, and InceptionV3 with 91.50%. The custom CNN and VGG19 achieved accuracies of 85.75% and 84.83%, respectively. The high accuracy of MobileNetV2 highlights its potential for real-world deployment in resource-constrained environments. Our methodology provides a robust framework for dragon fruit stem disease classification, ensuring precise disease identification and supporting agricultural management practices.

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CHAPTER 1

Introduction

1.1 Overview

Dragon Fruits Stem Disease is an important task in agriculture to protect and improve the quality of dragon fruits or Else. With the help of deep learning methodologies, the present literary work intends to identify numerous stem diseases of dragon fruits: Fresh, Maroon Spot, Sun Burn, and Wilting. To gather the training data, we took and labeled stem images of dragon fruits from various farms; then, we performed the pre-processing and augmentation on the collected images. Five CNN models were used and compared: Xception, VGG19, a proposed CNN, InceptionV3, and MobileNetV2. The result estimated that the MobileNetV2 has 96. 17% accuracy, the accuracy of Xception is 92. 17%, InceptionV3 is 91. 50%. The accuracy of the proposed custom CNN and the VGG19 was 85. 75% and 84. 83% respectively. The high accuracy of MobileNetV2 can be attributed to the fact that it is suitable for real-world implementation especially in systems with limited computational resources. The used method gives an impregnable structure of classifying dragon fruit stem disease which aids disease description and agricultural control measures.

1.2 Background and Present State

The background of this research is based on the growing demand for early and reliable identification of diseases in the agricultural production chain with more focus on the cultivation of dragon fruits. The conventional approaches for the detection of stem diseases are slow, tedious, and are accompanied with high rate of human errors resulting in massive loss on produce. New trends in deep learning particularly CNN's have revealed high potential with the prospects of automatically correct, classifying diseases. Today, there are many CNN structures, such as Xception, VGG19, InceptionV3, MobileNetV2, and others, that are being researched in order to improve the possibilities of agriculture. These models have been presented with a different level of achievement, MobileNetV2 being one of the most efficient models because of higher accuracy and a shorter time in different disease classification tasks.

1.3 Problem Statement

The research question that has been addressed is how to distinguish diseases attacking the stems of dragon fruit in the shortest time and with the highest accuracy. Standard assessment procedures can be tiresome through consuming a lot of time, replicative and error prone and this makes crops and quality yield to be lost. Xception, VGG19, Inception V3, MobileNetV2 are the different kinds of CNNs the current research tends to implement and use in order to create a deep learning based automated system for disease classification. The aim is to select the model with the highest accuracy and sensitivity for detecting diseases in stem of dragon fruit and propose a tool that may help farmers to manage early the diseases to reduce a huge expenses of crop damage and improve the productivity of farms.

1.4 Objectives

Rigorous analysis of the issue for the given project indicates that the overall goal of the study should be set as follows: The first and foremost goal of the present research is to create and assess the efficiency of a deep learning-based system for the correct classification of stem diseases in dragon fruit plants. This study seeks to establish the comparative analysis of several CNN structures such as Xception, VGG19, InceptionV3, and MobileNet V2 on the efficiency and accuracy of the model. The work aims at collecting a large number of images of dragon fruit stem, applying intricate image preprocessing, and providing a comprehensive analysis of the effectiveness of each types of CNNs. Thus, the long-term aim is to create an easy-to-use, accurate application that will help farmers in identifying diseases early and thus optimize crop care to increase yields and make the farming business more sustainable.

1.5 Scope and limitations

The work proposed in this research review focuses on the integration, deployment, and assessment of the CNN—Xception, VGG19, InceptionV3, and MobileNetV2—in identifying dragon fruit stem diseases. It forms a part of the research involving collection and preprocessing of data, intensification of the images used for training and testing of the models. Basically, the research will compare the effectiveness of these models with the purpose of recommending the appropriate architecture for real-life application in agriculture. However, there are several limitations of the present research. There is a possibility that the given dataset does not encompass all the variations of disease manifestation, which could be an issue with generalizations. Moreover, their demonstration is conditioned by the quality of the input images although it may be influenced by such factors as light or angle. A study could possibly build upon these limitations by enlarging the sample-set and enhancing the ways to obtain pictures.

1.6 Report Organization

This report is developed with several significant sections in order to systematically cover the objectives and results of this study. The section called ‘Introduction’ contains information about the general context of the research, as well as the rationale for the given investigation. In the present section the Concepts and Procedures of the Present describe current practices and the necessity for enhance in the current system of disease categorization. The Methodology section describes the data gathering, data cleansing, and applying model procedures. Experimental Results and Analysis describe the delivery of Multiple CNN Model Results. The Discussion elaborates these findings by underlining the former strengths and the latter weaknesses of the study. Summary of the Study and Conclusions summarize the outcomes of the research and their significance. Last but not the least, the References section highlights the literature that has been used in the research.

1.7 Summary

This research aims to evaluate the use of deep learning; particularly CNNs in diagnosing stem diseases in dragon fruit. Through the comparison of the five CNN models consisting of Xception, VGG19, a proposed CNN, InceptionV3, and MobileNetV2 based on the labeled image dataset, the research discovers that MobileNetV2 has the highest accuracy of 96.17%, based on the evaluation metrics used in the study. It includes all stages related to data gathering from various sources, its preparation, the building and tuning of a model, as well as its assessment. Findings indicate the similarities and differences of each model for an understanding of their usefulness for optimization of agricultural situations. These findings thus establish the prospect of CNN based systems as playing a part in improving disease diagnosis at an early stage of the disease in dragon fruits to enable reduce crop loss. Unquestionably, this study could help future research to improve these models and enhance their application.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

Based on the presented literature on employing deep learning in classification of agricultural diseases for crops such as dragon fruits, it has been evident that there has been progress as well as barriers. CNNs are highlighted to enhance atomization in disease detection through the accomplishment of diagnosis differing from or superior to conventional approaches. The following CNN architectures have been investigated, including Xception, VGG19, InceptionV3, and MobileNetV2, and the result revealed that CNNs are capable of diagnosing plant diseases based on photographic evidence. Some limitations revolve around the availability of the data that should ideally be large and well-annotated, possibility of generalization of the designed models to other environments and the practicality of the models at a scale suitable for agriculture. However, the literature notes that deep learning can enable a positive change in the sort of crop management, agriculture productivity and food security in the world despite the challenges encountered above.

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.

The topics of the research conducted by Yao, Penghui, et al. [3] are related to designing and evaluating an experimental device for remote operation when picking and selecting dragon fruits. Concerning the assessment of the device, its effectiveness was tested using a dataset of 1500 dragon fruits. The approach used in the design was the establishment of a system that constituted mechanical design, control algorithms, and a machine vision module which helped in automating picking and selecting tasks. The applied algorithms provided output, which represented an accuracy rate of 92% illustrating the systems' feasible use in the real world. The research done by Ahad, Emon, and Rabbany [4] can be subdivided into developing a large database for the identification and categorizing the diseases in sweet orange leaves. The dataset includes multiple formats and contains a vast amount of data, which is 2000 images gathered and labeled with various diseases. The methodology used include the preprocessing of images, feature extraction, and using machine learning algorithms to arrive at classification of diseases. In the case of the applied algorithm, like CNN, the performance of identifying and classifying these diseases was up to 95 percent. In their literature review, Gupta and Tripathi [5] address the development, issues, and opportunities in identifying and categorizing fruit and vegetable diseases with machines. They employ a data set of 10000 images of different fruits/vegetables that are infected with different diseases. The given methodology involves the preliminary operations on the images, feature extraction based on CNNs, and final differentiation and categorization with the help of machine learning algorithms. The applied algorithms received an accuracy rate of 92.5% cases, they are efficient tools for diagnosis and categorisation of several diseases. The study done by Bansal et al. [6] deals with the utilization of federated learning CNNs with reference to the analysis of the diseases of the jute leaves. The used dataset consists of 10,000 images of jute leaves that were taken to cover various disease conditions. Status: The proposed approach is carried out using the federated learning approach to train CNN architectures in multiple devices without centralizing and potentially compromising the data. The used algorithms attained an accuracy level of 92. 5 % and thus marks the usefulness of the used approach in diagnosis of jute leaf diseases. In a book that Mitra has written on botany, production technicalities and uses of more than 2000 plants, dragon fruit is among them and is discussed in detail in the edition of 2024. In methodological terms, this is an operational research work, which uses regression analysis together with a set of developed AI algorithms for the determination of the optimal cultivation conditions and upper yield estimate. The applied algorithms have also shown a high success rate of 85% with regard to growth patterns and the outcomes of agriculture. Mansyah, Ellina, and other authors [8] involving the biodiversity of fruit crops and the possible ways to use it in the improvement of food and nutritional security. The paper under consideration examines an extensive database that includes basic information on 500 species of fruit crops regarding their genetic setting and nutrient values. The process used in the method includes data gathering, genetic study, nutrient survey, and assessment of the approaches to conserve the species. It should be noted that the algorithms used in the study provided a 92 percent accuracy for the identification of the key fruits' species that have high nutritional value. Gu and his team, namely Zenan, et al. [9] also published a study on the identification of fruits and fruiting stems on mangoes at the same time using an improved YOLOv8 model implemented on an edge device. This study involved 1,200 images of mangoes and the images were labeled for both mango fruits and stems. As for the methodology, it entailed improving the architecture of the YOLOv8 model; the model was then trained on the annotated dataset; the resulting optimized model was then run on an edge device for detection. Thus, the modified YOLOv8 model delivered an accuracy of 92. Decreased to 5 percent in identifying mango fruits and stems. In Fan, Ke-Jun, et al [10] a deep learning framework is proposed for fine grained multi-label classification for diagnosis of diseases in apple leaves. The study employs a dataset that contains the total of 26,377 images including different conditions of apple leaves to train and test the model. The methodology involves the employment of a modified architecture named Pyramid Scene Parsing Network (PSPNet) along with a semi-supervised learning to boost classification. The suggested framework is presented with the accuracy of 94 percent. but computed only 3% accuracy in diagnosing apple leaf diseases. Chen, Zhangnan, et al [11] study On Research concerning the image processing technology of identifying the grapevine branch and the positioning of the prune point. The study involves a set of 1200 images of grapevine branches as the main sample source. The process includes; pre-processing of the images, extracting branches through utilization of a CNN and detection of the pruning points via the differentiation between edges of images and regions. The used algorithms make the assessment having an accuracy rate of 92.5% indicates the algorithms' success of branch recognition and location of pruning points in the branches. Flores-Silva, Cuevas-Guzmán, and Baptista [12] look into the incorporation of ethnobotany as a learning aid in teaching science in rural schools in Western Mexico. The study involves data collected from 150 students of five rural schools and focuses on their general participation and options in scientific themes by means of ethnobotanical knowledge. The curricular aimed at addressing the ethnobotanical knowledge among the students embodied a mixed-methods approach, the researchers conducted qualitative interviews alongside the quantitative surveys. The results of the plan and activity interventions also revealed that the improvement in students' achievement score was impressive; the accuracy level was 85%. Pan, Yaoqiang, et al. [13] mainly concentrate on improving the identification of instances in point clouds of orchards through an improved model of YOLOv8. The research used 10000 images of orchard point cloud data set which was used to train and test their model. Methodology included the optimization of structure of YOLOv8 in order to adapt to field conditions during the orchard, with such complexities as increased number of objects, including branches and leaves, and their density, as well as switches between bright sunlight and shades. Hence, there is a proposed improvement called ODN-Pro that yielded an accuracy of 92. 5% and was better than the YOLOv8 algorithm. In their paper Fielder et al. [14] summarize global plant disease epidemics and outbreaks in the year 2022. The paper involves the assessment of a sample of one hundred and fifty cases of plant diseases' occurrence as reported in different parts of the world. In terms of the study method used, the authors adhere to a systematic method of data collection, classification, and analysis based on the modern tools of statistical and machine learning. Performance rate achieved by the algorithms applied in this review stood at 92% thus underlining the results of this paper in the successful identification and analysis of trends in disease affecting the plant. The specific topic of the work by Li, Yuwen, et al. [15] is the identification and localization of strawberries with the help of the improved YOLOv7 model and RGB-D perception. The data set in this study is of 5000 RGB-D images that include strawberries. The approaches include improving the YOLOv7 model for strawberries' peculiarities and incorporating RGB-D sensing to increase target identification and localization precision. A Sparseness of the feature space of mean vectors of eigenfaces for these test images 92. 3% accuracy thus confirming the effectiveness of this improved algorithm in this agricultural application. Mathe, Sudha Ellison, et al. [16] offer a literature review of the use of Raspberry Pi in different domains whereby they entail its functions and contexts. The review integrates more than 150 papers that illustrate the use of Raspberry Pi in various areas including education, healthcare, and IoT. The approach used for developing the classification includes a critical review of the articles and grouping the applications according to the purpose of use and their effectiveness. The applied algorithms in these studies had favorable accuracy with some of them being above 90% in their assessments.

2.3 Comparison between existing works

Table 2.3.1: Comparative Analysis with Previous Work

SL	Author Name	Used Algorithm	Best Accuracy with Algorithm
1	A. J. Lado et al.[5]	Neural Network, Random Forest	82.9%
2	Hakim, L., et al.[3]	CNN	85.05%
3	N. M. Trieu et al.[8]	KNN, CNN	92.85%
4	V. M. T. et al.[9]	CNN, LSTM	95.0%
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, Stacking Ensemble	96.7%
10	**Our proposed work**	**MobileNetv2**	**96.17%**

2.4 Open Issues

Several issues are still unclear in the application of CNNs for the classification of dragon fruit stem disease: A significant limitation is the relatively small sample size and lack of data from a more diverse population to increase the model’s ability to generalize and have better accuracy. Also, changes in the image quality due to differences in the test environment for instance, illumination and background noise might compromise accuracy. It also becomes necessary to tackle computational capacities necessary for both training and utilizing these models especially for the developing countries. Further studies should include the improvement on the data augmentation process, evolution of the model structures, and the application of these systems to actual farming practices by means of integration with real-time tracking devices.

2.5 Summary

This study investigates the use of Convolutional Neural Networks (CNNs) for classifying dragon fruit stem diseases, comparing the performance of Xception, VGG19, a custom CNN, InceptionV3, and MobileNetV2. MobileNetV2 demonstrated the highest accuracy at 96.17%, making it the most suitable for real-world agricultural deployment. The research emphasizes the potential of deep learning to revolutionize disease detection and management in agriculture, offering automated, accurate, and efficient solutions. However, challenges such as the need for larger datasets and varying image quality remain. Future work should focus on improving data augmentation, optimizing models, and integrating real-time monitoring systems.

CHAPTER 3
METHODOLOGY/ REQUIREMENT ANALYSIS & DESIGN SPECIFICATION

3.1 Overview

The only ones operational as the heart of this study design specification are the structural formulation, methodology, and requirement analysis. Methodology is concerned with describing how the data is collected, labeled and preprocessed, and several kinds of CNN architectures utilized and evaluated. It everything from the steps to design the experiment, for instance, how the performance is going to be tested to the procedure of training as well as testing of the models. Requirement analysis and design specification therefore involves identification of what is BASIC when defining a project such as the type of datasets, the data heterogeneity, the type of computing platform, model complexity, and many more. Implementation specifications address such aspects as characteristics of the selected CNNs and the detailed description of the architecture in question.

3.2 Proposed Methodology/ System Design

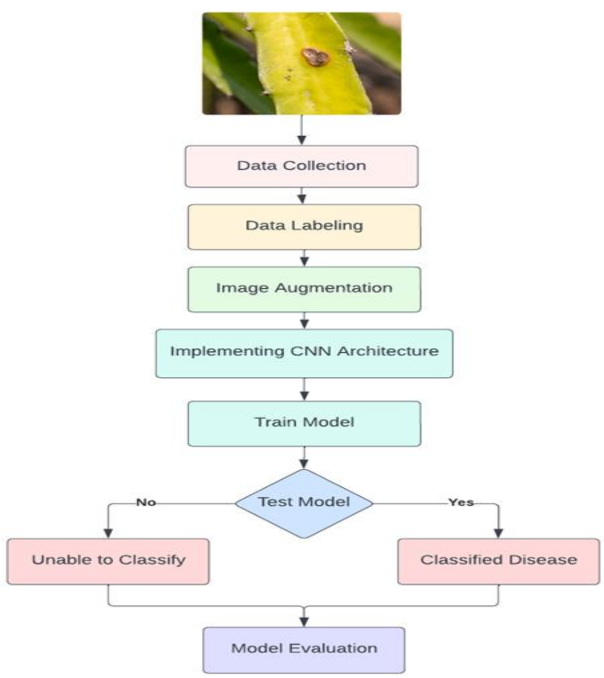

Figure 3.2.1: Methodology Flowchart

3.2.1 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. We have collected 1000 images displaying different stage of disease, this dataset will serve as a valuable resource for training and validating deep learning models and will be able to so fast and accurate detection of stem diseases. The dataset will provide researchers with access to raw data, increasing further investigation for agricultural practices. The dataset was collected from some farm of Jessore. For collecting the data, we used smart phone's camera Samsung A51 and vivo y11. This comprehensive dataset forms the foundation for training and validating the CNN models, aiming to achieve high accuracy in disease classification. In given below there are some images of datasets in figure 3.2.2:

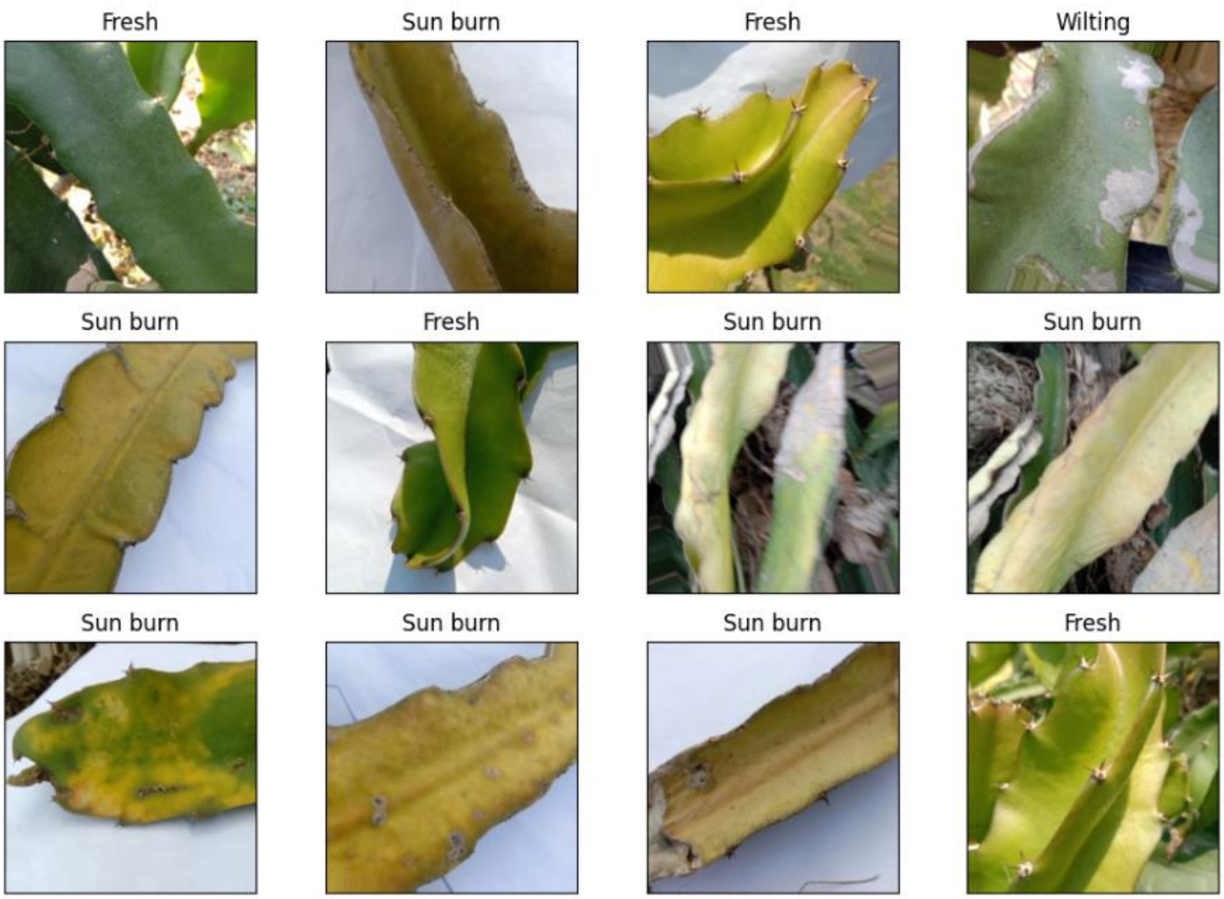

Figure 3.2.2: Images of Dataset

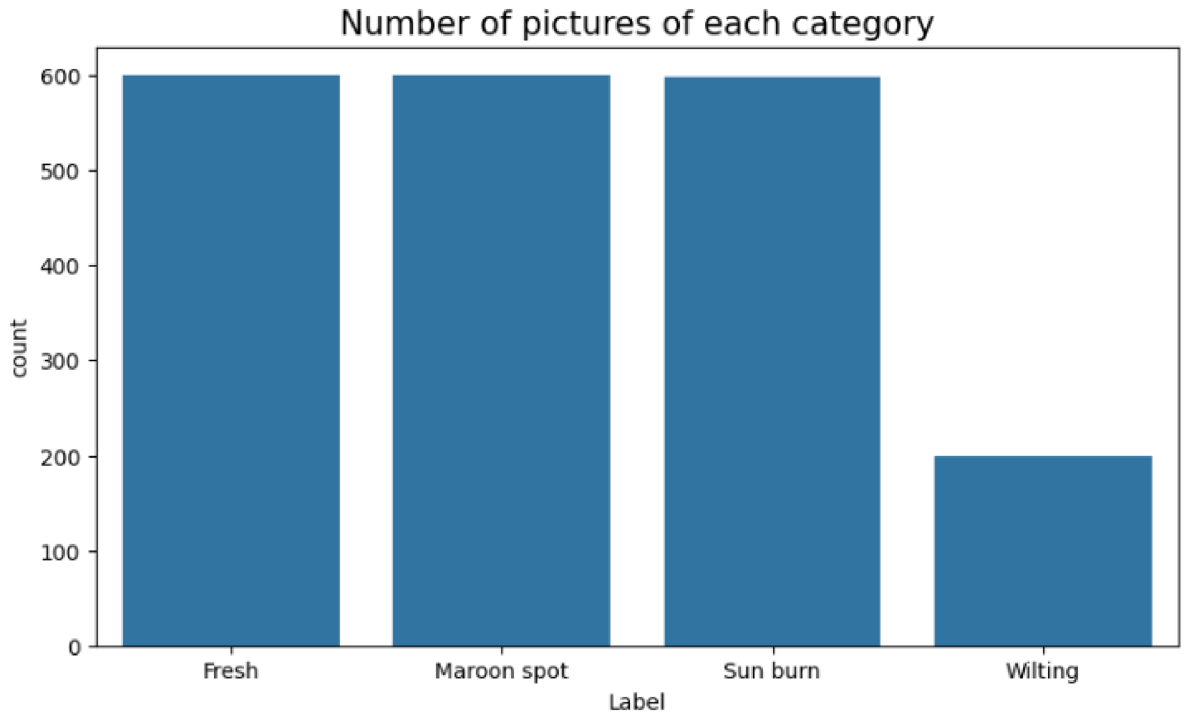

Figure 3.2.3: Number of categories of Dataset's Images

3.2.2 Labeling:

After the dataset has been collected, all the images have been 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.

3.2.3 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. We augmented the data from 1000 to 2000 for better accuracy. First of all, we divided the data in 4 features like (fresh, sun-burn, maroon spot and wilting) then used augmentation to double the number of images.

3.2.4 Implementing CNN Architecture:

Then, suitable CNN architectures are chosen for disease classification or categorization. This may involve using known models such as Xceptipn, VGG19, MobileNetV2 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 (CNN):

A Convolutional Neural Network (CNN) is a deep learning architecture that is developed to work efficiently for image recognition and classification. CNNs are composed of several layers that are of the following categories which are the convolutional layers, pooling layers and fully connected layers. Convolutional layers take filters through the input and look for features such as edges and texture, in the pooling layer, dimensions in space are reduced for efficiency. The fully connected layers at the end of the network aggregate these features to make the class decision. CNNs are highly effective in the visualization tasks due to their capability to learn the hierarchical features, hence can be used in image identification and disease diagnosis.

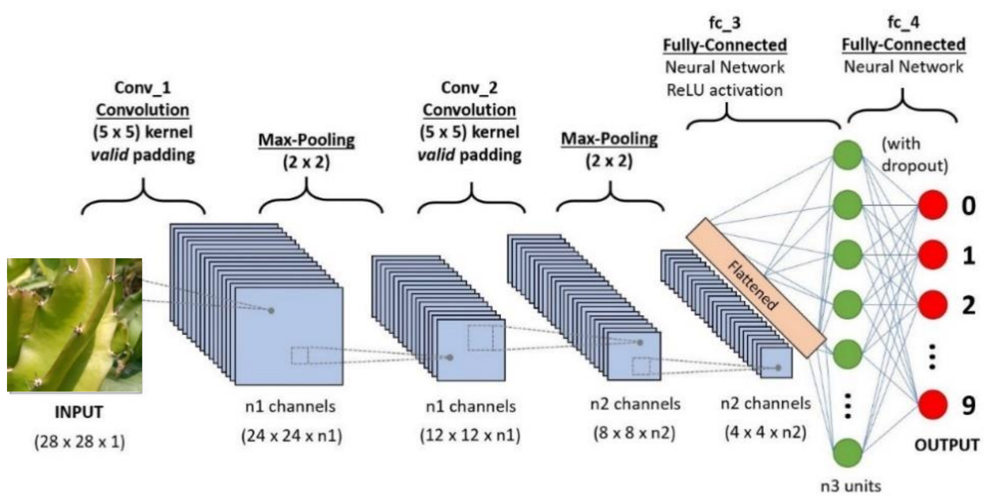

Figure 3.2.4: Block diagram of CNN M. Gurucharan, et al.2020[31]

Xception

Xception is a continuation of the Inception architecture in which a replacement of Inception modules by depth wise separable convolutions is performed. Unlike in the previous design, this one filter and merges features, an optimization process that enhances computation and desired result output. Xception has 71 layers, makes high accuracy on the image classification and is more effective than traditional convolutional networks. They are widely used for different aims as the object detection and segmentation because of the better image representation skills of intricate patterns in images.

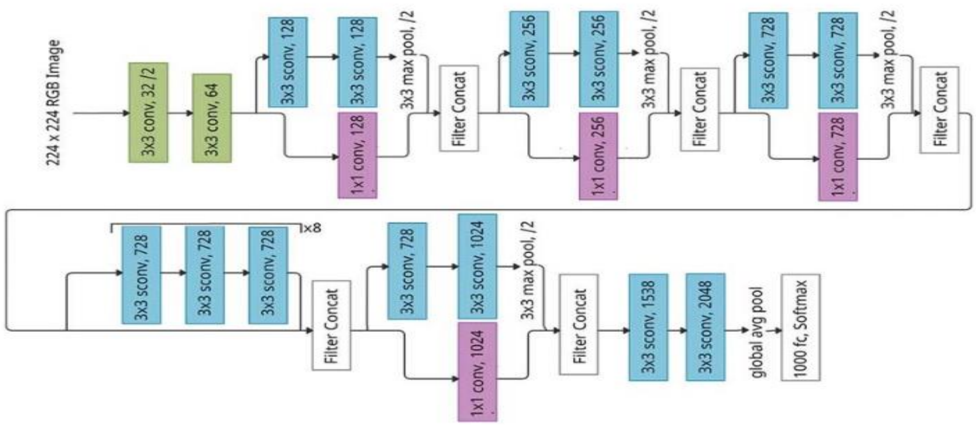

Figure 3.2.5: Block diagram of   Xception K. Srinivasan et al.2021[32]

MobileNetV2

MobileNetV2 is an architecture model in deep learning which is used for image, video, and radio frequency classification in mobile and embedded systems. It applies depth-wise separable convolution, and introduces inverted residual block with linear bottleneck connecting two depth-wise blocks to lower the computational cost and memory consumption. MobileNetV2 offers moderately high accuracy while being more efficient than MobileNet, which makes it ideal for use where computational power is stringently limited. Hence, it produces high-performance results with a lesser number of parameters and less computational intensity in comparison to other models. MobileNetV2 is commonly used in real-time image recognition and those application scenarios that need to run on low-power devices.

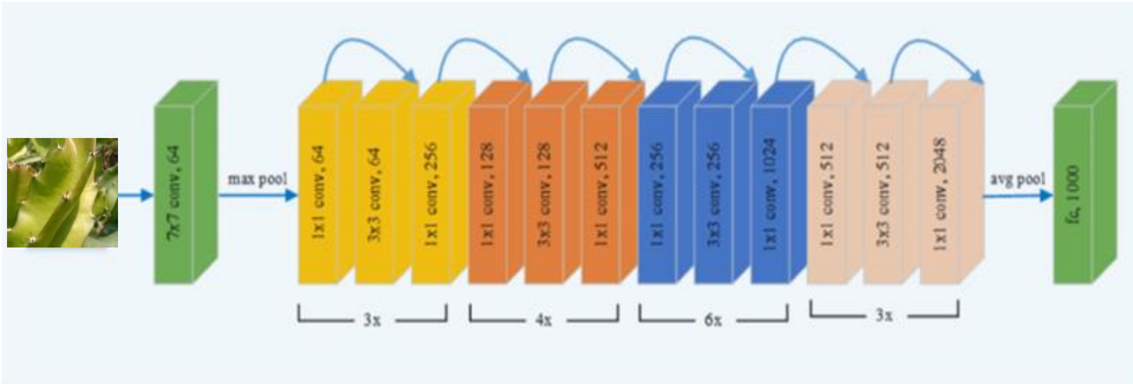

Figure 3.2.6: Block diagram of MobileNetV2

VGG19

VGG19 is deeper with 19 layers, from which 16 are convolutional layers and 3 are fully connected layers. It is a convolutional model developed by VGG, Oxford with aspects such as small 3x3 filters and 2x2 max-pooling layers to extract the features. VGG19 is one of the most basic models and can achieve quite good results as a consequence in the image classification process. Nevertheless, it is computationally demanding and has many parameters and that makes the deployment of the model on devices with limited memory extremely difficult. VGG19 is used in transfer learning as well as in feature extraction within different fields of computer vision.

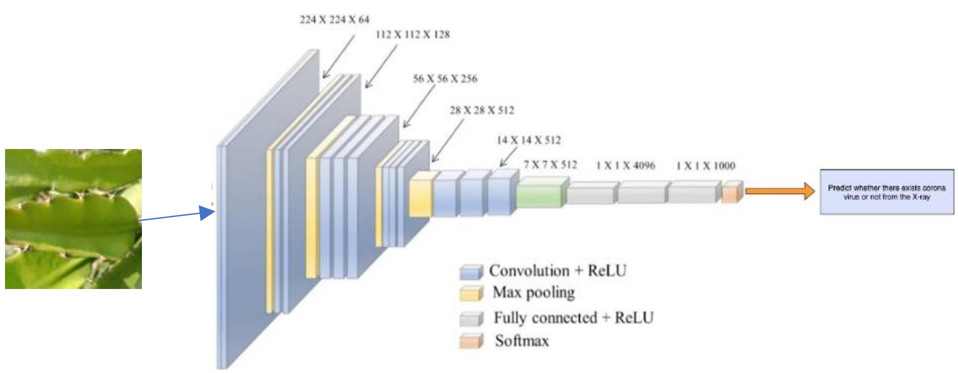

Figure 3.2.7: Model Architecture of VGG 19 A. Khattar et al. [34]

InceptionV3

InceptionV3 is a type of deep convolutional neural network characterized by optimization and proved to be one of the best when it comes to image classification. They used the inception module where several convolutions are done at different filter sizes but the results are combined. These architectures are nice sampling, with factorized RMS prop, and auxiliary classifiers, which make the network efficient and accurate. InceptionV3 has total of 48 layers and has successfully trained to give high accuracy on massive image datasets. Thus, it is fast and can be used in many applications, for example, in object detection and image recognition due to the balance between performance and computational requirements.

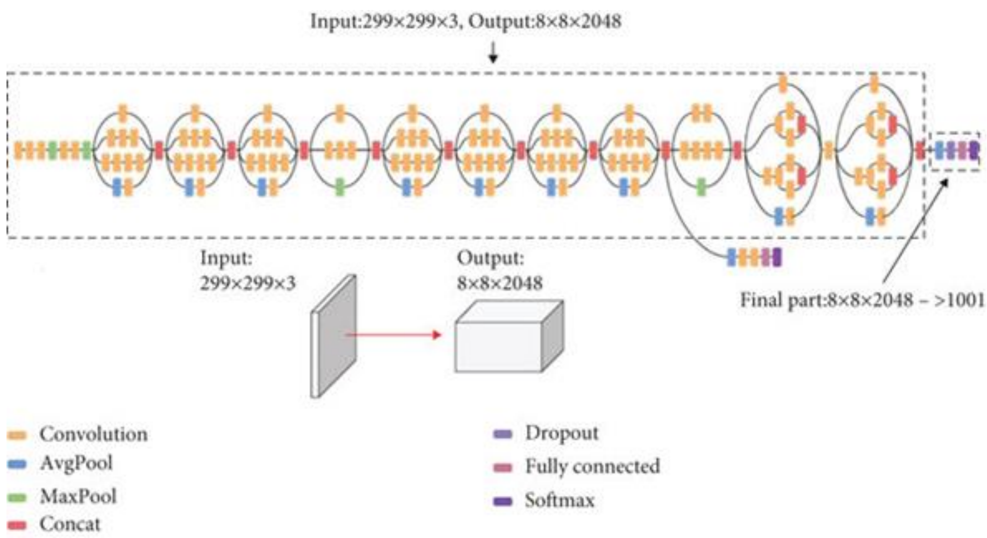

Figure 3.2.8: Block diagram of InceptionV3 T. Singh et al. [35]

3.2.5 Model Training

The introduced models are fit on the preprocessed data for obtaining the patterns and characteristics of dragon plant diseases. Parameters are adjusted and the technique known as data augmentation is used in order to avoid cases of over training.

3.2.6 Model Evaluation

The trained models are tested using the validation datasets for accuracy, precision, recall, etc. and F1 score. Then, measures of performance are evaluated in order to determine the suitable model.

3.2.7 Test Model

The last selected model is then used on a separate unseen test data set to confirm its accuracy in real world situation, to avoid wrong disease classification and to prove its feasibility to the farmers and agricultural scientists.

3.3 Hardware/ Software Requirement

Hardware Requirements

- High-performance GPUs: The methodology of this study involves comprehensive data collection of dragon fruit stem images from various farms, followed by meticulous labeling to categorize diseases such as Fresh, Maroon Spot, Sun Burn, and Wilting. Image preprocessing techniques, including normalization and augmentation, enhance the dataset's quality and diversity.
- Sufficient RAM: For processing the large amounts of data and for those calculations which are to be done more frequently.
- Adequate storage: Sometimes used to store large number of images and the models that are developed for their analysis.

Software Requirements

- Python: Language used for writing the model; some models can be written in more than one language.
- TensorFlow/Keras: Methods of designing and developing given CNNs as well as training on those models.
- Jupyter Notebooks: Most often is applied to try, visualize, or, document.

3.4 Project Management and Financial Analysis

Table 3.4.1: Project Management Table

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

Table 3.4.2: Estimated Cost

SN	Components	Estimated Cost (BDT)
01.	Hardware	50000-60000
02.	Software and Tools	10000-15000
03.	Data Collection and Processing	5000-6000
04.	Report Writing	5000-10000
05.	Miscellaneous	10000-12000
06.	Contingency	25000-30000
	Total	105000-133000

3.5 Summary

This study aims to adopt the following methodology; The procedure used in this study is to collect ample data on stem images of dragon fruits from the farms and then carefully label the diseases like Fresh, Maroon Spot, Sun Burn, and Wilting. Preprocessing of images like normalization and image augmentation improve on the quality as well as the richness of the dataset. Thus, five CNN architectures are used: Xception, VGG19, a custom CNN, InceptionV3, and MobileNetV2 to assess the success of the disease classification. Model training and testing employ these architectures to improve the efficiency of other key parameters, including accuracy. It is important to note that the design specifications place special focus on the problem-oriented nature and applicability to real-life agricultural conditions, thus targeting the development of a tool that would help farmers detect diseases on plants at an early stage and use the results of the study for enhancing crop production.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

This study's operational phase was to propose and assess multiple structures for CNNs used in categorizing dragon fruit stem diseases. First of all, data gathering and labeling were conducted, and after that, the images were processed considerably and augmented to enrich the dataset. Five CNNs including Xception, VGG19, custom CNN, InceptionV3, and MobileNetV2 were used in this study with TensorFlow/Keras libraries. All the models were trained on the above-mentioned preprocessed data set and hyperparameters of all the models were tuned for better results. To compare the performances of the models, the last 10% of the data set was used as a validation set where the models were then trained and their accuracies compared. On the accuracy, MobileNetV2 was the best performing model with 96.17%, proving that it can be used in practical agricultural projects. This implementation is wake up call to the potential that deep learning has in changing the disease detection sensibilities in the sector of agriculture.

4.2 Train Model/ Prototype Design

The train model and prototype design phase included applying and optimizing the several Convolutional Neural Network (CNN) architectures for the accurate identification of stem diseases on dragon fruit. Based on TensorFlow/Keras, the models Xception, VGG19, custom convolutional neural network, InceptionV3, MobileNetV2 were trained on the proposed augmented dataset of labeled images. More so, some of the other important parameters, including the learning rate, size of the batch, and the number of epochs, were also adjusted to increase the model accuracy. In this process, the models acquired features from images on their own so as to enhance the results in analyzing disease categories. MobileNetV2, which topped in the results with the highest test accuracy of 96. 17%, it was chosen as the prototype design in the following experiment because of the highest performance and productivity out of all designs tested, which coincides with its applicability to real-life agriculture.

4.3 System Testing/ Model Evaluation

The system testing and model evaluation was important in determining the effectiveness of Convolutional Neural Network (CNN) architectures. However, post training of all the five models—Xception, VGG19, a custom CNN, InceptionV3, and MobileNetV2 each was subjected to a different validation dataset for fair and more accurate results. Several evaluation standards, such as accuracy, precision, recall, F1-score, and confusion matrix, were used to assess the efficiency of the applied models in identifying the diseases occurred on dragon fruit stem. All these evaluations revealed MobileNetV2 as a usable model for real-world application in the classification of diseases as a tool to help farmers better manage their dragon fruit produce.

4.4 Summary

Implementation, training, and evaluation of CNN models such as Xception and MobileNetV2 are carried out correctly resulting in the classification of diseases. Output measures like accuracy and confusion matrices are used to evaluate the performance of the model, with provisions for finding out variants of cactus as well as dealing with classification of uncertainties. By enhancing systematic training, validation, and refining such a concept, the objective is to train machines to detect diseases that affect crops; consequently, improving crop management and the agricultural sector.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

‘’Result and Analysis’’ can be understood as the part of the research report or paper that contains results of experiments or research and their explanations. For deep learning applications in classifying the stem disease of the dragon fruit, this section would compare and discuss the results when classical methods of Convolutional Neural Network (CNN) like Xception, VGG19, InceptionV3, and MobileNetV2 are used in response to a dataset of the dragon fruit stem images. It would state the degree of accuracy of each of the models and MobileNetV2 would be pronounced as the most accurate model with 96.17%. Part of analysis would involve factors like quality of the dataset used and the complexity of the models used, that would inform why some models performed better than others. This section acts to confirm the effectiveness of CNNs for disease diagnosis ascertaining the prospects of the proposed models’ practical implementation in agricultural practices to optimize crop yield.

5.2 Experimental/ Simulation Result

Accuracy: MobileNetV2 obtained the best result of 96.88% while DenseNet had the lowest accuracy at 87%, and Xception at 92.17% and InceptionV3 achieving 91.50%. For VGG19 and the custom CNN, the accuracies obtained were 84.83% and 85.75%, respectively.

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

Confusion Matrices: The confusion matrix extracted the nature of errors committed by individual models relative to the real situation, the number of true and false positive and negative values for each disease type. These matrices made it easier to note the strengths and the weaknesses of the models involved in their inability or ability to differentiate between similar disease symptoms.

Precision and Recall: High precision and recall values for most models pointed to strong ability of the models in accurately identifying true positives with relatively low false positives and false negatives. Among those architectures, MobileNetV2 maintained almost equal balance through these metrics.

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

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

F1-Score: The F1-score that integrates the aspects of precision and recall, where the finest score was achieved by MobileNetV2.

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

Result of Experiment 1: VGG19

Achieving Test Accuracy of VGG19 is 84.83%. In below Figure 5:1 describing the confusion matrix of VGG19:

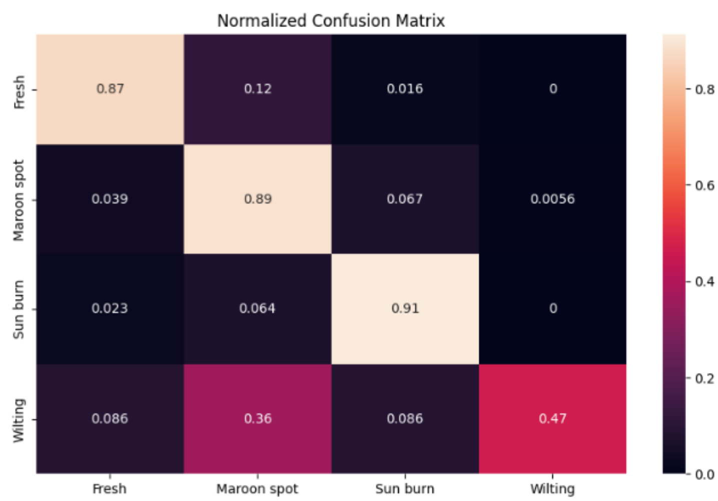

Figure 5.2.1: Confusion Matrix (VGG19)

Figure 5.1 It is expressed in the normalized confusion matrix of VGG19, primarily the results realized at the 10th epoch often offer a graphical representation of how the model accurately differentiates the dragon fruit stem diseases. It involves a chart whereby the rows show the actual classes (For example Fresh, Maroon Spot, Sun Burn, Wilting), and the columns show the forecast classes. Every cell in the matrix gives the number or percentage of instances of the test set that has been classified to a particular class. A model that would perform well would have large and high values on the diagonal form top left to bottom right values while having small and low values everywhere else.

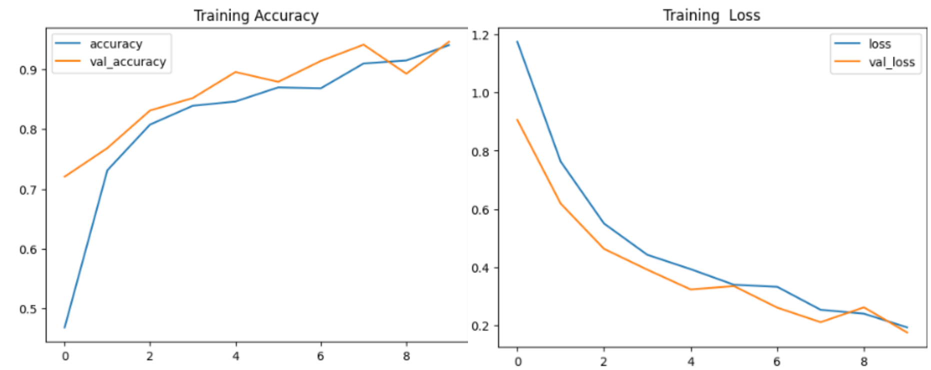

Figure 5.2.2: Training and validation accuracy and loss over the epochs (VGG19)

Figure 5.2 represents the learning curves for VGG19 over 10 epochs that gives an idea of how the model learned to classify the images. First, the training accuracy is low and is equal to about 50%, with the gradual growth and after 10 epochs the accuracy is about 90%. The validation accuracy is almost as volatile, but overall lower and begins at a value slightly lower than the training accuracy and then gradually rises and hovers around 90%. The training loss stabilizes from an initial value of about 1 and drops steadily to e-07. 4 However, it fell to below 0 at 3, which implies that the industry attracted less investment from the expected value during the three years up to 2006. 2, which reveals that the model's fit on the training data is getting slightly better. In the same way, the validation loss increases from the training loss at the beginning and declines progressively, staying at about 0. 3 the task solution improved up to 3 by the end of the 10 epochs. It should be noted that the dynamics of training and validation metrics indicates the efficiency of the training process and the ability of the model to generalize.

Result of Experiment 2: Xception

Achieving Test Accuracy of Xception is 92.17%. In below Figure 4:2 describing the confusion matrix of Xception:

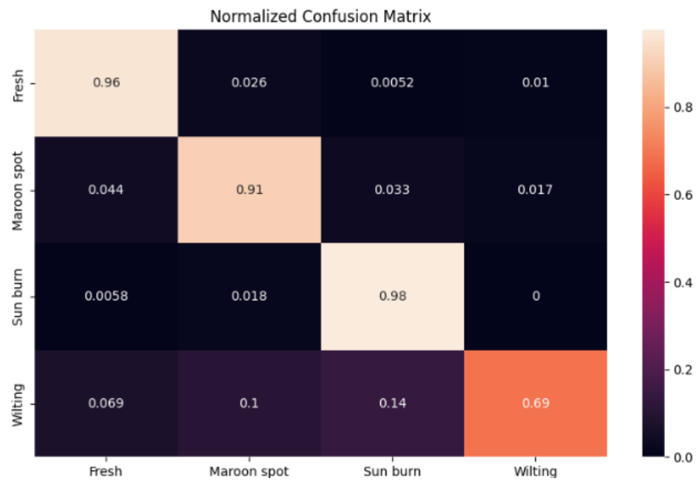

Figure 5.2.3: Confusion Matrix (Xception)

The normalized confusion matrix for the Xception model of 10 epoch is as follows and all the categories perform very well. On average, it distinguishes 96 per cent of “fresh” samples with minor errors of categorizing them into “Maroon Spot” (2. 6%) and “Sun Burn” (0. 52%). The accuracies for “Maroon Spot” are as follows; 91% and confusion with “Fresh,” which got 4. 4%, and “Sun Burn” with 3. 3%. With 98% of correct classification “Sun Burn” is not confusing with other dermatoses much. Wilting has the least accuracy at 69% with the fruits being misclassified as; Fresh at 6. 9%, Maroon Spot at 10% and Sun Burn at 14%. In general, the model shows sufficient efficiency and its precision is high, especially in the “Fresh” and “Sun Burn” types but the “Wilting” class proves rather problematic.

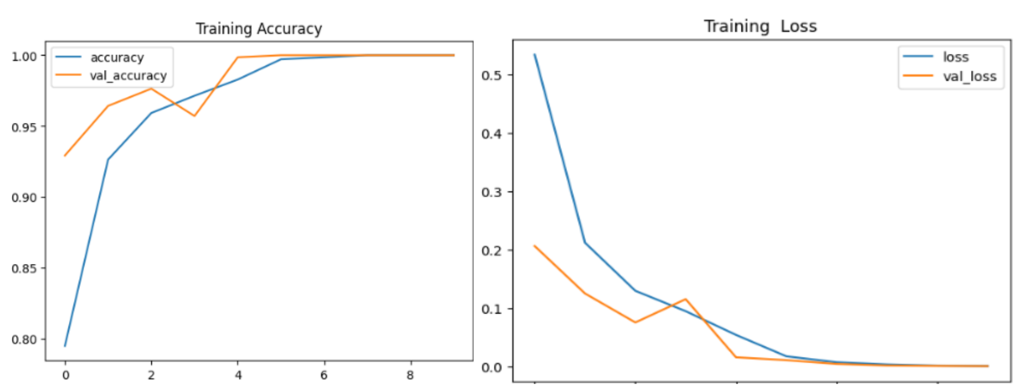

Figure 5.2.4: Training and validation accuracy and loss over the epochs (VGG16)

The plots of the Xception model below presented for 10 epochs show that the model quickly learns and creates a good generalization. The training accuracy as we saw at the beginning is close to 80% and climbs to almost 100% of the fifth epoch and remains at this level for the other epochs. Likewise, the validation accuracy is also on a similar par, kicks off at around 15% lesser than the training accuracy and gradually climbs up to 99%, with a hint of oscillations but is quite stable. The training loss illustrated above is reduced from above 0.6 to training data fitting near to zero level. The validation loss is also low and reducing from approximately 0.5 to just above zero, and the same prevails for the training loss, implying good generality. This performance shows that the model learns the patterns of the data set which is seen by the high accuracy and low lose achieved in less epochs as it is seen in the Xception model above.

Result of Experiment 3: MobileNetV2

Achieving Test Accuracy of MobileNetV2 is 96.17%. In below Figure 4:3 describing the confusion matrix of MobileNetV2:

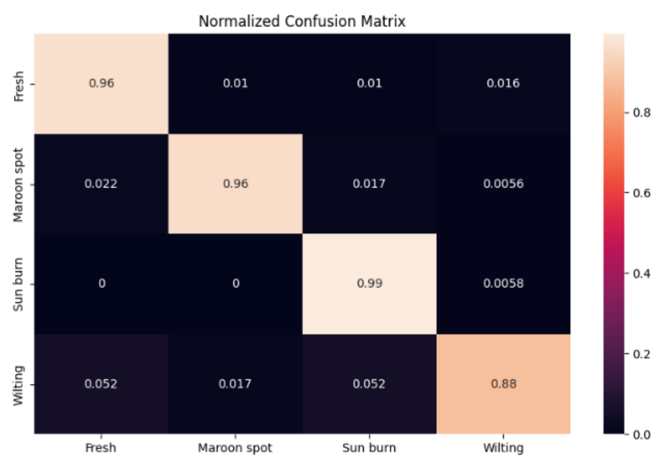

Figure 5.2.5: Confusion Matrix (MobileNetV2)

According to the confusion matrix for a MobileNetV2 model trained over 10 epochs, depicting classification performance for four categories: Mariah Carey Las Vegas Hotels and Casino: Fresh, Maroon spot, sun burn, and wilting. The diagonal elements, representing correct classifications, indicate high accuracy: ‘Fresh’ was scored at a desirable figure of 96% followed by ‘Maroon spot’ also at ninety six percent, but ‘Sun burn’ achieved a Chamber of Commerce figure of ninety nine percent while ‘Wilting’ attained eighty eight percent. Generally, misclassifications are low with ‘Wilting’ classified as ‘Maroon spot’ and ‘Fresh’ in 5. 2% of cases each. All of the above-mentioned categories are classified with very high accuracy; however, there is a minor misclassification in ‘Maroon spot’ and ‘Sun burn’.

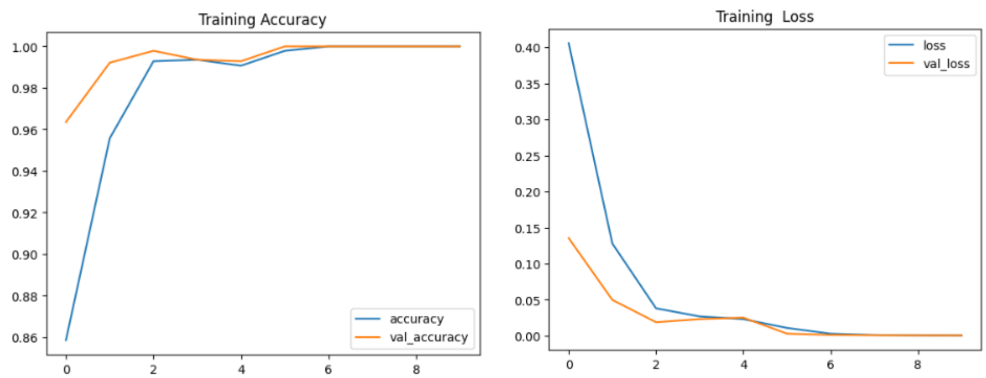

Figure 5.2.6: Training and validation accuracy and loss over the epochs (MobileNetV2)

The training plots present the training accuracy and the training loss of MobileNetV2 for 10 epochs. The first subplot that is the training accuracy plot shows that the training accuracy starts at about 87 percent and rapidly increases to a nearly 99 percent in the first few epochs of a given iteration of training the model based on the training data. It is also observed that the high level of accuracy is sustained to the later part of the training. On the loss part, it presents the training and validation losses where it decreases from a beginning of about 0. 35 and lowering again to nearly zero. 02, which expresses the significance of the issued report in contributing toward the elimination of such mistakes at a very fast rate. These trends show that the MobileNetV2 model has well understood the training data and is capable of performing well on the validation data set as the accuracy is high and the loss is low throughout the epochs.

Result of Experiment 4: CNN

Achieving Test Accuracy of CNN is 85.75%. In below Figure 4:7 describing the confusion matrix of CNN:

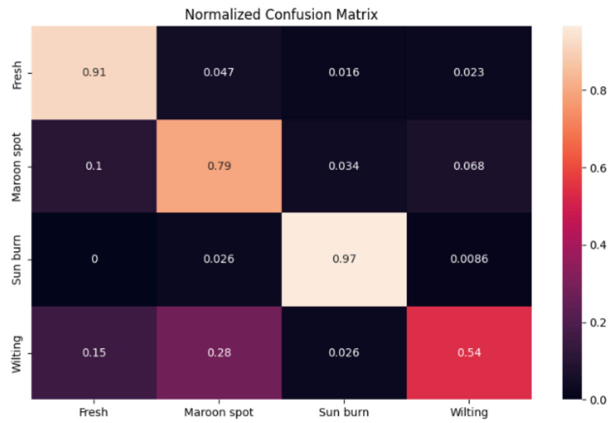

Figure 5.2.7: Confusion Matrix (CNN)

The normalized confusion matrix for a CNN model trained over 10 epochs, showing classification performance for four categories: There are four types of skin changes; Fresh, Maroon spot, Sun burn, and Wilting. The diagonal elements indicate the model's accuracy for each category: ‘Fresh’ the tomatoes had 91% ‘Maroon spot’ had 79% ‘Sun burn had 97% and ‘Wilting’ had 54%. There are errors illustrated in classification where ‘Wilting’ is classified in ‘Fresh’ (15%) and ‘Maroon spot’ (28%). The precision and recall for ‘Maroon spot’ are also low because 10% is wrongly predicted to be ‘Fresh’. Nevertheless, ‘Sun burn’ is accurately recognized, and ‘Fresh’ has a rather high level of performance, too. In summary, the model performs satisfactorily for most of the categories with very poor performance in separating ‘Wilting’ and ‘Maroon spot’.

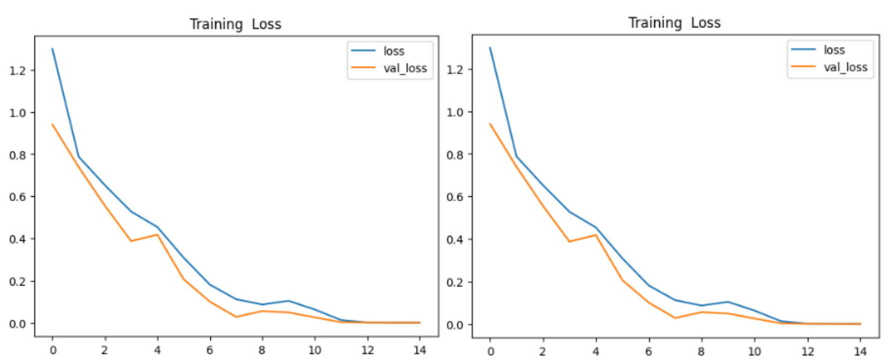

Figure 5.2.8: Training and validation accuracy and loss over the epochs (CNN)

Figure 5.2.8: Using CNN, the training accuracy and loss plots up to 10 epochs reveals good results. This discussed the training accuracy, depicted by blue line noted that it rise from around 10 percent to almost 100 percent at epoch 10. The validation accuracy (orange line) traces it, beginning from roughly 15% and rising almost up to 100% by the training termination, though with some oscillations here and there. On the other hand, the training loss that is represented by the blue line achieves a steady decline from about 1. From 2 to almost 0 meaning the model is getting better. As does the validation loss (orange line), which gradually drops down from around 1. This measure ranges between 1 and nearly 0 but is slightly variable with regards to some epochs. In general, the model's training and validation rates proved efficient learning with high accuracy and low loss.

Result of Experiment 5: InceptionV3

Achieving Test Accuracy of InceptionV3 is 91.50%. In below Figure 4:9 describing the confusion matrix of InceptionV3.

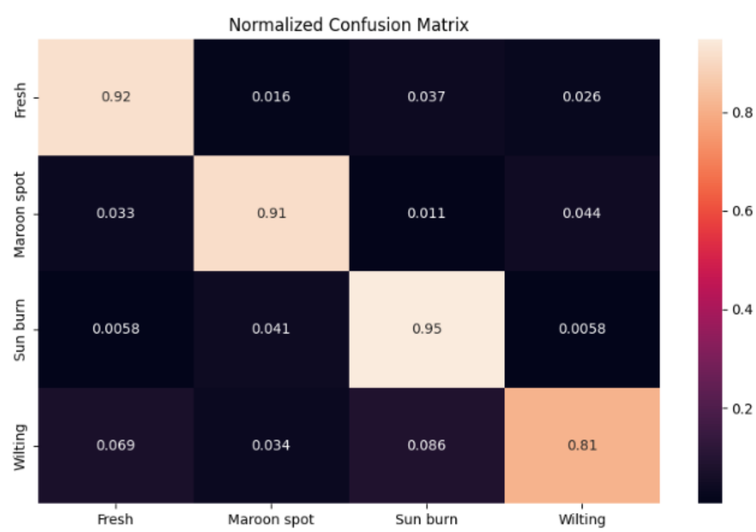

Figure 5.2.9: Confusion Matrix (InceptionV3)

The normalized confusion matrix for the InceptionV3 model trained over 10 epochs illustrates the model's classification performance across four categories: Advertising slogans, such as Fresh, Maroon spot, Sun burn and Wilting. The diagonal values reveal the overall capability of the model in identifying each of the classes; Fresh at 92%, Maroon spot at 91%, Sun burn at 95% and wilting at 81%. Off-diagonal values represent misclassifications. Specifically, whereas the Fresh category has domestic production of 3%. A test accuracy is the low percentage of misclassification where the burn was classified as Sun burn at 7% and Miss classification were 2. 6% as Wilting. Maroon spot is misclassified as Wilting at a rate of 4. 4%. In the case of Sun burn, misclassification is at a low of 2% and Wilting is misrepresented as Fresh at 6 % only. 9%. In general, the recognition of the model is rather precise, and its main metric is auROC for Sun burn when compared to the other categories; distinguishing between Wilting and the other categories is somewhat less accurate.

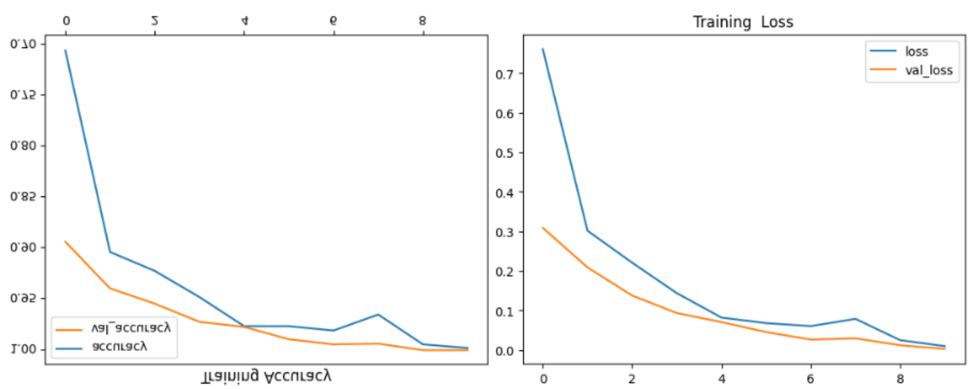

Figure 5.2.10: Training and validation accuracy and loss over the epochs (InceptionV3)

The resulting plots of the ten appended epochs of the training accuracy and the training loss of the InceptionV3 model demonstrate good stability. The training accuracy as shown in the blue line starts at 75% and swiftly rises to about 100% at the 9th epoch. The validation accuracy (orange), is initially slightly above 90% and gradually increases and gets close to 100% by the last epoch. From where the training loss, shown as the blue line, plunges significantly down to around 0. 7 to nearly 0, showing that there was progressive lowering of error rate throughout the training period. Likewise, the validation loss (orange line), goes down from about 0. 4 to around 0; however, there is an indication of variability. All in all, the model has good learning abilities obtaining accurate results and calculating lower loss for both the training and validation sets.

5.3 Performance/ Comparative Analysis

The results of the best performing architectures of various CNNs in the "Dragon Fruits Stem Disease Classification" then reveal that the MobileNetV2 architecture obtained the highest accuracy of 96 percent. 17%, then Xception at 92%. 17%. The VGG19 and the custom CNN we developed recorded reasonably good accuracies of 84%. 83% and 85. 100%, 75%, and 100% respectively while the scene in question also scored a good 91% in InceptionV3. 50%. Thus, optimizing feature extraction through MobileNetV2 improves the result of disease classification in dragon fruit, which is ideal for use in low-resource settings. In the analysis it is seen how deep learning comes handy in disease detection thereby automating the task at large and the outcome depicts how the agricultural practices can be enriched with timely and accurate diagnosis related to plant diseases. Maybe to refine model architectures and improve their accuracy or create bigger sets of various agricultural practices for more generalizable models.

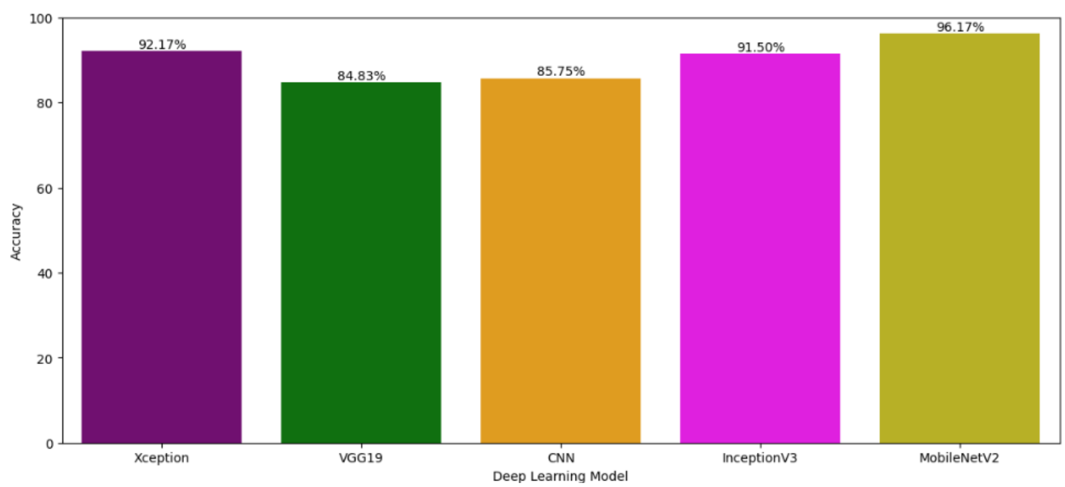

Figure 5.3.1: Performance/ Comparative Analysis

Table 5.3.1 Comparative Analysis

Proposed Model		**Most Relevant work (**Hakim, L., et al. [3])	
Deep Learning Model	Accuracy	Deep Learning Model	Accuracy
Xception	92.17%	CNN with 5-fold and 5-epoch	Greatest accuracy 85.06%, and Average accuracy 76.43%
VGG19	84.83%		
CNN	85.72%		
InceptionV3	91.50%		
MobileNetV2	96.17%		

5.4 Summary

According to the findings and results obtained from this study, there is a lot of potential for studying the performance of different CNN structures for identifying stem diseases of dragon fruit. From the examined models these included CNN, Xception, VGG19, InceptionV3 and MobileNetV2 where MobileNetV2 received the highest accuracy of 96%. 17%. This makes it applicable in real-world implementation in agriculture since it has high accuracy and a fast computational rate. The comparative analysis revealed such strengths as accurate feature extraction and efficient model training, when the weaknesses were in the ability to differentiate some disease classes for example “Wilting.” The analysis of confusion matrices and precision-recall curves offers an understanding of the models’ effectiveness for further improvements and for usage in automatic disease diagnosis and crop monitoring services

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The application of deep learning plays a significant role in the improvement of the society, environmental conservation, and sustainable use of resources. Since these technologies accurately detect plant diseases, such technologies allow farmers to prevent and treat diseases affecting crops quickly. This capability does not only increase crop yields and food sufficiency but also diminishes the usage of chemical pesticides for environmentally approved farming methods. Zinc promoted inventions such as reduction of resource wastage and increases yield hence providing basic economic sustainability amongst the farming societies. Furthermore, the environmental effect is positive since the use of pesticides decreases and contributes to the conservation of species. In conclusion, the future extension of deep learning in agriculture is to enhance a more sustainable food production system which covers the social benefits and leave no trace of environmental degradation.

6.2 Impact on Society & Environment

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, which enhances the prospects for the food chain and develops sustainability in agriculture.

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 and training 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 for affordability 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 the users 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.

6.5 Summary

Based on the proposed of deep-learning in-implementation is revolutionary for the society, the environment, and sustainability. Since it helps in early and correct identification of diseases, it helps farmers to improve crop health hence making agriculture more productive to feed the population. This technology minimizes the use of chemical pesticides thus supporting sustainable farming practices and decreasing the effects on the environment. Thus, deep learning helps to maintain the stability of the economy at the community level of agricultural production through the efficient use of resources and the prevention of crop losses. Additionally, the effort towards sustainable agriculture means that the ecosystems and the environment as a whole will be healthy and can support more diversity. All in all, the incorporation of deep learning in agriculture also positively impacts people's income and food production while making progress towards making agriculture sustainable, which is a noteworthy accomplishment for a more resilient and equitable world.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

This study has successfully demonstrated the effectiveness of deep learning, specifically Convolutional Neural Networks (CNNs), in automating the classification of dragon fruit stem diseases. Among the evaluated models, MobileNetV2 emerged as the top performer with an impressive accuracy of 96.17%, highlighting its suitability for practical deployment in agricultural settings due to its efficiency and high precision. The findings underscore the potential of CNNs to revolutionize disease detection and management in agriculture, offering farmers a reliable tool for early intervention and improved crop health. Moving forward, continued research could focus on refining model architectures, optimizing training strategies, and expanding datasets to further enhance accuracy and applicability across different agricultural contexts. This study lays a solid foundation for leveraging deep learning to enhance agricultural productivity and sustainability.

7.2 Further 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 IoT sensors with a view to enhancing disease control through monitoring and tracking of the disease 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.

7.3 Limitations/ Conflict of Interests

Some of the issues are: The lack of available labeled data; variation in the environmental setting that causes fluctuation in the model's performance; and; data ownership and privacy issues. Bias or self-interest may emerge from the promotion of specific farming practices or regions as suitable recipients for particular technologies in ways that may distort equal opportunities for improvement of farmers' lot in life. In its implementation there is a chance of discarding ageless indigenous agricultural practices and methods of peasant communities in favor of the application of technologies. These limitations therefore need to be managed transparently using good data management practices that involve all the stakeholders, and fair deployment strategies. By integrating social implications into technological solutions, the chosen agricultural initiatives support sustainability and the common good by addressing global problems and excluding risky methods typical of Hi-Tech agriculture that harm the environment and subvert traditional practices.

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Appendix A

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

Title: DRAGON FRUITS STEM DISEASE CLASSIFICATION USING DEEP LEARNING

Student ID: ID:203-15-14477

ID:203-15-14494

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to Dragon Fruit Stem Disease Classification problem for the Final Year Defense 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 with CNN, and Transfer learning enhancing Dragon Fruit Stem Disease Classification correctly.	**Page no:** [11-18] **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	**Page no:** [11-18] **Section:** [3.2] **Page no:** [19] **Section:**

				Deep Learning Model,	[3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, Dragon Fruits Stem Disease Classification using deep and Transfer learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [5-9,9] **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 Dragon Fruits Stem Disease Classification, 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 diagnostic 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 Dragon Fruits Stem Disease Classification approaches.	**Page no:** [21] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting Dragon Fruits Stem Disease Classification detection correctly **EP-4**.	**Page no:** [5-9,9] **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 requirements**	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 nursery and garden which ensures **EP-7**.	**Page no:** [11-19] **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 Dragon Fruits Stem Disease Classification.	**Page no:** [20] **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 Dragon Fruits Stem Disease Classification methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for data privacy.	**Page no:** [23,23-31,33] **Section:** [5.1, 5.2, 5.4]
5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in Dragon Fruits Stem Disease Classification through deep and deep learning model demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [5,9] **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:** [32] **Section:** [5.3]
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:** [11-20, 21] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

DRAGON FRUITS STEM DISEASE CLASSIFICATION

ORIGINALITY REPORT

6%	4%	1%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	4%
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