BANGLADESHI JUJUBE LEAF 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 “Bangladeshi Jujube Leaf Disease Classification Using Deep Learning Techniques”, submitted by **Sazid Hasan & Jobaer Ahmed** 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 13-07-2024.

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

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ABSTRACT

This paper explores the use of deep learning algorithms in identifying diseases affecting Bangladesh jujube leaves, with the goal of improving crop yields and yields' management. A dataset comprising 2400 images was curated, encompassing four target attributes: These are the diseases such as Jujube Sun Burn, Jujube Anthracnose, Jujube Fresh, and Jujube Brown Spot. Applying the steps of data augmentation techniques, the dataset was preprocessed to make the model more effective. Deep learning models such as Xception, VGG19, InceptionV3, MobileNetV2 and a Custom CNN was used. Hence, MobileNetV2 was identified as the model with the highest accuracy of 98.75% higher than other models for disease classification. As a result, this study has proved that transfer learning produces high accuracy and efficient models for detecting diseases to implement the models practically for disease management in agricultural fields for perpetuating sustainable farming practices and food security in Bangladesh.

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CHAPTER 1

Introduction

1.1 Overview

Plant disease diagnosis is an important strategy in the agriculture fraternity that plays a huge role in preventing certain plant diseases and increasing the yield of crops. In the context of Bangladesh agriculture jujube is one of the important crops and frequently they fall prey to diseases like Sunburn, anthracnose and brown spot. Early accurate diagnosis of these diseases assists the farmers in applying the right measures or treatment hence reduce on loss and improve yields. Current approaches to disease detection are also based on the knowledge of doctors and direct examination of the object, which is considered very inefficient. Previously, due to the limitations of manual classification, plant diseases could not be classified efficiently; however, with the help of deep learning techniques, this process has become possible. This project uses the advanced embedded deep learning techniques to create an efficient system to diagnose Bangladeshi jujube diseases with the help of its leaves. The process includes several steps, namely that at first, we collect data, which is a set of jujube's leaves photos, then we label them with the help of specialists to make the labeling as precise as possible. Some of the adopted preprocessing strategies include image augmentation to enrich the data set, and this data set is used the different deep learning models including Xception, VGG19, InceptionV3, and MobileNetV2. It is supposed that these models are adjusted and validated in order to determine which of them should be utilized in the given task. Thus, the use of these advanced techniques as the components of the project will help to achieve the key objectives to develop an accurate and efficient disease classification system for the agricultural applications. This system will act as a strong asset to the farmers in that they will be able to easily identify diseases at their early stages where measures to correct the situation can be taken, thereby increasing their crop production yield.

CNN

A custom CNN means a CNN that has been developed for some specific task or is designed for a specific dataset. Choosing the number and type of layers, activation functions, as well as the other parameters of neural networks, is determined by the peculiarities of the data and the specificity of the problem when designing a custom CNN. Custom CNNs have the advantage of optimizing the performance and use of flops required to complete a certain task for a given application, so the architecture can be focused on what the jujube leaf disease classification or any other operation in the computer vision is seeking to achieve.

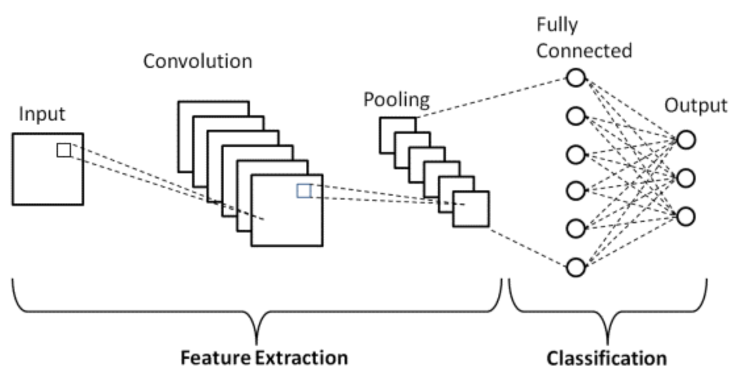

Figure 1.1: CNN Architecture M. Gurucharan, et al.2020[26]

Xception

Xception, or Extreme Inception, is a deep CNN architecture based on the Inception architecture. It elaborates on depth wise separable convolutions, which considerably decrease the parameter count while preserving the model’s accuracy. Due to the above efficiency, Xception can be applied to mobile and embedded systems along with other tasks that require limited computational power while offering acceptable accuracy in image classification problems.

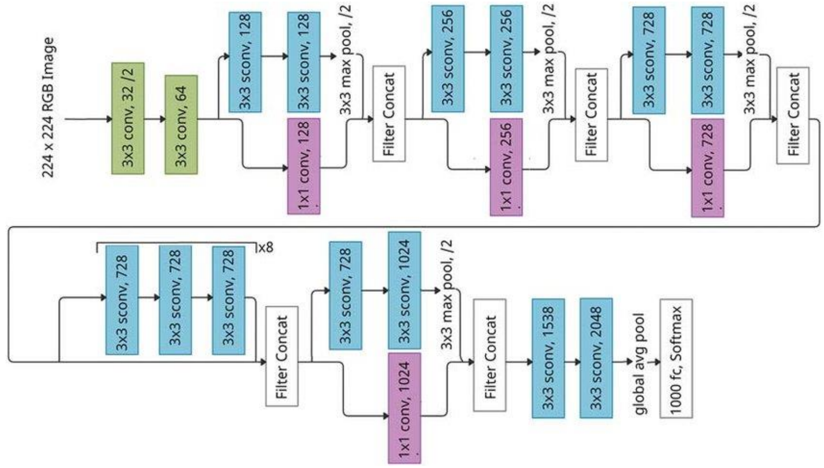

Figure 1.2: Xception Architecture K. Srinivasan et al.2021[27]

VGG19

VGG19 can be classified as a deep CNN structure that is simple and yet highly efficient. It includes 19 layers of small convolutes with 3×3 filters and max-pooling layers and fully connected layers. That is why VGG19 is easy to comprehend and utilize; this model is often used as the reference point and for feature extraction in numerous computer vision tasks. Compared to other newer architectures xception, Mobilenetv2, It has a deeper architecture that enables it to learn many features and patterns in images but at a cost of high computational power.

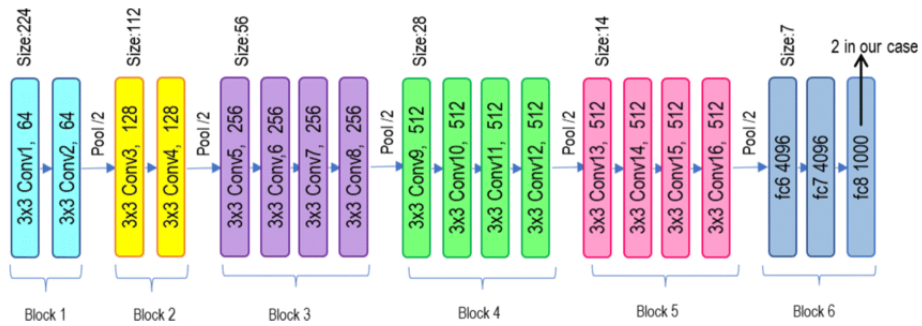

Figure 1.3: VGG19 Architecture A. Khattar et al.2022[28]

InceptionV3

InceptionV3 or GoogLeNetv3 is developed based on the Inception family, which is a type of CNN. It is characterized by inception modules that facilitate efficient computational operations by including filters of different sizes (1×1, 3×3, 5×5) in the same layer. This design ensures that the network has not only a deep architecture but also a wide one, which is useful for capturing features of various scales. InceptionV3 compromises between the network complexity and computation time; it can be used in real-time applications with high accuracy.

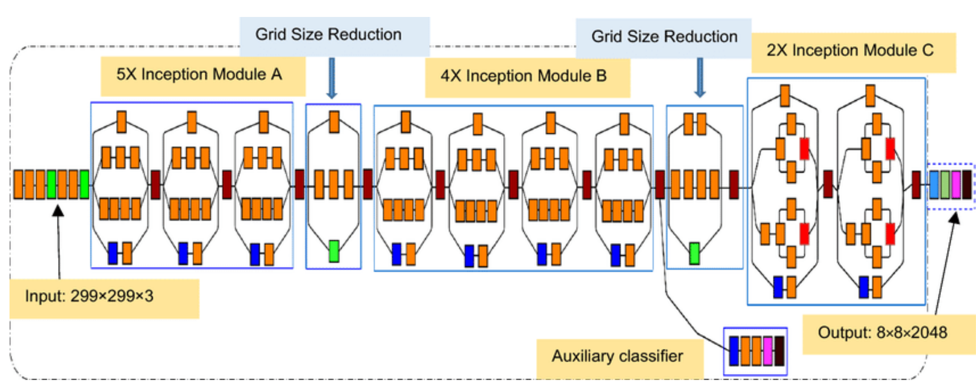

Figure 1.4: InceptionV3 Architecture T. Singh et al.2020[29]

MobileNetV2

MobileNetV2 is supposed to be used in mobile as well as embedded vision systems, which makes it highly optimized in terms of computational complexity and latency. It uses depth wise separable convolutions and inverted residuals with linear bottlenecks to minimize the Fig parameters and operations and maintain accuracy. This particular architecture of MobileNetV2 enables the model to run efficiently on low-end and resource-limited environments like smartphones and IoT gadgets.

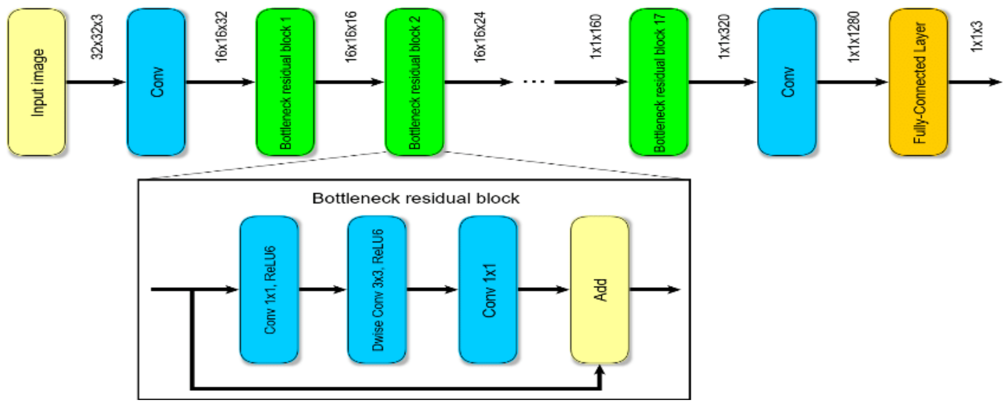

Figure 1.5: MobileNetV2 Architecture U. Seidaliyeva et al.2020[30]

1.2 Background and Present State

Plant diseases are matters of grave concern in the agricultural sector and for a long time, the sector has been facing difficulties in timely and accurate diagnosis of these diseases. By using traditional means, the detection is carried out by experts using their naked eyes, which is time-consuming and can lead to inaccurate results. Deep learning is the new generation of machine learning techniques, which optimizes the process of image classification and provides fast and accurate solutions. Some architectures such as Xception, VGG19, InceptionV3, and MobileNetV2 have been very effective in many applications ranging from medical imaging to object detection. The use of these models for agricultural purposes especially in classification of diseases affecting plants is thus viable course in enhancing the management of crop health. This project proposed a deep learning model for identification of diseases in the Bangladeshi jujube leaves to reduce the losses for farmers by providing them an early detection system.

1.3 Problem Statement

Diagnosis of diseases in Bangladeshi jujube leaves critically depends on the proper identification of diseases, which is an arduous process affecting timely interventions and large-scale production losses. Conventional paradigms used in the identification of diseases involve inspection, which is compounded by some inconveniences such as taking time,

uses a lot of workforces, and may be erroneous due to differences in level of experience among operators. This gap therefore requires an automated, accurate and faster means of diagnosing jujube leaf diseases. Through the use of deep learning, this project seeks to establish a strong model that is able to perform accurate diagnosis of jujube leaf diseases; namely sunburn, anthracnose and brown spot. The proposed system will also help farmers to diagnose diseases at an early stage, apply correct treatment on-time, and improve crop quality and production – one acute problem of farming industry.

1.4 Objective

The principal goal of this project is to establish an effective and precise deep learning strategy that would allow for classifying diseases in Bangladeshi jujube leaves. Using more complex models such as Xception, VGG19, InceptionV3, MobileNetV2 the given project shall seek to automate such identification for the most prevalent jujube leaf diseases such as sunburn, anthracnose, and brown spot. This means giving a detailed and well documented dataset, and basic image processing on data, besides, it involves strict training and testing procedures of the selected models for the best performance. The objective is to achieve an efficient and easy-to-use instrument to help the farmers identify the diseases in the early stages and thus to monitor and treat them accordingly. It will also aid in enhancing the crop health and productivity which in turn shall help the Asian jujube farmers from Bangladesh to stabilize their economical returns from agriculture.

1.5 Scope and Limitations

The range of this study concerns the construction of a deep learning model for determining diseases of Bangladesh jujube leaves. This research work entails gathering a large database of jujube images and labeling the images, using data preprocessing methods as well as developing state of the art deep learning models including Xception, VGG19, InceptionV3, MobileNetV2. In its operations, the system is intended for helping farmers identify diseases correctly and on time thus fostering correct and timely intercessions. However, the above project may have the following difficulties. The presented model has the limitation of its accuracy with the variation of the existing data set, which may not cover all the relevant types of diseases in the plants' leaves. Preprocessing images and their contrast due to which, illumination during the image capture also influences the model. Moreover, the computation needed to train deep learning models will reportedly still be a problem to some users due to high computational demand. Finally, even for the real-world applications, there could be a constant update to the weights resulting in an almost perfect solution each time it is used.

1.6 Report Organization

The following sections are included in this report to ensure a systematic approach towards presenting the study on the classification of Bangladeshi jujube leaf diseases by deep learning. This section defines the purpose of the research through presenting the background to the study, the research problem, the aims and objectives and the research questions or hypotheses, the justification of the study and the scope of the proposed research. Collection of prior work and gadgets with respect to plant disease classification and deep learning models. describing the procedures done in the project covering data acquisition, data pre-processing, model identification, model development, validation, and testing. Sows the proposed ideas and evaluation criteria of the developed deep learning models for the disease classification. Summarizes the findings, describes the issues that may have arisen and outlines ideas on how to enhance it further or what should be done in the subsequent study. Restates the findings of the project and describes its importance and relevance, and possible implications for practices in agriculture. Gives details of all the sources that may have been used in the entire report listing each and every source used.

This style of systematic arrangement is believed to aid its readers who have interest in agricultural technology and the use of deep learning in achieving their understanding of methodology, results and implications of the project.

1.7 Summary

The introduction part of the study justifies the need for correct identification of the diseases affecting jujube leaves in Bangladeshi agriculture to improve productivity. Incidental methods cannot be relied on due to the fact that they require one to manually examine the tumors leading to a call for deep learning for automated identification of these diseases.

There is a plan to use sophisticated models Xception, VGG19, InceptionV3, and MobileNetV2 in this project to create a stable classification system. Major goals are differentiating data, preprocessing images, and training/evaluating models respectively. I believe that by addressing these issues, the project aims at helping farmers will have a proper tool to identify diseases in their plants in its early stage hence improving on yield in Bangladesh.

CHAPTER 2

Literature Review

2.1 Overview

This paper aims on analyzing jujube tree and fruit and reviewing the literature includes a variety of techniques and innovation on agricultural practices. A number of deep learning models are CNNs that can be introduced with other learning transfer processes and specific modules for improving the classification results of jujube defects, resulting in higher than 94% recognition rates. Other machine learning algorithms are also applied for disease diagnosis and quality detection with the accuracy rate of 73%-98%. Hyperspectral imaging comes out as a useful tool for precise studies enhancing the classification performances in detecting diseases and quantifying other variables of interest like chlorophyll content. Some of these are multispectral imaging integrated with deep learning for accurate outcomes in estimating quality characteristics such as sugars in fruits. We cannot underestimate the role of the technologies in improvement of agricultural practices as seen in this research, disease control, fruit grading, and yield prediction in jujube production.

2.2 Related Works

By examining the literature on analysis of jujube tree and fruit some of the most advanced techniques include convolution neural networks that use CNN with transfer learning, machine learning, and hyperspectral images. These methods improve the level of accuracy in diagnosing diseases, quality and quantity determination of fruits, and in general, are testimony to developments of modern agricultural technologies. The technologist notes that the methods applied for solving problems related to jujube growing process, disease diagnosis included, demonstrate high efficiency in increasing the quality and productivity of fruits.

In given below, I am writing a similar paper review, which will help me a lot:

H. Zheng et al. [1] proposed an innovative strategy combining CNNs with transfer learning, SE module insertion, triplet, and center loss functions to improve classification accuracy. The suggested method successfully transfers information to the jujube defects dataset through using pre-trained models from ImageNet. It achieves a high recognition rate of 94.15% and beats existing models in challenging situations. W. Zhang et al. [2] presented a robust algorithm for identifying six common diseases in jujube trees. The method uses morphological, color, and texture data to produce excellent classification accuracies for diseases, ranging from 73.00% to 94.00%. A neural network-based model with thirty training photos and fifteen test images shows promising promise for precise illness diagnosis in jujube trees. X. Meng et al. [3] introduced a novel deep convolutional neural network for fine-grained jujube classification, employing a two-stream network to capture shape and fine-grained features simultaneously, along with different learning from image pairs. A carefully selected collection of more than 1700 jujube photos in various varieties is also included. The suggested model outperforms benchmarks such as SVM, AlexNet, VGGNet-16, and ResNet-18 with an amazing average accuracy of 84.16%, demonstrating its effectiveness in fine-grained jujube classification. Z. Ban et al. [4] determined relationships between maturity and physicochemical parameters such as TSS, TA, and fruit piercing force to estimate the ideal maturity level for winter jujube. The best fruits for eating are those that are fully crimson. With the use of ResNet-50 and an enhanced iResNet-50 model that was trained on datasets with five maturity grades, the study's winter jujube quality identification yields high accuracy (98.35%). This provides insightful information for screening on assembly lines, real-time monitoring throughout shipping, and quality categorization during harvesting. F. Liu et al. [5] analysed winter jujubes from various geographic origins using hyperspectral imaging in the near-infrared and visible regions. For quality evaluation, pixel-by-pixel spectra are preprocessed and subjected to PCA analysis. Pixel-wise classification using SVM, LR, and CNN models is examined; CNN based on all origins achieves the highest accuracy (>85%) and shows possibilities for real-time detection, providing perspectives for the development of online bruise detection systems for winter jujubes in the future.

2.3 Comparison between existing works

Together with the type of analysis, it is seen that the current studies on jujube tree and fruit differ in terms of their methods and results. Several studies, include those reported studies that employ deep learning models such as CNNs with transfer learning and specialized modules, can attain disease detection and quality assessment up to 94 % depending on the used metrics of classification. Current general machine learning methods, although quite efficient, provide accuracies that are slightly lower ranging from 0.73 to 0.98 for similar contracts. Hyperspectral imaging is characterized by high spectral resolution and can positively affect accuracy in the identification of diseases and other physiological manifestations such as chlorophyll content. Literally recent fantastic works that use multiple spectral imaging together with deep learning exhibit the best performance of primary yield quality attributes such as sugar content. Such comparisons aim at emphasizing the significance each of the used approaches and demonstrating their complementarity in the progress of precision agriculture in jujube production.

Table 2.3: Comparative analysis with previous work

SL	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	H. Zheng et al.[1]	CNNs with transfer learning, SE module insertion	94.15%
2.	W. Zhang et al.[2]	Neural network-based model	94.00%
3	X. Meng et al.[3]	Deep convolutional neural network	84.16%
4	Z. Ban et al.[4]	ResNet-50, enhanced iResNet-50	98.35%
5	F. Liu et al.[5]	SVM, LR, CNN	>85%
6	Proposed Model	CNN & Transfer Learning Model	MobileNetV2= 98.75%

2.4 Open Issues

There are still some open issues related to jujube tree and fruit analysis, even though important progresses have been made. First of all, there is the question of the environmental conditions that influence diseases' symptoms and manifestation, and their stability, which often pose challenges to the stability and accuracy of models. Another type of problem that seems to emerge as an issue to be addressed in the fine tuning of classification accuracy and system stability is the issue of data heterogeneity, for instance, real time environmental data and historical disease information is likely to be heterogeneous. Finally, the future works need to focus on two aspects: one is the cross varieties and regions, which must be tested to make sure the models developed can be generalized to all jujube varieties and different regions. The protocols of data acquisition and the approaches to image processing require standardization to improve the inter-study comparability and reproducibility. Solving these open issues could help in providing better and more accurate ways of managing diseases, assessing quality and estimation of yield in jujube production.

2.5 Summary

To sum up, the analysis of jujube tree and fruit characteristics has been developed by employing deep learning models, machine learning method, and hyperspectral imaging. Such methodologies have enhanced the early detection of diseases, and the evaluation of fruits quality as well as the estimation of yield. CNNs with transfer learning are the most commonly used models for classifying images and getting the classification accuracy higher than 94%, the other methods also got good accuracy between 73% and 98%. It improves the spectral imagery for better output in disease diagnosis and determining the physiological parameters of the body. There are challenges like, variability in the environment, data integration at the heterogeneous sources and scalability which is still a research question. Mitigating these challenges will improve the advancement of predictive models and improve their utility as regards sustainable practices of growing jujube fruits.

CHAPTER 3

Methodology

3.1 Overview

In this case, the methodology of this project comprises a methodical approach towards designing a DL framework and approach for diagnosing diseases that affect Bangladeshi jujube leaves. First, the targeted data is gathered, then it is properly labeled, followed by the image preprocessing step. For depth an improved deep learning models such as Xception, VGG19, InceptionV3, and MobileNetV2 are chosen. The project equally focuses on the generation of a large database, the use of sturdy image processing methods and the proper evaluation of the model. Requirement's analysis emphasizes functional and quality characteristics while in contrast, design specification consists of the architectural and implementation requirements necessary for proper classification of diseases. This structured approach is important in order to create a stable and useful tool in the assisting of the farmers concerning the disease identification and crop cultivation.

3.2 Proposed Methodology

Using the model-based approach, a structured research method is used to propose and assess deep learning algorithms for classifying Bangladeshi jujube diseases in the leaves. It includes data gathering, data cleaning, model selection, model training, and strong contingency testing. Thus, this methodology applies the new architectures of CNN including Xception, VGG19, InceptionV3, MobileNetV2, and the train models of CNN to enhance accuracy and efficiency of the disease detection and classification. The methodology encompasses several key steps:

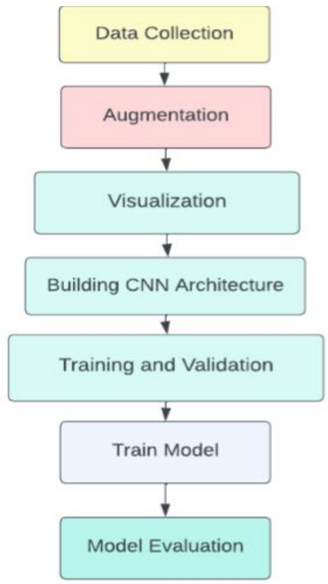

Figure 3.1: Working Flow

Data collection:

The project starts with building a diverse dataset of Bangladeshi jujube leaf images where images of disease conditions and healthy are both acquired from different orchards and different environments. In this study, we independently conducted a survey data collection from nurseries and gardens. It is essential to note that the total number of images in the dataset is equal to 4112; out of these, 1,712 is the raw picture, whereas 2,400 consumed augmented.

Table 3.2: Image Category

Image Category Name	Raw Data	Augmented Data
Jujube Anthracnose	418	600
Jujube Brown Spot	438	600
Jujube Fresh	436	600
Jujube Sun Brun	420	600

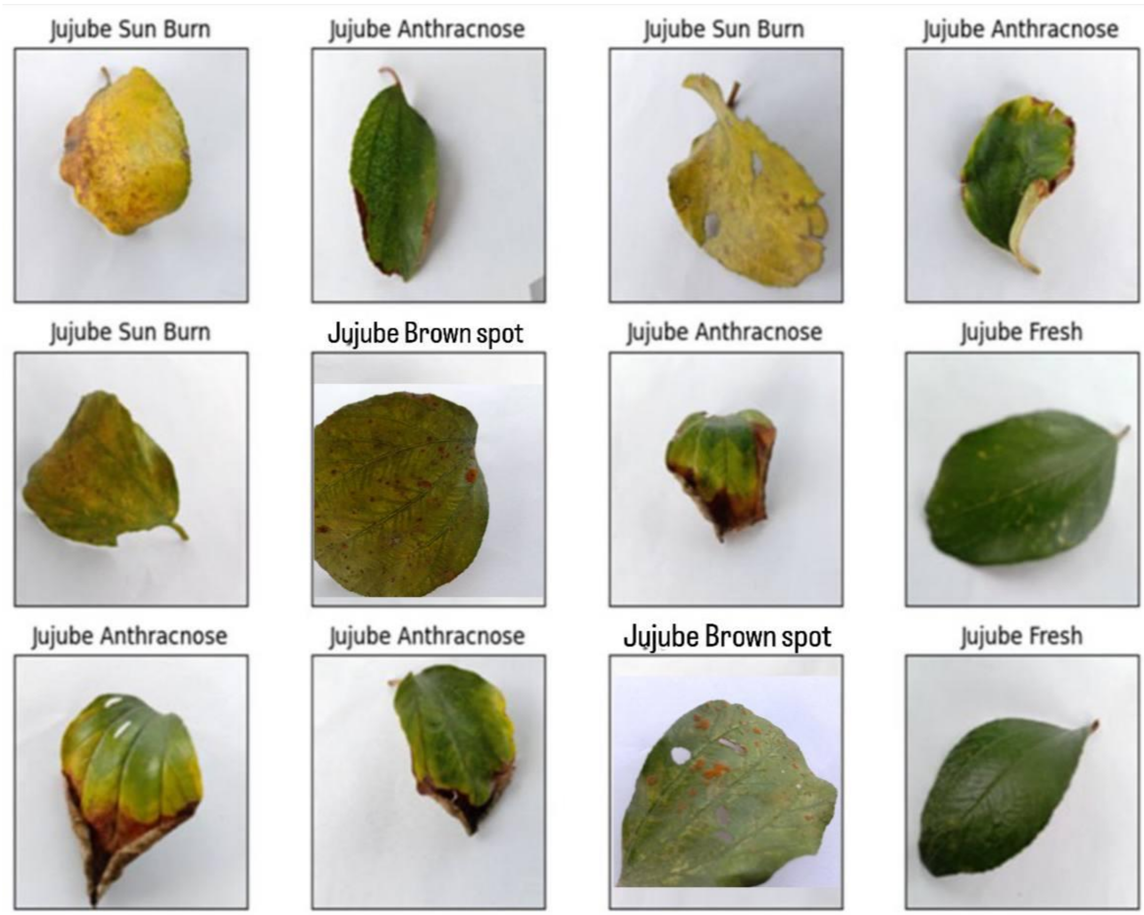

Figure 3.2: Dataset

Labeling

The gathered images undergo expert annotation to further organize the image into disease types or even at the level of types of diseases such as sunburn, anthracnose, brown spot, and normal/healthy ones for appropriate training and assessment.

Image Processing

The labeled data is preprocessed to standard dimensions, statistical characteristics or other similar procedures such as resize, normalize, and augmentation which are rotation, flip, and zoom etc.

Model Selection

Deep learning models such as Xception, VGG19, InceptionV3, and MobileNetV2 are also assessed and chosen depending on the classification problem and amount of time required for processing.

Model Training

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

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.

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

For the project, the participant indicates a need for a computer with adequate computational capacity to perform deep learning tasks. Incorporation of a GPU (Graphics Processing Unit) is encouraged for faster training especially where large datasets and/or complex model is involved such as the Xception or the VGG19 model. At least 16 GB of RAM is recommended to handle operations with big data properly. The foremost coding language used for creating the deep learning models, with the help of the TensorFlow or PyTorcNumPy or TensorFlow or PyTorch to design and train the deep neural networks. For the preprocessing of jujube leaf images OpenCV or PIL (Python Imaging Library) can be used. For the code writing and experimenting we can suggest Jupyter Notebook, Spyder, or PyCharm. And in data manipulation, Panda’s library is more effective while in numerical computing, the NumPy is the best library for Python. These are the software applications that are used in dataset manipulation, model creation, model training, model assessment, and system structure of jujube leaf disease classification system with the application of deep learning algorithms.

3.4 Project Management and Financial Analysis

This paper stresses the importance of the efficient management of the jujube leaf disease classification project; this would involve planning and developing of objectives of the project, identification of resources for use, precise definition of the risks involved, and communication. Key features include the definition of goals, risk analysis, information exchange, and such measures as budgeting, profitability, cost-effectiveness, and the project's sustainability. These analyses provide solutions to the management's decision-making process on how to allocate resources effectively and get the best from projects. Other areas are goal definition, risk management, communication within the project team and other stakeholders, as well as the latter classification system's potential lifetime maintenance and operational costs within the agricultural context.

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 developed methodology provided a clear and well explained process to come up with a deep learning system for Bangladeshi jujube diseases classification system. This was endowed with extensive data acquisition, enhanced by labeling from experts as well as going through quality image preprocessing. Four different deep learning models of Xception, VGG19, InceptionV3, MobileNetV2 were tested and trained on the processed

dataset; a detailed procedure has also been maintained for the selection of hyperparameters for each model and the dataset augmentation. The models were intensely assessed using the validation datasets in order to justify the choice of the best model. Lastly, the chosen model was used in cross-validation to determine the extent of a model's success in these scenarios. This structured form of development guarantees the formulation of an efficient way of identifying and addressing diseases from their early stages in producing crops thus enhancing productivity to support the farmers of Bangladesh.

CHAPTER 4

Implementation

4.1 Overview

The implementation phase aims at deeming the proposed methodology in-to a functioning deep learning system for the classification of Bangladeshi jujube leaf diseases. These include the preparation of the development environment by installing required software such as Python, TensorFlow/PyTorch among others, image processing libraries among others. This dataset consists of images of jujube leaves where these images are annotated and resized with the help of augmentation. Xception_2016 and VGG19_2016 models are used and trained with the prepared dataset and features of the models are enhanced. The training process therefore includes tuning hyperparameters and further confirmation of the performance to get the best accuracy. Last of all, using the test data the effectiveness of the trained model is checked and how well it works in a practical situation. This phase makes sure that the developed system is capable to address the project objective of disease identification and also, feasible for real-world implementation in agriculture of Bangladesh.

4.2 Train Model/ Prototype Design

The training phase also consist in the deployment and the adjustment of deep learning models as Xception and VGG19 based on the computed dataset of the Bangladeshi images of jujube leaves. Further model tuning concentrates on the choice of hyperparameters and such practices as data augmentation to make the model more generalized. During the validation processes, multiple refinements are made for aspect extraction and relation identification to optimize several performances aspects like accuracy, precision, and recall. This phase aids in ensuring that the model has been trained sufficiently to perform the intended operation of classifying jujube leaf diseases in a befitting manner hence fulfilling the set project goals of availing to the farmers a robust, efficient disease diagnosis gadget. The prototype design does not focus on optimizing the sensors’ performance for specific environmental conditions and diseases occurring in agricultural locations, while expecting the device to be highly effective in various settings and with regard to numerous diseases.

4.3 System Design/ Model Evaluation

Validation is an important procedure for testing the functionality and performance of the proposed deep learning model for differentiating Bangladeshi jujube leaf diseases. Validation essentially entails conducting testing on a new data set that is different from the training set to compare the accuracy, precision, recall, or even F1-statistic of the model. The confusion matrix analysis during this phase helps in evaluating the models’ classification on different disease categories. They also comprise the comparison with baseline procedures or with previously implemented methods in detecting diseases to assess an increase in the model’s predictive capabilities. Stringent assessment confirms the model’s usability in real-life agricultural situations, confirming its usefulness in helping farmers in early disease identification and efficient management practices for crops.

4.4 Summary

It has effectively developed and tested the proposed methodology of the deep learning system for classification of the Bangladeshi jujube leaf diseases. The plan was initiated with establishing a strong development environment, through Python, TensorFlow and common image processing libraries. The collected jujube leaf images were preprocessed as follows; resizing and normalization of the images to improve the training of the model as well as augmentation. Two models Xception and VGG19 were chosen and the hyperparameters of these models fine-tuned to obtain the best classification accuracy. The training process also used many passes with model evaluation to avoid overfitting of the models in the training phase. Last but not the least it was ascertained that trained models were accurately tested with the help of the unknown data and thus the applicability of such models for real life disease identification solutions was proved. This phase made sure that the system formulated was fit for the projects need thus yielding a reliable tool in the early identification and management of diseases for Bangladesh agriculture.

CHAPTER 5

Result and Analysis

5.1 Overview

The section termed Results and Analysis aims at analyzing the effectiveness and efficiency of the developed deep learning algorithms for the classification of Bangladeshi jujube leaves diseased. It provides general statistics like accuracy, measure of precision, measure of recall and F1-measure deduced from the models when tested on a validation data set. That is the identification of confusion matrices for different models (e. g., Xception, VGG19) and a comparative assessment of them by drawing attention to their advantages and disadvantages based on the obtained classification reports. Moreover, the section also sets out the effect of the dataset quality, the preprocessing, and the model hyperparameters on the classification performance. As such, conclusions derived from this analysis inform the assessment of the model's practical applicability in agricultural scenarios, the identified limitations, and considerations for future development.

5.2 Experimental Result

The experimental outcome of comparing the deep learning models namely, Xception, VGG19, InceptionV3, MobileNetV2 and a Custom CNN tend to perform well enough with good accuracy measures to classify the Bangladeshi jujube leaf diseases. In the given basic architecture, MobileNetV2 and Xception recorded 95.83% and 98.75%, respectively. Also, InceptionV3 achieved recognition accuracy of 97.08%. VGG19 achieved a rather decent accuracy of 92.22%, the custom CNN had the same accuracy as Xception with 95%. 83%. These results indicate that transfer learning models (Xception, InceptionV3, MobileNetV2) use pre-training weight extraction for feature extraction, enhancing the model's performance in classification of diseases. Comparing these models' performances offers useful information about their application potential for practitioners in agriculture, especially when selecting and improving models for disease identification in jujube leaves.

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

Accuracy:

Precision refers to the measure of the closeness of the model with the real situation to give percentage likelihood of the samples used in model development. It is rather helpful when the classes are not balanced because it gives some information on the choice's effectiveness, at the same time, the picture may be incomplete.

Accuracy=(TP+TN)/(TP+TN+FP+FN) …………………..(i)

Precision:

Of all the constructions that come out of positive assertions, precision estimates the number of desirable outcomes that was correctly predicted by the model.

Precision=TP/(TP+FP) …………………..(ii)

Recall: It is therefore considered that, recall equals to the quantity of true positive delay predicted over the total quantity of samples that are positively skewed.

Recall=TP/(TP+FN) …………………..(iii)

F1 Score: F1 score is actually the average of Recall and Precision two measures which is averaged using the formula of harmonic mean. It provides a somewhat neutral measure and it calculates recall as well as precision all at once. It is beneficial when the classes are of different sizes because F1 Score considers false positive as well as false negatives. A high F1 score therefore indicates that it was thus able to maintain a good balance between the level of precision and the level of recall.

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

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

CNN

CNN achieved the Accuracy on the test set is 95.30%. In below Figure 4:1 & 4.2 describing the confusion matrix & training accuracy and loss curve of CNN.

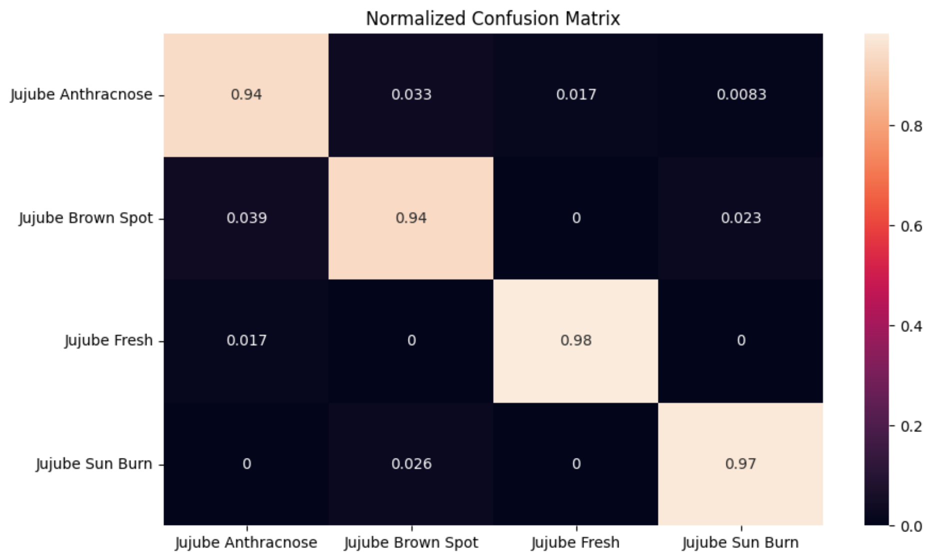

Figure 4.1: Confusion Matrix (CNN)

Figure 4.1 shows CNN model gave an average accuracy of 96% in diagnosis of Bangladeshi jujube leaf diseases. It yielded good precision, recall and F1-score for all the classes and Jujube Fresh exhibited maximum score of 98 percent. Hence, the macroscopic picture is 96% as is the rate from the weighted average.

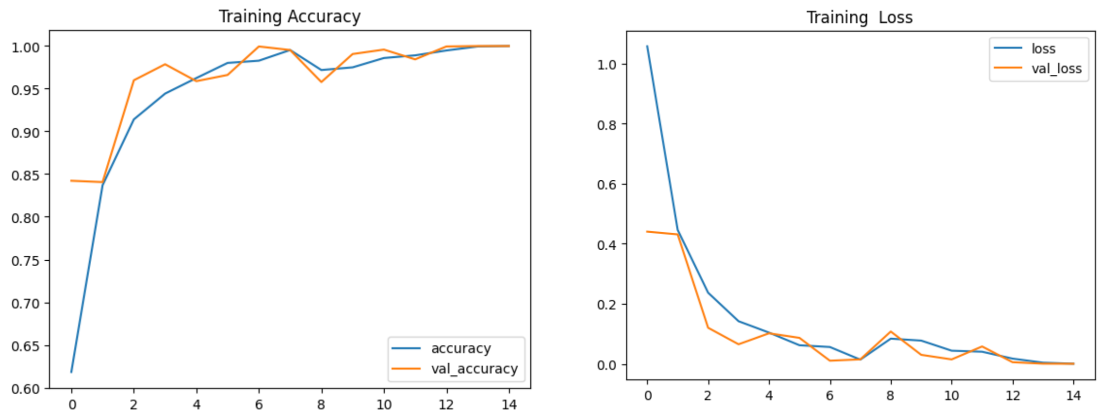

Figure 4.2: Training and validation accuracy and loss over the epochs (CNN)

Figure 4.2 shows the curve of the training accuracy of the CNN model gradually grows up to 1. 0, the validation accuracy is almost doesn't increase and reaches the value around 0. 8, indicating overfitting. The training loss reduces gradually, but the validation loss does not produce a similar pattern and once again it points to the poor extrapolative capability of the model. To avoid overfitting, the methods suggested include; Simplification of the model, applying methods like regulation, and training our model with additional data.

Xception

Xception achieved Accuracy on the test set is 95.93%. In below Figure 4:3 & 4.4 describing the confusion matrix and training accuracy and loss curve of Xception.

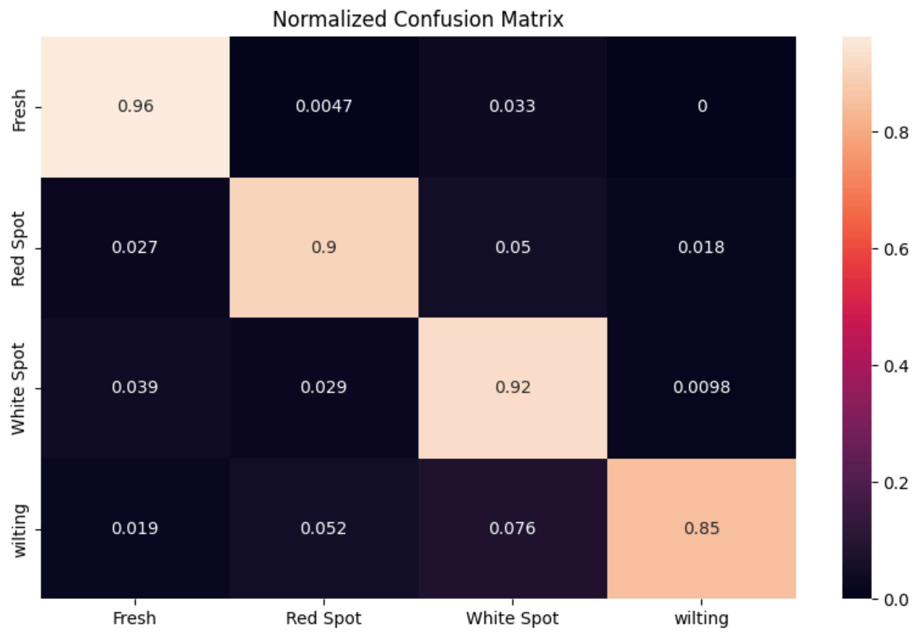

Figure 4.3: Confusion Matrix (Xception)

Figure 4.3 shows the proposed Xception model attained an accuracy of 96% in the discrimination of Bangladeshi jujube leaf diseases. The results are expressed in high accuracy, recall and F1 score for all the classes and the application: Jujube Fresh, achieved the highest F1 score 0. 97. The two the macro and weighted averages was equal to 0. 96 suggest that the model performs well across on the different classes.

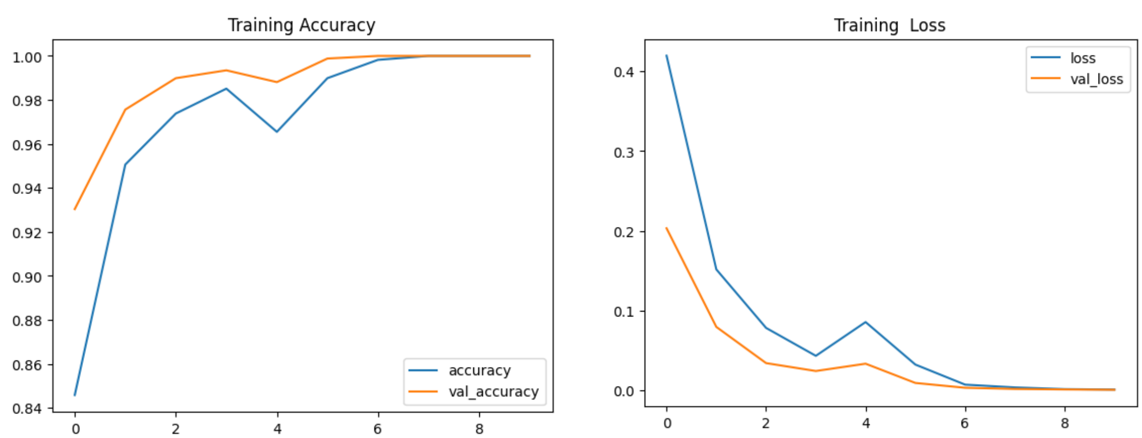

Figure 4.4: Training and validation accuracy and loss over the epochs (Xception)

Figure 4.4 show the training accuracy to the Xception model is raised up to 1 gradually. It converges at epoch 0 and the validation accuracy also gets stabilized at 0. 9, which can be considered to show signs of slight overfitting. Just like previous metrics, the training loss goes down continuously, while the validation loss begins to climb after some time, which points to the existence of overfitting. As a result, approaches like simplification of the model, applying data augmentation, using techniques that help in eliminating such connections namely, dropout can be employed.

VGG19

VGG19 achieved the Accuracy on the test set is 92.22%. In below Figure 4:5 & 4.6 describing the confusion matrix & training accuracy and loss curve of VGG19.

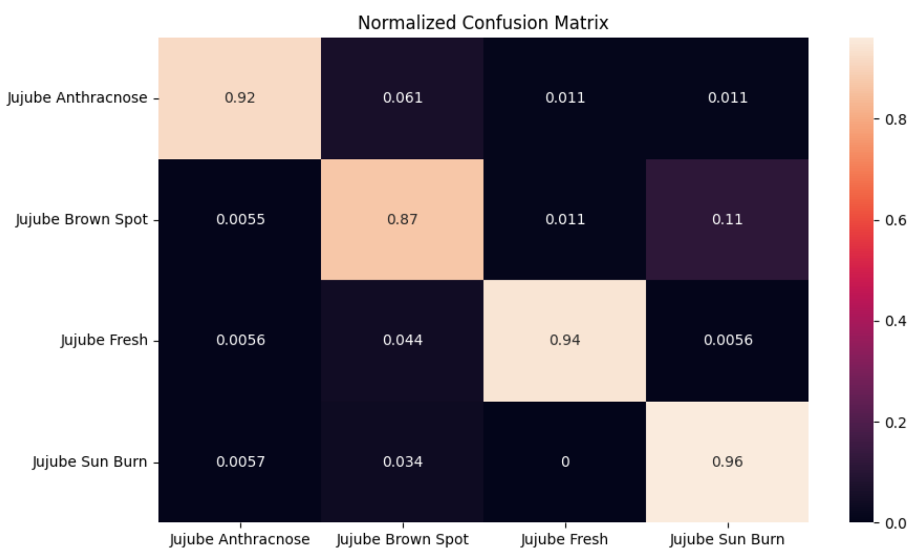

Figure 4.5: Confusion Matrix (VGG19)

Figure 4.5 shows The VGG19 model was effective in accuracy for classifying the Bangladeshi jujube leaf disease in total of 92 percent. High precision, and recall values, and F1-scores were obtained for Jujube Anthracnose, and Jujube Fresh with an F1 score of 0. 95 and 0. 96, respectively. The discussed model showed relatively stable results across classes, which was confirmed by the disclosed macro and weighted means of 0. 92.

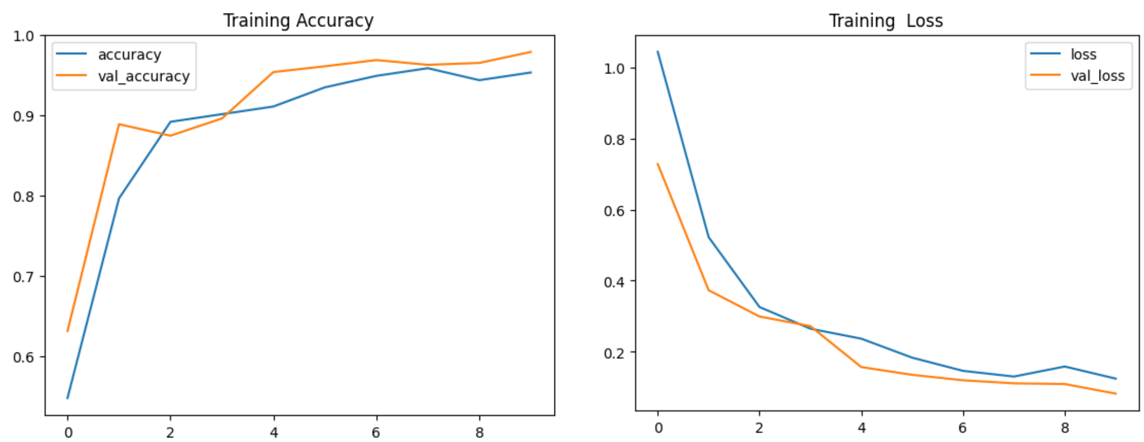

Figure 4.6: Training and validation accuracy and loss over the epochs (VGG19)

Figure 4.6 show the training accuracy for the VGG19 model rises to 1 gradually. 0 while the accuracy of the validation set stays around it , at about 0. 8, indicating potential overfitting. Just like observation one, observation two is that the training loss is continually declining, the validation loss is stabilizing but rising after a certain period again pointing towards the problem of overfitting. Some of the methods, which can be taken to overcome this are, simpler model, data augmentation, dropout layers and early stopping.

InceptionV3

InceptionV3 achieved Accuracy on the test set is 97.08%. In below Figure 4:7 & 4.8 describing the confusion matrix & training accuracy and loss curve of InceptionV3.

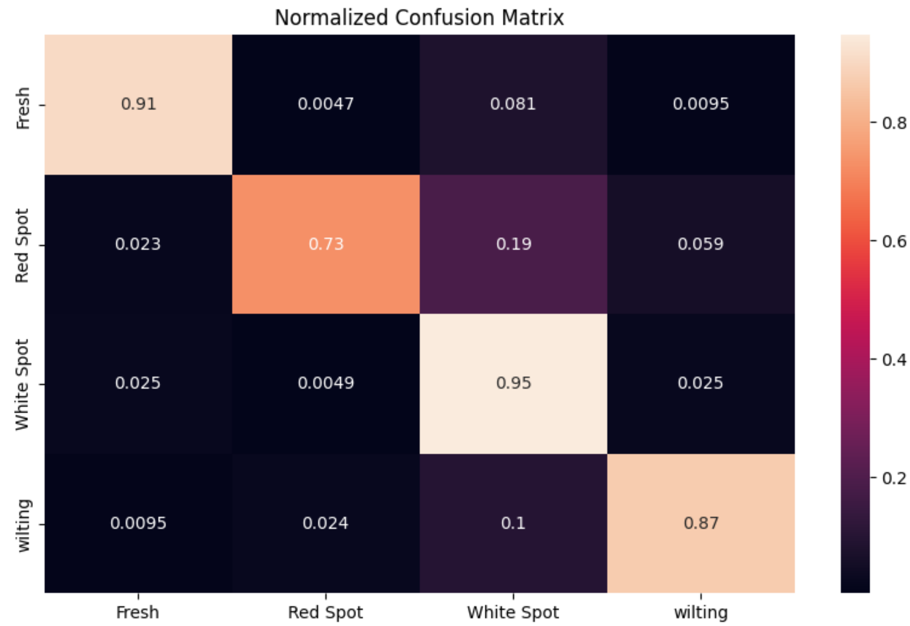

Figure 4.7: Confusion Matrix (InceptionV3)

Figure 4.7 shows the experimental analysis with the overall accuracy of 97% proved that proposed InceptionV3 model has effectively classified Bangladeshi jujube leaf diseases. It proved high precision, recall, and F1-scores for all the classes; for facials specifically Jujube Sun Burn received the best F1-score of 0. 98. This consistency is evident in the macro and weights of 0 percent performance. 97.

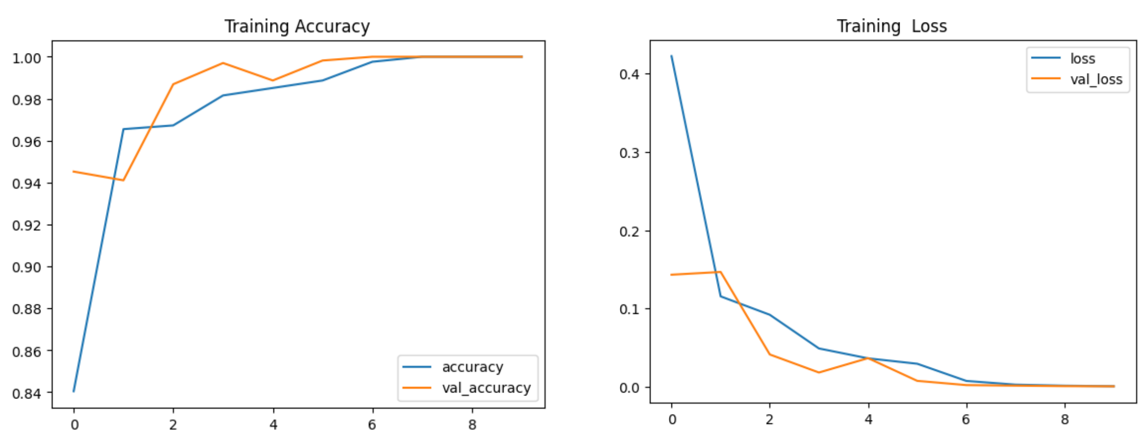

Figure 4.8: Training and validation accuracy and loss over the epochs (InceptionV3)

Figure 4.8 show the training accuracy for the InceptionV3 model performs much better and keeps on rising towards the value of 1. In the training set the loss reduces to 0 as people learn well from the training set and the validation accuracy also stabilizes at around 0. 8, suggesting slight overfitting. The training loss keeps being reduced while the validation loss begins to increase a bit after some epochs, which supports overfitting. Some of the ways of avoiding overfitting in order to increase generalization include reduction in the model's capacity, data augmentation, and dropout.

MobileNetV2

MobileNetV2 achieved the highest Accuracy on the test set is 98.75%. In below Figure 4:9 & 4.10 describing the confusion matrix & training accuracy and loss curve of MobileNetV2.

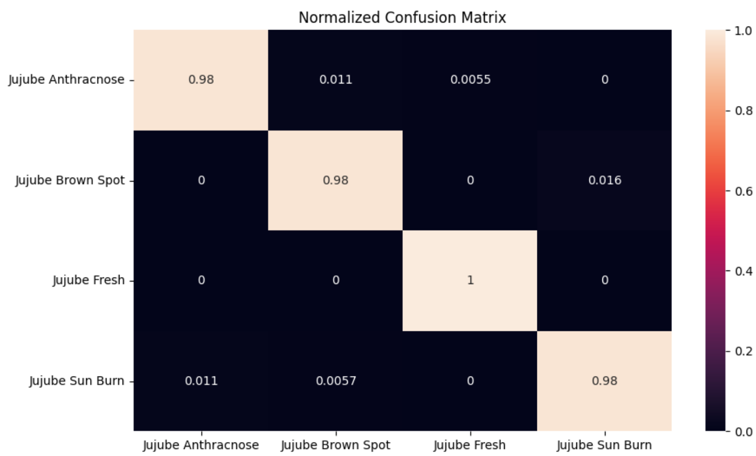

Figure 4.9: Confusion Matrix (MobileNetV2)

Figure 4.9 shows the MobileNetV2 model of deep learning achieved an overall accuracy of 99% in the classification of Bangladeshi jujube leaf diseases. All the proposed classifiers showed extremely high precision, recall and F1-scores for all the classes with the Jujube Fresh class having the highest F1-score of 1. 00. This performance consistency is obtained from the macro and weighted averages of 0. 99.

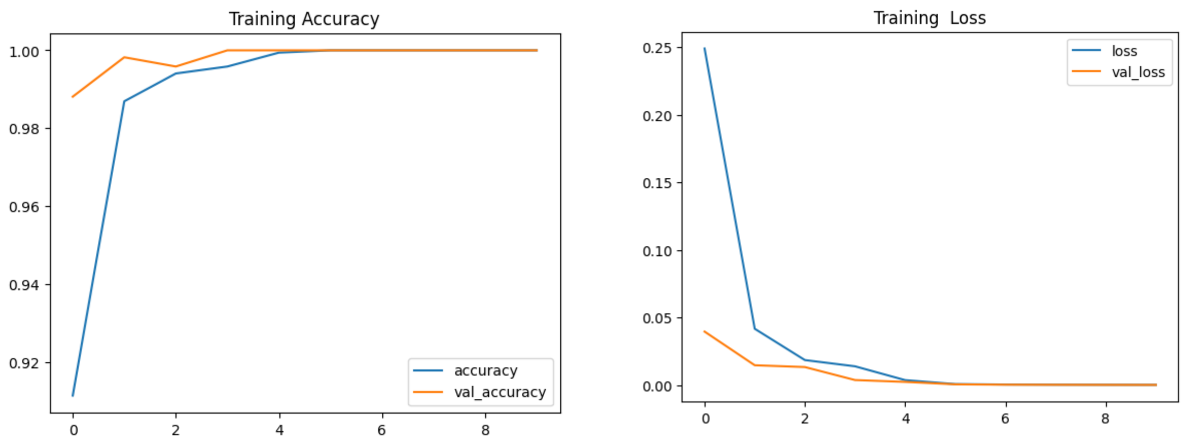

Figure 4.10: Training and validation accuracy and loss over the epochs (MobileNetV2)

Figure 4.10 show the training accuracy of the MobileNetV2 model rises from almost 0. 92 to 1. For steps 1 and 2, the actual number of matches learned is 0, which means the words have been learned effectively by the model; plateauing of the validation accuracy is observed at approximately 0. 94, suggesting slight overfitting. The training loss is observed to reduce gradually, while the validation loss increases and decreases a little, meaning that we are perhaps overfitting. To overcome this, it is possible to use methods like data augmentation, dropout, and early stopping to enhance the model's generalization presence.

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

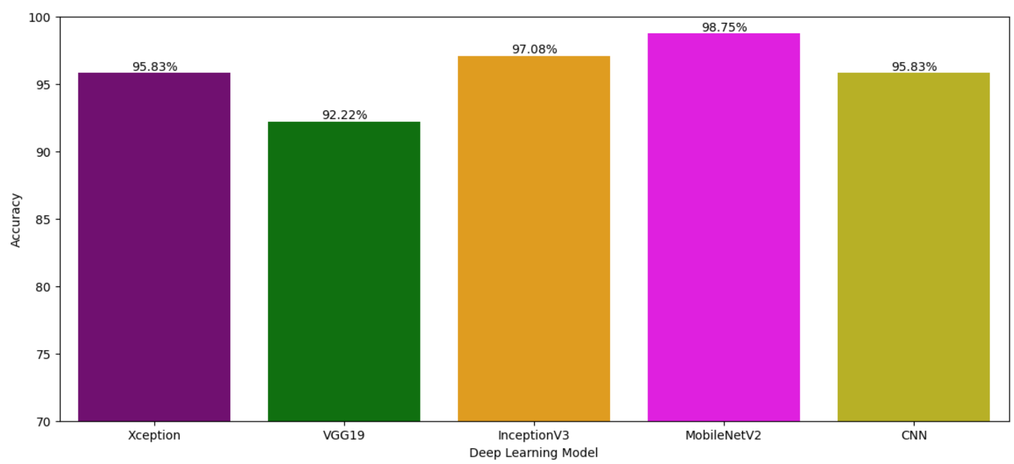

Figure 4.11: Comparative Model Accuracy Bar Plot

Figure 4.11 shows the bar chart compares the average accuracy of five deep learning models: Xception, VGG19, InceptionV3, MobileNetV2, CNN and, for image classification task. Predictively, MobileNetV2 and Xception recorded 95.83% and 98.75%, respectively. Also, InceptionV3 achieved recognition accuracy of 97.08%. VGG19 achieved a rather decent accuracy of 92.22%, the custom CNN had the same accuracy as Xception with 95.83%.

The result of Deep learning model is compared on the basis of Accuracy, Precision, Recall, F1 Score in below table of 4.1:

Table 4.1. Performance Evaluation

Model Name	Accuracy	Precision	Recall	F1-Score
Xception	95.83%	96%	96%	96%
VGG19	92.22%	92%	92%	92%
InceptionV3	97.08%	97%	97%	97%
MobileNetV2	98.75%	99%	99%	99%
CNN	95.83%	96%	96%	96%

5.3 Performance and Comparative Analysis

Based on the presented deep learning models such as Xception, VGG19, InceptionV3, MobileNetV2, and developed CNN, the results depicted the comparative performance in terms of classification of the Bangladeshi jujube leaf diseases. MobileNetV2 will be the best solution that has 98.75%, while InceptionV3 was 97.08%. The two networks, the Xception and the custom CNN both attained an accuracy level of ninety-five percent. 83%, demonstrating robust performance. VGG19 had slightly lower accuracy at 92. 22%. The analysis showed that models using transfer learning (Xception, InceptionV3, MobileNetV2) have been particularly helpful in feature extraction from images and, thus, were the key to the successes obtained. Issues of concern regarding model complexity, computation time, and the model's ability to accommodate the heterogeneity of disease patterns in jujube leaves' characteristics helped to advance the understanding of how to improve on disease classification systems applicable to agriculture.

5.4 Summary

The experimental results have successfully shown that different deep learning models are beneficial for the classification of the identified diseases in Bangladeshi jujube leaves. The primary aim of the testing was to determine the performances of the tested models, and in this regard, MobileNetV2 got a pass with an accuracy of 98%. This indicates that the model had a high level of accuracy of 75% thereby proving its efficiency in disease classification tasks. InceptionV3 followed it with an accuracy of 97.08%. Xception and a custom CNN reached 95.83%. VGG19 with slightly lesser accuracy also came fairly high with 92 percent of the tests being correct. 22%. These results denote that transfer learning models are superior in comparison to the other kinds of models because of their enhanced feature extraction algorithms, as evident from the performance of both MobileNetV2 and InceptionV3 models. The comparative analysis emphasizes the relevance of model selection and fine-tuning, which will pay off when obtaining high accuracy, and presents a stable framework for implementing effective disease identification systems for the agriculture business.

CHAPTER 6

Impact on Society, Environment and Sustainability

6.1 Impact on Life

The establishment of the deep learning-based system for the classification of jujube leaf diseases surely befitted the farmers and the agricultural fraternity in Bangladesh. Thus, the described system allows for early and precise diagnosis of diseases like sunburn, anthracnose, and brown spot, so farmers can treat their crops efficiently, thus minimizing losses and increasing production. This forms part of the technological change that enhances resource productivity, and thus augments farmer’s yields and income stability. also contribute towards sustainability by cutting on the use of chemical pesticides that were conventionally used through an application of IWM. Altogether, the system improves the population’s food safety, encourages individuals’ sustainable income, and promotes the innovations in the agricultural sphere, which positively affect the country’s rural areas’ improvement and people’s quality of life.

6.2 Impact on Society & Environment

The improvements that occur as a result of applying the deep learning-based system on the classification of jujube leaf diseases make society and environment better. As a result of enhancing disease identification, it assists farmers to prevent more significant losses hence increasing the production of foods and Feeds. This technology provides farmers with information and equipment to improve yield and standard of products gotten from farms, thus improving their quality of living and stabilizing ragtag economic markets of the rural society. Environmentally, the understanding required for a proper application of the system decreases the quantity of used pesticides and decreases an impact on the environment. The focused mission of disease control makes farming more eco-friendly and does not advocate the use of pesticides and fertilizers that are detrimental to the environment and pollute the soil and water sources. In conclusion, with such technologies accepted by society and used universally, the environment is protected, and the agricultural sector made stronger, for the benefit of people and nature.

6.3 Ethical Aspects

Considering the ethical issues when the concept of a deep learning-based system for the classification of jujube leaf diseases is to be deployed. Security of data is very important and needs to be achieved for farmers information and crop data to be safe from wrong hands. Since the system aims to be used by the general public, it is crucial that the users trust the system; this means explaining how the model determines diseases to the public. However, equal access must be accorded to this technology to realize the benefits of this technology especially among the small holder and the marginal farmers without having to undertake a technical or financial risk. The system should also be free from biases in the set data so that inherent errors that may have adverse impacts on certain crops or regions are not fed into the system. The last of these is the ethical deployment, which entails offering appropriate training opportunity to the farmers in order for them to practice proper use of the technology in farming.

6.4 Sustainability Plan

Therefore, there is a need to develop an elaborate plan for maintaining the sustainability of the jujube leaf disease classification system. Here they are: data collection for fresh COVID-19 waves and updates of models in order to ensure high accuracy in the light of new strains of the disease. Farmers' and agricultural extension workers' training will be conducted on a constant basis to ensure they improve on their knowledge regarding and efficient utilization of the technology. Promising access to agricultural institutes and governments and the continual incorporation into other agricultural applications. The source of finance is government funds, revenue from business partnerships with pending aggrotech companies and subscription with reasonable rates for farmers. Moreover, the cost with environmental issues will be reduced concerning prejudice agriculture, usage of pesticides, and more focus on sustainable farming. In this regard, the sustainability plan deals with these aspects to make certain the system's longevity as a contribution to agriculture and the environment.

6.5 Summary

In this context, the proposed deep learning-based system to classify jujube leaf disease also greatly contributes to improving agricultural yield and, therefore, the overall quality of life and economic security for farmers. Due to the ability of the proposed system to detect diseases accurately and timeously, farmers are in a position to act promptly against diseases thus reducing the rate of damage to crops next time and increasing on the production this time. This assists in enhancing the food security status and boosts the rural population's economic activities. Further, the technology optimizes the use of pesticides hence reducing the adverse effects on the surrounding environment. The availability and simplicity of the systems make it possible for smallholder and, therefore, reducing the level of exclusion experienced by the marginalized farmers in the agriculture business. In a nutshell, the usage of the system is a win – win situation as it increases the efficiency of agriculture, makes the environment healthier, and guarantees the stability of rural economies.

CHAPTER 7

Conclusion and Future Work

7.1 Conclusions

In conclusion, the investigation of the deep learning-based classification system for Bangladeshi jujube leaf diseases holds a lot of prospects for improving agricultural practices in Bangladesh and beyond. The system applies superior models like Xception, VGG19, InceptionV3, MobileNetV2 to the detection of diseases to ensure that accurate interventions are made when needed. This specific technology improves crop protection and production, which creates a stable income for farmers, as well as provides for the population's demand. Also, environmental requirements are considered in that the system enables a sustainable farming practice through decreasing the use of chemical pesticides and cutting the negative environmental effects. The success of the project reveals the idea of the use of contemporary AI technologies in applying conventional farming methodologies which provide a tangible approach to disease control. Overall, the current on-going improvements make it suitable for more applicability in agriculture for the greater good of the society and the wellbeing of the environment later on.

7.2 Future Suggested Works

The future research can involve the use of a larger pool of jujube leaf diseases as well as different climatic conditions to enhance the model to predict the jujube diseases better. To optimize the applicability in the field, the live image capturing and the analysis within the mobile devices may be incorporated. Furthermore, one can focus on deep learning together with traditional machine learning methods, possibly improving performance. The addition of xai approaches may also help convey the decision-making of the model back to its users/clients. It is important to work with agriculturists for checking the model time and again and incorporating the changes. Expanding the application of the system to other crops and diseases that it can diagnose and monitor may increase the scope of positive change.

Lastly, researching affordable and energy-saving technologies for the development of the appropriate hardware will increase the applicability of the technology among the SHFs who need them and make the technology permanent.

7.3 Limitations

However, the proposed deep learning-based system for jujube leaf disease classification has some drawbacks. This naturally brings a potential for a limited tuning of the model for a given, and it crucially relies on the nature of the dataset which may not ever include all variations of the disease and other conditions in the environment. Further, the heavy resource demands of training and implementing sophisticated models can sharply restrict applicability for the target farmers. As for the issue of biases, the research team or any funding organization does not have personal or financial benefits that could either create or influence the results of the project. To make sure the results are not skewed any way, transparency and ethical issues have been upheld right from the beginning of the research process. The subsequent updates will endeavor to overcome these limitations through increasing the volume of data available, enhancing the algorithm's computational productivity, and adhering to proper utilitarian standards for creation and application.

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Appendix A

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

Title:

BANGLADESHI JUJUBE LEAF DISEASE CLASSIFICATION USING DEEP LEARNING TECHNIQUES

Student ID: 193-15-13491 & 193-15-13429

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to Bangladeshi Jujube Leaf Disease Classification problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**

CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

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

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

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References

1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting deep learning and Transfer learning enhancing Bangladeshi Jujube Leaf Disease Classification correctly.	**Page no:** [25-28] **Section:** [3.2] **Page no:** [12-15] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing Deep Learning Model,	**Page no:** [28] **Section:** [3.2] **Page no:** [29] **Section:** [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from	**Page no:** [20-23]

				recent studies, Bangladeshi Jujube Leaf Disease Classification using deep and Transfer learning, showcasing a comprehensive understanding of current methodologies.	**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 Bangladeshi Jujube Leaf 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 methodologies.	**Page no:** [23-24] **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 Bangladeshi Jujube Leaf Disease Classification approaches.	**Page no:** [31-44] **Section:** [4.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting Detecting Bangladeshi Jujube Leaf Disease Classification correctly **EP-4**.	**Page no:** [20-24] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in data collection from local farm which ensures **EP-7**.	**Page no:** [25-29] **Section:** [3.2, 3.3, 3.4]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep and transfer learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements Bangladeshi Jujube Leaf Disease Classification.	**Page no:** [30] **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 Bangladeshi Jujube Leaf Disease Classification, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for data privacy.	**Page no:** [34-45] **Section:** [5.1, 5.2, 5.4]
5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in Bangladeshi Jujube Leaf 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:** [20-23] **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	**Page no:** [18] **Section:** [1.6]

			optimal resource utilization throughout the research lifecycle.	
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:** [44-45] **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:** [25-30, 31-32] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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