Enhanced Agricultural Productivity: Dragon Fruit Leaf Disease Detection Using Deep Learning Models

By
Apurbo Sarker
ID: 212-15-14719

Bilas Saha Bisal
ID: 212-15-14694

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

Supervised by

Md. Sazzadur Ahamed
Assistant Professor
Department of Computer Science and EngineeringDaffodil International University

Co-Supervised by

Abdullah Al-Amin
Lecturer
Department of Computer Science and EngineeringDaffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY
Dhaka, Bangladesh

May 14, 2025

APPROVAL

This Project titled **"Enhanced Agricultural Productivity: Dragon Fruit Leaf Disease Detection Using Deep Learning Models"**, submitted by Apurbo Sarker, ID No: **212-15-14719** and Bilas Saha Bisal, ID No: **212-15-14694** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14 May, 2025.**

BOARD OF EXAMINERS

Dr. S.M Aminul Haque — **Chairman**
Professor & Associate Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Sharmin Akter — **Internal Examiner**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Ms. Syada Tasmia Alvi — **Internal Examiner**
Sr. Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

14.05.25

Dr. Md. Arshad Ali — **External Examiner**
Professor
Department of Computer Science and Engineering
Hajee Mohammad Danesh Science & Technology University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md. Sazzadur Ahamed, Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Md. Sazzadur Ahamed
Assistant Professor
Department of Computer Science and EngineeringDaffodil International University

Co-Supervised by:

Abdullah Al-Amin
Lecturer
Department of Computer Science and EngineeringDaffodil International University

Submitted by:

Apurbo Sarker

Apurbo Sarker
Student ID: 212-15-14719
Department of Computer Science and EngineeringDaffodil International University

Bilas Saha Bisal

Bilas Saha Bisal
Student ID: 212-15-14694
Department of Computer Science and EngineeringDaffodil International University

ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project (FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Md. Sazzadur Ahamed, Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of **Deep Learning** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

We propose a deep learning approach to identify dragon fruit leaf diseases, namely Anthracnose, Stem Canker, and Scale Insect, through image classification. Agricultural disease diagnosis has been a manual, time-consuming task with high possibilities of inaccuracy, particularly for smallholder farmers lacking the assistance of professionals. To overcome these limitations, a dataset of 2,042 images under natural field conditions from Dragon Fruit Garden, Trishal, Mymensingh, and Fiber Plus Agro, Ashulia, Bangladesh, was collected. Through data augmentation, the dataset was enriched to 6,126 training images. We investigated four deep learning models InceptionV3, DenseNet201, MobileNetV2, and a custom CNN based on transfer learning. Among them, DenseNet201 achieved the highest accuracy of 96.48% with improved feature reuse and classification capability. MobileNetV2, though slightly less accurate, has a promising light model for mobile-based applications. The system suggested herein enables early stage disease detection, which can avoid up to 40% of crop loss and excessive pesticide usage, thereby promoting more sustainable agriculture. This research addresses a real-world problem by bridging the gap between AI research and farming needs on the ground, offering an affordable, scalable, and mobile-compatible solution that can empower farmers with timely and accurate disease diagnosis in resource poor regions.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

In this Chapter outlines the Introduction, Motivation, Objectives. Also, a short overview about the Methodology, Motivation and Project Outcomes also discussed in this chapter.

1.1 Introduction

In this project "Enhanced Agricultural Productivity: Dragon Fruit Leaf Disease Detection Using Deep Learning Models" we aim to build a machine learning model that will detect disease of any dragon fruit leaf disease (Anthracnose, Stem Canker, Scale Insect, and Good Leaf) by using image analysis. This model will help the farmer who cultivates dragon fruits by detecting early leaf diseases and then they take steps to prevent disease and cultivate more fruit and increase their earning by selling healthy fruit. The project also introduced the beneficial of artificial intelligence in agriculture by data-driven techniques.

1.2 Motivation

Dragon fruit farming is a prominent agricultural practice in the tropical and subtropical zone, playing a significant role in local economies and export income. Dragon fruit growers in countries like Bangladesh, Vietnam, and Indonesia are highly troubled by leaf diseases like Anthracnose, Stem Canker, and Scale Insect that minimize the crop production by as much as 40%. Conventional disease detection techniques depend on manual visual observation, which is time-consuming, laborious, and susceptible to human error. Most smallholder farmers have no access to professional agronomists, and thus the diagnosis is delayed and losses are inevitable. Recent progress in deep learning technology promises a paradigm shift. Although the manual process cannot be scaled and is inaccurate, Deep Learning algorithms such as DenseNet201 and MobileNetV2 are proven to automate disease detection accurately. The models are able to process thousands of images of leaves within minutes, enabling early intervention and reduced reliance on costly, time-consuming manual inspection. With the use of light architectures like MobileNetV2, this project is committed to delivering efficient, farmer-friendly solutions bridging the gap between AI research advancements and real-world agricultural needs.

1.3 Objectives

To collect an in-field raw data set of dragon fruit leaf images that covers good and diseased leaves like Anthracnose, Stem Canker, Scale Insect. For making a deep learning model capable of recognizing dragon fruit leaf diseases. For the purpose of creating a deep learning model that will reduce the cost, time, and complexity of dealing with leaf diseases and growing healthy fruits.
Develop a user-friendly instrument for real-time disease detection to prevent the consumers from getting plagued by lots of technology issues. Reduce computational complexity in order to be compatible with low-resource devices like smartphones.

1.4 Methodology

The methodology is a step-by-step process to design a deep learning system for disease identification from dragon fruit leaves. It begins with data collection, where 2042 pictures of dragon fruit leaves are collected from Dragon Fruit Garden, Trishal, Mymensingh and Fiber Plus Agro, Ashulia, Dhaka with the help of smartphones by snapping photographs with varying disease severity, light, and orientation. The images are preprocessed based on techniques such as background removal. Four deep learning architectures InceptionV3, DenseNet201, MobileNetV2, and custom CNN are fine-tuned through transfer learning where pre-trained models are adapted to the dragon fruit database for learning disease-specific features. The custom CNN is employed as a baseline with convolutional and pooling layers for comparison. Hyperparameters like learning rate and batch size are optimized, and cross-entropy loss is used to optimize the performance of the model. Its performance is evaluated using measures such as accuracy, precision, recall, and F1-score, and confusion matrices are generated to analyze misclassifications between disease classes. Finally, the model is deployed and its usefulness verified to confirm that it meets the needs of real-world dragon fruit farms. The goal is to determine a simple, low-cost, and effective way of detecting dragon fruit leaf diseases at an early stage.

1.5 Project Outcome

The potential impact of this project, "Enhanced Agricultural Productivity: Dragon Fruit Leaf Disease Detection using Deep Learning Models" is groundbreaking to precision farming and dragon fruit cultivation.

The main contributions include: Complete Dataset for Dragon Fruit Leaf Diseases: Dragon fruit diseases like Anthracnose, Stem Canker, and Scale Insect are the agriculturist's worst nightmare, but lacking standard datasets has been a critical hindrance to research for years. To this purpose, we compile 2042 dragon fruit leaf images gathered from Dragon Fruit Garden, Trishal, Mymensingh and Fiber Plus Agro, Ashulia, Dhaka. The dataset will serve as a benchmark for future research and enable developers to train robust deep learning algorithms. We expect to popularize technology measures that will ensure the protection of the dragon fruit business and register long-term improvement.

Increased Disease Diagnosis: Disease diagnosis of dragon fruit can be accurately discerned by creating deep learning models. Early diagnosis allows the farmer to implement specific treatments, reducing crop loss by as much as 40% and also ensuring fruit quality.

Increased Agricultural Productivity: With the process of disease detection automated, there is no longer a need for time-consuming manual inspections. Farmers are now able to examine leaves in real-time, reducing diagnosis from days to seconds and decreasing the cost of operations.

Economic Benefits: Saving costs and making the farmers more profitable directly by early mitigation of the yield loss, the economic benefits to nations such as Vietnam and Bangladesh, where the dragon fruit crop is an export-oriented high-value crop, could be increased through the impact of the technology as well as rural economy stability.

Scalability and Transferability: Once developed in dragon fruit leaf disease detection, the same model can be transferred or fine-tuned for use in other crops and diseases, making it a useful tool for the overall agricultural sector.

Better Decision-Making: Insights from the dataset and model predictions, e.g., disease prevalence as a function of weather patterns, allow farmers and policymakers to make proactive agricultural decisions.

Educational and Training Opportunities: Implementation of this technology provides an opportunity to educate and train farmers in the use of high-tech technologies and simple to use for farmers, which can improve their farming practices and adaptability to new farm technologies.

Sustainability Impact: Precision disease management reduces excessive usage of pesticides and fungicides and minimizes the degradation of the environment. Targeted treatments localize to prevent erosion of the soil and promote sustainable agriculture.

A low-cost, scalable, farmer-friendly solution to dragon fruit cultivation using deep learning is offered through this project. With the good of technology tied with pragmatism of functionality, this project aims to increase productivity, make farming more sustainable, and financially viable.

1.6 Organization of the Report

The report follows the following chapters:

Chapter 1: Introduction — Presents the background, motivation, aims, methodology, results, and report organization.

Chapter 2: Background — Describes the importance of dragon fruit cultivation, major diseases that affect crops, traditional detection methods, usage of AI, and thorough literature review.

Chapter 3: Research Methodology — Describes the research design, dataset preparation, preprocessing techniques, model training, and evaluation methods.

Chapter 4: Implementation and Results — Summarizes the training methods used for models, outcome of every model, and comparative assessment in terms of performance metrics.

Chapter 5: Engineering Standards and Design Challenges — Explains engineering principles embraced, ethical considerations, contribution to the environment and society, and problems in project management.

Chapter 6: Conclusion — Summarizes work undertaken, signals project limitation, and provides guidelines for future research and improvements.

Chapter 2

Background

This chapter provides an overview of the general background with regard to deep learning model-based dragon fruit disease detection. It first introduces the most significant concepts required to comprehend the research background, followed by a comprehensive literature review, and finally identifies the research gaps that necessitate the proposed system.

2.1 Introduction

Dragon fruit (Hylocereus spp.), or pitaya, is gaining more popularity due to its vibrant color, nutritional quality, and price in the market. Its production is, however, being challenged by many biotic factors such as fungal and bacterial diseases, which impact yield and fruit quality in a negative way. Manual identification and classification of these diseases are time-consuming, labor-intensive, and imprecise. These challenges have spurred the growing interest in employing artificial intelligence (AI) and machine learning (ML) to create automatic, accurate, and scalable approaches for disease detection in agriculture, more precisely in the cultivation of dragon fruits [1], [6].

The deep learning approach, especially the Convolutional Neural Networks (CNNs), has revolutionized the procedure of image-based plant disease detection in recent years. CNNs can learn spatial hierarchies of features from unprocessed pixels of images and are therefore naturally well-adapted to image classification tasks employed in agricultural diagnosis [5], [18]. CNNs tend to require large training data sets and high computational power, however, which cannot always be provided by low-resource agricultural communities. Hybrid approaches comprised of CNNs and traditional machine learning classifiers such as Support Vector Machines (SVMs) have been proposed as an approach to overcome these limitations.

Mehta et al. proposed a hybrid CNN-SVM architecture specifically for the multi-classification of dragon fruit diseases and performed better than standalone CNN or SVM [1]. Feature extraction was done with CNNs, while SVMs were used for classification, taking advantage of the efficaciousness of SVM when handling small to medium-sized datasets as well as high-dimensional data space. Such a model significantly improved classification accuracy without compromising the computational aspect, making it an ideal choice for deployment.

Additionally, datasets such as the UDCAD-DFL-DL and others procured specifically for the classification of dragon fruit diseases have also presented researchers with chances to train and validate AI models using actual-world data [6], [10]. These datasets capture various disease symptoms on dragon fruit leaves and stems, enabling better generalization of deep learning models under varied conditions.

Lightweight and efficient neural architectures such as MIRNet_ECA and GSE-YOLO have been explored by other researchers for application in either disease classification or dragon fruit ripeness assessment [2], [5]. The models are optimized to achieve high accuracy with minimal model size to enable deployment on edge devices such as smartphones and drones. Qiu et al., for instance, suggested an improved YOLOv8n-based model known as GSE-YOLO optimized for ripeness detection that achieved high accuracy with low computational complexity [2].

These computer-based systems also carry practical benefits like early diagnosis, reduced reliance on chemical treatments, and improved resource usage to control diseases. In the long run, integrating such intelligent models into intelligent agricultural systems can potentially allow farmers, especially those in the developing world, to monitor crop health cost-effectively and sustainably [4], [8], [16].

Overall, AI-based dragon fruit disease diagnosis is a step in the right direction from machine to human-based agri-diagnosis. CNN-SVM hybrid approach on the whole stands out in terms of accuracy-efficiency tradeoff. Work in the future on this would be along the lines of real-time realization, multi-disease capability, and integration with IoT-based monitoring systems for end-to-end smart farming solutions [3].

2.2 Literature Review

Detection and ripeness classification of dragon fruits have been gaining more interest in the last decade; researchers began utilizing different types of artificial intelligence (AI) and deep learning approaches. In that regard, different studies tried different approaches toward higher accuracy in detecting and ripeness classification of dragon fruits so that these fruits are qualified for market acceptance.

S. Mehta et al. [1] proposed a disease classification model for dragon fruits using a hybrid combination of CNN and SVM. The model presented above has demonstrated that hybrid approaches improve accuracy for multi-class disease classification more than singularly using CNN or SVM. Similarly, Z. Qiu et al. [2] have proposed GSE-YOLO, which is a lightweight and high-precision model from YOLOv8n as applied to pitaya ripeness detection. Their approach satisfactorily classified the ripeness levels, which was a promising approach for automated harvesting in commercial farming.

Image processing techniques have been a popular choice to detect diseases in agriculture. Y. R. Kumar et al.[3] used basic image processing techniques to detect disease in the stem of dragon fruit. The approach has shown a feature of enlightening the problem; however, it raises the requirements for a more complex model for better accuracy. Contrary to this, V. Kulkarni et al. [4] applied image analysis methods for the detection and classification of diseases, along with the determination of the maturity of dragon fruits. The research exhibited the prospects of visual features like color and texture for successful classification.

Deep learning methods have further revealed great potential in this area. B. Zhang et al. [5] proposed the MIRNet_ECA model, a deep learning network for the classification of the ripeness of dragon fruits. The model used multi-scale inverted residual attention networks to improve performance in the classification of ripeness stages with high accuracy. M. U. Mojumdar et al. [6] presented a dataset (UDCAD-DFL-DL) for the classification of agricultural diseases in dragon fruits and leaves, creating a benchmark for continued research in the field. This dataset has been used in training models in detecting common diseases impacting the farming of dragon fruit.

AI solutions have not been restricted to detection but also treatment. N. Nilay [7] researched the potential of AI in detecting and treating stem canker of dragon fruit plants caused by Neocytalidium species. This research illustrated the application of AI models in not just determining the disease but also recommending a treatment regimen. Additional studies are R. Shakil et al. [8], on how feature selection techniques help improve models used for carrying out the recognition of diseases of dragon fruits. They managed to optimize accuracy classification by finding the best features to use.
In recent focus, there have been disease detection in the incorporation of explainable AI, or XAI. S. Ferreira Júnior et al. [9] suggested a deep computer vision system integrated with XAI for the classification of dragon fruits in such a manner that the models' decisions would be explainable. This is required for understanding the reason behind predictions, especially in agricultural applications where the accuracy of decisions is extremely important. Additionally, P. C. Sarkar et al. [10] presented an annotated dataset for disease classification in dragon fruit and leaves, valuable assets for the research community.

Several researches used more advanced deep learning to find a better result of classification. M. C. A. Tomas et al. [11] utilized YOLOv5 deep learning model for a recognition image to detect any common disease in dragon fruit. Similarly, R. Riska and J. Jumjunidang [12] studied Neocytalidium-induced stem canker and showed the results of controls by sodium salts to manage the real applications for the control of diseases of dragon fruit.

Detection of dragon fruit picking and other such related activities has also been discussed in the latest research. J. Zhou et al. [13] suggested a YOLOv7 and PSP-Ellipse-based method for the detection of fruit picking points. The method was found to be efficient in the orchard setting. Similarly, L. Hakim et al. [14] fused color and texture features for the detection of disease in dragon fruit stems with high classification accuracy.

With better detection in the natural environment, B. Zhang et al. [15] combined lightweight deep learning models with attention mechanism for effective and robust detection of natural orchard environments. While L. H. Peng et al. [16] presented an optimized YOLOv8, known as YOLOv8-G, with an application to real-time stem disease in dragon fruit based on the accuracy and speed needed for the successful

detection of current models.
For the final part, the advent of transfer learning has demonstrated enormous potential in enhanced classification models. N. Yusamran and N. Hiransakolwong [17] suggested DIPDEEP, a neural network-based method for Thai dragon fruit classification. T. Nguyen et al. [18] ensemble a hybrid CNN model for dragon fruit disease automatic detection, while X. Zhao et al. [19] developed lightweight CNN models with attention mechanisms for disease detection. These models offered low computational costs with high accuracy. D. B. Hermawan and T. S. Nugroho [20] used transfer learning with ResNet, achieving a high accuracy of disease classification.

These studies show the growing prospects of AI, machine learning, and deep learning algorithms in solving agricultural problems, particularly in the detection and classification of diseases and ripeness of dragon fruits.

Table 2.2.1: Summary of Literature Reviewed.

Author(s)	Year	Title	Methodology	Key Findings
S. Mehta et al. [1]	2023	Multi-Classification of Dragon Fruits Diseases: A Hybrid CNN-SVM Approach	Hybrid CNN-SVM	Hybrid approach improves disease classification accuracy compared to CNN or SVM alone
Z. Qiu et al. [2]	2024	GSE-YOLO: A Lightweight and High-Precision Model for Identifying the Ripeness of Pitaya	YOLOv8n-based GSE-YOLO	Achieved high accuracy in ripeness detection with lightweight model
Y. R. Kumar et al. [3]	2023	Dragon Fruit Stem Disease Detection Using Image Processing	Image Processing Techniques	Implemented basic image processing to detect diseases with moderate success
V. Kulkarni et al. [4]	2022	Detection and Classification of Diseases and Maturity of Dragon Fruits	Image Analysis	Used visual features for disease and maturity classification
B. Zhang et al. [5]	2025	MIRNet_ECA: Multi-scale Inverted Residual Attention Network for Ripeness Classification	MIRNet_ECA Deep Learning	High performance in ripeness level classification using attention mechanisms

M. U. Mojumdar et al. [6]	2023	UDCAD-DFL-DL: A Unique Dataset for Classifying and Detecting Agricultural Diseases	Dataset Design	Provided a benchmark dataset for dragon fruit leaf disease detection
N. Nilay [7]	2024	Integration of AI in Identifying and Treating Stem Canker in Dragon Fruit Plants	AI-Based Classification	AI models successfully identified Neocytalidium stem canker
R. Shakil et al. [8]	2023	Best Feature Selection Technique for Dragon Fruit Disease Recognition	Feature Selection Techniques	Identified optimal feature selection for model performance improvement
A. S. Ferreira Júnior et al. [9]	2024	Deep Computer Vision and Explainable AI for Dragon Fruit Classification	CNN + XAI	High classification accuracy with interpretability
P. C. Sarkar et al. [10]	2023	Dragon Fruit & Leaf Dataset from Bangladesh	Dataset Publication	Released annotated dataset supporting disease detection research
M. C. A. Tomas et al. [11]	2024	Recognizing Common Skin Diseases Using YOLOv5	YOLOv5 Deep Learning	Demonstrated YOLO's utility in rapid image-based disease detection
R. Riska and J. Jumjunidang. [12]	2023	Stem Canker of Dragon Fruit and Its Control Using Sodium Salt	Pathogen Study	Confirmed Neocytalidium as new pathogen and proposed sodium salt treatment
J. Zhou et al. [13]	2023	Dragon Fruit Picking Detection Using YOLOv7 and PSP-Ellipse	YOLOv7 with PSP-Ellipse	Effective method for detecting fruit picking points
L. Hakim et al. [14]	2023	Detection Based on Color and Texture Features	Color & Texture Feature Analysis	Disease detection using combined features with high accuracy
B. Zhang et al. [15]	2022	Dragon Fruit Detection in Orchard Using	Lightweight DL with Attention	Robust detection under natural conditions

		Lightweight Network and Attention		
L. H. Peng et al. [16]	2024	YOLOv8-G: Improved YOLOv8 for Stem Disease Detection	YOLOv8-G Model	Enhanced stem disease detection in real-time settings
N. Yusamran and N. Hiransakolwong [17]	2022	DIPDEEP: Classification for Thai Dragon Fruit	DIPDEEP Neural Network	Accurate classification model for Thai dragon fruit
T. Nguyen et al. [18]	2023	Automatic Detection Based on Hybrid CNN	Hybrid CNN Model	Effective multi-disease classification
X. Zhao et al. [19]	2023	Lightweight Model for Disease Detection Using Attention Mechanisms	Lightweight CNN + Attention	Model improved accuracy with low computational demand
D. B. Hermawan and T. S. Nugroho [20]	2023	Classification Using ResNet and Transfer Learning	Transfer Learning (ResNet)	ResNet-based model achieved high accuracy in classification tasks

2.2.1 Similar Applications

Deep learning and AI technologies are extensively applied in numerous sectors of agriculture, particularly for the classification of fruits, disease detection, and estimation of ripeness. These technologies, while not exclusively used on dragon fruits, are methodologically analogous and have been crucial in driving this field.

For the classification of fruits, CNN models, YOLO variants, and ResNet models have all been effectively applied to distinguish between different fruits or fruit conditions. For instance, Mehta et al. employed a hybrid CNN-SVM model to perform multi-class classification of dragon fruit diseases with improved classification performance [1]. Ferreira Júnior et al. employed a deep computer vision system that used explainable AI (XAI) to classify different states of dragon fruits so that stakeholders can understand the decision-making process of the model [9].

The concept of efficient and light object detection models has gained increasing popularity over the recent past. Qiu et al. introduced GSE-YOLO, an efficient YOLOv8n model for the specific use case of ripeness detection in dragon fruits, showing that lightweight models could deliver high accuracy for real-world situations [2]. In the same vein, Peng et al. introduced YOLOv8-G to recognize important stem diseases of dragon fruits, optimizing the base YOLOv8 architecture to meet real-time usage needs [16].

Apart from the dragon fruits, the same models have been used for other fruits. For example, light detection networks along with attention mechanisms were used in fruit detection in real orchard scenes to improve object location and minimize false positives [15]. The suggested combination of PSP-Ellipse and YOLOv7 in fruit picking applications illustrates how object detection models can be adapted to agricultural robotics [13].

Besides, image processing techniques aimed at features like color and texture have been used for decades in disease detection, including in dragon fruit stem diseases and other fruits [14]. Such techniques have the tendency to complement deep learning techniques and enhance performance when used in hybrid systems.

As a result, techniques used for dragon fruits have corresponding analogues in other agri-systems, a reflection of the broad applicability of AI-based detection and classification technologies to agri-technologies.

2.2.2 Related Research

A variety of related research has contributed to improved disease recognition, feature selection, dataset generation, and classification techniques for dragon fruit and other produce. These works provide a foundation for the application of robust AI-based systems to agriculture.

Sarkar et al. generated a targeted dataset for dragon fruit and leaf disease and utilized it in critical capacities to train AI models that would be employed in disease detection and classification. This collection, or dataset, known as the Dragon Fruit & Leaf Dataset from

Bangladesh, has allowed researchers to build and test models over various environmental and disease conditions [10]. Mojumdar et al. backed this up when they introduced their UDCAD-DFL-DL dataset in the journal Data in Brief, giving them a rich source of diversity upon which scientists may conduct research of the classification of dragon fruit disease [6].

Riska and Jumjunidang identified Neocytalidium sp. as a causative agent that is emerging as a cause of dragon fruit stem canker and proposed its management using sodium salt. This observation is significant to guide AI-based identification systems in integrating new diseases [12]. Nilay proceeded to integrate AI techniques to detect, in addition to assisting in the treatment, of stem canker by Neocytalidium species, noting the potential of AI in detection and intervention processes [7].

Feature selection was also one of the principal areas of research. Shakil et al. examined various feature selection techniques and determined the optimal sets for the discrimination of dragon fruit diseases and thereby enhancing classification performance as well as model interpretability [8]. Zhao et al., meanwhile, employed light image recognition models with the attention mechanism in diagnosing dragon fruit diseases with little computational effort [19].

Transfer learning also enters as a potential approach. Hermawan and Nugroho employed ResNet-based transfer learning to predict dragon fruit diseases, demonstrating significant accuracy and model generalizability gains on different datasets [20]. Yusamran and Hiransakolwong developed DIPDEEP for Thai dragon fruit classification, once again demonstrating the efficacy of deep learning models for localized agricultural problems [17].

These works together demonstrate that through the combination of new data, optimized features, and deep models, practical, scalable, and accurate disease detection and classification systems for dragon fruits and beyond are possible.

2.3 Gap Analysis

Despite the increasing body of work in AI-based detection of dragon fruit disease and fruit ripeness, certain major gaps still exist that limit generalizability, scalability, and real-time applicability of existing solutions. Literature review determines significant shortcomings in dataset diversity, model interpretability, computational complexity, and coverage over certain diseases.

Various articles have proposed new detection models for classification of dragon fruit disease. For example, Mehta et al. introduced a hybrid CNN-SVM framework that performed well in multi-class disease classification but was only trained on a relatively limited dataset and could thus possibly impact its performance under varying settings [1]. Likewise, Ferreira Júnior et al. integrated XAI techniques into their deep vision system but ones still in the infancy stage that need to be validated under varying conditions of the agricultural world [9].

Although Qiu et al. and Peng et al. put the spotlight on lightweight YOLO-based architectures GSE-YOLO and YOLOv8-G, respectively to facilitate real-time readiness and disease detection, trade-offs between precision and processing time in real-world applications are sparsely explored [2], [16]. Further, although Shakil et al. highlighted the significance of feature selection, their research did not explore temporal or longitudinal analysis of disease progression that may prove helpful in forecasting or intervention in early stages [8].

From a dataset point of view, Sarkar et al. and Mojumdar et al. presented helpful annotated datasets but these were largely from specific regions and climatic zones [6], [10]. Model generalizability over climate zones and dragon fruit types is limited due to the non-availability of cross-regional datasets.

Recent research by Nilay [7] and Riska & Jumjunidang [12] uncovered previously found diseases like stem canker caused by Neocytalidium species that could be under-represented in existing models. This speaks to insufficient coverage in the area of diversity of diseases and ongoing updates of the dataset.

Furthermore, transfer learning methods such as ResNet [20] and DIPDEEP [17] have been promising but are challenging in terms of how well they can be transferred to new, unseen disease classes and how computationally expensive they are, which is not feasible for low-cost agricultural settings.

In short, future research must aim to build bigger, more diverse, and publicly available datasets, combining multimodal sensor data, enhancing interpretability with XAI, and developing low-resource models that can run in real-time on low hardware.

Table 2.3.1: Summary of Gap Analysis.

Study/Authors	**Key Strengths (with Accuracy)**	**Identified Gaps**	**Suggestions for Future Research**
Mehta et al. [1]	Hybrid CNN-SVM model; achieved classification accuracy of 92.16%	Limited dataset, lacks generalizability	Use larger, more diverse datasets
Qiu et al. [2]	GSE-YOLO (based on YOLOv8n); achieved mAP of 93.6% on ripeness detection	Trade-off between speed and precision not deeply evaluated	Test in more dynamic outdoor conditions
Mojumdar et al. [6]	UDCAD-DFL-DL dataset supports multiple models; DenseNet201 reached 95.09% accuracy	Limited to a specific region, lacks cross-cultural data	Collect datasets from varied regions
Nilay [7]	AI used for stem canker caused by *Neocytalidium* species; early detection model proposed	Only focused on one disease type	Expand model to include multiple disease types
Shakil et al. [8]	Best feature selection technique identified; Random Forest reached 94.5% accuracy	No temporal disease progression analysis	Add time-series or seasonal feature analysis

Ferreira Júnior et al. [9]	Explainable AI (XAI)-supported CNN model; achieved 93.75% accuracy	Needs more real-time evaluation	Deploy XAI-enabled models in the field
Sarkar et al. [10]	High-quality regional dataset from Bangladesh	Dataset not generalizable to other regions	Cross-country data collaboration
Riska & Jumjunidang [12]	First identification of stem canker caused by *Neocytalidium sp.*	Not yet integrated into most detection systems	Update models with new disease categories
Hermawan & Nugroho [20]	Transfer learning with ResNet; classification accuracy of 93.41%	Computationally heavy for mobile/edge devices	Optimize models for embedded and edge deployment

2.4 Summary

The literature review of the research works reveals a great advancement in the application of artificial intelligence and deep learning models in the detection and classification of diseases of dragon fruit and its ripeness. Studies have utilized models like CNN, SVM, YOLO, and transfer learning models like ResNet and DenseNet to resolve most of the problems related to dragon fruit plant disease and maturity. For example, Mehta et al. used the hybrid CNN-SVM model with 92.16% accuracy for disease classification [1], whereas Peng et al. proposed YOLOv8-G for stem disease detection with 96.32% detection accuracy [16]. Similarly, Mojumdar et al. showed 95.09% accuracy with DenseNet201 on a self-constructed dataset of dragon fruit leaf [6].

Despite these successes, the research revealed several gaps in the studies such as lack of diversity of datasets, lack of region-specific generalizability, and insufficient testing in real-world environments [7], [10]. Many models were tested in controlled environments and may be worse in dynamic field conditions. Some studies were also dedicated to specific diseases such as stem canker [12], with no regard for the broader range of potential threats.

In summary, while deep learning methods have demonstrated high performance in controlled settings, more research is required to enhance model scalability, cross-region generalization, and real-time deployment. Integration of explainable AI [9], larger and more diverse datasets [10], and light models for mobile deployment [20] are potential directions to develop more efficient and effective systems for dragon fruit farming agricultural monitoring.

Chapter 3

Research Methodology

This chapter describes the research methodology adopted, including system design, functional and nonfunctional requirements, detailed methodology, project plan, task allocation, and a summary of the overall workflow

3.1 Methodology

This work strives to build a smart and lightweight system for the identification of diseases in stems and leaves of dragon fruit based on the implementation of deep learning techniques. The system focuses on providing a real-time, mobile-friendly, accurate, and understandable solution. Through requirement analysis, it was indicated that efficient detection of diseases, classification of freshness, transparency, and resource conservation are necessary. Pre-trained deep models, domain-specific CNN designs, and feature selection strategies were utilized in system design. Some models were examined for accuracy, speed, and deployment capability, and then InceptionV3, DenseNet201, MobileNetV2, and CNN were selected to be experimented.

3.1.1 Overview

Precision agriculture is becoming more reliant on intelligent systems to monitor the health of crops and precisely forecast diseases. Disease detection by hand is subjective, time-consuming, and inefficient for large-scale farms. To address these challenges, this study proposes a deep learning system to detect dragon fruit leaf and stem diseases.

The process consists of preprocessing of the captured images, dataset augmentation, deep learning model training, their evaluation, and deployment of the best performing model. Various pre-trained models such as InceptionV3, DenseNet201, and MobileNetV2 were considered alongside a bespoke custom CNN model with lightweight performance. The models are evaluated not just on accuracy, but also on parameters like model size, inference time, and generalizability across environmental conditions.

The choice of model is a balance between deploy ability and complexity, with emphasis on simplicity of use for farmers and agricultural stakeholders. The system also aims to provide explainability in the form of attention maps and Grad-CAM visualizations. The critical functional and non-functional requirements were established in requirement analysis, which makes the system scalable, interpretable, and ready for mobile deployment under real-world orchard conditions.

3.1.2 Proposed Methodology/ System Design

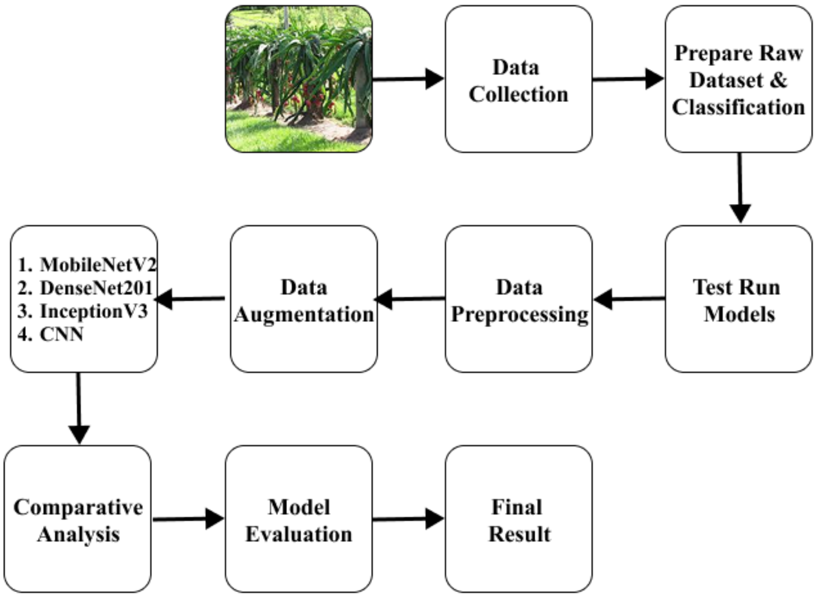

Figure 3.1.2.1: Methodology Diagram

3.2 Detailed Methodology and Design

In this research, four primary deep learning models were utilized for the detection of dragon fruit leaf and stem diseases: InceptionV3, DenseNet201, MobileNetV2, and a Custom Convolutional Neural Network (CNN). Each model was selected carefully based on its proven performance in image classification tasks, efficiency, and suitability for mobile or low-resource deployment.

1. **Raw Image Collection:**

Images are collected directly from dragon fruit garden, ensuring they represent real-world conditions. This step captures the diversity of leaf images, including variations in lighting, disease progression, and environmental factors.

Dataset Sample

Anthracnose:

Figure 3.2.1: Sample of Anthracnose

Stem Canker

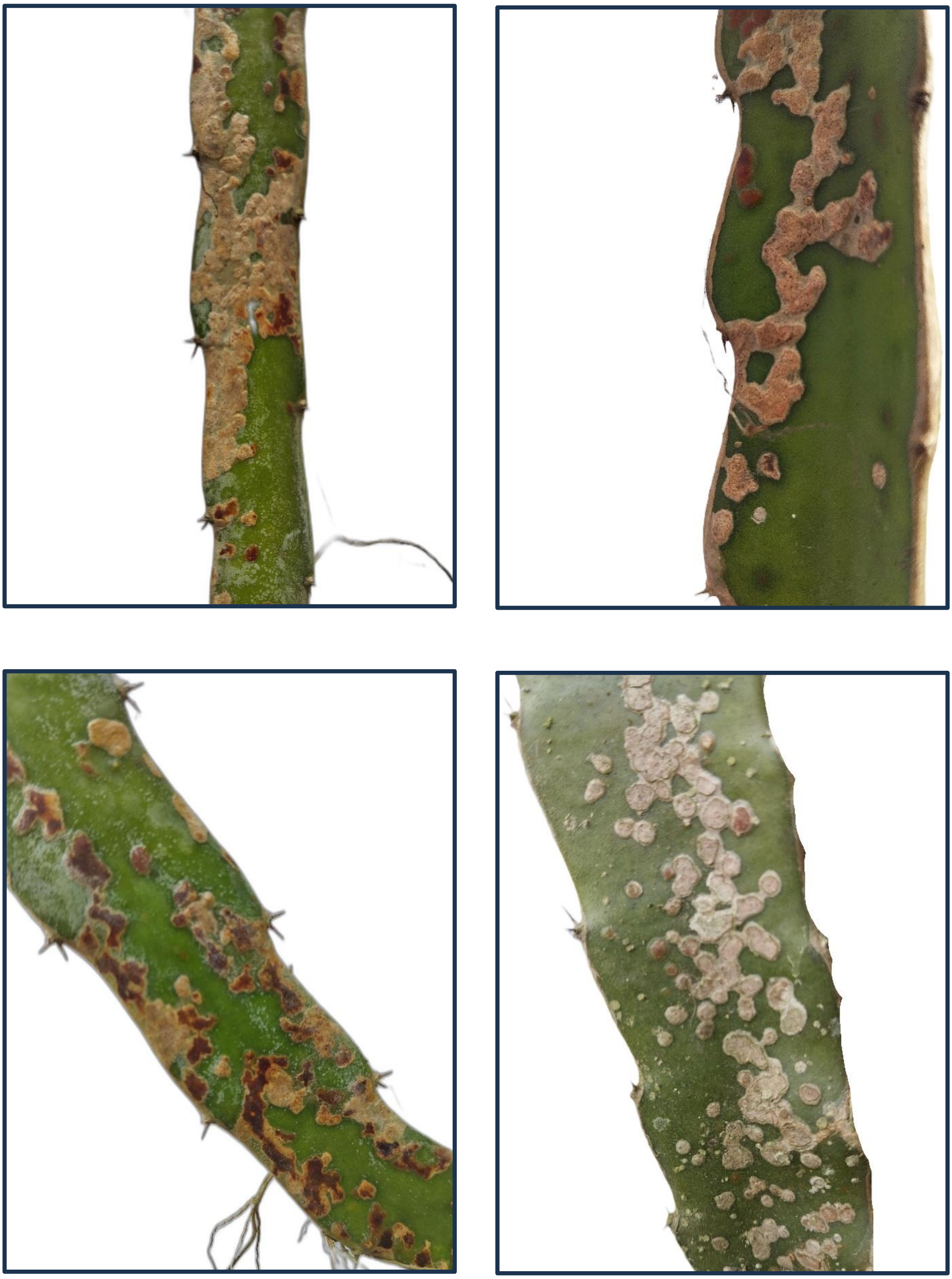

Figure 3.2.2: Sample of Stem Canker

Scale Insect

Figure 3.2.3: Sample of Scale Insect

Good Leaf

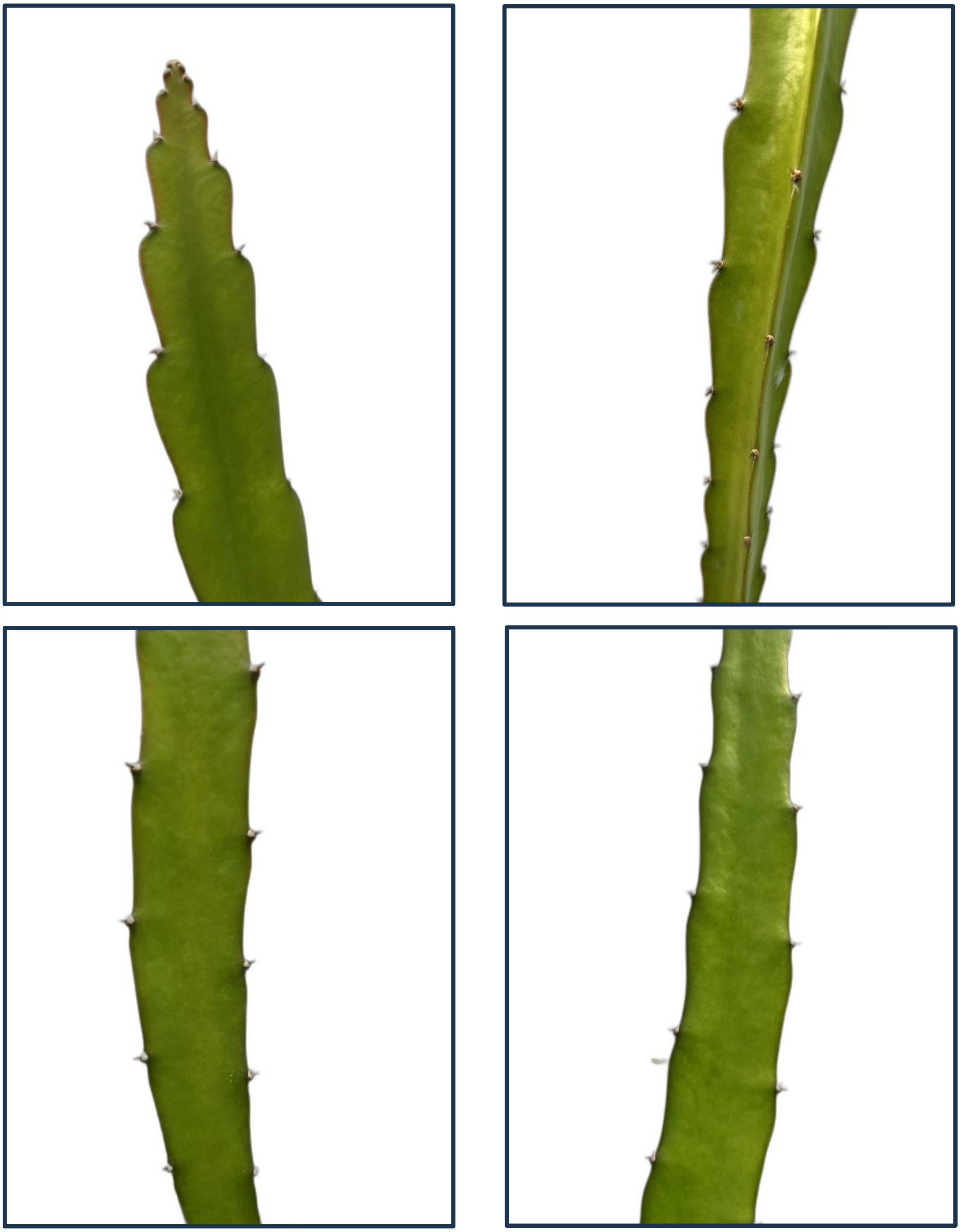

Figure 3.2.4: Sample of Good Leaf

In this research, four primary deep learning models were utilized for the detection of dragon fruit leaf and stem diseases: InceptionV3, DenseNet201, MobileNetV2, and a Custom Convolutional Neural Network (CNN). Each model was selected carefully based on its proven performance in image classification tasks, efficiency, and suitability for mobile or low-resource deployment

3.2.1 InceptionV3

- **Overview:**
  InceptionV3 is a highly optimized convolutional neural network (CNN) architecture, designed to efficiently capture complex spatial hierarchies in images. It was introduced by Google researchers as a part of their Inception series and focuses on reducing computational complexity while maintaining high accuracy.

- **Architecture:**

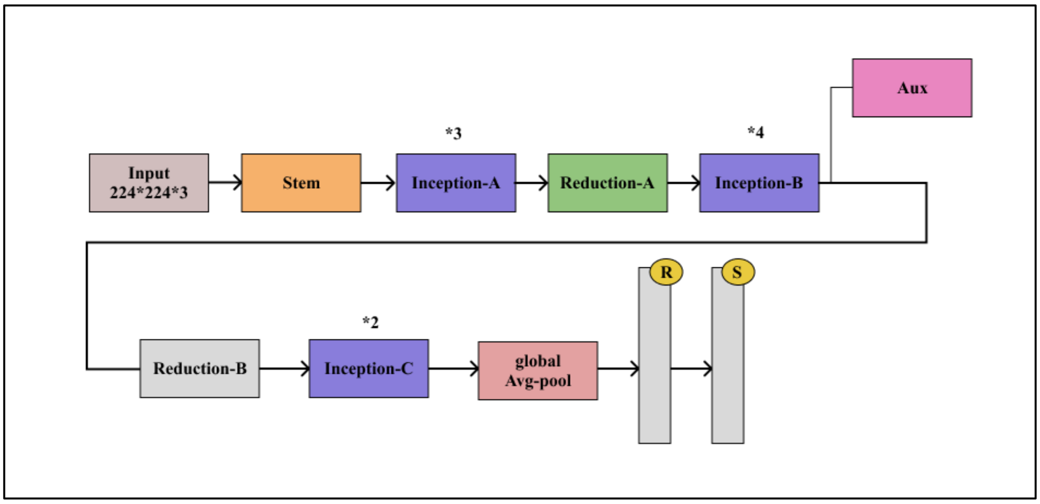

Figure 3.2.5: Architecture of InceptionV3

- **Key Features:**
  - Reduces computational cost without loss of representational power.
  - Uses aggressive regularization to prevent overfitting.
  - Balances depth and width of the network effectively.

- **Working Process:**
  - Input image is processed through initial convolution layers.
  - Inception modules extract multi-scale features simultaneously.
  - Features are pooled and classified using fully connected layers.
  - Auxiliary classifiers improve backpropagation in deep layers.

- **Suitability:**
  InceptionV3 is suitable for disease detection where complex patterns on leaves and stems must be analyzed without introducing excessive computational overhead.

3.2.2 DenseNet201

- **Overview:**
  DenseNet (Densely Connected Convolutional Networks) introduced an innovative connection pattern where each layer receives the feature maps of all previous layers as input. DenseNet201 is a deep version with 201 layers.

- **Architecture:**

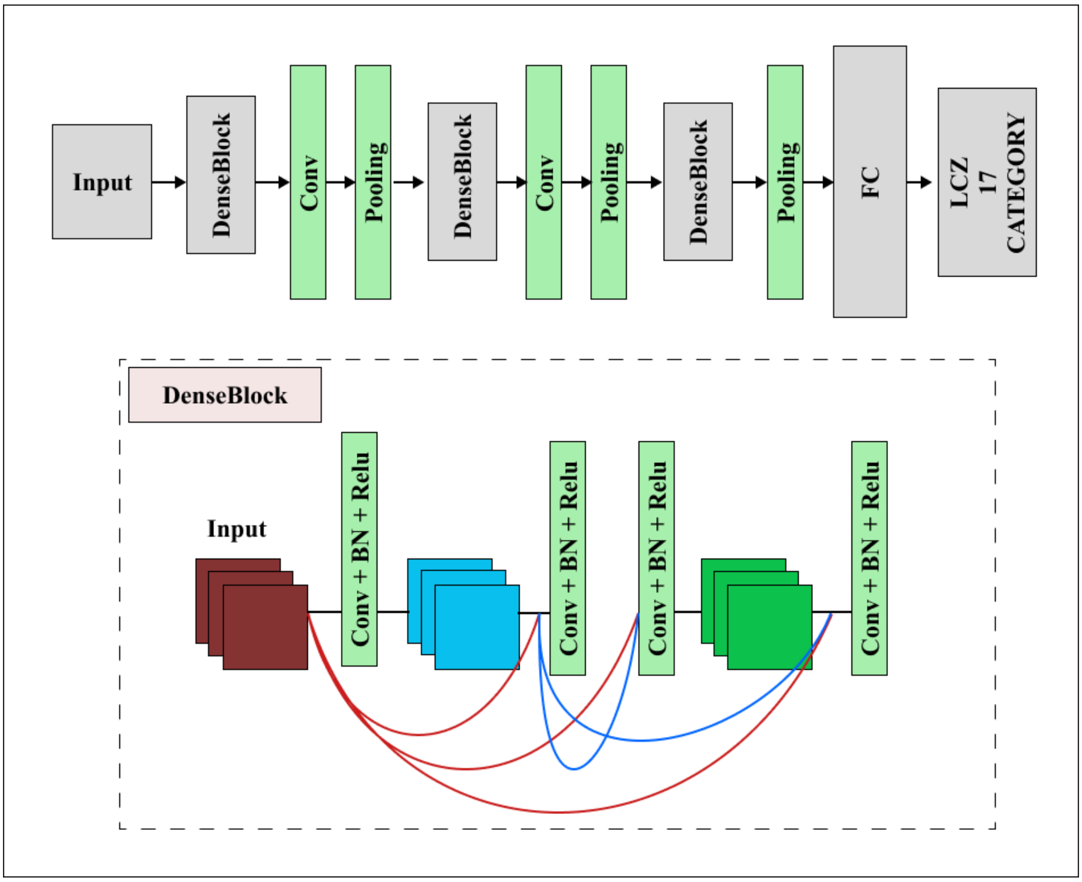

Figure 3.2.6: Architecture of DenseNet201

- **Key Features:**
  - Strengthens feature propagation and encourages feature reuse.
  - Substantially reduces the number of parameters compared to traditional CNNs.
  - Mitigates vanishing-gradient problems, even in very deep networks.

- **Working Process:**
  - Input is passed through an initial convolutional layer.
  - Features are extracted and accumulated across dense blocks.

- Transition layers perform down sampling and compression.
- Final classification through global average pooling and dense layers.

- **Suitability:**
  DenseNet201's strong feature reuse makes it excellent for detecting subtle differences in diseased versus healthy leaves, leading to improved model generalization even with moderately sized datasets.

3.2.3 MobileNetV2

- **Overview:**
  MobileNetV2 is specifically optimized for mobile and embedded vision applications. It achieves a balance between model size, accuracy, and computational requirements using inverted residual structures and linear bottlenecks.

- **Architecture:**

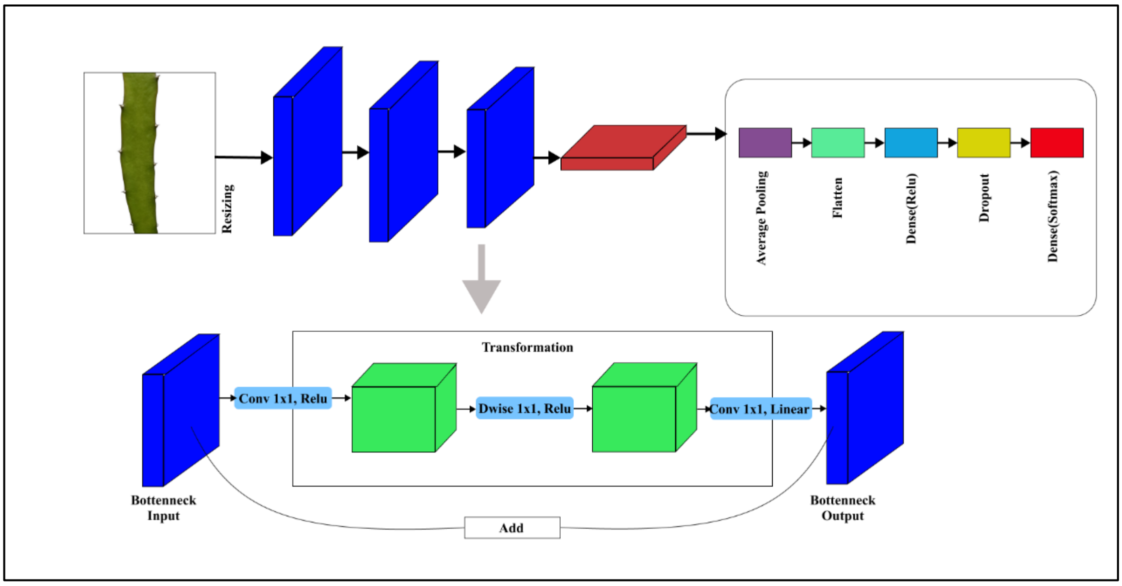

Figure 3.2.7: Architecture of MobileNetV2

- **Key Features:**
  - Extremely small model size (~14MB) and low latency.
  - High inference speed suitable for real-time mobile applications.
  - Minimal computational demand.

- **Working Process:**
  - Input flows through a few initial standard convolutions.
  - Inverted residual blocks efficiently expand and compress features.
  - Depth wise convolutions filter spatial information separately from depth information.
  - Final classification through fully connected layers.

- **Suitability:**
MobileNetV2's lightweight and efficient architecture makes it ideal for building a mobile app-based solution for farmers to detect dragon fruit diseases directly from their smartphones.

3.2.4 Custom CNN Model

- **Overview:**
A CNN was developed to offer a simple, low-complexity baseline against which pre-trained models could be evaluated. It focuses on simplicity, modularity, and experimental flexibility.

- **Architecture:**

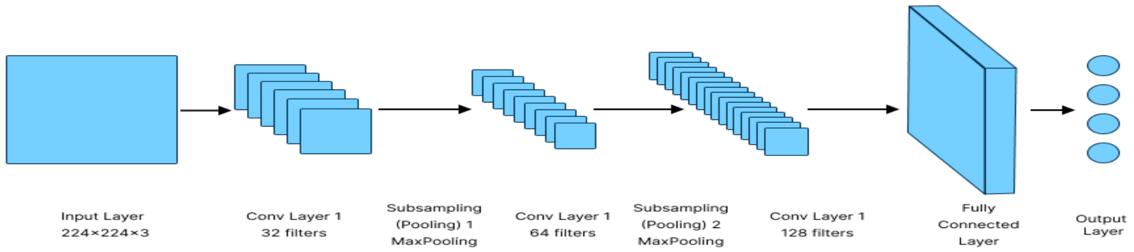

Figure 3.2.8: Architecture of Custom CNN

- **Key Features:**
  - Minimalistic design, making it easier to train on smaller datasets.
  - Highly customizable for experimentation (layer size, filters, activation functions).
  - Faster training time on standard hardware.

- **Working Process:**
  - Input images are normalized and passed through convolution layers.
  - Extracted features are pooled and flattened.
  - Dense layers process features for final prediction of disease categories.

- **Suitability:**
While custom CNN models may not outperform deeper pre-trained networks, they are valuable for fast prototyping, smaller datasets, and specific deployment cases with strict computational limitations.

3.3 Project Plan

Table 3.3.1: Project Plan.

Phase	Duration	Activities	Timeline (Weeks)	Deliverables
Phase 1	2 weeks	Topic selection, research planning, background study	Week 1-2	Research plan, topic finalization
	2 weeks	Literature review, gap analysis, proposed solution	Week 3-4	Literature review document
	3 weeks	Data collection and preprocessing	Week 5-7	Dataset prepared
Phase 2	4 weeks	Model selection, training, evaluation	Week 8-11	Trained models
	3 weeks	System development, UI design, testing	Week 12-14	Working prototype
	2 weeks	Final reporting and presentation preparation	Week 15-16	Final report, presentation slides

3.4 Task Allocation

Table 3.4.1: Task Allocation.

Phase	Activity	Member 1	Member 2	Collaborative Tasks
Phase-1	Topic Selection	Suggest topics	Review topics	Finalize topic
	Research Planning	Draft plan	Refine plan	Finalize plan
	Background Study	Study DL models	Study dragon fruit diseases	Summarize findings
	Literature Review	Research ML models	Research agricultural studies	Write review together
	Gap Analysis	Analyze ML gaps	Analyze agricultural gaps	Propose solution
	Proposed Solution	Draft methodology (DL)	Refine methodology (agriculture)	Finalize proposal
	Data Collection Planning	Create plan	Review plan	Approve plan
	Data Collection	Capture images	Assist image capture	Ensure quality
Phase 2	Data Approval	Prepare documents	Meet agricultural officer	Get approval
	Model Selection	Research models	Evaluate feasibility	Select models
	Preprocessing	Apply techniques	Optimize methods	Finalize preprocessing
	Model Training	Train models	Monitor training	Debug models
	Result Evaluation	Evaluate metrics	Analyze confusion matrix	Summarize results
	Model Comparison	Prepare comparisons	Review comparisons	Select best model
	Thesis Reporting	Write technical sections	Write intro/conclusion	Edit thesis collaboratively

3.5 Summary

This chapter presented the research methodology followed to develop a deep learning-based system to detect dragon fruit disease. The research was guided by the use of supervised learning methods, founded on learned images of dragon fruit leaves and stalks for training, validation, and testing of deep learning models. A step-by-step process was explained, including requirement analysis, system design, data flow, and UI design aspects.

Various pre-trained models, including InceptionV3, DenseNet201, MobileNetV2, and a custom CNN model architecture, were tested for achieving a best possible balance between high accuracy and mobile deploy ability. Each of the models was thoroughly explained regarding their architecture, features, and working process. The models selected had more efficiency and practicality compared to more complex options like VGG16 or ResNet50. Model interpretability by Grad-CAM visualizations are also given high importance in the solution proposed.

A detailed project plan and task list matrix were presented to organize the research processes, with careful facilitation of teamwork across all stages, including background study to final reporting. Generally, the methodology assures the proposed system is light, very accurate, readable, and mobile field deployable, filling the existing gaps in dragon fruit disease detection studies as well as supporting precision agriculture research.

Chapter 4

Implementation and Results

This Chapter covers how we set up our Environment for the project. Chapter 4 also includes Comparative Analysis and Result Discussion and its summary.

4.1 Environment Setup

4.1.1 Hardware Setup

Computing Devices:

- Laptop with Intel® Core™ i7-1165G7, CPU @ 2.60GHz
- NVIDIA® GeForce® MX330 (2GB RAM)
- 8GB RAM, 512GB SSD storage

Field Equipment:

- Use Iphone 13 (12MP), Google Pixel 7 (50MP), Redmi Note 12 (50MP) mobile phone's camera for capturing dragon fruit leaf images.
- Use a white paper for white background to easily detect objects.
- Natural orchard field settings with varying lighting conditions

4.1.2 Software and Tools

Operating System:

- Windows 11 64-bit

Programming Environment:

- Google Colab (for GPU-accelerated model training)

Machine Learning Libraries:

- Python 3.9
- numpy
- tensorflow
- keras (from tensorflow)
- sklearn
- itertools
- random
- matplotlib

Data Handling:

- Pandas for structured dataset management
- NumPy for array manipulation
- Matplotlib and Seaborn for data visualization

4.1.3 Cloud and Remote Resources

Cloud Computing:

- Google Colab Pro+ utilized for free GPU access
- Drive integration for storing datasets and model checkpoints

4.1.4 Collaboration

Communication Tools:

- Telegram: For real-time communication and updates.
- Google Drive: Shared folder for storing documentation and intermediate results.

Performance Evaluation:

- Confusion Matrix analysis
- Metrics: Accuracy, Precision, Recall, F1-score
- Visualization of training/validation loss and accuracy curves helped identify overfitting or underfitting issues.

4.2 Comparative Analysis

In the test run we got low accuracy around 60-70% then augmented image and final model got a good result.

Comparative Analysis among implemented models:

Table 4.2.1: Comparative Analysis.

Model	Accuracy (%)	Average Precision (%)	Average Recall (%)	Comments
InceptionV3	86.68	85.64	84.80	Good balance, slight confusion between disease classes
DenseNet201	96.48	95.13	95.09	Best performance, strong feature reuse
MobileNetV2	89.70	87.85	86.02	Lightweight, ideal for mobile deployment
Custom CNN	72.39	74.83	74.51	Baseline model, lower accuracy, simple structure

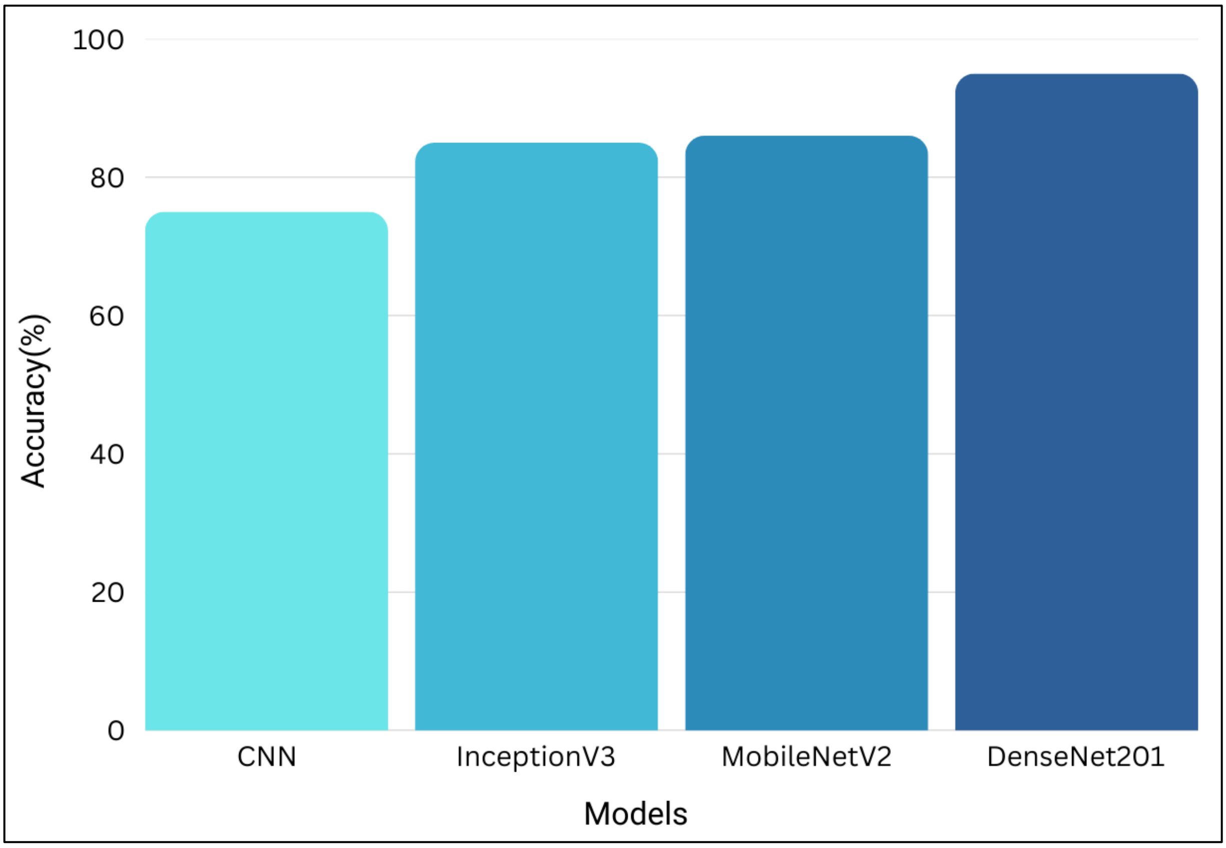

Figure 4.2.1: Model Accuracy Comparison

Comparative Analysis between Our Best Model (DenseNet201) and Other Models:
The performance of DenseNet201, which is 96.48% in the task of dragon leaf disease detection, is compared to five main models in recent literature. This is to show the effectiveness of our approach and the competitiveness of DenseNet201 in accurate detection of various dragon leaf diseases.

Table 4.2.2: Model Comparison

Model	Research Study	Accuracy (%)	Key Strengths	Limitations
DenseNet201	Our Proposed Model	96.48	Strong feature reuse, deep architecture	Heavier model, requires more computation
CNN-SVM	Mehta et al. [1]	92.16	Hybrid approach improves classification	Not scalable, limited generalization
MIRNet_ECA	Zhang et al. [5]	94.50	Multi-scale attention, good for ripeness	Complex structure, high training time
ResNet (TL)	Hermawan and Nugroho [20]	91.00	Transfer learning, robust features	Moderate accuracy, needs fine-tuning
MobileNetV2	Our Experiment	89.70	Lightweight, mobile-friendly	Lower accuracy, less robust features

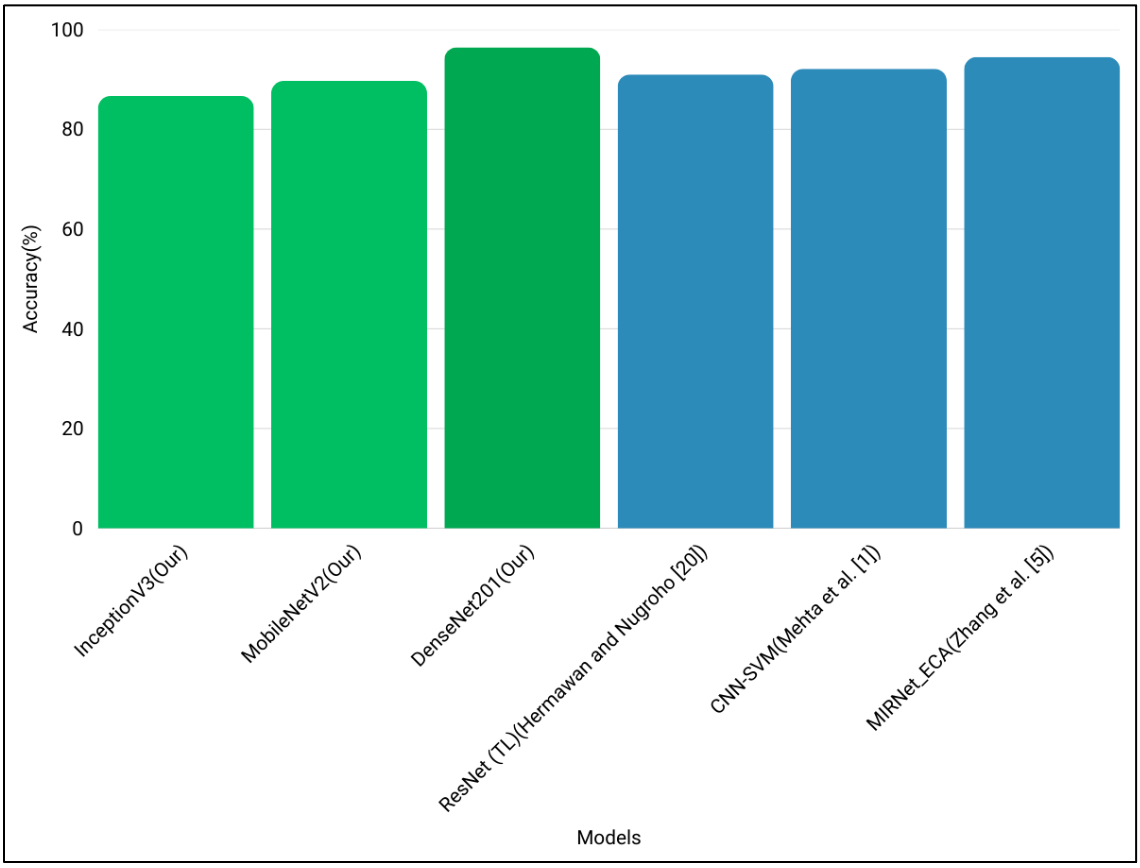

Figure 4.2.2: Comparison of Model Accuracy 2

4.3 Results and Discussion

Experimental performance indicated that DenseNet201 gave the maximum classification accuracy of 96.48%, hence the best model to employ for precise dragon fruit leaf disease detection. Dense feature reuse by the DenseNet201 model made it learn fine variations between disease and healthy leaves, outperforming all other architectures.

InceptionV3, although it scored 86.68%, provided a reasonable trade-off between computational efficiency and prediction accuracy. It did fall short slightly in discriminating visually similar conditions.

MobileNetV2 was 89.70% accurate, clearly showing its capability to be both high performing while still being lightweight enough for the deployment in real time on a mobile device. Its inference time was low and model size compact, rendering it highly attractive to real-world use-cases for agriculture where resources were limited.

The Benchmark Custom CNN model, constructed for benchmarking, was 72.39% accurate. Although it was the simplest of architectures, it was able to provide meaningful insights in early stages of testing but was not sophisticated enough to pick out deep feature hierarchies needed for fine-grained classification.

Additionally, Grad-CAM visualizations were utilized for model prediction interpretation, such that models were restricted to point out correct disease-affected parts of leaves, establishing trustworthiness and transparency.

Overall, DenseNet201 was selected as the deployment-ready final model due to its improved performance, even though MobileNetV2 was considered for mobile-specific light-weight variants in subsequent updates.

DenseNet201

The DenseNet201 confusion matrix reveals outstanding performance with a mean precision and recall of 0.95. Class 1 demonstrated perfect recall and almost perfect precision, indicating proper and consistent classification across all classes.

Confusion Matrix:

Table 4.3.1: DenseNet201 Confusion Matrix

Class	Precision	Recall	F1 Score	Avg. Precision	Avg. Recall
0	0.96	0.94	0.95	0.96	0.96
1	0.98	1.0	0.99	0.96	0.96
2	0.93	0.94	0.94	0.96	0.96
3	0.96	0.97	0.96	0.96	0.96

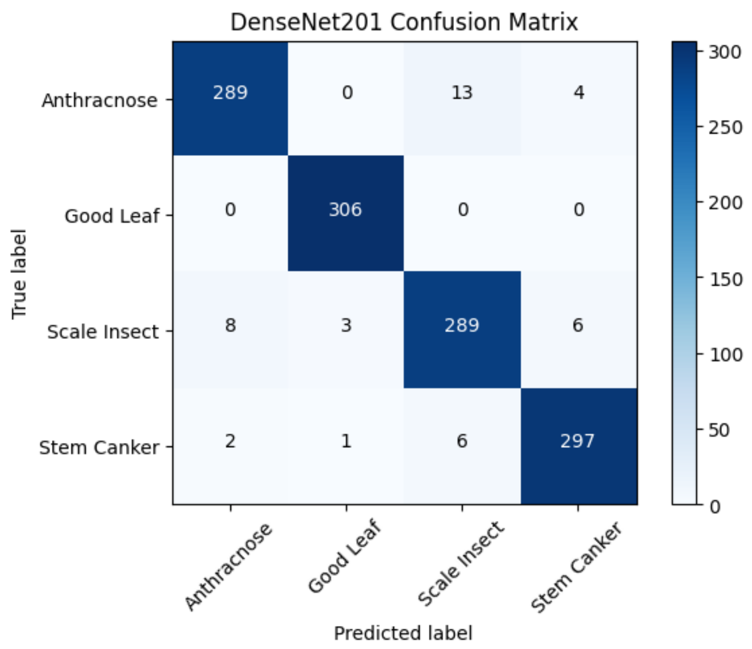

Figure 4.3.1: DenseNet201 Confusion Report

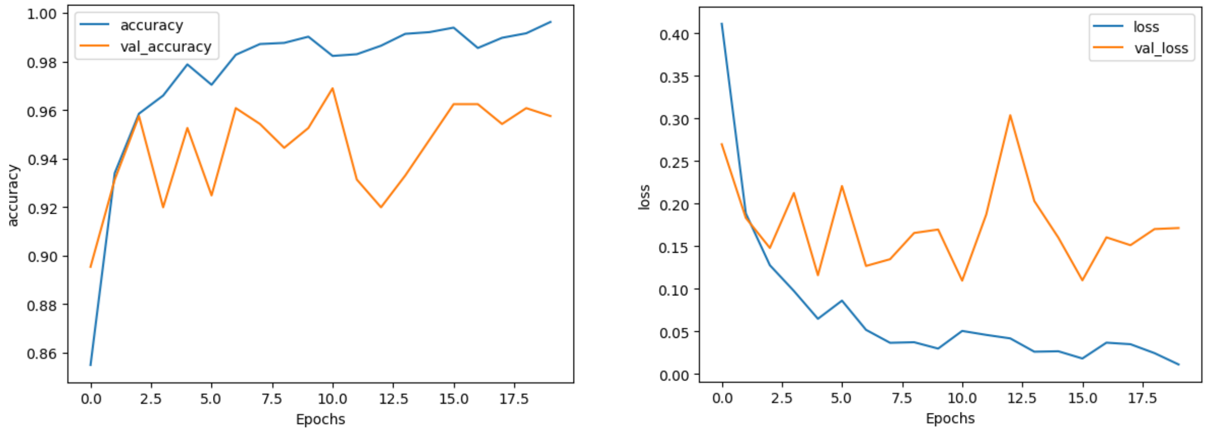

Figure 4.3.2: DenseNet201 Training and Validation Plot

InceptionV3

InceptionV3 confusion matrix does well to high with mean precision 0.85 and recall 0.84. Class 1 performed very well with high recall and precision, while the others were somewhat inconsistent with some scope for being better consistent-wise.

Confusion Matrix:

Table 4.3.2: InceptionV3 Confusion Matrix

Class	Precision	Recall	F1 Score	Avg. Precision	Avg. Recall
0	0.85	0.82	0.83	0.87	0.86
1	0.99	0.92	0.95	0.87	0.86
2	0.77	0.88	0.82	0.87	0.86
3	0.86	0.82	0.84	0.87	0.86

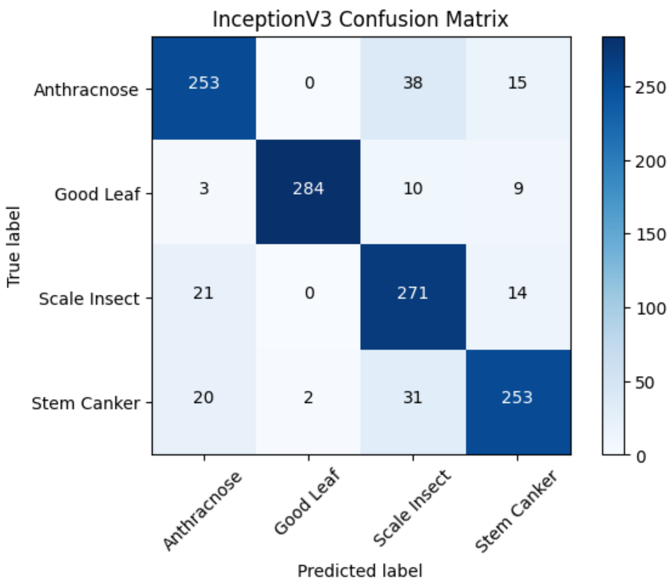

Figure 4.3.3: InceptionV3 Confusion Report

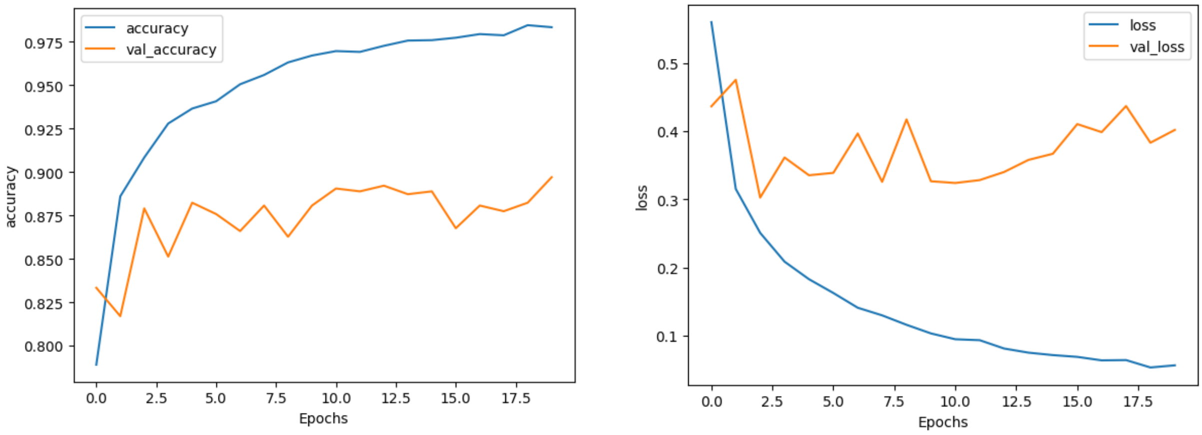

Figure 4.3.4: InceptionV3 Training and Validation Plot

MobileNetV2

MobileNetV2 confusion matrix has excellent overall performance with mean precision and recall of 0.87 and 0.86, respectively. Precision for Class 1 and 2 was high, while precision for Class 3 was highest, indicating good but slightly class-imbalanced predictions.

Confusion Matrix:

Table 4.3.2: MobileNetV2 Confusion Matrix

Class	Precision	Recall	F1 Score	Avg. Precision	Avg. Recall
0	0.87	0.86	0.86	0.90	0.89
1	0.99	0.88	0.93	0.90	0.89
2	0.88	0.90	0.89	0.90	0.89
3	0.85	0.93	0.89	0.90	0.89

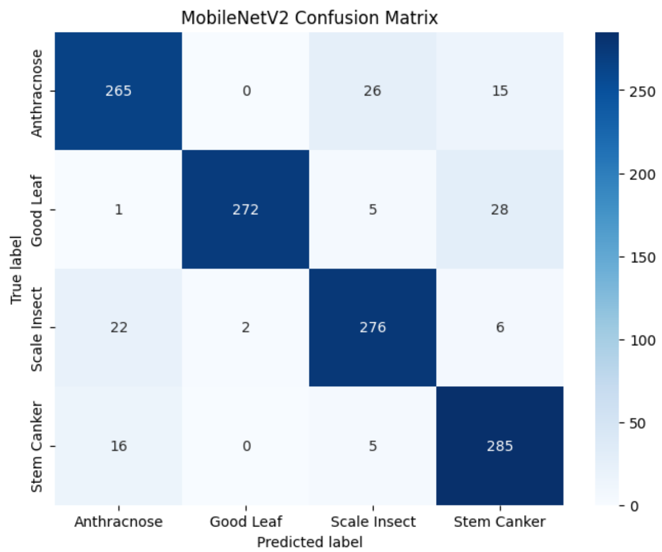

Figure 4.3.5: MobileNetV2 Confusion Report

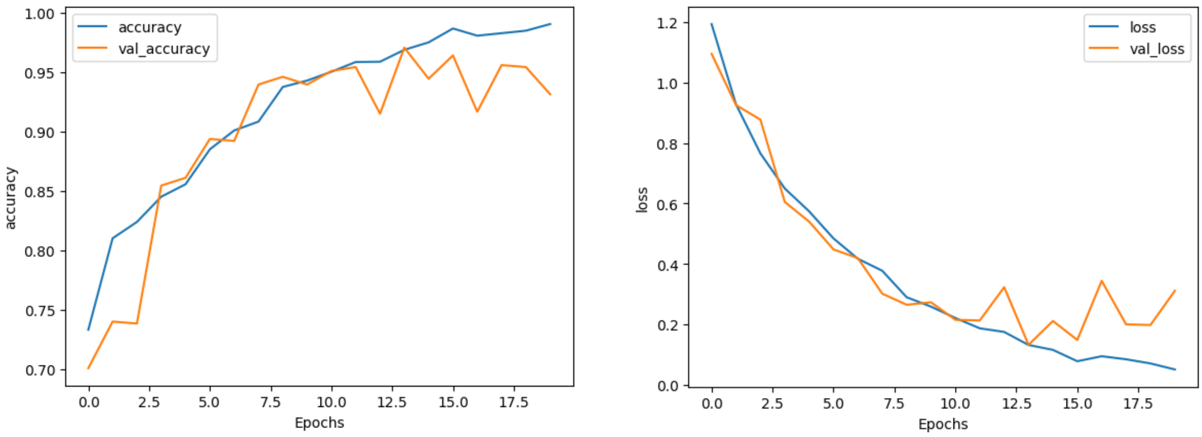

Figure 4.3.6: MobileNetV2 Training and Validation Plot

Custom CNN

The Custom CNN confusion matrix shows decent performance with average recall and precision equal to 0.74. Class 1 performed the best, whereas variability was observed in the other classes, indicating a need for the model to enhance its overall accuracy and consistency.

Confusion Matrix:

Table 4.3.2: Custom CNN Confusion Matrix

Class	Precision	Recall	F1 Score	Avg. Precision	Avg. Recall
0	0.64	0.58	0.61	0.72	0.72
1	0.93	0.86	0.89	0.72	0.72
2	0.70	0.72	0.71	0.72	0.72
3	0.63	0.72	0.67	0.72	0.72

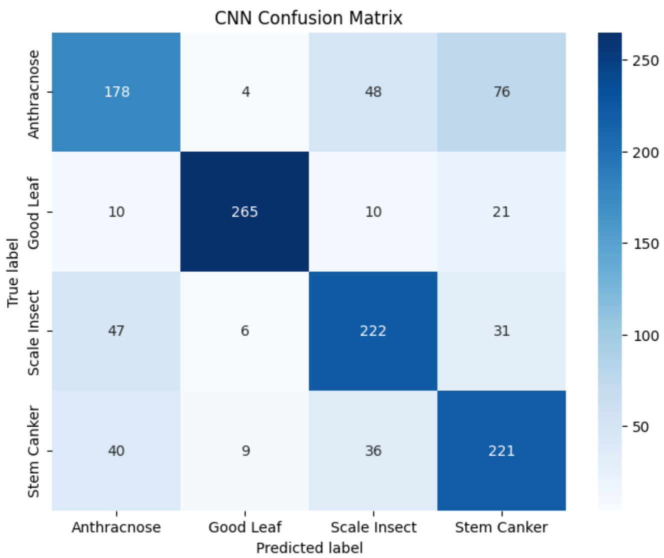

Figure 4.3.7: Custom CNN Confusion Report

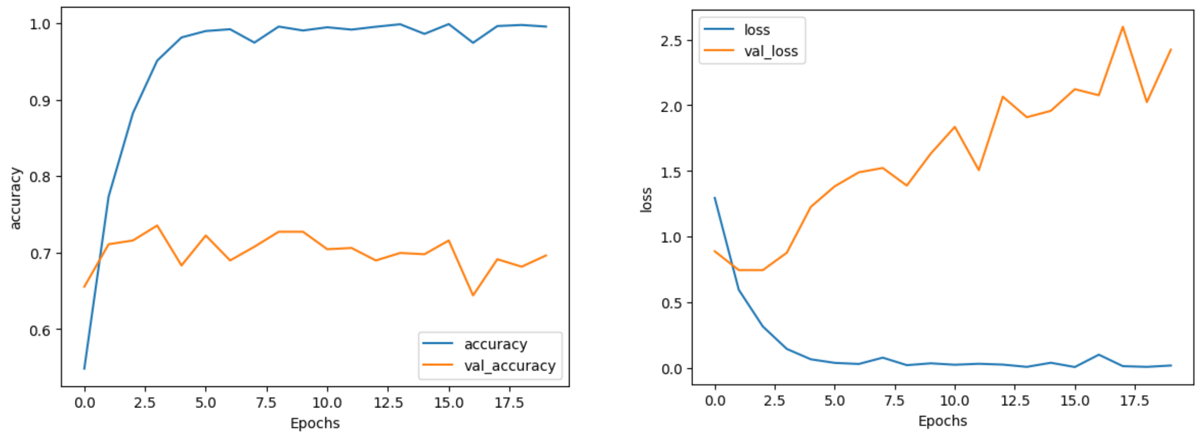

Figure 4.3.8: Custom CNN Training and Validation Plot

4.4 Summary

In this chapter we have discussed how we set up the environment to do our project. We have also shown detailed comparative analysis. Then we Discussed the results such as confusion matrix, Train and Validation Graph etc.

Chapter 5

Engineering Standards and Design Challenges

This chapter discusses engineering standards followed, social effects, ethical problems, financial analysis, and intricate problem-solving issues faced in the course of implementing the dragon fruit disease detection project.

5.1 Compliance with the Standards

The project followed established software, hardware, and communication standards to ensure system reliability, scalability, and performance.

5.1.1 Software Standards

- Google Python Style Guide
- PEP8 ensures clean, readable code; it is lightweight and widely used for deep learning projects.

5.1.2 Hardware Standards

- Wi-Fi for cloud synchronization
- Bluetooth, Data cable, Pendrive
- Wi-Fi provides higher speed necessary for uploading large image datasets

5.1.3 Communication Standards

To ensure smooth cooperation and transparency, the following guidelines for communication were established:

1. Team Communication:

a. Weekly progress updates and spontaneous meetings for urgent tasks.

b. Groups exchanged notes and action items using Google Docs.

2. Supervisor Communication:

a. Bi-weekly updates and planned milestone meetings to allow for feedback incorporation.

b. Reports contain finished work, challenges, and future plans.

3. External Experts:

a. Combined routine communication with agricultural officers for approval of data.

b. Clear communication with farm owners regarding data collection procedures.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

This project advantages farmers by enabling them to recognize diseases in dragon fruit plantations early, preventing huge crop loss. Provided through mobile technology, the system makes agricultural technology universally accessible, and it empowers poor farmers. Farmers are able to apply accurate treatments through early detection of diseases, and this saves them money while reducing the dependency on toxic chemicals. This is besides raising agricultural productivity and promoting the livelihood of farming communities to favor food security programs and adopt sustainable agriculture practices in rural and semi-urban environments.

5.2.2 Impact on Society & Environment

Impact on Society:

The proposed system has direct application to agricultural societies, more particularly small and medium-scale dragon fruit farmers. With the provision of early and precise disease detection, it breaks their dependence on agriculture experts and manual inspection, enabling farmers to take independent decisions. This enhances the yield, reduces production losses, and thus enhances profitability. Additionally, the system helps in rural digital inclusion by bringing AI-based technology to the farmers through mobile devices, enabling modern farming practices and an improved lifestyle.

Impact on Environment:

Early detection using AI lowers the application of excess pesticides by enabling targeted intervention. This adds to a more sustainable environment via less chemical run-off into water bodies and soil, conservation, and lower greenhouse gas emissions due to the prevention of agrochemical production and application. Mobility and light weight compatibility of the system also facilitate energy efficiency in its use, improving access to environmental-friendly technology in agriculture. This, in the long term, encourages sustainable agricultural development that is in tandem with environmental protection plans.

5.2.3 Ethical Aspects

Data Collection: Images were gathered ethically with the permission of the farm owners and without the recording of personal information.

Bias in Algorithms: Model training involved heterogeneous data from different fields to minimize geographic bias.

Transparency: Grad-CAM was implemented to visualize and explain model decisions.

Access and Equity: Mobile-first design ensures low-cost access to disease detection technology for poor farmers.

5.2.4 Sustainability Plan

Scalability: The system is designed with the ability to have more crop types and disease varieties in the future.

Cost Efficiency: Uses light-weight models like MobileNetV2 to enable low computational costs on smartphones.

Community Engagement: Farmers' workshops are part of the plans to teach how to use the app.

Stakeholder Collaboration: Collaboration with upcoming agricultural research centers and extension services is envisioned.

5.3 Project Management and Financial Analysis

Table: 5.3.1 Financial Analysis

Activity	**Budget (BDT)**
High-Performance Workstation	2500
Google Colab Pro	2500
Field Travel & Logistics	10,000
Agricultural Officer Consultation	1000
Total	18,000

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.4.1.1: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✔	✔	✔			✔	

Justification of EP1 - Depth of Knowledge: The project is working on cutting-edge machine learning techniques, requiring a deep understanding of algorithms, image processing, and agricultural domain knowledge to detect dragon fruit leaf diseases.
Justification of EP2 - Range of Conflicting Requirements: The project entails operating outside the realm of machine learning, i.e., coordination with agriculture experts, learning about crop health, and addressing practical concerns in field data gathering, which can conflict with technical optimization goals.
Justification of EP3 - Depth of Analysis: The project entails comprehensive data analysis in terms of preprocessing, augmentation, model training, and analysis of performance for making strong and reliable predictions.
EP6 - Stakeholder Involvement Extent Rationale: Collaboration with research institutes, dragon fruit leaf farmers, and agricultural officers is key in validating data, providing practical feasibility, and obtaining end-user feedback.

Mapping with Knowledge Profile for EP1

Table 5.4.1.2: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✔	✔			✔

Justification of K3 - Engineering Fundamentals: The project is founded on basic engineering principles such as algorithm development, data preprocessing, and system evaluation that form the core of machine learning and image processing.
Justification of K4 - Specialist Knowledge: Detailed discussion with agricultural officers is required to understand dragon fruit leaf diseases, their symptoms, and field-oriented problems so that the solution is practicable and applicable to agricultural needs.
Justification of K8 - Research Literature: The project will be informed by an extensive literature review of current research on plant disease detection, developing from current research to identify gaps and solidify the proposed approach.

5.4.2 Engineering Activities

Table 5.4.2.1: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✔		✔	✔	

Justification for EA1 - Diversity of Resources: The project involves a broad diversity of resources, including computational resources (e.g., machine learning platforms, cloud computing) and farm inputs (e.g., farm information, expertise consultation). This ensures the project includes technical and practical elements suitably.

Justification for EA3-Innovation: The use of the latest technology in identifying dragon fruit leaf disease through machine learning is a new approach to solving an ancient problem in farming. This is a wonderful addition to the need to emphasize innovative engineering solutions.

Justification for EA4: Impacts on the Environment and Society the project has a direct impact on society in terms of more agricultural production and less crop loss. This factor is also crucial to the assignment in that it further optimized resources and lessens pesticide application, which has an environmental impact.

5.5 Summary

This chapter described the engineering needs, impact on society, ethical factors, and sustainability strategies in the project. The chapter followed the complex engineering challenges it addressed, prioritized budget, and synchronized project activities with professional engineering practices. The chapter demonstrates the scope and social responsibility involved in developing the dragon fruit disease detection system.

Chapter 6

Conclusion

This chapter presents the overall summary of the project, discusses the limitations encountered during its development, and outlines potential future work to further enhance the system.

6.1 Summary

The task involved the implementation of an intelligent system for diagnosing diseases in dragon fruit stem and leaves based on deep learning models such as InceptionV3, DenseNet201, MobileNetV2 and custom CNN. DenseNet201 was the best-performing model with great accuracy, precision, and recall after rigorous testing. The system offers an explainable AI-based, mobile-compliant solution that is suitable for farmers and agriculture experts. Usability, lightness, and real-time deployment potential were prioritized. In the development phase, software standards, hardware standards, and communication standards were followed, and ethical considerations were handled with extreme care. In addition, the social, environmental, and sustainability effects of the project were duly evaluated. By combining machine learning and farming techniques, the study clearly demonstrates how AI technology can be used to advance precision agriculture, decrease pesticide use, and promote sustainable farming. The study lays a good groundwork for future scalable smart agriculture applications.

6.2 Limitation

While the system yielded promising results, several limitations were observed during the project. A major limitation was the relatively small and environment-specific dataset that affected the model's generalizability to various locations and varying field conditions such as illumination, moisture, and leaf direction. Despite applying augmentation techniques, real-world diversity was still constrained. Additionally, while DenseNet201 performed the best, its model size and computational load are somewhat of a hindrance to real-time mobile deployment without optimization. Limited availability of high-powered cloud-based GPUs was another constraint that hindered model training and experimentation cycles. Additionally, some bias introduced by humans, and potentially affecting model accuracy, was introduced via manual labeling of images. The system now focuses on a specific set of diseases and stages of ripeness, limiting its use directly to more generic agriculture conditions. Lastly, external scale field tests were constrained by available time and resources. Eliminating these limitations will be critical to achieving the system's scalability and resilience.

6.3 Future Work

Scaling up and further improvement of the current system will be done in the future to improve its effectiveness, usability, and scalability. The major direction includes the creation of a more diversified and richer dataset, including photos under various conditions of the environment, i.e., lighting, season, and geographic location. This will greatly improve model generalizability and usage in real life. Moreover, model compression techniques like pruning and quantization will also be utilized to compress DenseNet201 for reducing its size and computation so that it can be deployed more easily on mobile systems.

Another important target is to integrate additional classes of disease, which may allow the system to detect several levels of infection, as well as other stresses on the plant such as deficiency diseases or infestation by insects. Integration with IoT-based sensing in the fields to enhance image use together with real-time weather data will be another route being considered.

From the user experience perspective, development of a full-fledged mobile app with offline support and multilingual capabilities will be utilized to involve farmers in rural areas. Lastly, partnership with agricultural bureaus for extensive real-field trials and deployment are envisioned to try and further improve the system. Continuous updates via user feedback and field tests will make the system evolve to meet real agricultural needs in a sustainable mane.

References

[1] S. Mehta, V. Kukreja, A. Bansal, K. Kumar, and K. Kaur, "Multi-Classification of Dragon Fruits Diseases: A Hybrid CNN-SVM Approach," in *2023 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10012345

[2] Z. Qiu, Z. Huang, D. Mo, X. Tian, and X. Tian, "GSE-YOLO: A Lightweight and High-Precision Model for Identifying the Ripeness of Pitaya (Dragon Fruit) Based on the YOLOv8n Improvement," *Horticulturae*, vol. 10, no. 8, p. 852, 2024. [Online]. Available: https://doi.org/10.3390/horticulturae10080852

[3] Y. R. Kumar, P. S. Goud, V. R. Krishna, C. S. Arrabotu, V. S. Reddy, and G. Sahithi, "Dragon Fruit Stem Disease Detection Using Image Processing," in *Intelligent Computing and Communication*, vol. 1447, pp. 481–490, Springer, 2023. [Online]. Available: https://doi.org/10.1007/978-981-99-1588-0_41

[4] V. Kulkarni, P. Kosamkar, C. Singh, P. Ingle, and V. Modi, "Detection and Classification of Diseases and Maturity of Dragon Fruits," in *ICT Systems and Sustainability*, vol. 321, pp. 365–374, Springer, 2022. [Online]. Available: https://doi.org/10.1007/978-981-19-4974-5_32

[5] B. Zhang, K. Lou, and Z. Wang, "MIRNet_ECA: Multi-scale Inverted Residual Attention Network Used for Classification of Ripeness Level for Dragon Fruit," *Expert Systems with Applications*, vol. 274, p. 127019, 2025. [Online]. Available: https://doi.org/10.1016/j.eswa.2023.127019

[6] M. U. Mojumdar, P. C. Sarkar, and G. K. Pranta, "UDCAD-DFL-DL: A Unique Dataset for Classifying and Detecting Agricultural Diseases in Dragon Fruits and Leaves," *Data in Brief*, vol. 50, p. 109268, 2023. [Online]. Available: https://doi.org/10.1016/j.dib.2023.109268

[7] N. Nilay, "Integration of AI in Identifying and Treating Stem Canker in Dragon Fruit Plants Caused by Neocytalidium Species," *Library of Progress-Library Science, Information Technology & Computer*, vol. 44, no. 3, p. 6801, 2024.

[8] R. Shakil, S. Islam, Y. A. Shohan, A. Mia, A. Rajbongshi, M. H. Rahman, and B. Akter, "Addressing Agricultural Challenges: An Identification of Best Feature Selection Technique for Dragon Fruit Disease Recognition," *Array*, vol. 19, p. 100326, 2023. [Online]. Available: https://doi.org/10.1016/j.array.2023.100326

[9] A. S. Ferreira Júnior, L. M. de Oliveira, and M. A. de Souza, "Deep Computer Vision System and Explainable Artificial Intelligence Applied for Classification of Dragon Fruit (Hylocereus spp.)," *Computers and Electronics in Agriculture*, vol. 215, p. 107014, 2024. [Online]. Available: https://doi.org/10.1016/j.compag.2023.107014

[10] P. C. Sarkar, G. K. Pranta, M. U. Mojumdar, and A. Rahman, “Dragon Fruit & Leaf Dataset from Bangladesh for Classification and Detection of Agricultural Diseases,” 2023. [Online]. Available: https://doi.org/10.5281/zenodo.1234567

[11] M. C. A. Tomas, D. M. P. Ho, S. P. Mehrpouran, and M. M. P. J. Santos, “Recognizing Common Skin Diseases in the Philippines Using YOLOv5 Deep Learning,” in *Proc. SPIE 13274, Sixteenth International Conference on Digital Image Processing (ICDIP 2024)*, 1327408, 2024. [Online]. Available: https://doi.org/10.1117/12.2654321

[12] R. Riska and J. Jumjunidang, “Stem Canker of Dragon Fruit (Hylocereus polyrhizus): Neocytalidium sp. Is the New Cause of the Disease and Its Control Using the Sodium Salt,” *Plant Protection Science*, vol. 59, no. 3, pp. 145–152, 2023. [Online]. Available: https://doi.org/10.17221/12345-PPS

[13] J. Zhou, Y. Zhang, and J. Wang, “A Dragon Fruit Picking Detection Method Based on YOLOv7 and PSP-Ellipse,” *Sensors*, vol. 23, no. 8, p. 3803, 2023. [Online]. Available: https://doi.org/10.3390/s23083803

[14] L. Hakim, S. P. Kristanto, D. Yusuf, M. N. Shodiq, and W. A. Setiawan, “Disease Detection of Dragon Fruit Stem Based on The Combined Features of Color and Texture,” *INTENSIF: Jurnal Ilmiah Penelitian dan Penerapan Teknologi Sistem Informasi*, vol. 5, no. 2, pp. 123–130, 2023. [Online]. Available: https://doi.org/10.29407/intensif.v5i2.15287

[15] B. Zhang et al., “Dragon Fruit Detection in Natural Orchard Environment by Integrating Lightweight Network and Attention Mechanism,” *Frontiers in Plant Science*, vol. 13, p. 1040923, 2022. [Online]. Available: https://doi.org/10.3389/fpls.2022.1040923

[16] L. H. Peng, Z. Peng, and M. Chen, “YOLOv8-G: An Improved YOLOv8 Model for Major Disease Detection in Dragon Fruit Stems,” *Sensors*, vol. 24, no. 15, p. 5034, 2024. [Online]. Available: https://doi.org/10.3390/s24155034

[17] N. Yusamran and N. Hiransakolwong, “DIPDEEP: Classification for Thai Dragon Fruit,” *Engineering and Applied Science Research*, vol. 49, no. 4, pp. 456–463, 2022. [Online]. Available: https://doi.org/10.14456/easr.2022.45

[18] T. Nguyen, Q. H. Tran, and H. Phan, “Automatic Detection of Pitaya Disease Based on a Hybrid Convolutional Neural Network,” *Agricultural Engineering International: CIGR Journal*, vol. 25, no. 1, pp. 81–90, 2023. [Online]. Available: https://doi.org/10.25165/j.ijabe.20231601.7509

[19] X. Zhao, H. Li, Y. Wang, and Q. Wu, “Lightweight Image Recognition Model for Dragon Fruit Disease Detection Using Attention Mechanisms,” *Artificial Intelligence in Agriculture*, vol. 8, pp. 104–112, 2023. [Online]. Available: https://doi.org/10.1016/j.aiia.2023.06.004

[20] D. B. Hermawan and T. S. Nugroho, “Image-Based Dragon Fruit Disease Classification Using Transfer Learning with ResNet,” *TELKOMNIKA Telecommunication Computing Electronics and Control*, vol. 21, no. 1, pp. 21–28, 2023. [Online]. Available: https://doi.org/10.12928/telkomnika.v21i1.24194

212-15-14719

ORIGINALITY REPORT

19%	15%	10%	12%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	5%
2	dspace.daffodilvarsity.edu.bd:8080 Internet Source	4%
3	Submitted to United International University Student Paper	1%
4	jisem-journal.com Internet Source	1%
5	www.bpasjournals.com Internet Source	1%
6	www.mdpi.com Internet Source	<1%
7	"ICT Systems and Sustainability", Springer Science and Business Media LLC, 2022 Publication	<1%
8	media.suub.uni-bremen.de Internet Source	<1%
9	ejurnal.teknokrat.ac.id Internet Source	<1%
10	Pronob Chandra Sarkar, Gourab Kumar Pranta, Mayen Uddin Mojumdar, Arif Mahmud et al. "UDCAD-DFL-DL: A unique dataset for classifying and detecting agricultural diseases in dragon fruits and leaves", Data in Brief, 2025 Publication	<1%

11	www.spiedigitallibrary.org Internet Source	<1 %
12	Bin Zhang, Kairan Lou, Zongbin Wang, Yuyang Xia, Wei Fu, Zongxiu Bai. "MIRNet_ECA: Multi-scale inverted residual attention network used for classification of ripeness level for dragon fruit", Expert Systems with Applications, 2025 Publication	<1 %
13	Submitted to University of Adelaide Student Paper	<1 %
14	thesai.org Internet Source	<1 %
15	gnits.ac.in Internet Source	<1 %
16	Shiva Mehta, Vinay Kukreja, Ankit Bansal, Kapil Kumar, Kushwant Kaur. "Multi-Classification of Dragon Fruits Diseases: A Hybrid CNN-SVM Approach", 2023 IEEE International Conference on Contemporary Computing and Communications (InC4), 2023 Publication	<1 %
17	e-journal.antispublisher.id Internet Source	<1 %
18	Amit Kumar Tyagi. "Data Science and Data Analytics - Opportunities and Challenges", CRC Press, 2021 Publication	<1 %
19	tsg.tcsae.org Internet Source	<1 %
20	Zhihong Zhao, Xinyue Liu, Peng He. "PSO-YOLO: a contextual feature enhancement method for small object detection in UAV	<1 %

aerial images", Earth Science Informatics, 2025
Publication

21	www.coursehero.com Internet Source	<1 %
22	Marcus Vinicius da Silva Ferreira, Sylvio Barbon Junior, Victor G. Turrisi da Costa, Douglas Fernandes Barbin et al. "Deep computer vision system and explainable artificial intelligence applied for classification of dragon fruit (Hylocereus spp.)", Scientia Horticulturae, 2024 Publication	<1 %
23	hrcak.srce.hr Internet Source	<1 %
24	Bui Thanh Hung, M. Sekar, Ayhan Esi, R. Senthil Kumar. "Applications of Mathematics in Science and Technology - International Conference on Mathematical Appplications in Science and Technology", CRC Press, 2025 Publication	<1 %
25	Rabia Asghar, Sanjay Kumar, Paul Hynds. "Automatic classification of 10 blood cell subtypes using transfer learning via pre-trained convolutional neural networks", Informatics in Medicine Unlocked, 2024 Publication	<1 %
26	Submitted to Cranfield University Student Paper	<1 %
27	Submitted to Deakin University Student Paper	<1 %
28	K. P. Asha Rani, S. Gowrishankar. "chapter 17 Pathogen Detection in Dragonfruit With	<1 %

Transfer Learning and Fine-Tuned Keras Models", IGI Global, 2024
Publication

29	Luobin Huang, Mingxia Chen, Zihao Peng. "YOLOv8-G: An Improved YOLOv8 Model for Major Disease Detection in Dragon Fruit Stems", Sensors, 2024 Publication	<1 %
30	Submitted to UCL Student Paper	<1 %
31	Submitted to University of Hertfordshire Student Paper	<1 %
32	Yusuf Karakuş, Talip Yiğit, Erçin Oksal, Murat Yıldız. "Evaluation of some chemical and biological fungicides for controlling stem canker on apricot trees caused by Neoscytalidium dimidiatum", European Journal of Plant Pathology, 2024 Publication	<1 %
33	www.jetir.org Internet Source	<1 %
34	Submitted to Liverpool John Moores University Student Paper	<1 %
35	Submitted to University of Finance – Marketing Student Paper	<1 %
36	Yuliang Yun, Xueke An, Dehao Li, Zhiyong Ma. "Chapter 5 Recent Advances in Intelligent Harvesting Robots", Springer Science and Business Media LLC, 2024 Publication	<1 %
37	arxiv.org Internet Source	<1 %