A Computer Vision System for Dragon Fruit and Leaf Disease Classification Using Deep Learning

By
Arup Biswas
212-15-4190

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

Dewan Mamun Raza
Assistant Professor
Department of Computer Science and EngineeringDaffodil International University

Co-Supervised by
Md Assaduzzaman
Assistant Professor
Department of Computer Science and EngineeringDaffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY
Dhaka, Bangladesh

September 17, 2025

APPROVAL

This Project titled **"A Computer Vision System for Dragon Fruit and Leaf Disease Classification Using Deep Learning"**, submitted by Arup Biswas, ID No: **212-15-4190** 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 **17 September, 2025**.

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Dr. Arif Mahmud (AM)
Associate Professor and Associate Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

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Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner

Dr. Md. Manowarul Islam
Professor
Department of Computer Science and Engineering
Jagannath University

External Examiner

DECLARATION

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

Supervised by:

Dewan Mamun Raza
Assistant Professor
Department of Computer Science and EngineeringDaffodil International University

Co-Supervised by:

Md Assaduzzaman
Assistant Professor
Department of Computer Science and EngineeringDaffodil International University

Submitted by:

Arup Biswas

Arup Biswas
Student ID: 212-15-4190
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 **Dewan Mamun Raza**, **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

Production of dragon fruit is of economic importance but is severely affected by fungus and insect outbreak, especially stem canker and scale insects that reduce production and quality. The conventional disease identification approaches that rely on manual observation are labour intensive, subjective and inapplicable to extensive agriculture. The paper is based on the deep learning-powered computer vision model that can simultaneously classify fruit and leaf health as good, bad, good, stem canker, and scale insect. The data set was a collection of 2,547 in-field pictures; this data was pre-processed using the technique of augmentations to enhance generalization. Four models were trained and analyzed through transfer learning and optimization with the help of InceptionV3, DenseNet201, MobileNetV2, and a custom CNN. DenseNet201 had the highest accuracy (99.63) with good precision and recall whereas MobileNetV2 had good performance (96.75) with computational efficiency that can be applied to mobile development. InceptionV3 provided high quality classification of 95.05 and custom CNN was used as a baseline of 86.14. Findings point to a case of trade-off between accuracy and deployability, showing that DenseNet201 is better suited to controlled settings and MobileNetV2 to real-time and resource-constrained settings. It is proposed that the system would decrease the use of manual inspection, better disease suppression and would offer a solution that is scalable and sustainable to increase productivity and farmer profitability in growing dragon fruit.

Table of Contents

Approval i

Declaration ii

Acknowledgements iii

Abstract iv

List of Figures vii

List of Tables viii

1 Introduction 1

1.1 Introduction 1
1.2 Motivation 2
1.3 Objectives 3
1.4 Methodology 3
1.5 Project Outcome 4
1.6 Organization of the Report 5

2 Background 6

2.1 Introduction.. 6
2.2 Literature Review 6
2.2.1 Similar Applications 12
2.3 Gap Analysis 12
2.4 Summary 14

3 Research Methodology 16

3.1 Methodology/Requirement Analysis & Design Specification 16
3.1.1 Overview 16
3.1.2 Proposed Methodology/ System Design 17
3.2 Detailed Methodology and Design 17
3.3 Project Plan 27
3.4 Task Allocation 28
3.5 Summary 29

4 Implementation and Results 31

4.1 Environment Setup 31
4.2 Comparative Analysis 32

4.3 Results and Discussion 32
4.4 Summary 41

5 **Engineering Standards and Design Challenges** **42**
5.1 Compliance with the Standards 42
5.1.1 Software Standards 42
5.1.2 Hardware Standards 42
5.1.3 Communication Standards 42
5.2 Impact on Society, Environment and Sustainability 43
5.2.1 Impact on Life 43
5.2.2 Impact on Society & Environment 43
5.2.3 Ethical Aspects 43
5.2.4 Sustainability Plan 44
5.3 Project Management and Financial Analysis 44
5.4 Complex Engineering Problem 45
5.4.1 Complex Problem Solving 45
5.4.2 Engineering Activities 46
5.5 Summary 47

6 **Conclusion** **48**
6.1 Summary 48
6.2 Limitation 48
6.3 Future Work 49

References **50**

List of Figures

3.1 Methodology Diagram......17
3.2 Sample of Good Leaf. 18
3.3 Sample of Scale Insect......19
3.4 Sample of Stem Canker......20
3.5 Sample of Good Fruit. 21
3.6 Sample of Bad Fruit......22
3.7 Architecture of InceptionV3 23
3.8 Architecture of DenseNet201 24
3.9 Architecture of MobileNetv2. 25
3.10 Architecture of Custom CNN. 26
4.1 Model Accuracy Comparison. 31
4.2 Comparison of Model Accuracy-2. 32
4.3 DenseNet201 Confusion Matrix 34
4.4 DenseNet201 Training and Validation Plot 34
4.5 InceptionV3 Confusion Matrix. 35
4.6 InceptionV3 Training and Validation Plot 36
4.7 MobileNetV2 Confusion Matrix 37
4.8 MobileNetV2 Training and Validation Plot......37
4.9 Custom CNN Confusion Matrix. 38
4.10 Custom CNN Training and Validation Plot. 39

List of Tables

2.1 Summary of Literature Reviewed. 08
2.2 Gap Analysis....13
3.1 Project Plan....27
3.2 Task Allocation. 28
4.1 Comparative Analysis....30
4.2 Model Comparison. 31
4.3 DenseNet201 Confusion Matrix 33
4.4 InceptionV3 Confusion Matrix....35
4.5 MobileNetV2 Confusion Matrix. 36
4.6 Custom CNN Confusion Matrix....38
5.1 Financial Analysis 42
5.2 Mapping with Complex Problem Solving 43
5.3 Mapping with Knowledge Profile. 44
5.4 Mapping with Complex Engineering Activities. 44

Chapter 1

Introduction

1.1 Introduction

Hylocereus spp or dragon fruit or pitaya has emerged as one of the most valuable tropical fruits due to its nutritional values and commercial potential [1]. The fruit fruit is a source of antioxidants, vitamins, minerals and dietary fiber, which have made it a functional food with both domestic and export market [2]. It is also a crop of economic and social importance to the developing countries because dragon fruit cultivation is also a source of income [3]. In spite of these advantages, its productivity and quality is very susceptible to several biotic and abiotic stresses. Diseases and pest infestations of plants in specific cases can lead to massive losses in yield, decrease the quality of fruit, and cut profits [4].

Fungal infections, including the stem canker that is caused by Neocytalidium species, and pests including the scale insects are among the most threatening [5],[6]. Stem canker causes both necrosis and structural tissue damage, whereas the scale insects decrease the general plant vigor and undermine the fruit appearance. The mishandling, changes in temperature and unfavorable postharvest environment are also examples of abiotic stresses that cause fruit spoilage and economic losses [7]. The agricultural experts and farmers have traditionally used manual inspection to detect diseases and quality flaws. But, this is a slow method that is expensive to manage, and very prone to error particularly in large farms where timely intervention is crucial [8].

Artificial intelligence (AI) and computer vision provided solutions to these challenges in the past few years that have been promising [9]. The computer vision methods enable the automated analysis of plant images, and therefore, it is possible to detect diseases, determine quality, and track maturity. Deep learning also extends these systems by directly learning complex hierarchical features in these systems directly based on the image data, eliminating the constraints of handcrafted approaches [10]. Specifically, Convolutional Neural Networks (CNNs) have recorded the state of art in image classification and detection tasks in fields of medicine, industry and agriculture [11]. In the case of the dragon fruit, CNNs are capable of detecting minute visual signs of the ailments and the stages of ripeness in a very precise way.

Deep learning-based agricultural systems have some benefits to their adoption. They have quick, stable and scalable analysis that is not reliant on expert availability. Notably, customizable lightweight models are now accessible to run on edge devices and smartphones, which enable real-time detection of diseases and the ripeness of products, right on the field [12]. This holds particularly well in situations of resource scarce agriculture where mobile phones are rampant and agricultural support services are scarce. Recent research validates that small deep learning models are able to provide actionable information to smallholder farmers with low-cost [13].

In spite of it, the majority of current studies about dragon fruit were limited with the objectives like single-disease detection [5], ripeness classification [2], or even developing datasets [6]. Although said and true, these studies are still piecemeal. Indicatively, Kumar et al. [17] showed that the classical image-processing techniques could only get moderate results in terms of detecting the stem disease. Equally, Kulkarni et al. [18] conjoined disease and maturity classification based on image features and had a hard time generalizing across different conditions. At a higher level, some other models like MIRNet_ECA [3] and YOLOv8-G [14] achieved impressive results in terms of detecting ripeness in fruits and classifying stem diseases, but they were tested to solve the problems separately and not through a common framework.

To seal this gap, the current study presents a multi-classification of dragon fruit to monitor its health. The system breaks down the images into five groups namely good fruit, bad fruit, good leaf, stem canker, and scale insect. These classes represent the most prevalent real life situations of the farmers. They apply four models, including InceptionV3, DenseNet201, MobileNetV2, and a custom CNN. They have specific strengths: InceptionV3 is more efficient in extracting multi-scale features, DenseNet201 is ideal in reusing the features and gradient flows, MobileNetV2 is more efficient to implement and deploy, and the custom CNN is flexible to applications [11].

The works of this work are three-fold. Its first strength lies in the fact that it presents a multi-class framework integrating fruit and leaf health assessment as opposed to prior studies that have focused on them independently. Second, it compares various deep learning models and offers a comparative assessment of accuracy, efficiency, and applicability to the real agricultural environment. Third, it shows the practicability of lightweight models on mobile-based applications in providing information on the accessibility and sustainability of applications to enable farmers in resource-limited environments to monitor diseases [12].

To sum up, pests, diseases, and post-harvest are major challenges that are threatening dragon fruit production. The use of the manual inspection method cannot satisfy the large-scale farming requirements. This research combines the understanding of deep learning and computer vision, which gives it a powerful and scalable method of detecting diseases and evaluating their quality. The products not only broaden the academic knowledge about the use of AI in agriculture but also provide useful tools to farmers to improve their productivity, profitability, and sustainability in dragon fruit production.

1.2 Motivation

Dragon fruit cultivation is increasing at a rapid pace, especially in tropical and subtropical regions. Dragon fruit cultivation is now being threatened by diseases like stem canker and pests like scale insects. They are causing low yields, post-harvest loss, and fruit quality, directly affecting farmers' returns. Visual detection of disease regularly is labor-intensive, prone to human error, and not applicable in large-scale production.

Recent advances in deep learning and computer vision offer robust resources for disease detection in agriculture. Models such as InceptionV3, DenseNet201, and MobileNetV2 are some of the models that have high image classification features, while homegrown CNNs provide flexibility in their corresponding datasets. By integrating these models in an easy-to-use system, precise real-time disease classification is done, enabling farmers to make appropriate pest control and treatment strategies.

Through overcoming the detection of disease, the project aims to contribute to sustainable dragon fruit production, reduce economic loss, and promote modern precision farming methods that can also be adopted by other crops.

1.3 Objectives

- Design a deep learning-based system of classifying dragon fruit and leaf diseases.
- Model: good fruit, bad fruit, good leaf, stem canker, scale insect, etc. five classes.
- Performance Compare InceptionV3 and DenseNet201 and MobileNetV2 with a custom CNN in terms of classification.
- Trade-offs between accuracy and lightweight real-time applicability.
- Give farmers an automated device to save manual inspection and facilitate the management of diseases in time.

1.4 Methodology

The process is a step-by-step procedure for developing a deep learning model to identify the leaves and fruits of dragon fruit. The process begins with data preparation, where five-class images (Good Leaf, Good Fruit, Stem Canker, Scale Insect, and Bad Fruit) are collected under varied conditions such as illumination, orientation, and disease propagation. The images collected are preprocessed using methods like background stripping and augmentation for increasing model robustness. Four deep learning architectures (InceptionV3, DenseNet201, MobileNetV2, and a custom CNN) are employed. The pre-trained models are fine-tuned from transfer learning to suit the dragon fruit dataset, with the custom CNN being a baseline with convolutional and pooling layers for comparison. Hyperparameters such as batch size and learning rate are optimized for optimal performance, and cross-entropy loss as the objective function. The performance of the model is monitored on accuracy, precision, recall, and F1-score, and confusion matrices have been plotted in an attempt to analyze classification error between the five classes. The best-performing ultimate model is subsequently fine-tuned for deployment such that it can be used in real-world dragon fruit farm environments, particularly concerning simplicity, cost-effectiveness, and deployability to low-resource devices.

1.5 Project Outcome

The possible implications of this project, A Computer Vision System to Classify Dragon Fruit and Leaf Disease Using Deep Learning, are of high importance to the field of precision farming and enhancing the cultivation of dragon fruit.

The key contributions are: Full Dataset of Dragon Fruit and Leaf Conditions: Diseases and defects of dragon fruit that include stem canker, scale insects, and bad fruit and healthy samples of dragon fruit including good leaf and good fruit are some of the major factors that influence the quality and crop yield of the fruit. To overcome the problem of non-standardized datasets, this project assembles an in-field dataset of images representing these five classes. The dataset will be used as a baseline in future research and assist developers to produce powerful deep learning algorithms applicable in practice in the field of farming.

Accurate Disease and Condition Classification: This project is able to properly classify the status of the leaves and fruits with the usage of four deep learning networks (InceptionV3, DenseNet201, MobileNetV2 and a custom CNN). Considerable quality products can be enjoyed because timely and correct identification of farming results in timely action by the farmers to help reduce losses of produce.

Better Productivity: Automated process of classifying products results in a situation where manual and slow inspection is unnecessary. Conditions can be diagnosed in real time, and since farmers can detect the conditions within a few seconds, operational costs are minimized because the detection process would have taken hours or days.

Economic Benefits: The technology boosts farmer profitability by eliminating losses on yields and enhancing crop quality. In countries where dragon fruit is a valuable crop like in Bangladesh or Vietnam, a better export quality and the improvement of the economy of the rural areas can be achieved.

Scalability and Adaptability: The developed system can be adapted to other crops and plant diseases and will become a versatile system to increase the scope of agricultural applications.

Better Decision-Making: Farmers and policy-makers can make informed choices about crop management and prevention based on the outputs of a model, such as (but not confined to) the incidence of diseases.

User-Friendly and User-Accessible: The system must be user-friendly and accessible to low-resource devices such as smartphones so that it can be conveniently used in the field without advanced technical expertise.

Sustainability Impact: The system results in less wastage of pesticide, as the treatment targets a specific area, which is beneficial in terms of environmental preservation and sustainable farming.

This venture provides high-cost, scalable, and farmer-friendly dragon fruit production solution. It integrates state-of-the-art deep learning with practicality to boost productivity and sustainability and to maximize the economic success of farmers.

1.6 Organization of the Report

The report is organized as follows:

Chapter 1: Introduction – provides the background, motivation, objectives, methodology, the expected outcomes, and the structure of the report.

Chapter 2: Background – explains the importance of growing dragon fruit, typical diseases and anomalies of the leaves and fruit, conventional methods of detection, and a literature review of related studies, in which deep learning was used.

Chapter 3: Research Methodology – describes the procedure of the research, data preparation, pre-processing, model building, and the evaluation metrics adopted in the study.

Chapter 4: Implementation and Results – provides the implementation of each of the four models, their performance outcomes, and the comparison of their quality in terms of accuracy, precision, recall, and F1-score.

Chapter 5: Engineering Standards and Design Challenges – talks about the engineering standards used, ethical issues, environmental concerns, and challenges faced in the project implementation.

Chapter 6: Conclusion – Overviews the project findings, limitations, and offers future research recommendations and directions that might be useful to improve the results.

Chapter 2
Background

2.1 Introduction

Dragon fruit (Hylocereus spp.), or pitaya, increasingly has been an economically significant horticultural crop for its quality, aesthetic value, and commercial potential in both domestic markets as well as export markets [1]. Vietnam, Thailand, and Bangladesh have embraced its cultivation, but the crop highly suffers from many biotic stresses with the involvement of fungi, bacteria, and insects [6]. Fungal, bacterial, or scale insect infestation causes an appreciable loss in yield as well as fruit quality, which is an economically serious risk for cultivators [7].

The current traditional approach for the detection of diseases relies on human observation by the farmer or an expert. Although widely practiced, the task becomes cumbersome, human-intensive, and inexact when practiced on a scale [8]. In the face of these issues, early detection with high accuracy is an urgent need for future endeavors.

Rising trends in artificial intelligence (AI) as well as deep learning, have generated considerable hype for the creation of autonomous systems for identifying plant diseases using pictures [5]. Convolutional Neural Networks (CNNs), lightweight models (e.g., MobileNet, variants of YOLO), have shown remarkable performance for agricultural disease diagnosis [2]. Subsequent works hold promises for effective, understandable, as well as scale-appropriate solutions crafted for the resource-limited agricultural context [3].

2.2 Literature Review

The last ten years have seen growing interest in detection and ripeness classification of dragon fruits, with scientists investigating artificial intelligence (AI), computer vision, and deep learning to enhance the results of agriculture. Many options have been tried to have a better accuracy in detecting the disease and classifying the ripeness so that the dragon fruits could be marketed as per the market demand.

S. Mehta et al. [1] introduced a hybrid CNN-SVM model in the process of multi-classification of the disease in dragon fruits. They showed that both deep learning and traditional machine learning improved the accuracy of their approach when compared to CNN or SVM. In the same way, Z. Qiu et al. [2] proposed GSE-YOLO as a lightweight model based on YOLOv8n and identified ripeness, which demonstrated a high degree of accuracy with lower computational complexity, which is used in automated harvesting and market-level applications.

Conventional methods also played a good role. Y. R. Kumar et al. [17] have applied classical image-processing techniques to detect stem disease which provides information but is weak at resisting visual variation. Continuing on this, V. Kulkarni et al. [18] used handmade color and texture attributes in order to categorize diseases and maturity of fruits. Their output was a moderate success, but the high-performance in deep learning methods was more certain.

The models of deep learning were very important breakthroughs. B. Zhang et al. [3] designed MIRNet_ECA that integrated multi-scale inverted residuals with effective channel attention that not only ensured compact but also drastically accurate ripeness classification even in mobile devices. In the meantime, M. U. Mojumdar et al. [4] alleviated the limitations of datasets and published UDCAD-DFL-DL, a large annotated dataset of dragon fruit and leaves, which allows stronger training and evaluation of classification models.

The applications of AI to studies concerning treatment have also been done. N. Nilay [5] applied transfer learning based on AI in the detection and treatment of stem canker caused by Neocytalidium. This demonstrated the significance of AI in diagnosis and proposing interventions. On the same note, R. Shakil et al. [6] compared feature selection methods and demonstrated that optimized sets of features increased recognition rate and minimized computation cost.

Explainability was also taken up. A. S. Ferreira Junior et al. [7] have used CNNs along with XAI techniques including the Grad-CAM technique to ensure that accuracy is high but still interpretable by the farmers. In addition to this, P. C. Sarkar et al. [8] have posted an annotated Bangladeshi dataset, which is useful in conducting localized research and enhancing data resources to classify diseases.

Cross-domain applications were also a source of more knowledge. M. C. A. The transferability of object detection models is demonstrated by Tomas et al. [9] who applied YOLOv5 to the human skin disease detection. On the biological side, R. Riska and J. Jumjunidang [10] the causal agent of stem canker was found to be Neocytalidium and the incidence of the disease was found lower when sodium salt treatments were applied under field conditions.

Research on automation also came up. J. Zhou et al. [11] combined YOLOv7 with PSP-Ellipse to identify the fruit-picking points, which further improved the harvesting efficiency in difficult orchards conditions. On the same note, L. Hakim et al. [12] also used color and texture features to detect stem diseases, with the fruitful outcomes being complimentary to those of deep learning-based methods.

Real-world deployment models have been essential and lightweight. B. Zhang et al. [13] used attention-enhanced lightweight networks in detecting the orchards, and this method was found to be robust to different lighting conditions. In this direction, L. H. Peng et al. [14] proposed YOLOv8-G, an optimized model to detect the disease of dragon fruits in stems with an increased level of accuracy and speed.

Transfer learning methods pushed more limits. N. The DIPDEEP of Yusamran and N. Hiransakolwong [15] was created as a classifier of Thai dragon fruits with a focus on region-sensitive models. On the same note, T. Nguyen et al. [16] suggested a hybrid CNN in detecting multi-diseases, and the generalization was effective. X. Zhao et al. [19] scaled CNNs with attention to allow faultless but computationally efficient detection to make them mobile. Lastly, D. B. Hermawan and T. S. Nugroho [20] used ResNet based-transfer learning hitting high accuracy using small amounts of labeled data.

In general, studies no longer focus on simple image processing but rather on sophisticated methods based on AI. Advances extend to hybrid designs, attention-based lightweight designs, explainable AI, and transfer learning. Collectively, these publications demonstrate that construction of trustworthy, efficient, and scalable systems, which assist the farmers and enhance sustainability in the production of dragon fruits is essential.

Table 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	The hybrid approach improved 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	High ripeness-detection accuracy with a lightweight model suitable for edge deployment.
B. Zhang et al. [3]	2025	MIRNet_ECA: Multi-scale Inverted Residual Attention Network for Ripeness Classification	MIRNet_ECA with ECA attention	High accuracy in ripeness classification with very small model size and fast inference.

M. U. Mojumdar et al. [4]	2023	UDCAD-DFL-DL: A Unique Dataset for Classifying and Detecting Agricultural Diseases	Dataset creation /curation	Released a large annotated benchmark dataset useful for training and evaluation.
N. Nilay [5]	2024	Integration of AI in Identifying and Treating Stem Canker in Dragon Fruit Plants	AI-based classification + transfer learning	Identified stem canker (Neocytalidium) reliably; supports early detection in field conditions.
R. Shakil et al. [6]	2023	Best Feature Selection Technique for Dragon Fruit Disease Recognition	Feature-selection comparison (ReliefF, Chi-square, PCA)	Optimal feature sets improved classifier accuracy and reduced computational load (~4% gain).
A. S. Ferreira Júnior et al. [7]	2024	Deep Computer Vision and Explainable AI for Dragon Fruit Classification	CNN + XAI (Grad-CAM)	High classification accuracy with interpretable model outputs for stakeholder trust.
P. C. Sarkar et al. [8]	2023	Dragon Fruit & Leaf Dataset from Bangladesh	Dataset publication (annotated images)	Published annotated dataset that supports disease-detection research in local contexts.
M. C. A. Tomas et al. [9]	2024	Recognizing Common Skin Diseases Using YOLOv5	YOLOv5 deep learning	Demonstrated YOLO's effectiveness for fast, accurate image-based disease detection (medical domain transferability).
R. Riska & J. Jumjunidang [10]	2023	Stem Canker of Dragon Fruit and Its Control Using Sodium Salt	Pathogen identification + control assays	Confirmed Neocytalidium as causal agent and showed sodium-salt treatment reduced incidence.

J. Zhou et al. [11]	2023	Dragon Fruit Picking Detection Using YOLOv7 and PSP-Ellipse	YOLOv7 + PSP-Ellipse	High detection accuracy for picking points; robust under occlusion and variable lighting.
L. Hakim et al. [12]	2023	Disease Detection of Dragon Fruit Stem Based on Color and Texture Features	Color and texture feature analysis	Combining color and texture features yielded strong detection performance, complementing DL methods.
B. Zhang et al. [13]	2022	Dragon Fruit Detection in Orchard Using Lightweight Network and Attention	Lightweight network + attention modules	Robust detection in natural orchard scenes; reduced false positives and improved localization.
L. H. Peng et al. [14]	2024	YOLOv8-G: Improved YOLOv8 for Major Stem Disease Detection	YOLOv8-G (architectural optimizations)	Improved stem-disease detection accuracy with real-time capability.
N. Yusamran & N. Hiransakolwong [15]	2022	DIPDEEP: Classification for Thai Dragon Fruit	DIPDEEP neural network	Achieved accurate classification tailored to Thai dragon fruit varieties.
T. Nguyen et al. [16]	2023	Automatic Detection of Pitaya Disease Based on Hybrid CNN	Hybrid CNN model	Effective multi-disease classification with improved generalization.
Y. R. Kumar et al. [17]	2023	Dragon Fruit Stem Disease Detection Using Image Processing	Classical image-processing techniques	Moderate detection accuracy; demonstrated potential of traditional image analysis methods.

V. Kulkarni et al. [18]	2022	Detection and Classification of Diseases and Maturity of Dragon Fruits	Region-based CNN (R-CNN) + SVM	Classified diseases and maturity; automated grading reduced manual errors but had limited generalization.
X. Zhao et al. [19]	2023	Lightweight Model for Dragon Fruit Disease Detection Using Attention Mechanisms	Lightweight CNN + attention	Improved accuracy with low computational cost; suitable for edge/mobile devices.
D. B. Hermawan & T. S. Nugroho [20]	2023	Image-Based Dragon Fruit Disease Classification Using Transfer Learning with ResNet	Transfer learning (ResNet)	ResNet-based transfer learning achieved high accuracy; useful when labeled data is limited.

2.2.1 Similar Applications

Despite impressive strides in applying AI and deep learning to monitor dragon fruit diseases and detect wapiti, some key challenges remain that limit how well these solutions can be generalized and how resilient they are. One of the most important problems is the diversity of the dataset. The majority of available datasets, including UDCAD-DFL-DL [7], are regional and are not representative of a wide range of climatic conditions and of varieties of dragon fruit. This weakness limits the ability of the model to generalize in new settings where diseases can take different forms.

The other gap is crucial disease coverage. Although literature has focused on typical conditions, such as canker of stems and scale insect infestations [12], some new pathogens, such as Neocytalidium species, are poorly represented in existing datasets [7]. Consequently, most of the models do not represent the entire range of biotic stresses to which the dragon fruit plants are exposed, and therefore their usefulness is limited.

Scalability and computational efficiency are also challenges. Although lightweight models such as GSE-YOLO [6] and MIRNet_ECA [5] may be applicable to mobile implementation, trade-offs between accuracy and processing speed in the real-time field environment have not been adequately studied. This makes it difficult to adopt them when resources are limited and efficiency matters as much as accuracy.

Moreover, model interpretability remains in its infancy. The use of Explainable AI (XAI) in disease detection systems has been investigated [4], although most models are black boxes, meaning the farmers and agronomists do not know how the predictions were made. Poor transparency diminishes trust and restricts massive implementation.

Finally, there is little literature on the topic of temporal analysis and early disease prediction. The existing models categorize fixed images, and timely detection of disease development would allow timely responses and avoid large-scale losses of crops [8].

To recap, there is a need in the future to build cross-regional datasets, increase disease coverage, improve computational efficiency, and introduce explainable and predictive capabilities. The endeavor to fill these gaps will make AI-based systems transition out of the laboratory and into the farm.

2.3 Gap Analysis

Although this study achieved promising results in classifying dragon fruit leaves and fruits using deep learning, several limitations remain that reflect broader gaps in the existing literature and practice. These gaps relate to dataset diversity, disease coverage, environmental adaptability, and real-time deployment feasibility.

The dataset collected for this project consists of five classes: Good Leaf, Good Fruit, Stem Canker, Scale Insect, and Bad Fruit. All 2,547 images were captured in daylight using smartphones, which ensures clarity but limits variation in lighting, weather conditions, and backgrounds. Similar to the dataset limitations noted by Sarkar et al. [7] and Mojumdar et al. [10], this controlled capture setting helped models like DenseNet201 achieve near-perfect accuracy (99.63%) and F1-score (99.62%), but leaves questions about robustness under cloudy, rainy, or nighttime conditions.

Certain disease categories remain absent. While Stem Canker and Scale Insect are represented, other conditions like Anthracnose and bacterial wilt, which have been documented in prior works [13], are not included. This restricts the system's ability to serve as a fully comprehensive diagnostic tool for dragon fruit cultivation across regions.

In terms of model performance, DenseNet201 clearly outperformed the other three models, with MobileNetV2 and InceptionV3 also delivering high accuracy, and the custom CNN trailing at 86.14%. However, as highlighted in lightweight deployment studies [1], [6], high-performing but resource-intensive models such as DenseNet201 may not be practical for low-resource environments. MobileNetV2, while less accurate, offers better suitability for mobile and edge devices, yet the precision–speed trade-off in real farm conditions remains unexplored.

Finally, although this project focuses on still-image classification, temporal or progression-based analysis of diseases emphasized as a future direction in Shakil et al. [11] has not been addressed. Such analysis could allow earlier detection of disease onset, enabling preventative action before visible damage becomes severe.
Closing these gaps will require expanding the dataset to multiple environmental conditions and geographic locations, adding more disease classes, testing lightweight models in actual farm environments, and exploring sequential monitoring for disease progression.

Table 2.2: Gap Analysis

Features	**InceptionV3**	**DenseNet201**	**MobileNetV2**	**Custom CNN**	**Proposed System**
Transfer learning applied	Yes	Yes	Yes	No	Yes
Lightweight architecture	No	No	Yes	Yes	Yes
Accuracy ≥ 95%	Yes	Yes	Yes	No	Yes

Suitable for edge/mobile deployment	No	No	Yes	Yes	Yes
Computational efficiency	Medium	Low	High	High	High
Dataset augmentation used	Yes	Yes	Yes	Yes	Yes
Handles multiple classes	Yes	Yes	Yes	Yes	Yes
Requires large dataset	Yes	Yes	No	No	No
Model interpretability (XAI)	No	No	No	No	Planned
Real-time prediction capability	No	No	Yes	Yes	Yes

2.4 Summary

Chapter 2 also examined the previous literature and summarized the relevant lessons to create a successful dragon fruit disease detection system. The survey revealed that there are three continuous foundations: curated in-field datasets, model families (both lightweight and deep classifiers) and hybrid or explainable strategies to enhance trust and robustness. Transformer-style and attention-augmented models have shown enhanced fine-grained symptom recognition [3] and dataset efforts give the required training base and benchmark capability [4].

Object-detection families (YOLO variants) are still the most suitable when localization and speed are important; optimized or refined variants such as YOLOv8-G are capable of real-time stem-disease detection and can be applied to automation work [14]. Lightweight attention-enhanced models can support on-device deployment with minimal significant accuracy loss, a feature valuable to farmer-facing devices [19]. To classify, multi-scale residual and dense architectures achieve the highest accuracy at a higher computational cost; transfer-learning with ResNet-style backbones provides an effective trade-off when fewer labeled data are available [20].

Feature-engineering and traditional image-processing techniques are still in a complementary position. Morphology, texture, and color-based techniques may be employed to assist deep models in data-poor scenarios or as good baselines [17]. Hybrid pipelines (traditional classifiers with CNN feature extractors) and hybrid CNN models showed good performance on multi-disease tasks and can prevent overfitting for medium-sized datasets [1].

The chapter also uncovered gaps: limited cross-regional datasets, under-sampled disease classes, and insufficient field-tested assessments of accuracy-versus-latency trade-offs. Experiments on picking-point detection and orchard-level systems show higher application potential but also indicate integration challenges for end-to-end solutions [11]. They directly inform our experimental setup: we will emphasize varied in-field data, compare high-capacity and small-footprint models, and evaluate deployability on resource-restricted devices but with support for interpretability for trust of users [14].

Chapter 3

Research Methodology

3.1 Methodology

The methodology determines the logical approach that is employed in developing the classification system. The images collected were subjected to background removal, resizing, and normalization in order to enhance uniformity. The improvement of diversity through data augmentation strategies (rotation, flipping, scaling, and brightness adjustment) also increased the capability of the model to generalize. Four models were used, including InceptionV3 and DenseNet201, MobileNetV2, and a custom CNN baseline. The CNN was trained on its own, whereas the fine-tuning of the pre-trained networks was done using transfer learning. Training was conducted using stratified splits, Adam optimization, learning rate scheduling, and early stopping. The reliability of the performance was tested using accuracy, precision, recall, F1-score, and confusion matrices.

3.1.1 Overview

It was done in stages to provide the research methodology with a very technical and practical approach. Image preprocessing was done as the first stage whereby the images of the obtained fields were processed to remove the background images, resized and normalized to have uniformity and reduction of noises. Data augmentation was used to increase variability by rotating, applying varying brightness levels, scaling, and flipping on the data so that the models could be trained to predict a wide variety of situations that are representative of real-world farming scenarios.

The modeling strategies are combined with the combined transfer learning and the baseline deep learning. They used three pre-trained models, InceptionV3, DenseNet201, and MobileNetV2, using the fact that they already have a feature extractor. CNN was trained on a different dataset to create a custom CNN and to have a baseline to compare the Snowball CNN. To obtain reliable results, data have been divided into training, validation, and test data sets with equal representation of all classes.

The Adam optimizer, batch size optimization, and early stopping strategies were used to optimize the model and curb overfitting. The assessment was carried out on class-specific and general performance measures, backed by confusion matrices. The last step was to prune and quantize the best model, resulting in a lightweight model, which can be deployed on mobile devices to use in the field in agricultural applications.

3.1.2 Proposed Methodology/ System Design

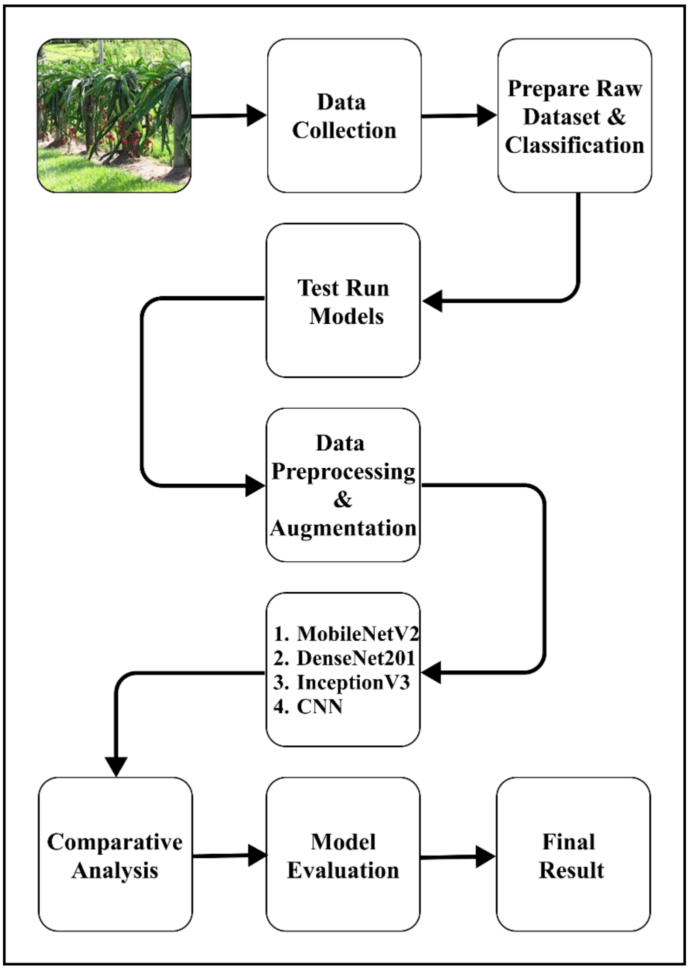


Figure 3.1: Methodology Diagram

3.2 Detailed Methodology and Design

The research design unites raw image processing with image acquisition and augmentation with complete deep learning models, such as InceptionV3, DenseNet201, MobileNetV2, and a home-made CNN. All models were systematically trained and tested in order to obtain accurate, reliable, and scalable disease classification of dragon fruits under a realistic farming environment.

1. **Raw Image Collection:**

The dragon fruit and leaf photos were captured in the natural farming condition directly using different lighting and background conditions to make the dataset diversified and captured healthy, diseased, and ripeness stages of the fruits to successfully train the model.

Dataset sample

Good Leaf:

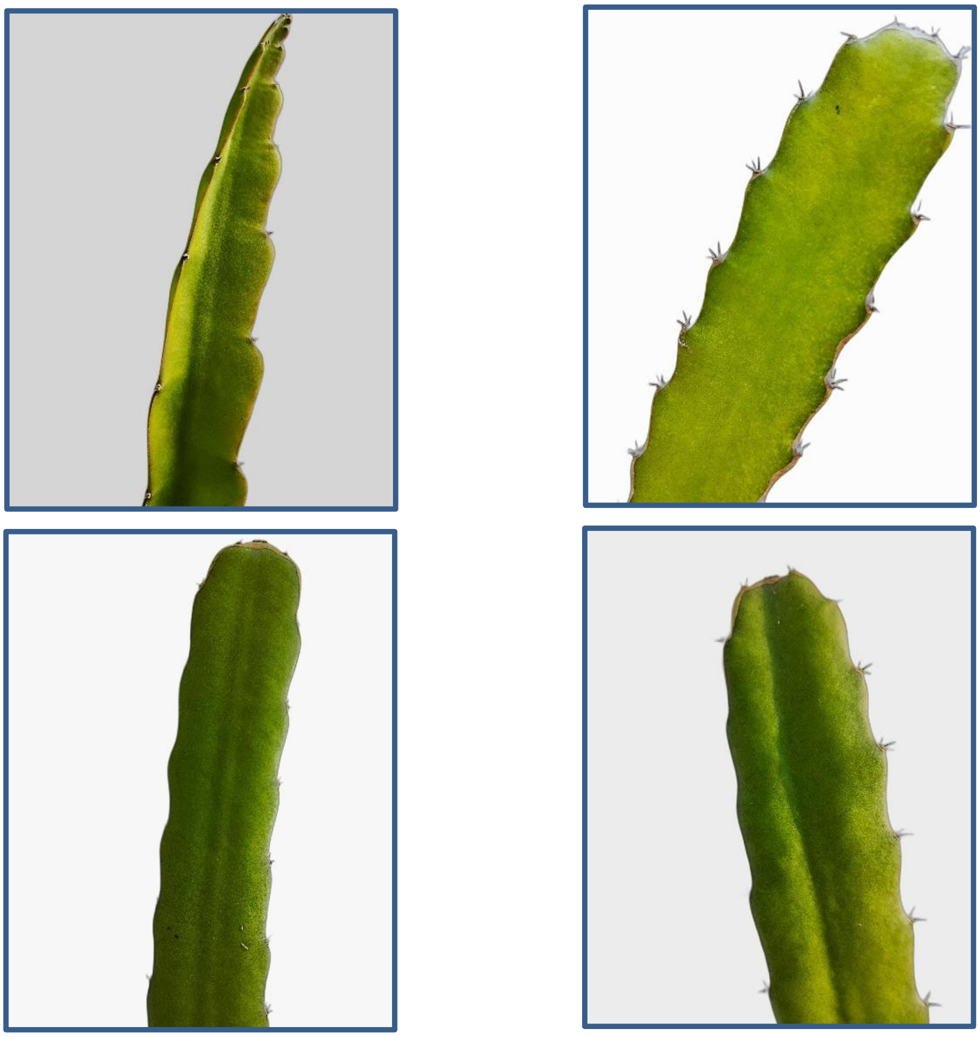


Figure 3.2: Sample of Good Leaf

The leaf of a healthy dragon fruit, of normal green hue, smooth, without any disease or insect marks.

Scale Insect:

Figure 3.3: Sample of Scale Insect

small insects that stick to leaves and stems consuming plant sap. On the surface they are seen as groups of white, brown or waxy bumps. Large infestations retard growth, diminish production and predispose plants to additional infections.

Stem Canker

Figure 3.4: Sample of Stem Canker

This is a fungus and it forms dark, sunken, or reddish-brown spots on the stems of the dragon fruit. With time, the infected areas fracture and exude leading to tissue degeneration. Otherwise, it can cause the plant to deteriorate quickly and become widespread.

Good Fruit:

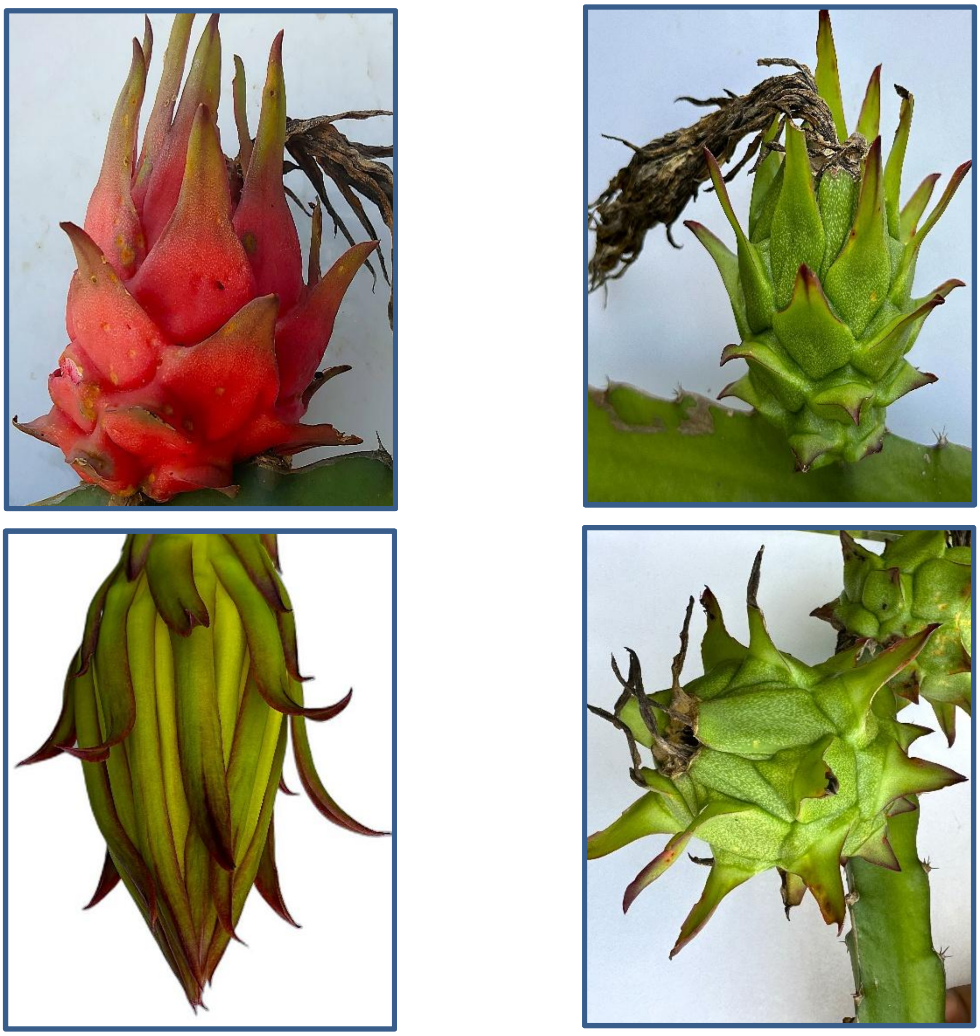


Figure 3.5: Sample of Good Fruit

Healthy, fresh dragon fruit with skin that is smooth, colorful and no traces of rot, blemishes and insect infestation.

Bad Fruit:

Figure 3.6: Sample of Bad Fruit

These sample pictures indicate the usefulness of the data set because there are multiple classes of healthy fruits, healthy leaves, stem canker, scale insect, and diseased fruits. They demonstrate how natural changes in color, texture, and environment impact an effective deep learning model and are crucial in the training of such a model to identify the disease.

3.2.1 InceptionV3

- **Overview:**
  InceptionV3 is a deep convolutional neural network, used to classify images, and utilizes inception modules which use several different kernel sizes at once to efficiently sample features at different spatial scales.

- **Architecture:**

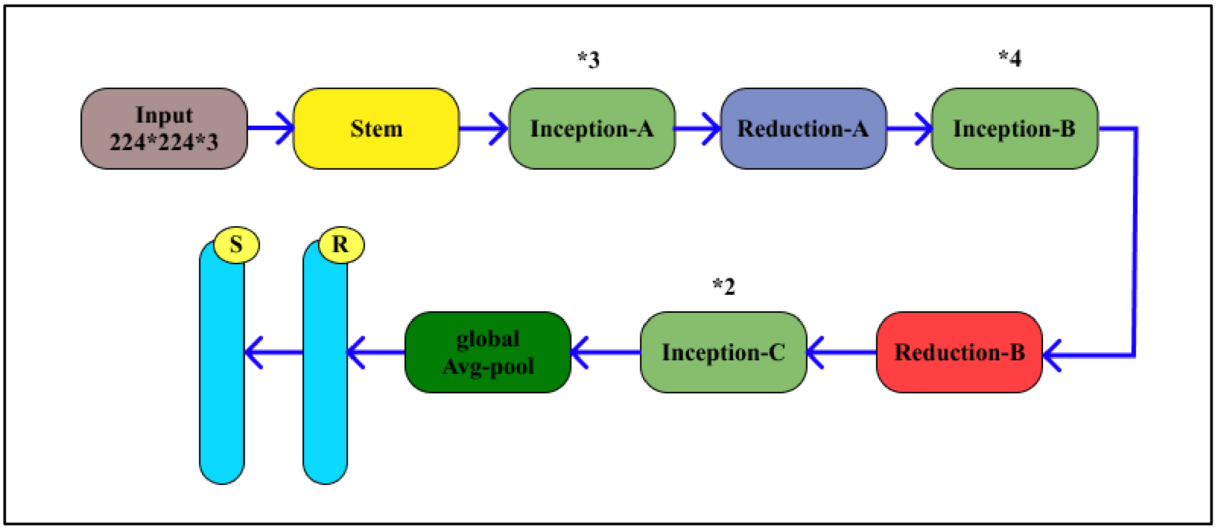


Figure 3.7: Architecture of InceptionV3

- **Key Features:**
  - Multi-scale feature partaking inception modules.
  - Additional classifiers to overcome the problem of vanishing gradient.
  - Quick computation using fewer parameters than other comparable models.

- **Working Process:**
  - The input images are scaled and processed by stacked convolutional and pooling layers.
  - Parallel convolutions extract the features in several receptive fields.
  - Richer representations can be formed with a concatenation of feature maps.
  - Complete thick layers categorize the image to different classes.

- **Suitability:**
  Most effective when dealing with complex image classification problems with very high accuracy and a high computational efficiency.

3.2.2 DenseNet201

- **Overview:**
  DenseNet201 adds dense connections between layers, with each layer taking the input of all the preceding layers, allowing reuse of features and improving gradient flow.

- **Architecture:**

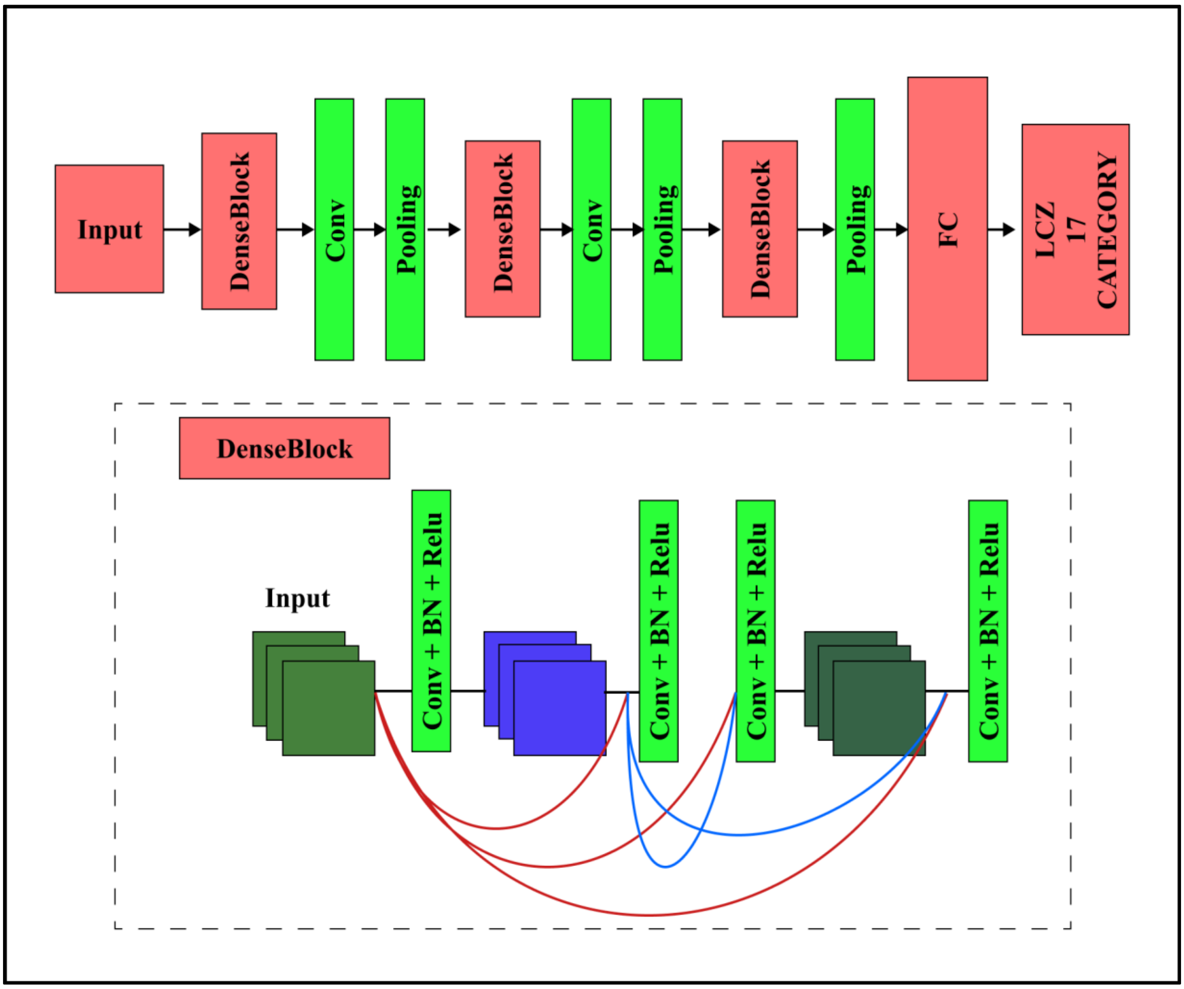


Figure 3.8: Architecture of DenseNer201

- **Key Features:**

  - Thick interconnection between layers.
  - Less vanishing gradient problems.
  - Less parameters which propagate highly on the features.

- **Working Process:**

  - Output images pass through convolution and pooling layers.
  - The output of each layer is passed to all the other layers.

- The feature reuse supports the representations.
- Fully connected layer last-level classification.

- **Suitability:**
  Applications that require precision, larger architectures, and complex applications the best option.

3.2.3 MobileNetV2

- **Overview:**
  MobileNetV2 is a lightweight deep neural network suitable for mobile and embedded systems, and it makes use of depthwise separable convolutions and residual inversion functions.

- **Architecture:**

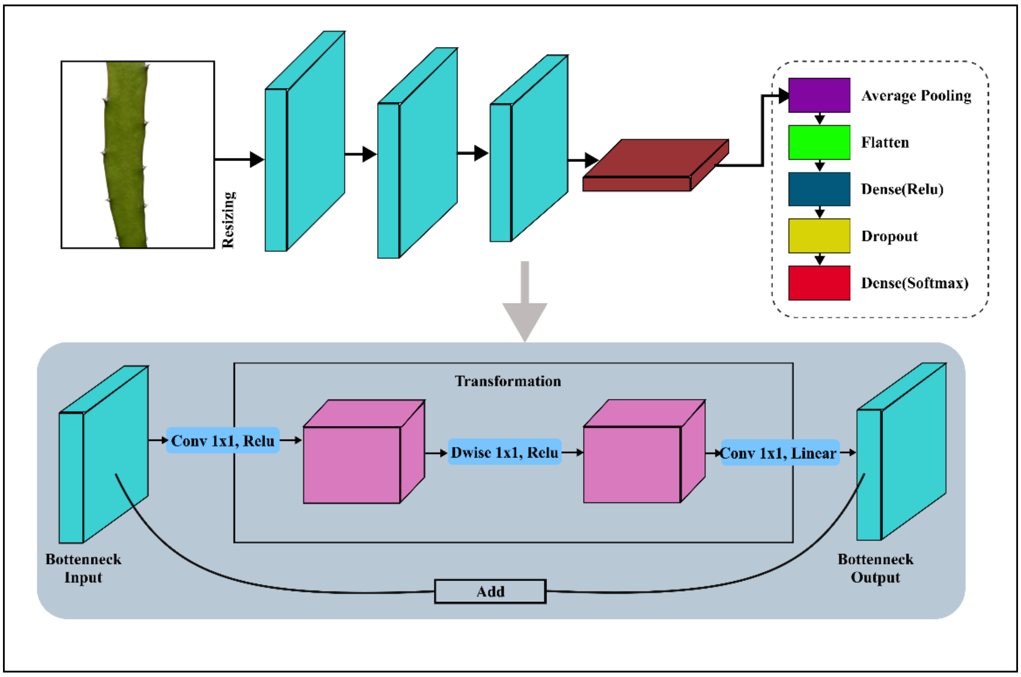


Figure 3.9: Architecture of MobileNetV2

- **Key Features:**
  - Depth wise separable convolutions are less computationally expensive.
  - Inverted bottle-necked lines.
  - Extremely high precision and considerably less memory usage.

- **Working Process:**
  - These input pictures are convolved and normalized in batch first.
  - Depth wise convolutions have proven useful for spatial feature detection.
  - Inverted blocks of the residues increase the flow of information.

- The final classification result is given by dense layers.

- **Suitability:**
  Very well adapted to real-time, resource-constrained applications such as mobile deployment in agricultural disease detection.

3.2.4 Custom CNN Model

- **Overview:**
  The dragon fruit disease classification was developed on a custom CNN whose architecture can be edited to allow the classification of new diseases.

- **Architecture:**

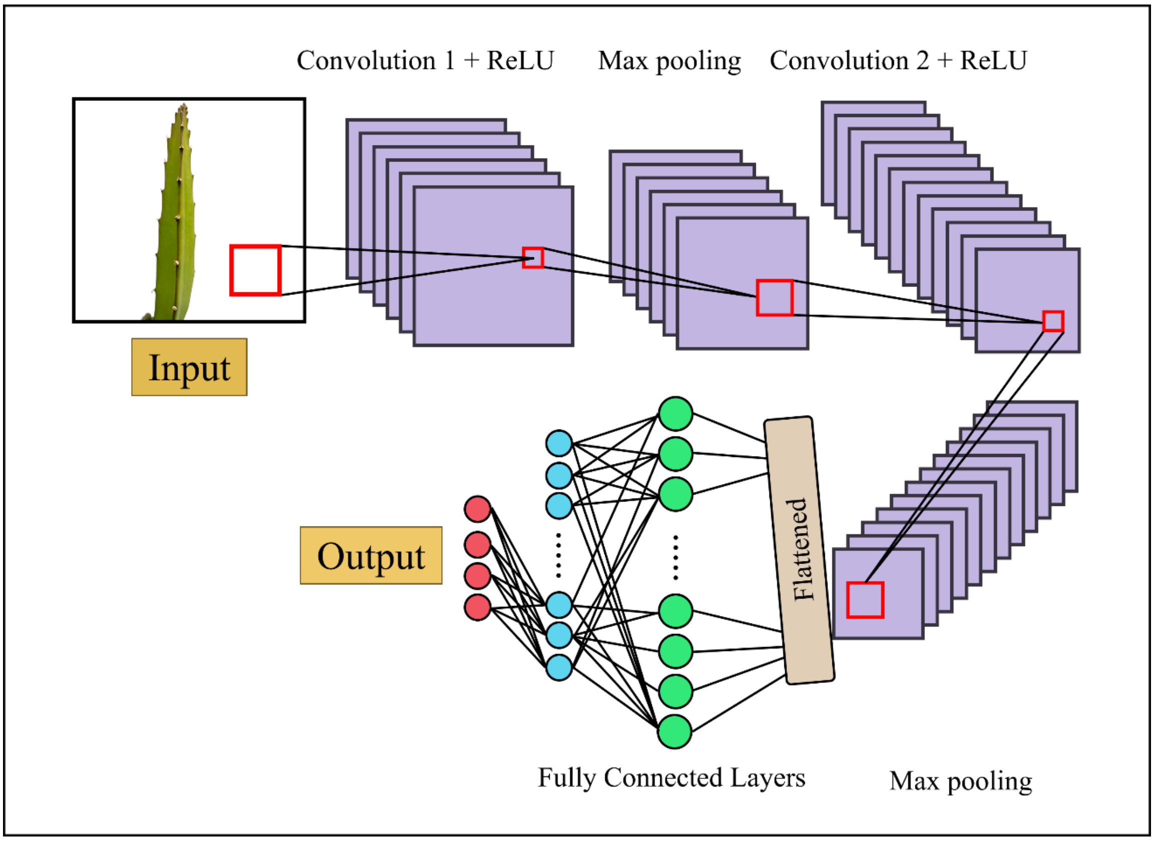


Figure 3.10: Architecture of Custom CNN

- **Key Features:**
  - specialized especially to dataset properties.
  - Pooling and convolutional layers can be edited.
  - Tried as a learning model transfer point.

- **Working Process:**
  - When convolutional and pooling are performed on images, they are used to pull out features.

- Non-linearity is offered in activation functions.
- Flattened features go through fully connected layers.
- The output layer makes the final classification of types of diseases.

- **Suitability:**
  Best to construct special-purpose models and analyze gains realized by state-of-the-art transfer learning architectures.

3.3 Project Plan

Table 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	Prepared dataset
Phase 2	4 weeks	Model selection, training, and evaluation	Week 8–11	Trained deep learning models
	3 weeks	System development, UI design, and testing	Week 12–14	Working prototype
	2 weeks	Final report writing and presentation preparation	Week 15–16	Final report, presentation slides

3.4 Task Allocation

This table depicts the timeline of the principal activities in each period of the project, from week 12 to week 48.

Table 3.2: Project Plan.

Phase	Activity	Tasks (Single Researcher)
Phase 1	Topic Selection	Explore possible research areas, shortlist relevant topics, and finalize the research title.
	Research Planning	Draft the research plan, refine objectives, and finalize methodology outline.
	Background Study	Study deep learning models and review dragon fruit diseases; summarize key findings.
	Literature Review	Collect and study existing works on machine learning and agricultural studies; write a literature review.
	Gap Analysis	Identify research gaps in current approaches; propose the need for an integrated solution.
	Proposed Solution	Draft the methodology, refine the approach for both deep learning and agriculture aspects, and finalize the proposal.
	Data Collection Planning	Design a data collection plan, including the number of images, sources, and conditions.
	Data Collection	Capture images, preprocess, and ensure dataset quality.
Phase 2	Model Selection	Research candidate deep learning models, evaluate feasibility, and finalize model choices.
	Preprocessing	Apply preprocessing techniques (resizing, normalization, augmentation).
	Model Training	Train models, monitor the training process, and handle debugging if errors occur.
	Result Evaluation	Evaluate performance metrics, analyze confusion matrix, and summarize results.
	Model Comparison	Compare different models' performance and select the best-performing one.
	Thesis Reporting	Write technical sections, introduction, and conclusion; edit and finalize the report.
	Presentation Prep	Design presentation slides and prepare for

		defense/presentation.

3.5 Summary

This chapter presents the methodology used to develop a computer vision system for classifying dragon fruit diseases. The approach commenced with the systematic acquisition of in-field images of healthy and diseased plant organs. The raw images were preprocessed and augmented to increase data quality, diversity, and insensitivity to changes in environmental factors such as illumination, orientation, and background noise. Methodological design employed a step-by-step pipeline to ensure replicability and reliability.

To address the challenge of classification, four models were employed: InceptionV3, DenseNet201, MobileNetV2, and a custom CNN. These models were selected for some benefits, ranging from the good multi-scale feature extraction of InceptionV3 to the improved gradient flow and feature reuse of DenseNet201, low-resource device efficiency of MobileNetV2, and the range of a custom CNN baseline. Training included application of optimization methods such as Adam optimizer, batch-size optimization, and early stopping, whereas evaluation measures were accuracy, precision, recall, F1-score, and confusion matrices for detailed performance analysis.

Finally, deployment was addressed, wherein pruning and quantization were applied to optimize the top-performing model for real-time deployment. Overall, this approach combines technical expertise with real-world usability so the resultant system is efficient, accurate, and feasible for real-world agricultural use.

Chapter 4

Implementation and Results

4.1 Environment Setup

The computer system comprised of a laptop powered by the Intel(r) Coretm i5-1135G7 (2.40GHz), Intel(r) Iris(r) Xe Graphics (128 MB), 8GB RAM and 512GB SSD. To collect images, iPhone 13 (12MP), Google Pixel 7 (50MP), and Redmi Note 12 (50MP) cameras were used to take image samples of dragon fruit and leaf samples under the natural orchard setting with different lighting and a background of white paper to make the sample visible.

The environment was a windows 11 (64-bit) version of Python 3.9 running with Google Colab Pro+ to train using a GPU and Google Drive to store data and checkpoints. The major libraries used were Pandas and NumPy to manage data, Matplotlib and Seaborn to visualize it, as well as inbuilt tools to use in monitoring performance.

In interaction and analysis, Telegram was used to communicate, and Google Drive to share results, and to analyze them used disjointed matrices, accuracy, precision, recall, F1-score, and loss/accuracy curve visualisation to follow model behaviour.

4.2 Comparative Analysis

Comparative analysis contrasts existing research models with our deployed structures. Through comparison of accuracy, strengths, and drawbacks of different studies, we establish performance trends, practical shortcomings, and verify the competitiveness of the proposed system with respect to existing benchmarks.

Table 4.1: Comparative Analysis.

Model	Accuracy (%)	Average Precision (%)	Average Recall (%)	Comments
InceptionV3	95.05	95.03	95.02	High accuracy; heavier than MobileNetV2.
DenseNet201	99.63	99.62	99.63	Best accuracy; high computational cost.
MobileNetV2	96.75	96.74	96.73	Good accuracy; efficient for mobile use.

Custom CNN	86.14	86.26	86.27	Lightweight; lowest performance.

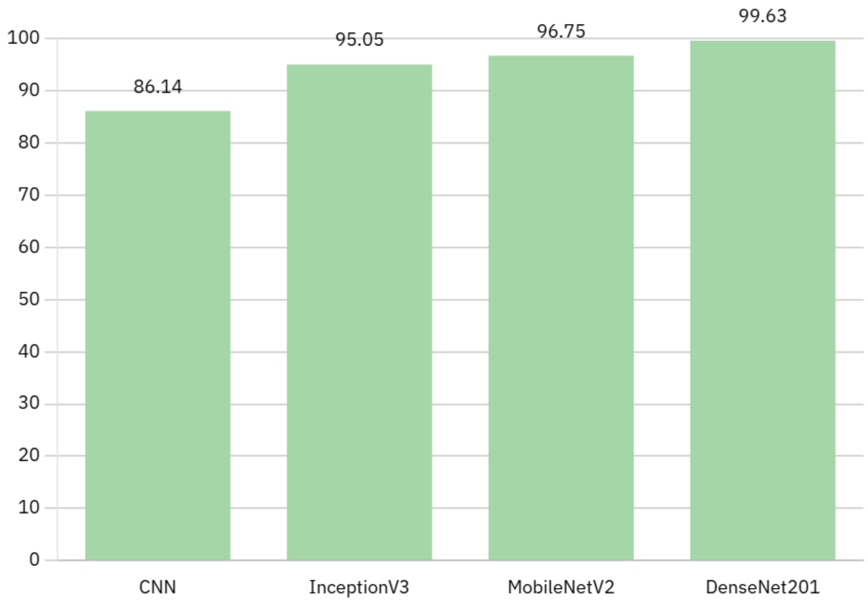


Figure 4.1: Model Accuracy Comparison

Comparative Analysis between Our Best Model (DenseNet201) and Other Models:

DenseNet201 achieved an improved accuracy of 99.63%, outperforming InceptionV3, Custom CNN, and MobileNetV2 through the use of dense connectivity, efficient feature reuse, and reduced vanishing gradients, ensuring strong tea leaf disease classification.

Table 4.2: Model Comparison

Model	Research Study	Accuracy (%)	Key Strengths	Limitations
Hybrid CNN-SVM	Mehta et al. [1]	98.4	Strong multi-class classification; effective on medium datasets	Requires hybrid training; limited scalability
GSE-YOLO	Qiu et al. [2]	85.2 (mAP50 90.9)	Lightweight; real-time detection; reduced false/missed detections	Struggles with complex environments; limited to ripeness classification

MIRNet_ECA	Zhang et al. [5]	95.9	Compact model (1.61 MB); suitable for mobile use	Specialized for ripeness; limited disease testing
YOLOv8-G	Peng et al. [16]	96+	Accurate stem disease detection; real-time performance	Focused only on the stem; generalization is limited
ResNet (Transfer Learning)	Hermawan & Nugroho [20]	94+	Reliable transfer learning; robust feature extraction	Computationally expensive; requires high resources
DIPDEEP	Yusamran & Hiransakolwong [17]	93+	Accurate Thai dragon fruit classification	Regional dataset; less generalizable
DenseNet201 (Proposed)	Our Study	99.63	Highest accuracy; excellent feature reuse; robust classification across five classes	Computationally heavier than lightweight models

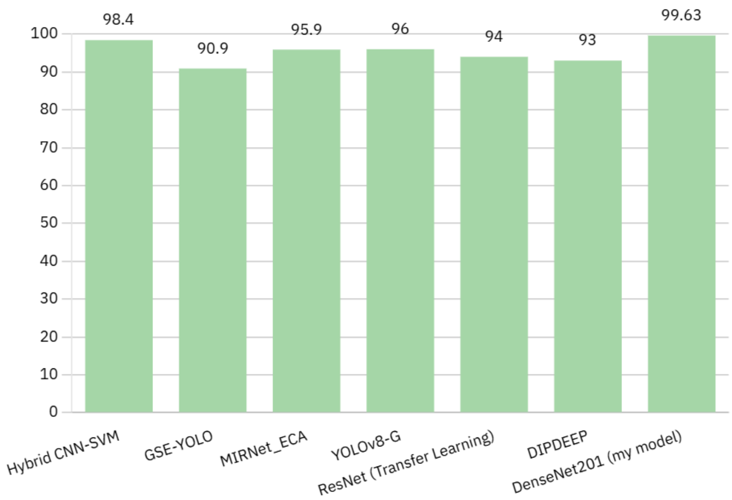


Figure 4.2: Comparison of Model Accuracy-2

4.3 Results and Discussion

This study demonstrated that deep learning models can identify and classify dragon fruit diseases into five distinct categories. Four models were used in the study: DenseNet201, InceptionV3, MobileNetV2, and a custom CNN. They were trained and evaluated based on performance indicators such as precision, recall, F1-score, and overall accuracy. The most successful was denseNet201, which achieved 99.63% accuracy, F1-score of 0.9963 on average, proving its ability to identify and reuse fine-grained features to generate robust classification.

InceptionV3 also performed well, yielding a 95.05% accuracy and balanced precision-recall tradeoff. This indicates the relevance of inception modules used to handle spatial features at different scales. MobileNetV2 light is achieving a promising 96.75 percent accuracy, which can be deployed to mobile and edge devices, where resource consumption is a primary consideration.

The traditional CNN that achieved a relatively poor accuracy of 86.14, yet provided useful baseline performance, demonstrated the challenge in training models developed over the underlying basic neural network with relatively large datasets. However, there were some limitations of the CNN, but it gave information on the complexity of the dataset and the advantages of transfer learning as far as enhancement of classification performance is concerned.

Generally, the performance comparison shows that the lightweight and custom models can be implemented in a limited environment, whereas the DenseNet201 can be trusted to yield the most accurate and robust performance in cases where high accuracy and high robustness are the priorities.

DenseNet201

DenseNet201 was the highest performing model with an accuracy of 99.63% and an average F1-score of 0.9963. Its high degree of connectivity allowed it to reuse features and enhanced gradient flow, resulting in very high reliability in classification over all classes.

Confusion Matrix:

Table 4.3: DenseNet201 Confusion Matrix

Class	**Precision**	**Recall**	**F1 Score**
Bad Fruit	0.9922	0.9961	0.9941
Good Fruit	0.9963	0.9926	0.9944
Good Leaf	1.0000	1.0000	1.0000
Scale Insect	1.0000	0.9930	0.9965
Stem Canker	0.9929	1.0000	0.9964
Average	0.9963	0.9963	0.9963

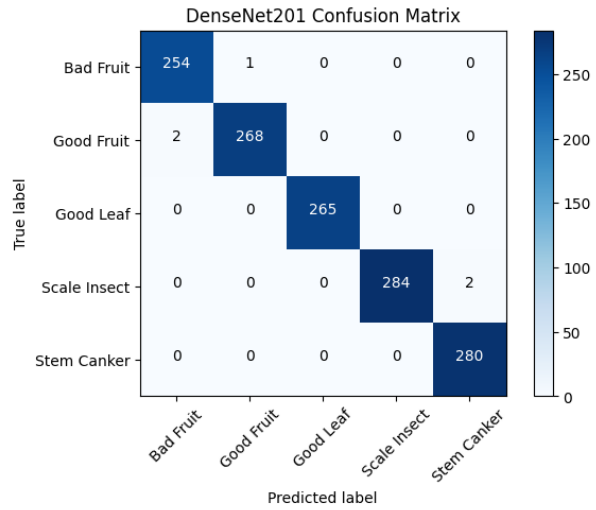


Figure 4.3: DenseNet201 Confusion Matrix

The DenseNet201 model has an impressive classification performance as indicated by the confusion matrix of all five classes. The majority of the predictions are on the diagonal which means they are highly accurate. There are few misclassifications, and some instances of Bad Fruit being given as Good Fruit, and infrequent mix-ups of Scale Insect and Stem Canker. This is indicating that DenseNet201 is able to differentiate between quality of fruits, the health status of leaves and disease among others with insignificant accuracy errors.

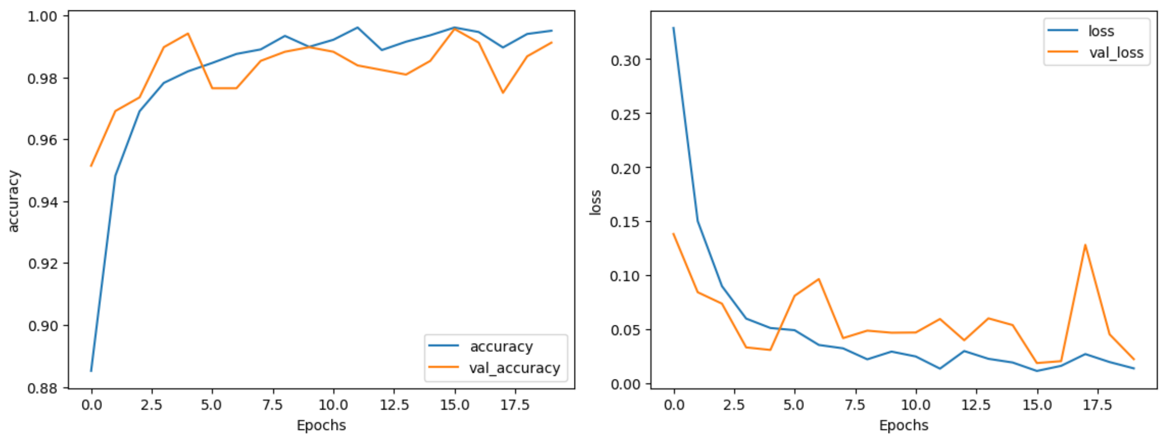


Figure 4.4: DenseNet201 Training and Validation Plot

Inception V3

InceptionV3 has a precision balance and recall equal to 95.05% accuracy, which is quite effective to capture multi scale features using inception modules. It showed robust classification accuracy but less effective when compared to DenseNet201 to identify diseases on a fine-scale.

Confusion Matrix:

Table 4.4: Inception V3 Confusion Matrix

Class	**Precision**	**Recall**	**F1 Score**
Bad Fruit	0.9176	0.9176	0.9176
Good Fruit	0.9257	0.9222	0.9239
Good Leaf	0.9925	0.9962	0.9944
Scale Insect	0.9485	0.9650	0.9567
Stem Canker	0.9673	0.9500	0.9586
Average	0.9503	0.9502	0.9502

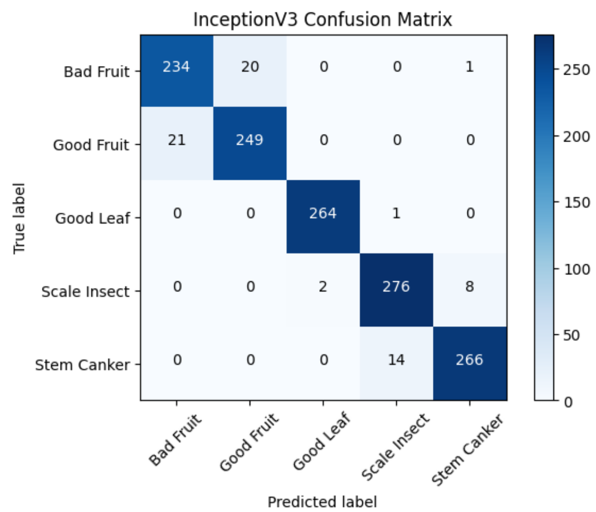


Figure 4.5: InceptionV3 Confusion Matrix

The confusion of InceptionV3 demonstrates a good overall classification with a little bit higher misclassification rates than with DenseNet201. There are significant mistakes both between Bad Fruit and Good Fruit and a bit of mixing between Scale Insect and Stem Canker. Regardless of these, most samples are rightly identified, which proves the effectiveness of InceptionV3 but shows that it could use the improvement of the ability to differentiate visually similar classes.

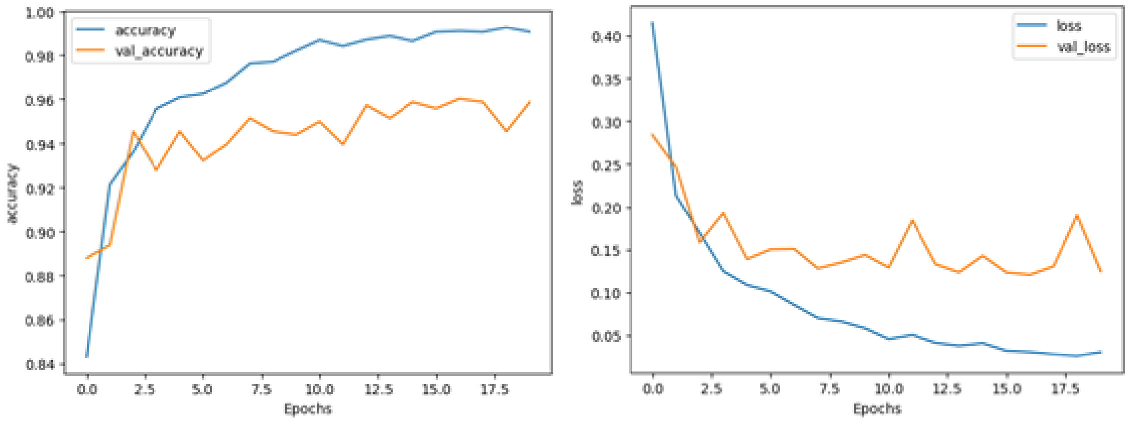


Figure 4.6: InceptionV3 Training and Validation Plot

MobileNetV2

MobileNetV2 achieved 96.75% accuracy, which led to its applicability in real-time in the mobile devices. Its depthwise separable convolutions were efficient, but slightly worse than DenseNet201 in total classification strength.

Confusion Matrix:

Table 4.5: MobileNetV2 Confusion Matrix

Class	**Precision**	**Recall**	**F1 Score**
Bad Fruit	0.8982	0.9686	0.9321
Good Fruit	0.9680	0.8963	0.9308
Good Leaf	0.9888	1.0000	0.9944
Scale Insect	1.0000	0.9720	0.9858
Stem Canker	0.9825	1.0000	0.9912
Average	0.9675	0.9674	0.9669

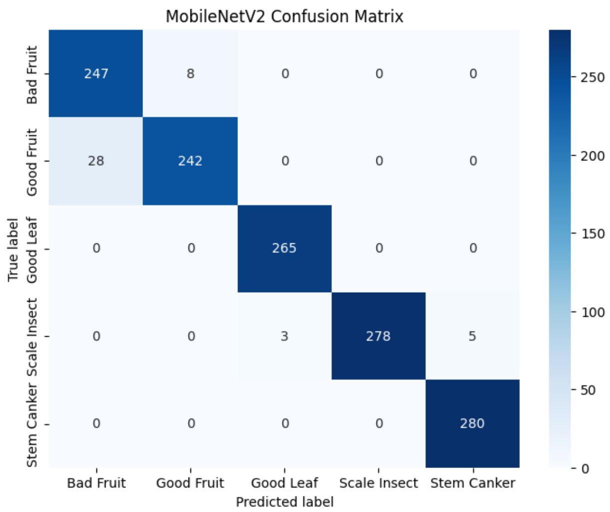


Figure 4.7: MobileNetV2 Confusion Matrix

The MobileNetV2 confusion matrix shows high classification accuracy in all classes with the majority of the predictions falling along the diagonal. Small confusions are seen in between Bad Fruit and Good Fruit, and some few cases where Scale Insect is mixed with Stem Canker. Altogether, it can be said that MobileNetV2 can be considered to be reliable in terms of performance, however, its ability to distinguish fruit quality has some slight shortcomings in comparison to leaf and disease classes.

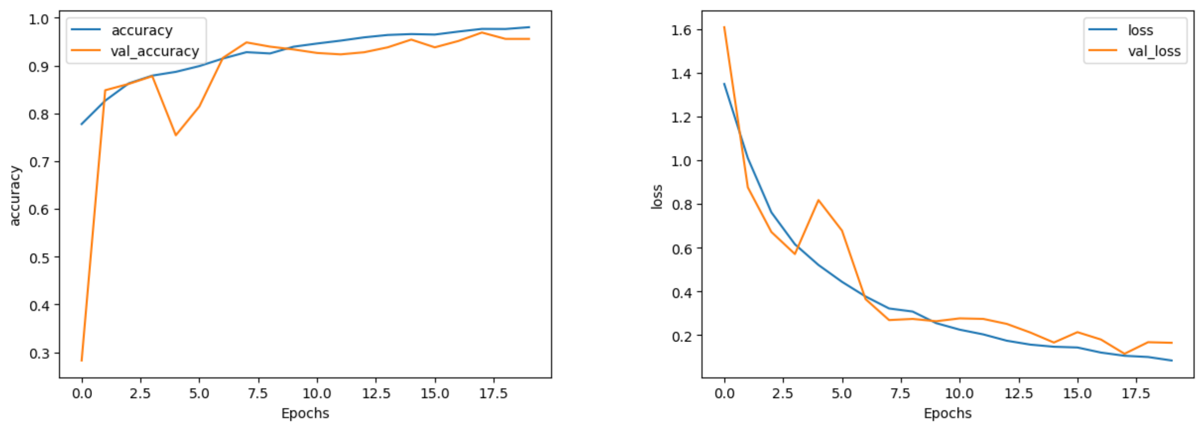


Figure 4.8: MobileNetV2 Training and Validation Plot

Custom CNN

The default CNN had a 86.14% accuracy, which can be used as a baseline. Although it was less accurate, it demonstrated that the dataset is complex and justified transfer learning to improve it.

Confusion Matrix:

Table 4.6: Custom CNN Confusion Matrix

Class	Precision	Recall	F1 Score
Bad Fruit	0.8650	0.9294	0.8960
Good Fruit	0.8477	0.8037	0.8251
Good Leaf	0.9336	0.9019	0.9175
Scale Insect	0.8511	0.8392	0.8451
Stem Canker	0.8160	0.8393	0.8275
Average	0.8627	0.8627	0.8622

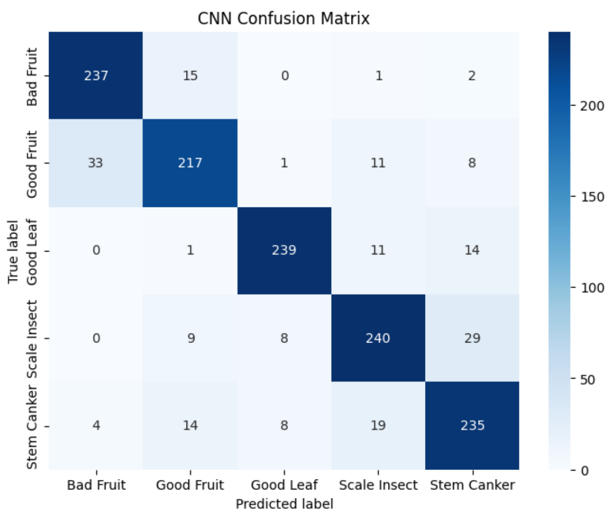
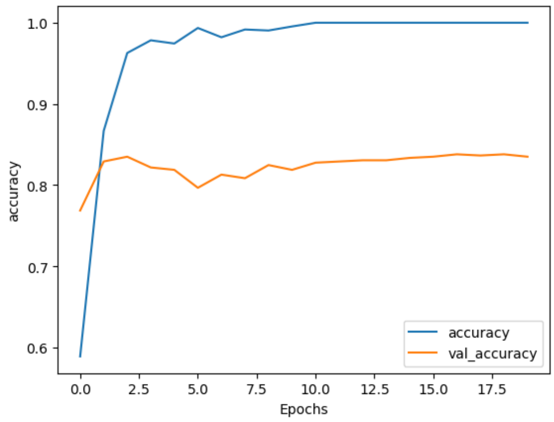


Figure 4.9 Custom CNN Confusion Matrix

The CNN model confusion matrix demonstrates a good baseline performance: most samples fall in their correct classification. All five categories are highly recognized in the model albeit being misclassified significantly. In particular, there are a large amount of incidences of Good Fruit being labelled as Bad Fruit and Scale Insect and Stem Canker exhibit mutual confusion with samples of each group incurring misclassification as the other. These mistakes illustrate the weakness of the CNN with regard to stronger architectures, but its capability to perform the correct classification of most of the examples illustrates its usefulness as a simpler benchmark model.



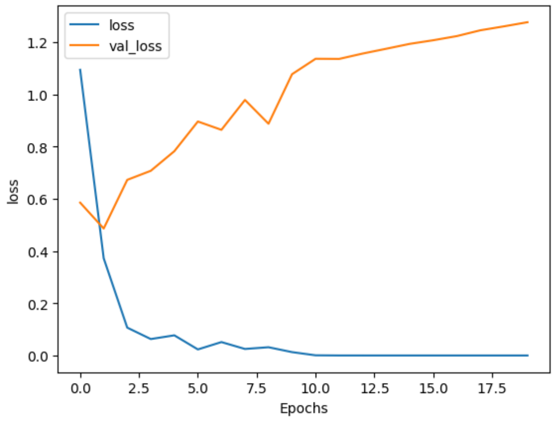


Figure 4.10: Custom CNN Training and Validation Plot

4.4 Summary

This chapter demonstrated performance evaluations of four deep neural models. DenseNet201 was the most accurate, yet MobileNetV2 offered superior light-weight deployment potential. Results indicate efficiency-accuracy trade-offs that guide future real-world use cases in agricultural disease detection.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

The system is compliant with current software, hardware, and communications practices to ensure reliability, interoperability, maintainability, and safe deployment in field and low-resource environments.

5.1.1 Software Standards

- Reusable ML pipeline with Git version control, semantic versioning, unit testing, and experiment tracking with hardened random seeds and saved model cards.
- Coding standards and quality checks through PEP 8, static analysis, automated CI, and documentation of datasets using datasheets for datasets.

5.1.2 Hardware Standards

- Device-targets-for-deployment meet consumer electronics and field accessory minimum EMC expectations as well as device safety.
- Image capture patterns follow common illumination and calibration procedures of camera sensors to ensure traceability.
- Power and thermal constraints are adhered to to maintain performance in smartphones and low-power devices.

5.1.3 Communication Standards

In order to promote smooth cooperation and transparency, the following communication guidelines were developed:

1. Individual Workflow:

a. Keep a research journal with day-to-day goals, actions and results.
b. Frequent commit messages with descriptive contents, and weekly tagged releases.

2. Supervisor Communication:

a. Weekly brief with metrics, risks and next actions; share artifacts prior to meetings.

b. Emergency escalation procedures when there is a problem with the dataset, performance regressions or ethical issues.

3. **External Experts:**
   a. Use agricultural officer / plant pathologists to validate labels and field limitations.
   b. Write brief memos with context, precise questions and time frames.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The system will allow detecting disease in the dragon fruit early on, preventing crop losses and income volatility among smallholders. More rapid diagnosis reduces anxiety, reduces time to intervention, and helps make safer decisions regarding pesticides. Smartphone enabled inference enhances accessibility in distant areas. Field knowledge also increases bargaining power with buyers and farmer confidence and accuracy of planning, which enhances long-term resilience and livelihoods.

5.2.2 Impact on Society & Environment

Impact on Society:

The enhanced diagnostic efficacy facilitates evidence-based cultivation, which strengthens productivity and value chain stabilization in the region. Local data and models promote capacity building in higher educational institutions and agro-technological startups. The solution will ease the burden on the few professionals, so that they can act on time in case of an outbreak. Clear model reporting and interfaces that are easy to use increase trust, digital literacy, and adoption among producer cooperatives and extension services.

Impact on Environment:

Specific solutions decrease blanket spraying, and thus chemical runoff, soil erosion, and damage to non-target species. Prior treatment periods reduce diseases transmission, reducing wastage and losses after harvesting. Effective scouting minimizes fuel consumption through field tours. In the long term, accurate management benefits biodiversity and healthier agro-ecosystems and in tandem with sustainable input utilization and climate-shrewd methods of agriculture.

5.2.3 Ethical Aspects

Data Collection: Obtain consent, anonymize where requested to, document collection procedures and mark provenance.

Bias in Algorithms: Monitor class imbalance, domain shift, and lighting variance to ensure that there are no systematic errors.

Transparency: Publicize model cards, recognized limitations, and test environments for reproducibility.

Access and Equity: Provide light models and open documentation to benefit low-resource farmers.

5.2.4 Sustainability Plan

Scalability: Modular pipeline can accommodate new classes and regions without redesign.

Cost Efficiency: Appreciate effective backbones and low-cost or no-cost tooling.

Community Engagement: Pilot co-design with farmers and mechanisms for feedback.

Stakeholder Collaboration: Engage extension services, cooperatives, and agri-offices for adoption.

5.3 Project Management and Financial Analysis

Table: 5.1 Financial Analysis

Activity	**Budget (BDT)**
High-Performance Workstation	2,500
Google Colab Pro	2,500
Field Travel and Logistics	10,000
Agricultural Officer Consultation	1,000
Total	16,000

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.2: 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: Task integrates image processing, deep learning, horticultural pathology, and field data capture. It requires knowledge of CNN transfer learning, camera capture limitations, and agronomic disease symptoms to map pixel characteristics to actionable diagnosis.

Justification of EP2 - Range of Conflicting Requirements: Range of Competing Demands: The design must find a balance between model size, latency, and precision and maintain interpretability and lighting and occlusion insensitivity. It must also balance farmer ease-of-use, smartphone capability, and regional practice and cultivar difference.

Justification of EP3 - Depth of Analysis: The pipeline consists of hyperparameter optimization, backbone ablation, class-specific stratified evaluation and confusion matrix-based error forensics. Trade-offs are measured along metrics to choose architectures that can be deployed at the edge.

EP6 - Stakeholder Involvement Extent Rationale: The labeling and assessment are based on agricultural officer and grower inputs. Feedback drives thresholds, interface text, and actionable recommendations, and technical validity is matched against real-world workflows and risk tolerance.

Mapping with Knowledge Profile for EP1

Table 5.3: Mapping with knowledge Profile.

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

Justification of K3 - Engineering Fundamentals: CNN training, loss behavior, and regularization are based on the principles of linear algebra, probability, and optimization. Augmentation, denoising, and illumination change resistance are informed by signal processing concepts when imaging in the field.

Justification of K4 - Specialist Knowledge: Class design and labeling have support provided by specialised knowledge of both plant pathology and image-based symptomatology. Transfer learning, feature hierarchies and deployment toolchain knowledge allow effective farming image adaptation.

Justification of K8 - Research Literature: Model variants, additions, and analysis are based on existing work on agricultural vision, lightweight architectures, and explainability. Previous work informs dataset practices, baseline choice and benchmarking to make credible comparisons.

5.4.2 Engineering Activities

Table 5.4: Mapping with complex engineering activities.

EA1 Range of re-sources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓		✓	✓	

Justification for EA1 - Diversity of Resources: The project combines field imagery, phones, cloud computing, and local workstations with open-source libraries and labeling software. It aligns human skills between growers and officers with the data, training, and validation systems that are automated.

Justification for EA3-Innovation: The system is a combination of optimized transfers learning with practice augmentations and field-tested classes. With a focus on deployment-ready lightweight backbones and focus on real-time, farmer-centric diagnosis, the use of costly hardware is not necessary.

Justification for EA4: Decisions influence the use of chemicals, work safety, and health of the ecosystem. Reliable detection saves undue sprays and losses. Developing ethical data management and an open reporting system is a way of protecting communities and enabling sustainable production activities.

5.5 Summary

This chapter recorded compliance with standards, lean communication to a solo researcher and quantified influences on livelihoods and ecosystems. It outlined ethics, sustainability, finances and formal mappings of complex problem requirements and engineering practices on a responsible basis to field deployment and long-term scalability.

Chapter 6
Conclusion

6.1 Summary

In this study, a deep learning system using computer vision was designed to classify diseases in dragon fruit under 5 categories, including good leaf, good fruit, stem canker, scale insect, and bad fruit. The models implemented and evaluated by their accuracy, precision, recall, and F1-score were four models: denseNet201, InceptionV3, MobileNetV2, and a custom CNN. The best results were obtained by DenseNet201, with accuracy of 99.63, the average precision and recall of 99.62 and 99.63 respectively, and its effectiveness in feature selection and disease classification. MobileNetV2 was very good with an accuracy of 96.75 and is lightweight and much more appropriate to run on mobile. InceptionV3 model has been carefully tuned to be accurate and recalling with a fantastic accuracy of 95.05%. The custom CNN, which is relatively weaker at 86.14% accuracy, was a useful performance benchmarking tool. The research carried out during development adhered to software, hardware and communication standards and was attentive to the issues of sustainability and ethics. This research paper illustrates the paradigm change of AI in precision farming by integrating deep learning with agricultural production to help achieve sustainable production, minimize chemical reliance, and guarantee increased production.

6.2 Limitation

Regardless of whether or not this research had rather promising outcomes, it still had several limitations. The information was rather small and local, and was collected under special circumstances that limits the extrapolation of this data to a large-scale farm environment. Although variability in illumination, seasonal effects and orientation of the vegetation are not well represented even though augmentation strategies were used. DenseNet201 is highly precise, yet computationally intensive, and real-time mobile deployment is impossible without optimization. The price of high level cloud-provided GPUs was extremely minimal, which deterred testing and slackened the procedure of simultaneously enhancing. Manual labeling also had the likelihood of human bias that could affect ground truth reliability and hence model accuracy. System is limited in the number of diseases and health classifications, and thus is less useful in diagnosing more general plant health issues, such as nutrient deficiencies or pest infestations. Besides this, full field validation across a range of conditions was not possible within the time constraints of the project due to limitations on resources. These limitations will have to be surmounted to achieve higher levels of resilience, greater adaptability and eventual success in field-based agricultural contexts.

6.3 Future Work

Future studies will be geared towards enhancing scalability, flexibility and field preparedness of the proposed system. To increase the generalizability and strength, a priority is to expand the dataset with photos obtained in various regions, seasons, and environmental conditions. DenseNet201 will be compressed with advanced optimization methods like pruning, quantization, and knowledge distillation so that high accuracy is not sacrificed and it can be deployed to smartphones and edge devices in real-time. It should also be expanded to cover other types of diseases, different levels of infection and abiotic stresses so as to equip the farmer with a comprehensive diagnostic tool. Integration with IoT devices and smart sensors like weather stations and soil measuring equipment will enable multimodal analysis to proactively predict diseases and intervene early. In terms of usability, the creation of a mobile application that is farmer-friendly, offline, and multilingual will improve accessibility in rural settings. Cooperation with farming associations and cooperative agricultural clubs will be mandatory in conducting extensive field-testing and implementation. The system will be refined through feedback loops and continuous improvement with end-users to a stable, cost-effective and sustainable solution to modern agriculture.

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