# DRAGON FRUIT MATURITY GRADING USING DEEP LEARNING MODEL

**A MAJOR PROJECT REPORT**

*Submitted by*

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*in partial fulfillment for the award of the degree*

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**BONAFIDE CERTIFICATE**

Certified that this Major project report entitled **"DRAGON FRUIT MATURITY GRADING USING DEEP LEARNING MODEL"** is the bonafide work of **"Y.ASHOK(21UEEA0139), K.ANKEETH (21UEEA0060) and V.SATHWIK(21UEEA0231)"** who carried out the project work under my supervision.

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## ABSTRACT

Maturity grading of dragon fruit is a key process to ensure fruit quality and readiness for market. Manual observations, which underpin traditional processes, are labor intensive, time consuming, and inconsistent. This paper presents a methodology based on deep learning to classify maturity of dragon fruit. A dataset of images of dragon fruit which was used to train a convolutional neural network (CNN) model to classify the images into mature, immature, and defective fruit. The proposed methodology increased the precision of accurately grading the fruit and decreased human intervention in the grading process. The tropical fruit known as dragon fruit, or pitaya, comes in a variety of forms, including red-fleshed and white-fleshed types. In addition to its unique look, it may have several health benefits. Among these are its profusion of nutrients and antioxidants, which support healthy heart, bones, and skin, help regulate blood sugar, and help maintain a strong immune system. As a result, developing countries like Bangladesh are benefiting economically from the global demand for dragon fruit, which emphasises the urgent need for an automated system that can determine the best time to harvest and distinguish between fresh and faulty fruits to guarantee quality. This paper presents a comprehensive collection of high-resolution dragon fruits in order to achieve this goal because efficient detection by A significant amount of data is required for machine learning models. With the invaluable help of domain experts, the dataset was meticulously collected over the course of four months from three different locations in Bangladesh. Potential uses of the dataset include robotic harvesting, quality assessment, and packaging systems, which would ultimately increase the efficiency of dragon fruit production processes. Researchers who are interested in dragon fruit may find the dataset to be a useful resource.

## LIST OF FIGURES

## LIST OF ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| **CNN** | Convolutional Neural Network |
| **UI** | User Interface |
| **API** | Application Programming Interface |
| **UAT** | User Acceptance Testing |
| **CNN** | Convolutional Neural Network |
| **GPU** | Graphics Processing Unit |
| **DL** | Deep Learning |
| **FCL** | Fully Connected Layer |
| **GUI** | Graphical User Interface |

# CHAPTER 1

# INTRODUCTION

## 1.1 Introduction

The ripeness of dragon fruit greatly impacts fruit quality and subsequently market value. The quality of fruit, logistics within the supply chain, and consumer preferences all rely on accurate and efficient grading of the fruit's ripeness. Traditionally, ripeness has been graded by the naked eye based on external characteristics, such as size, texture, and coloration. Nevertheless, this is a time-consuming and subjective activity that is subject to human error .

Deep learning provides a strong method for classifying and assessing the grade of fruit. It is especially suitable for the classification of dragon fruit and particularly convolutional neural networks (CNNs) – a common and powerful type of deep learning algorithm for image classification. These models can detect complex patterns and features in images, making them ideally suited to detect varying stages of ripeness of dragon fruit.

Gathering and preprocessing image datasets, training deep neural networks on labeled samples, and deploying the learned models for real-time are the steps involved in implementing deep learning for dragon fruit maturity assessment.Fruit cat- egorization has been investigated using a variety of architec- tures, including ResNet, VGG, and MobileNet, with encour- aging outcomes in terms of accuracy and efficiency.With an emphasis on various approaches, dataset needs, and performance evaluation measures, this study attempts to investigate the use of deep learning techniques for dragon fruit maturity grading.


Figure 1.1: Dataset of Maturity Levels

Fruits are categorised using maturity grading according to their ripeness stage in order to guarantee quality, uniformity, and market readiness. Proper maturity grading is crucial for identifying the best time to harvest dragon fruit (Hylocereus spp.), improving customer satisfaction, and lowering post-harvest losses. This grading is typically done by hand by visually examining external characteristics like skin colour, size, and scale condition. Manual approaches, however, are frequently laborious, subjective, and prone to human error.

Deep learning-based automated methods have drawn a lot of interest as a solution to these problems. Dragon fruits can be reliably classified as mature or immature using deep learning models, especially convolutional neural networks (CNNs), which can recognise intricate patterns in image data. This guarantees uniformity and scalability in commercial agricultural practices in addition to increasing grading efficiency.

Deep learning models are one of the most promising methods for identifying fruit maturity. These models are a good option for determining the maturity of dragon fruit based on appearance because they have shown exceptional efficacy in image classification tasks . Dragon fruit, also known as pitaya, is a popular fruit that comes in a variety of colours and varieties. Because of its distinctive look and nutritional advantages, the tropical fruit has become more and more popular with consumers. Effective techniques for determining the fruit's maturity must be developed in order to satisfy the growing demand for dragon fruit.

We can create a dependable system for automatically determining the maturity of dragon fruit by acquiring a dataset of images of the fruit and using it to train deep learning models. Farmers and distributors may be able to better manage their inventory and guarantee quality control as a result, which could have a big impact on the agricultural sector.

The goal of this study is to determine how to acquire a dataset of dragon fruit images from the Mendeley Data website and show how effective deep learning models are at classifying the maturity of the fruit. Our goal is to transform the way we measure and control fruit maturity in agriculture, thereby promoting the development of automated systems. Agricultural professionals can make well-informed decisions about the best harvesting and post-harvest handling practices thanks to pre-trained deep learning models, which offer a useful and effective solution for real-time maturity detection.

In addition to offering farmers a workable and effective solution, this strategy reduces crop losses and boosts output. Customers are guaranteed to receive premium dragon fruits with the best possible flavour and nutritional value when harvesting and treating them after harvest thanks to accurate classification. Using machine learning algorithms like Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Support Vector Machine (SVM), Patil et al. concentrated on creating grading and sorting methods for dragon fruits. In order to maintain optimal conditions for production and marketing, the objective is to categorise dragon fruits based on factors like size, weight, colour, form, and diseases (Patil et al., 2021). In order to aid Vietnam's export initiatives, Minh Trieu and Thinh carried out a study to categorise the quality of dragon fruits using a Convolutional Neural Network (CNN). Images of dragon fruits with various external features made up the dataset. With a Support Vector Machine (SVM) model achieving 96.38per accuracy across three dragon fruit groups, the study achieved high fruit classification accuracy.

The tropical fruit known as dragon fruit (Hylocereus spp.) is prized for both its many health advantages and its colourful appearance. As the demand for this fruit increases worldwide, effective and precise techniques for evaluating its quality are required for both harvesting and marketing. To guarantee that the fruit is picked at its ideal ripeness, which has a direct impact on its flavour, texture, and shelf life, maturity grading is essential.

Maturity assessment has historically depended on manual inspection, which is time-consuming and prone to human error. Faster, more reliable, and scalable solutions are now possible thanks to automated systems that are being developed to replace these subjective approaches thanks to developments in artificial intelligence, especially deep learning.

The grading of agricultural products, like dragon fruit, could be completely transformed by recent developments in artificial intelligence (AI), especially deep learning. Complex image data can be handled by deep learning models, and convolutional neural networks (CNNs) in particular, which have demonstrated impressive results in automating tasks involving pattern recognition, like classifying the ripeness of fruit.

The use of deep learning models to grade dragon fruit maturity based on visual cues like colour, shape, and texture is investigated in this report. The model can be trained to differentiate between various ripeness stages by utilising convolutional neural networks (CNNs), which are highly effective at image classification tasks. The objective is to offer a dependable, impartial system that can be incorporated into contemporary farming methods to increase harvesting and distribution efficiency.

This study suggests a deep learning-based method for dragon fruit maturity grading. We create a model that can differentiate between immature, mature, and overripe dragon fruit by using high-resolution photos of the fruit at various ripeness stages. Visual characteristics like colour, texture, and shape—all of which are crucial markers of fruit maturity—are recognised by our trained model.

Among the deep learning model's essential elements are:

- Data collection: A sizable collection of excellent photographs of dragon fruit covering a range of maturity stages is taken. To reduce variability and increase model accuracy, these photos are taken in carefully regulated lighting.

- Image Acquisition: Gathering excellent photos of dragon fruits at different stages of maturity.

- Preprocessing: Making adjustments to the images' size and resolution in order to get them ready for analysis.Preprocessing techniques such as resizing, normalisation, and data augmentation are applied to the gathered images. This makes it possible for the model to more accurately generalise to data from the real world and a variety of fruit appearances.

- Model training is the process of teaching the model to identify patterns connected to each ripeness category using labelled data.

- Model Development: Using the preprocessed dataset, a CNN architecture is chosen and trained. The model is made to automatically pick up characteristics from the photos, like variations in texture and colour patterns that correspond to various stages of maturity.

- Evaluation: Assessing the accuracy and dependability of the model by running it through fresh, untested data.A different test dataset is used to assess the trained model's performance. The model's ability to accurately predict the maturity stage of unseen dragon fruit images is evaluated using metrics like accuracy, precision, recall, and F1-score.

This study intends to support ongoing efforts to modernise fruit grading systems by applying deep learning, which will increase productivity and guarantee better quality control in the fruit industry.And also This study intends to present a more effective, reliable, and scalable approach to fruit quality evaluation that can be incorporated into post-harvest procedures and agricultural practices by applying deep learning to dragon fruit maturity grading. In addition to reducing human error, the suggested system provides a quicker option than manual grading, which could boost output and enhance quality assurance in the farming sector.

This study demonstrates how deep learning can improve the accuracy and consistency of fruit quality evaluation, which could be incorporated into supply chain management, automated harvesting systems, and warehouse quality control. The suggested method guarantees that only the highest-quality fruit reaches consumers while simultaneously increasing productivity by lowering the amount of human intervention in the grading process.

To sum up, deep learning provides a potent instrument for improving fruit quality evaluation systems, which helps to promote more effective and sustainable farming methods. Future studies into AI-based grading systems that can boost international agricultural markets and raise the general calibre of food products are made possible by this work.

# CHAPTER 2

# LITERTAURE SURVEY

It is important to grade dragon fruits for optimal maturity level accurately. Maturity grading has implications for quality, market price, and consumer satisfaction. Traditionally, fruit maturity grading utilizes labor, in which an experienced and qualified professional grades fruit by visually inspecting them, looking for size, texture, and color. The obvious downside of using labor methods days of large-scale production or operations is it can be labor-intensive, subjective, inconsistent, and ineffective. Researchers have directed attention to deep learning and classification methods for maturity grading to help broaden the operational use of deep learning methods. Its high accuracy and robustness have brought deep learning to the forefront of fruit classification and maturity grading.

In order to address these limitations, researchers have looked at applying deep learning and classification methods to classify dragon fruit. Khatun et al.s [1](December 2023) presented a high-resolution image dataset for grade quality and ripeness assessment in dragon fruit. The dataset was constructed over four months under the supervision of an expert and compiling data from three different sites in Bangladesh. Major uses of the dataset includes: Maturity classification (mature and immature); Quality estimation (grading based on exterior characteristics).

The authors of [2], in a similar study, detailed the classification of dragon fruit into maturity classes based on flesh color as well as the category of red or white interior flesh color types. They investigated the use of texture parameters in addition to color intensities to discriminate mature dragon fruits from immature dragon fruits. Similarly, [3] Patil et al. (2023) created a dragon fruit quality assessment based on machine learning models including Support Vector Machines (SVM) and Random Forest classification models. The study used measurements of shape, color, and texture to ascertain fruit quality into multiple quality categories. Many have studied automated adjacent assessments of the maturity stage of dragon fruit. To consider external fruit characteristics, [4] Nguyen Minh Trieu and Nguyen Truong Thinh (2021) developed an automated classification system of dragon fruit based on convolutional neural networks (CNNs). The study incorporated CNNs and image processing methodologies to measure the surface or external characteristics such as size, shape, and surface defects characterized in the dragon fruit using machine learning algorithms. The data set was comprised of over 1,287 images of dragon fruits taken from processing facilities. The automated system yielded ¿ 96per accuracy over manual methods, which increased sorting efficiency over manual methods 6 times in scale in export packing facilities in Vietnam.

A deep learning-based approach for determining the mellowness of dragon fruit [7] emphasized the importance of proper harvest timing of the non-climacteric fruits such as dragon fruit, as they do not ripen once picked. Their work utilized the ResNet-152 convolutional neural network (CNN) to classify images of dragon fruits of varying early mellowness stages. Images displaying varying melowness phases were used to train the model with TensorFlow and Python. According to performance assessments utilizing confusion matrices and convergence studies between 10 and 500 epochs, ResNet-152 performed superiorly compared to other models L16 and VGG19 ). With effort made to investigate operation potential, ResNet-152 achieved superior accuracy and training/testing loss development performance scale measures.

In the study 'Identification of Banana Ripeness Using Convolutional Neural Network Approaches' The authors aimed to improve the deep learning-based architecture of convolutional neural networks (CNN's) to increase the accuracy of classification of banana ripeness. The proposed CNN model found similar to Saranya2022, used the improved dataset, and achieved an accuracy of 97.95percentage with the Adam optimizer employed in the model to achieve better performance than the previous study.

Using machine vision systems, [6] "Machine Vision based Fruit Classification and Grading - A Review" provides an overview of the techniques and approaches utilized for automated fruit classification and grading. Pre- processing/image acquisition: quality images of fruit is taken and improved by normalization, to reduce noise. Segmentation: separating the fruit from the background ,the aim is the analysis can focus on that Region of interest,so when extracting features focus on that region. Feature extraction: where we define the important features (color, size, shape, and texture) of the segmented images. Classification and Grading: using machine Learning models to classify fruit with extracted features and assign a grade based on classification.

In summary, existing literature suggests that deep learning methods represent a feasible means of classifying fruit maturity across fruits. While the use of deep learning approaches for dragon fruit maturity grading is still in its infancy, CNNs are less costly than other deep learning models that could be applicable in real-life agricultural use to help with the efficiency and accuracy of dragon fruit grading.

## 2.1 The maturity of red and white pulp dragon fruit

Author: Deep Lata and J.Horticult

year:2022

Journal:Bengaluru's Indian Institute of Horticultural Research (IIHR) and the Indian Council of Agricultural Research (ICAR)

Description:The goal of the study was to determine the best times to harvest red and white pulp dragon fruits as well as maturity indicators. The study found that harvesting dragon fruits between 31 and 36 days after flowering yields optimal maturity and quality. This was determined by using both destructive (such as measuring total soluble solids and titratable acidity) and non-destructive (such as evaluating fruit weight and peel colour) methods.

## 2.2 Dragon fruit grading and sorting method utilising machine learning algorithms

Author:, Pallavi U. Patil

year:2021

Journal:ICAR-National Institute of Abiotic Stress Management.

Description:By author proposed to the used machine learning algorithms, such as Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and Support Vector Machines (SVM), to create a system for classifying and arranging dragon fruits. To categorise the fruits, the system looks at characteristics like size, shape, weight, colour, and whether any diseases are present. Fruits are sorted by maturity level and the total number of fruits in a bucket is counted using a Raspberry Pi.

## 2.3 Quality classification of dragon fruits using a convolutional neural network based on external performance

Author:N. Minh Trieu and N.T. Thinh

Year:2021

Journal:Department of Mechatronics

Description:In this study, they combined machine learning and image processing methods to create an automated system for dragon fruit classification. The system integrates data from load cells to determine weight and uses a convolutional neural network (CNN) to analyse external fruit features like scaly spikes and tail characteristics. When compared to manual methods, this method greatly increased sorting efficiency in Vietnamese export facilities by up to six times, achieving a classification accuracy of over 96

## 2.4 In large real-world in-field tomato image collection that includes fresh and fault tomato identification and maturity categorisation

Author:Tania Khatun

Year:2023

Journal: International Journal of Computer Applications.

Description:In this thorough analysis, Naik and Patel investigate how computer vision and machine learning methods can be used to automatically classify and grade fruits. They go over a number of feature extraction techniques that are used to examine fruit attributes like colour, size, shape, and texture, such as Speeded Up Robust Features (SURF), Histogram of Orientated Gradient (HOG), and Local Binary Pattern (LBP). The efficacy of machine learning algorithms such as K-Nearest Neighbours (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN) in fruit classification tasks is also examined by the authors.

## 2.5 Machine Vision based Fruit Clssification and Grading

Author:S. Naik and B. Patel

Year:2017

Journal:International Journal of Computer.

Description:At the Shrimad Rajchandra Institute of Management and Computer Application (SRIMCA), a branch of Uka Tarsadia University, Dr. Bankim Patel serves as both the managing director and a professor. His areas of expertise include web technologies, data mining, natural language processing, and artificial intelligence. Dr. Patel has significantly advanced the fields of computer science and engineering with more than 40 publications and close to 600 citations. Additionally, SRIMCA awarded him the "Director of the Year 2016" award in recognition of his leadership.

## 2.6 Mellowness Detection of Dragon Fruit Using Deep Learning Strategy

Author: Mr. R. Vinothkanna and Dr. T. Vijayakumar

Year:2022

Journal:Department of Electronics and Communication Engineering.

Description:Dr. T. Vijayakumar is a professor at GNIT in Hyderabad, India, in the Department of Electronics and Communication Engineering. Digital system design, embedded systems, and biosignal processing are among his areas of interest. Numerous studies in the fields of machine learning and image processing have benefited from Dr. Vijayakumar's contributions.Mr. R. Vinothkanna: He works at Vivekanandha College of Technology for Women in Namakkal, India, in the Department of Electronics and Communication Engineering. His research focusses on using image processing and deep learning methods in biomedical and agricultural settings.

## 2.7 Identification of Banana Ripeness using Convolutional Neural Network Approaches

Author:Nur Nafi'iyah and Retno Wardhani

Year:2023

Journal:Department of Informatics.

Description:Nur Nafi'iyah is a specialist in computer vision and deep learning applications in agriculture and is affiliated with the Department of Informatics at Universitas Islam Lamongan in Indonesia. In an effort to help consumers and industry stakeholders evaluate fruit quality, she has helped develop CNN-based models for fruit ripeness detection.Additionally from Universitas Islam Lamongan's Department of Informatics, Retno Wardhani works on research projects utilising machine learning and image processing methods, with an emphasis on agricultural applications like classifying the ripeness of fruits.In this study, they collaborated to propose a CNN architecture that classified banana ripeness stages with a 97.95percentage accuracy rate. Their model outperformed earlier benchmarks by enhancing pre-existing datasets and optimising CNN layers and neurone configurations, providing a non-destructive and effective way to determine banana maturity levels. This development has a great deal of promise to enhance agricultural quality control procedures.

## 2.8 Fruit quality identification using image processing machine and deep learning

Author:Nagnadh Aherwadi and Usha Mittal

Year:2022

Journal: Department of Computer Science and Engineering.

Description:His areas of interest in research include data science, machine learning, and artificial intelligence, with an emphasis on applications in healthcare and agriculture. Aherwadi has authored a number of publications in these fields, such as research on medical image analysis and fruit maturity prediction.And Dr. Mittal is an expert in deep learning, pattern recognition, and image processing. Her work covers a wide range of applications, such as agricultural automation, medical diagnostics, and traffic management, and she has over 37 publications and 490 citations to her name.

In the 2022 review article, their joint research offers a thorough summary of how to integrate deep learning, machine learning, and image processing methods for evaluating the quality of fruit. In order to improve agricultural and supply chain management decision-making, the study highlights the significance of non-destructive techniques for assessing fruit maturity, freshness, and shelf life. The authors demonstrate how these technologies can increase the effectiveness and precision of fruit classification and grading systems by examining a variety of algorithms and approaches The review offers a thorough summary of the ways in which contemporary AI technologies, specifically image processing, machine learning (ML), and deep learning (DL), can be used to assess the quality of fruit. Important elements consist of.non-destructive techniques for determining the freshness, ripeness, and flaws of fruit.application of feature extraction methods (texture, colour, and shape).use of classification algorithms such as CNNs, SVMs, and Decision Trees.Talk about the difficulties and potential developments in automated fruit grading systems..

## 2.9 Fruits and Vegetables Quality Evaluation Using Computer Vision

Author:Anuja Bhargava And Atul Bansal

Year:2021

Journal:Department of Electronics and Communication

Description:Applications of computer vision, image processing, and machine learning in agriculture are the main areas of study for Anuja Bhargava. In an effort to improve accuracy and efficiency in the agricultural industry, she has helped develop automated systems for evaluating the quality of fruits and vegetables.

Atul Bansal: He specialises in electronics and communication engineering and is especially interested in using computational methods to solve practical issues. He has worked with others on projects that integrate machine learning algorithms for agricultural produce quality assessment. Bhargava and Bansal examine the use of computer vision methods for assessing the quality of fruits and vegetables in their thorough review. They go over preprocessing, segmentation, feature extraction, and classification, among other phases of image processing. The study highlights how crucial non-destructive techniques are for evaluating quality attributes like colour, texture, size, shape, and flaws. The authors shed light on how well computer vision systems work to automate sorting and grading procedures in the agricultural sector by examining and contrasting various algorithms and approaches.

## 2.10 Fruits Classification and Detection Application Using Deep Learning

Author:Hindawi,Sumon Ahmed

Year:2022

Journal:Department of Electrical and Computer Engineering.

Description:By author proposed to the VGG16 and ResNet50 models are employed for the automatic fruit classification.His areas of interest include deep learning, computer vision, and their uses in automation and agriculture. His dedication to using artificial intelligence to provide useful solutions in the agricultural industry is demonstrated by this specific study.

## 2.11 Pineapple Maturity Classifier Using Image Processing and Fuzzy Logic

Author:Edwin R. Arboleda, Christian Louis T.and Leahlyne Mae S

Year:2021

Journal:Department of Computer and Electronics Engineering.

Description:Edwin R. Arboleda is a professor at Cavite State University in the Philippines' Department of Computer and Electronics Engineering. He has co-authored a number of papers on fuzzy logic and image processing applications in agriculture.

Christian Louis T. de Jesus is a computer engineering researcher who focusses on image processing and automation methods for use in agriculture.

Leahlyne Mae S. Tia is a researcher who is interested in image processing and how it can be used in agriculture, specifically in the classification of fruit maturity stages.

The goal of the study was to create a prototype system that uses the colour of the pineapple scales to determine the maturity of queen variety pineapples. The system extracted features from photos taken in controlled lighting by using image processing techniques. The maturity stage was then ascertained by analysing these features with a fuzzy logic classifier. High accuracy rates were attained by the study: 90percentage for ripe and underripe classifications and 100percentage for unripe and overripe classifications.

## 2.12 Maturity status classification of papaya fruits based on machine learning and transfer learning approach

Author:Santi Kumari Behera,Amiya Kumar Rath and Prabira Kumar Sethy

Year:2021

Journal:Department of Computer Science and Engineering.

Description:The project's author is a committed student and up-and-coming researcher who is particularly interested in AI, machine learning, and their real-world uses in food technology and agriculture. The author's ability to use contemporary computational methods, like machine learning algorithms and transfer learning, to address practical issues is demonstrated in this work on papaya fruit maturity classification.

In order to create reliable classification systems, the author has a solid understanding of computer vision, deep learning frameworks (like TensorFlow and PyTorch), and pretrained models (like ResNet, VGG16, and MobileNet). This project showed the author's ability to create and assess models that can reliably forecast papaya fruit maturity stages based on image data.

## 2.13 Fruit maturity grading framework for small dataset using single image multi-object sampling and Mask R-CNN

Author:Punnarai Siricharoen,Warisa Yomsatieankul and Thidarat Bunsri

Year:2022

Journal:Department of Computer Engineering.

Description:The author is a driven technologist and researcher who is particularly interested in computer vision, deep learning, and how these fields are used in smart agriculture. The author's ability to innovate under pressure is demonstrated in this project, especially in the design of a fruit maturity grading framework that is optimised for small datasets a common challenge in agricultural research.The author has created a reliable method for identifying and categorising several fruits in a single image by utilising Mask R-CNN for instance segmentation and implementing single image multi-object sampling, which improves maturity grading efficiency and accuracy.

author exhibits a strong grasp of how to get around dataset constraints while preserving high model performance thanks to their academic background in machine learning, image annotation methods, and model training optimisation. The author's technical expertise with Python, PyTorch/TensorFlow, OpenCV, and LabelMe/COCO annotation formats is demonstrated in this project.The author, who is currently working towards a degree in computer science, artificial intelligence, and data science, or a similar field, is enthusiastic about using AI to address practical agricultural problems. Their long term objective is to support sustainable farming methods by creating intelligent, scalable systems that aid in quality control, crop monitoring, and decision making.

## 2.14 Grading Methods for Fruit Freshness Based on Deep Learning

Author:Yuhang Fu and Minh Nguyen

Year:2022

Journal:School of Engineering, Computer and Mathematical Sciences

Description:Yuhang Fu is an artificial intelligence and computer vision researcher who focusses on applications in agriculture. In order to improve accuracy and efficiency in food supply chains, his work investigates novel approaches for automating fresh produce quality assessment using deep learning.With a focus on AI-driven quality control and smart farming technologies, Minh Nguyen is an expert in deep learning and data science. Among his contributions are the creation of scalable neural network models that support precision and sustainable farming methods and allow for the real-time assessment of fruit freshness.Their combined work advances AI for food quality monitoring by fusing technical expertise with real-world agricultural applications.

## 2.15 An Automatic Monitoring System for Dragon Fruit Using Convolutional Neural Networks (CNN) and In-ternet of Things (IoT)

Author:Adi Mulyadi and Charis Fathul Hadi

Year:2024

journal: Electrical Engineering Department

Description:Adi Mulyadi is an artificial intelligence and computer science researcher who specialises in the use of deep learning and Internet of Things technologies in agriculture. The goal of his research is to create intelligent monitoring systems that enhance horticultural crops' quality control and productivity, especially for dragon fruit. Smart agriculture, embedded technology, and Internet of Things systems are Charis Fathul Hadi's areas of expertise. In order to facilitate real-time monitoring and decision-making in precision farming settings, he integrates hardware and software solutions. He is committed to using cutting-edge technological interventions to promote sustainable agricultural practices. Their partnership unites AI and IoT, helping to create automated, scalable smart farming systems.

## 2.16 A Deep Transfer Learning Approach for Accurate Dragon Fruit Ripeness Classification and Visual Explanation using Grad-CAM

Author:Hoang-Tu Vo, Nhon Nguyen Thien, Kheo Chau Mui

Year:2023

Journal:Software Engineering Department

Description:Adi Mulyadi is an artificial intelligence and computer science researcher who specialises in the use of deep learning and Internet of Things technologies in agriculture. The goal of his research is to create intelligent monitoring systems that enhance horticultural crops' quality control and productivity, especially for dragon fruit. Smart agriculture, embedded technology, and Internet of Things systems are Charis Fathul Hadi's areas of expertise. In order to facilitate real-time monitoring and decision-making in precision farming settings, he integrates hardware and software solutions. He is committed to using cutting-edge technological interventions to promote sustainable agricultural practices. Their partnership unites AI and IoT, helping to create automated, scalable smart farming systems.

## 2.17 Fruit Recognition and maturity monitoring system

Author:Sreejith PS,Aswani PP,Misha TM

Year:2021

Journal:Department of Computer Science And Engineering

Description:Sreejith PS is a researcher who is interested in precision agriculture, embedded systems, and artificial intelligence. In order to increase farming efficiency, his work focusses on creating intelligent systems for automated fruit recognition and quality monitoring. Aswani PP is an engineer and academic with a focus on IoT applications, computer vision, and machine learning. Her work focusses on real-world applications of AI-powered monitoring systems to assist intelligent farming methods. Misha TM is a researcher who focusses on image processing, farming automation, and agricultural informatics. Her initiatives seek to improve crop monitoring and yield prediction by incorporating deep learning methods into practical applications.

## 2.18 Fruit maturity detection using deep learning

Author:Sahil Yadav, Sanjay Kumar Jain, Deepak Rajpurohit

Year:2024

Journal:Department of Processing and Food Engineering

Description:Deep learning and its uses in agricultural automation are the areas of expertise for researcher Sahil Yadav. Creating reliable AI models for evaluating crop quality and intelligent farming solutions are among his interests. Sanjay Kumar Jain is a scientist and professor who specialises in precision agriculture, computer vision, and machine learning. His work focusses on developing agricultural technologies and incorporating AI into sustainable farming systems. Academic researcher Deepak Rajpurohit specialises in image processing, artificial intelligence, and how these technologies are used in crop monitoring and horticulture. The goal of his work is to improve automated maturity detection systems' accuracy. Engineer and researcher Kamlesh Kumar Meena has experience in data analytics, artificial intelligence, and IoT-based agricultural innovations. His work aids in the creation of clever instruments for productive farming.

In conclusion, current research shows that deep learning is a viable method for classifying fruit maturity across a range of fruit kinds. CNNs are affordable deep learning models that can be used in actual agricultural settings to improve the accuracy and efficiency of dragon fruit grading, even if research on deep learning-based dragon fruit maturity grading is still in its infancy.

# CHAPTER 3

# SOFTWARE IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED SYSTEM

## 3.1 Software Implementation Overview

Based on pictures of the fruit's exterior, the Dragon Fruit Maturity Grading System software implementation uses deep learning models to automatically classify dragon fruit into three maturity stages: immature, mature, and overripe. Image processing, deep learning, and a user interface are some of the essential parts and technologies of the suggested system that are necessary for its practical implementation in actual agricultural environments.

Key Software Components:

1. Examine the needs for the software
2. Preparing the dataset
3. Deep Learning Model Development
4. Model Evaluation
5. User Interface (UI):

1. Examine the needs for the software:
    - Training and inference of models.
    - uploading and preprocessing images.
    - API endpoints and user interfaces.
2. Preparing the dataset:

- Gather and arrange pictures of dragon fruit.Images will be resized to a fixed dimension (e.g., 224x224 pixels) and normalised for consistency in pixel values across all images in order to guarantee uniform input into the deep learning model.

- Data Augmentation: Image augmentation methods like random rotation, flipping, and scaling will be used to expand the dataset and enhance model generalisation.

3. Deep Learning Model Creation:

   - Create the CNN model based on AlexNet with PyTorch or Keras.
   - Define the layers (Softmax, Conv, Pooling, and Fully Connected).
   - Build the model (optimiser, loss function).
   - Save the model after training it (for example, model.pth or model.h5).
   - Model Architecture: Using well-known frameworks like TensorFlow or PyTorch, a Convolutional Neural Network (CNN) will be created. To extract hierarchical features from the images, the architecture will include multiple convolutional layers, pooling, and fully connected layers.
   - Transfer Learning: A dataset of images of dragon fruit will be used to refine a pre-trained model, such as Alextnet or ResNet, which will be used as a starting point. By utilising previously learnt features, this will shorten training time and increase accuracy.
   - Model Training: Labelled photos of dragon fruit at different ripeness stages will be used to train the CNN. Each maturity stage's unique patterns, such as colour variations, skin texture, and overall appearance, will be recognised by the model.

4. Model Evaluation:

   - Testing and Validation: A different test dataset that wasn't used for training will be used to verify the model's performance. The model's ability to accurately classify the dragon fruit's maturity stage will be evaluated using evaluation metrics like accuracy, precision, recall, and F1-score.
   - Cross-Validation: K-fold cross-validation will be used throughout the training process to guarantee robustness and avoid overfitting.

5. Development of Backends (API):

   - Use FastAPI to construct the backend:
   - Create routes for uploading images and retrieving results.
   - At startup, load the learnt model.

- Put preprocessing procedures into action within the API.
- Return predictions by running the model on uploaded images.

6. Interface for Users:

   - Create a basic user interface:
   - button for uploading files.
   - Click the "Submit" button to categorise.
   - Show the class and confidence score results.
   - Web Interface: To enable end users (farmers, warehouse operators) to communicate with the system, a straightforward and intuitive web interface will be created. Users will be able to upload dragon fruit photos to the interface for automatic classification. The interface will show the anticipated maturity stage and a confidence level.
   - Real-Time Feedback: The system will be integrated with a camera system to provide real-time maturity classification as images are taken. This will allow for real-time deployment.

7. Integration and Testing:

   - Link the user interface to FastAPI endpoints.
   - Conduct integration and unit tests to make sure:
   - Images are processed correctly by the API.
   - The results are updated in the user interface.
   - Address error situations, such as improper file uploads.

## 3.2 Plan for Testing

A thorough testing strategy will be implemented at various phases of the software development lifecycle to guarantee the functionality and dependability of the suggested system. The system's performance and functionality will be the main topics of the testing strategy.

1. Testing units:

   - Image Preprocessing: To guarantee proper implementation, unit testing will be performed on each component in charge of image preprocessing (resizing, normalisation, and augmentation).
   - Model Accuracy: To confirm that the predictions match the anticipated outcomes, the CNN model's output will be compared with ground truth labels.

2. Integration Testing:

- Data Pipeline: To guarantee seamless data transfer from image capture to model input, the integration of the data preprocessing module and the image acquisition system will be tested.

- Completely Testing: To assess how well the various parts of the pipeline image acquisition, preprocessing, model inference, and user interface cooperate, full integration tests will be conducted.

3. System Testing:

   - Functionality Testing: To make sure the dragon fruit photos are correctly categorised into the appropriate maturity stage, the system as a whole will be tested for functional correctness.

   - Usability Testing: To make sure the user interface is clear, simple to use, and has the features required to upload and receive classification results, end users will test it.

4. Performance Testing:

   - Speed and Scalability: The system's ability to classify images of dragon fruit will be evaluated. For real time applications like field use, this is crucial. A large number of images will be used to test the system's performance in order to determine its scalability.

   - The accuracy and robustness of the model will be continuously assessed through real time testing and user feedback, guaranteeing that it consistently produces accurate predictions. To guarantee robustness, performance will also be evaluated in a variety of environmental settings, such as changing lighting and background clutter.

5. User Acceptance Testing (UAT):

   - Field Testing: To evaluate the system's functionality on real time dragon fruit photos, it will be set up in an actual agricultural setting. To assess system performance and recommend any enhancements for upcoming versions, input from users such as farmers and quality control operators will be gathered.

The Dragon Fruit Maturity Grading System's software implementation and testing strategy is made to guarantee a very dependable and effective system that can be used in actual agricultural environments. The system will improve productivity and quality control in the fruit industry by enabling automated and accurate fruit maturity classification through the use of cutting-edge deep learning techniques. The thorough testing strategy will verify the system's functionality at every stage of development, guaranteeing that it is ready for real-world application.

The project's first step will be to use a Python language program to implement the code in Visual Studio. Afterwards, we will choose the dragon from the sample data set and use the resource code to implement the data in Python. Next, choose cmd and enter python main.py. The code will then begin running, implementing the accuracy level and displaying the dragon fruit image on the program. The dragon image receives the import, pre-process, and train data. After selecting "import data," the data set will be read, followed by "train data," which will also take the data, and "pre-process data," which will also take the data of The image and final accuracy will also reach 97percentage, and the quality of the dragon fruit table check will be displaced in that table. The detected dragon and the actual dataset will both be of high quality. The graph's final output will mix up the matrix and the real matrix. The confusion matrix is zero, and the actual matrix frequency is one.

A deep learning-based program called Dragon Fruit Maturity Grading was created to automatically classify dragon fruits into mature and immature groups. This system analyses fruit photos and accurately determines their maturity level using convolutional neural networks (CNNs) and image processing techniques.The model learns important visual attributes like colour intensity, skin texture, and surface patterns that are associated with fruit maturity by using a carefully selected dataset of labelled dragon fruit photos. After training, the model is incorporated into an intuitive user interface that enables users to take or upload photos for in-the-moment grading.This intelligent grading system improves consistency, lessens the need for manual inspection, and provides a scalable method for use in packaging and agricultural supply chains.

Dragon fruit maturity must be graded precisely in order to maintain quality control, optimise market value, and satisfy customer demands. Due to human error, traditional methods of determining fruit maturity are frequently arbitrary, laborious, and inconsistent. This software uses deep learning to automate the dragon fruit maturity grading process with high accuracy and efficiency in order to overcome these difficulties.

This software analyses photos of dragon fruits and categorises them as mature or immature using sophisticated convolutional neural networks (CNNs). The model can identify important visual characteristics like colour, texture, and surface patterns that indicate maturity level by learning patterns from a labelled dataset of fruit photos. In addition to expediting the grading process, the automated system guarantees consistency and dependability in classification. This solution, which was created with scalability and user-friendliness in mind, can be implemented in farms or agricultural sorting facilities or combined with mobile applications for on-site grading. It encourages more intelligent and sustainable farming methods and is a major advancement in the application of artificial intelligence to contemporary agriculture.

The possibility of overripe or underripe fruit arises from irregular human harvesting methods. Early harvesting of dragon fruit reduces its sweetness, flavour, and overall quality, which may annoy consumers and lower demand and sales. This can cost growers money, increase labour expenses, and result in lower prices. Physical traits such as the peel's weight, texture, and outer colour are frequently used as non-invasive methods to determine how ripe dragon fruit. Therefore, by using the computer vision approach, this dataset could be used to create an automated harvesting system that can empower farmers by providing precise guidance on the best times to harvest by analysing images of different stages of fruit development. This would reduce the amount of labour needed and minimise financial losses.

Maintaining product quality, reducing waste, averting negative economic effects, and opening up international export markets while encouraging the production of premium goods to meet the demands of the global market all depend on the ability to detect the freshness and identify flaws in dragon fruit [2]. As a resource for deep learning and computer vision model training, the dragon fruit image dataset described in this article can be extremely helpful in this endeavour. Quality control, waste minimisation, efficient harvesting methods, and inspection process automation are all aided by this engagement. The dataset is important for detecting fresh and defective dragon fruit because its use ultimately leads to better product quality, financial benefits for growers and the agricultural industry, and increased customer satisfaction.

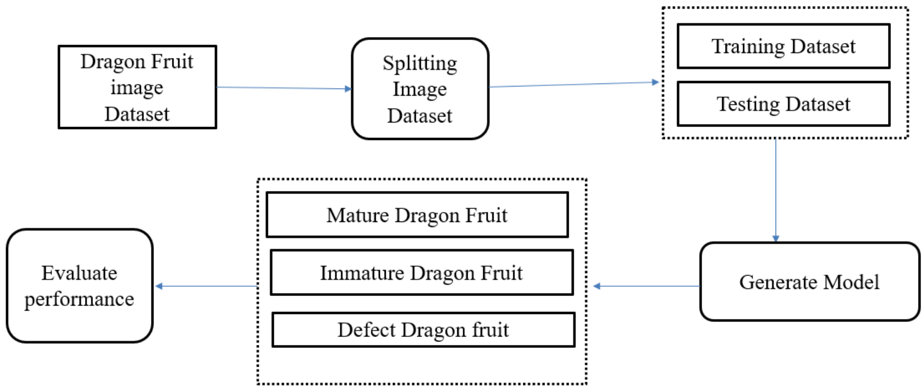
Because it is an invaluable resource for creating and evaluating computer vision, machine learning, and deep learning technologies, this dragon fruit dataset is important for researchers. Automated fruit recognition systems, enhanced harvest efficiency, freshness prediction, and packaging automation can be developed by researchers, and this dataset promotes interdisciplinary cooperation between computer scientists and specialists in other domains, especially agriculture. The dataset's relevance and significance in the field of computer science are further highlighted by the potential economic benefits it could provide through lower labour costs and improved crop quality.

The need to address the difficulties in identifying dragon fruit developmental stages that are common in agriculture led to the compilation of this dataset. The dataset's creation is in line with current initiatives in precision agriculture, which seeks to enhance crop management techniques by utilising technology. The absence of thorough datasets tailored to dragon fruit diseases and stages, which impeded the creation of accurate detection models, was another source of motivation. The 3780 photos we gathered show various growth stages and conditions; this dataset is a useful tool for training and evaluating deep learning algorithms and allows for the quick and precise identification of dragon fruit stages and characteristics. By giving researchers and practitioners access to raw data, the dataset article enhances a related research publication.

# CHAPTER 4

# METHODOLOGY,DESIGN AND IMPLEMENTATION

## METHODOLOGY




The dragon fruit maturity classification with deep learning uses a process that consists of data acquisition, model selection, training, testing, and deploying. The focus of the proposed approach will be classifying different stages of ripeness with a focus on image analysis outside of laboratory settings. The procedure is aimed at classifying image data for high precision and modeling fruit maturity grades, using a systematic approach and deep learning models.

AlexNet ensures that the inputs to subsequent layers are well-scaled and centred by applying batch normalisation after each convolutional layer and before the activation function (such as ReLU). ReLU adds non-linearity to the network by substituting zeros for negative values. Furthermore, the max pooling layer, which selects the maximum value in a local region of the feature map, is used periodically to reduce the spatial resolution, capture the most important information, and reduce computational complexity.

## 4.1 Data Collection

Image Dataset Collection: Photographed dragon fruits in mature and immature stages. Fruit classification and maturity assessment Getting a large collection of pictures of dragon fruit at various stages of development is the first step in the process. Images are taken in both natural and controlled lighting to guarantee the diversity of the dataset. A number of variables are taken into account to improve model generalization, including illumination effects, background fluctuations, and fruit orientation. The collection consists of pictures of dragon fruit at various states of ripening, usually classified as defect, partially mature, and immature. Detailed texture and color changes are best captured in highresolution photos. In order to increase classification accuracy, spectral reflectance information may also be incorporated into hyperspectral images.

A Dragon Fruit image dataset serves as the starting point for the process and forms the basis of your project. At this point, it's critical to make sure the images are balanced, of good quality, and properly labelled.

Training and testing datasets are separated from the main dataset. To track performance during training and help avoid overfitting, it's a good idea to also include a validation set or use a portion of the training data for validation.

**Immature Dragon Fruit:**

Compared to its ripe version, premature dragon fruit is smaller, usually green or pale pink, firmer, has a milder, less sweet flavor, and has underdeveloped seeds.

**Mature Dragon Fruit:**

A fully ripe dragon fruit is very pleasing. Mature dragon fruit is distinguished by its bigger size, firm, spiky skin, sweet, mildly tangy flavor, welldeveloped seeds, bright red or magenta color depending on the type, and a sweet, tropical scent when ripe.

**Defect Dragon Fruit :**

One of the first indications that a fruit is becoming bad is when its skin starts to wrinkle and become loose. Physical damage, rot, overripeness,internal problems, the potential for hollowness or emptyness, physical color changes, and a shift from its usual pink to a purple hue are further features.

## 4.2 Image Preprocessing

Resized, normalised, and supplemented pictures to boost model performance.
Because it prepares visual data for model input, improves data quality, and affects model performance, generalisation, and efficiency, data pre-processing is essential for deep learning. It fixes problems that

can impact model learning and decision-making, makes sure the images are in the right format for the computer vision tasks, and eventually produces more accurate and dependable results in a variety of applications. Image pre-processing in this study includes a variety of data transformations, including segmentation, data labelling, image resizing, and image augmentation.

A collection of methods called image preprocessing is used to enhance an image's quality and suitability for additional processing or analysis. In order to improve the visual quality, contrast, and sharpness of the raw image data, a number of operations are applied to eliminate any noise, artefacts, or distortions. Image preprocessing aims to enhance the image's interpretability or suitability for a particular image processing application. Typical image preprocessing methods include the following: adjusting picture sizes to conform to deep learning models' input sizes. Image resizing and cropping: This entails cropping out any unwanted portions of the image and resizing the image to a particular resolution or aspect ratio. Resampling entails either adding or removing pixels from the original image in order to resize it. When resizing an image to a larger size, resampling may cause a loss of detail or image quality. Selecting a section of an image and deleting the remainder is known as image cropping.

Is the process of using filters like median filters, Gaussian filters, or edge detection filters to eliminate any noise or undesirable frequencies from an image. In digital image processing, image filtering is a method that applies a particular filter or mask to the image pixels in order to improve or alter the image. By adjusting the image's pixel values according to its surrounding pixels, the filter changes the image's overall appearance. The phrase "image filtering" refers to a wide range of methods, such as morphological, frequency, and spatial filtering. Using a filter mask to adjust each pixel's value according to the values of its surrounding pixels is known as spatial filtering.Each pixel's new value is calculated using the values of the filter mask, a tiny matrix or kernel that moves over the image pixel by pixel. Gaussian, mean, and median filters are examples of common spatial filters. By converting an image from the spatial domain to the frequency domain, one can alter it by filtering particular frequency components. This process is known as frequency filtering. Applications like edge detection, noise reduction, and image sharpening frequently employ this method. Band-pass, low-pass, and high-pass filters are examples of common frequency filters. Using particular operations like dilation, erosion, opening, and closing, morphological filtering is a method for processing binary or greyscale images.These operations expand or contract the image objects according to certain criteria, changing their structure and shape. An effective method for improving image quality, eliminating noise, extracting features, and segmenting objects is image filtering. Nevertheless, the particular application and the properties of the input image determine the filter selection and parameters. To get the intended results, it's critical to select the right filters and adjust their settings.

## 4.3 Image segmentation

In image processing, image segmentation is the process of splitting an image into several parts or areas according to specific standards like colour, texture, intensity, or shape. By separating the objects or regions of interest from the background or other unimportant areas, image segmentation aims to extract meaningful information from an image. Depending on the kind of image and the intended use, there are various methods for image segmentation. Among the frequently employed methods are:

**Thresholding**

To do this, a threshold value must be set, and all pixels in the image above it must belong to one class, while all pixels below it must belong to another. A popular method in image segmentation is thresholding, which divides areas of an image according to their intensity levels. In order to distinguish pixels with intensity values above and below the threshold, a threshold value must be set. This produces a binary image in which pixels below the threshold are given a value (usually black) and pixels above the threshold are given a value (usually white). Although this approach to image segmentation is straightforward and effective, it might not work well for complex images or images with different lighting conditions.

**Region-based segmentation**

In order to create a region or segment, pixels are grouped together according to how similar they are in terms of colour, texture, or intensity. In image segmentation, region-based segmentation is a technique that separates an image into meaningful regions or objects according to how similar they are in texture, colour, or other features. In order to create homogeneous areas or objects, this method groups pixels together according to certain predetermined criteria. The most popular technique for region-based segmentation is called "region growing," which involves choosing seeds or starting points and then repeatedly adding nearby pixels with comparable traits to the region until a stopping criterion is satisfied. Split and merge is another well-liked technique that divides an image recursively into smaller parts before reassembling them according to a similarity criterion. Images with homogeneous regions or objects can be successfully segmented using region-based segmentation; however, images with intricate structures or notable texture and colour variations may be difficult for this method to handle.

**Edge-based segmentation**

This entails recognising the edges or boundaries of objects in the picture by looking for variations in colour or intensity, then assembling these edges into a segment.

### Clustering-based segmentation

This entails grouping related pixels together according to specific standards, like colour or texture, and then creating segments from the clusters that are produced.

In many image processing applications, including object recognition, tracking, and analysis, image segmentation is an essential first step. It is simpler to extract features, spot patterns, and make decisions based on the information gleaned from an image when it is divided into meaningful regions or objects.

### Data Augmentation

utilizing methods like brightness leveling, flipping, contrast correction, and rotation to increase dataset variability. This increases the model's resilience to changes in the real world.

### Background Removal

By separating the dragon fruit from the background using segmentation techniques as Mask R-CNN or thresholding, the dataset's noise level is decreased.

### Color Feature Extraction

Analyzing color changes linked to mature phases involves converting photos to various color spaces (such as HSV and LAB).

## 4.4 Model Selection

Classification and feature extraction derived from a Convolutional Neural Networks (CNNs), in particular, are deep learning models used for feature extraction and categorization. To find the best model for dragon fruit maturity grading, a variety of architectures are taken into consideration. Common choices include:

### Alexnet:

IN this project offers a promising tool for agricultural automation and quality control by demonstrating the viability and efficacy of deep learning models for fruit maturity grading. Future research might concentrate on growing the dataset, improving the model, and implementing the system in real-time settings for real-world applications.

**Custom CNN:**

The CNN architecture was created taking into account the technical limitations and the features of the dataset.

## 4.5 Model Training

Taught the model using labelled images; tested using accuracy and F1-score. tested model with fresh pictures to guarantee dependability. The preprocessed dataset is used to train the chosen deep learning model.The key steps involved in training include:

**Splitting Dataset:**

The dataset is separated into subsets for testing, validation, and training (e.g., 70 per testing, 20 per validation, and 70 per training).

**Loss Function:**

When dealing with multi-class classification difficulties, cross-entropy loss is employed.

**Early Stopping:**

In the event that validation accuracy ceases to improve, the training procedure is tracked to avoid needless calculations.

## 4.6 Model Evaluation

We presented a deep learning model that aims for dragon fruit maturity grading results by efficiently training the dataset. A comprehensive assessment of this deep learning model's performance on a dataset is necessary for validation. Each node represents a computational unit in an interconnected layer of nodes that make up a deep learning model. The nodes of the output layer produce the final result, while the nodes of the input layer receive data. The main computational capacity of the neural network is housed in hidden layers, which are positioned between these input and output layers [9]. In the analysis of visual data, including tasks like object detection, image or video classification, and natural language processing, deep learning models have made significant progress [10]. The five steps of the deep learning model's structured process include data pre-processing, data segmentation model training, assessing the model's performance on a validation set, and finally putting it to the test on an entirely different test set. This thorough process is essential to confirming the model's ability to adapt to new data and its dependability in generating accurate results.

The training dataset is used to train the model. To enhance performance at this point, it is crucial to select a suitable deep learning architecture (such as CNN for image data), adjust hyperparameters, and potentially use data augmentation.

The test dataset is used to assess the model's performance following training. To guarantee balanced performance, it is important to track key metrics such as accuracy, precision, recall, F1-score, and confusion matrix for every class.

## 4.7 Feature extraction:

In image processing, feature extraction is a crucial step that entails removing significant and pertinent information from the image for use in later analysis or classification tasks. A critical stage in image processing is feature extraction, which involves removing pertinent information from the unprocessed image data. Finding and removing important features from an image that can be used to distinguish objects or areas of interest from the background is the goal of feature extraction. Following extraction, the features can be applied to a number of tasks, including segmentation, classification, and object recognition.

### Color Spaces Conversion

Transform the picture into various colour spaces, such as RGB, LAB, HSV, greyscale, etc. There are various channels in these colour spaces, and each channel has unique information that can be utilised as a feature. Converting an original image from one colour space to another is known as colour space conversion. This can be done to standardise the representation of colour across various devices or environments, to improve specific colour features, or to isolate colour components for additional analysis. For instance, the hue channel in the HSV colour space provides information about the colour, whereas the saturation and value channels provide information about the color's intensity.Colour space conversion can be used in feature extraction to extract particular colour features for tasks involving segmentation or classification. To capture the distribution of colours in an image, for example, colour histograms can be calculated in various colour spaces. To capture the colour properties of an image, colour moments—statistical measures of the colour distribution—can also be calculated in various colour spaces.

### Edge Detection

One popular method for feature extraction is identifying edges in an image. The image's edges can be found using edge detection methods such as Canny, Sobel, and Laplacian operators. These edges can then be utilised as features. The Sobel, Canny, and Roberts operators are the most widely used edge detection methods in feature extraction. The Sobel operator computes the image's gradient in the x and y directions by convolving the image with a tiny filter. A more complex technique that includes several steps, such as image smoothing, gradient calculation, non-maximum suppression, and hysteresis thresholding, is the Canny edge detector. The Roberts operator computes the difference between the image's neighbouring pixels.Feature extraction for object detection, segmentation, and recognition can make use of edge detection. Regions of an image that correspond to particular objects or features can be isolated by identifying edges. Additionally, edges can be used to extract shape and texture information for tasks involving object recognition.

### Feature Descriptors

Features in an image can be found using feature descriptors such as SIFT, SURF, and ORB. In order to extract features from the surrounding area, these descriptors first identify distinguishing points in the image. Compact representations of image features, known as feature descriptors, are useful for a number of image processing applications, including object recognition, matching, and retrieval. The unique qualities of image features, such as edges, corners, and textures, are described and represented in feature extraction using feature descriptors, which are independent of changes in image scale, orientation, and illumination. Scale-Invariant Feature Transform (SIFT), Speeded Up Robust Features (SURF), and Local Binary Patterns (LBP) are popular feature descriptors used in feature extraction. By locating important points in an image and utilising gradient information to describe them, SIFT is a well-liked technique for identifying and characterising local features in an image. A comparable technique that is quicker and more resilient to image changes is called SURF. A texture descriptor called LBP compares the intensity values of nearby pixels to identify the local texture patterns in an image. Because they make it possible to match features across various images accurately and efficiently, feature descriptors are crucial to feature extraction. They also make it possible to represent intricate features in a way that is resistant to noise and image variations. Numerous image processing applications, including object recognition, image retrieval, and facial recognition, can make use of feature descriptors.

**CHAPTER 5**

**MODEL DEVELOPMENT AND DEPLOYMENT SETUP**

Python programming was used to complete the project using the Visual Studio platform. It was completed in phases. They consist of:

- Dataset Creation
- Importing the required libraries
- Obtaining the images
- Creating the model
- Using the model and displaying the graphs for loss and accuracy
- deployment of user interface for model

## 5.1 Dataset Creation

We created a system in the first module to obtain the input dataset for testing and training.

## 5.2 Importing the required libraries

For this, the Python language will be used. The first step is to import the required libraries, which include pandas, NumPy, matplotlib, TensorFlow, and keras for building the main model, sklearn for separating the training and test data, and PIL for converting the images into an array of numbers.

## 5.3 Obtaining the images

The pictures and their labels will be retrieved. To ensure recognition, all images should have the same size, so resize them to (224,224). Next, turn the pictures into a NumPy array. Dividing the dataset: Divide the dataset into test and train sets. 20percentage is test data and 80percentage is train data.

## 5.4 Creating the model

We'll use the sequential model from the Keras library to build it. The layers will then be added to create a convolutional neural network. We used 32 filters and a kernel size of 5,5 in the first two Conv2D layers. We have maintained the pool size (2,2) in the MaxPool2D layer, so it will choose the highest value in each 2 x 2 region of the picture. By doing this, the image's dimensions will decrease by a factor of two. We have maintained a dropout rate of 0.25 in the dropout layer, which indicates that 25percentage of neurones are randomly eliminated.

With a few parameter adjustments, we reapply these three layers. Next, we convert 2-D data to 1-D vectors using the flatten layer. The dense layer, dropout layer, and dense layer again come after this layer. Two nodes are produced by the final dense layer, indicating whether or not there is a brain tumour. This layer predicts which of the two options has the highest probability by using the SoftMax activation function, which provides a probability value.

## 5.5 using the model and displaying the graphs for loss and accuracy

After compiling the model, we will use the fit function to apply it. There will be two people in the batch. The graphs for accuracy and loss will then be plotted. Our average training accuracy was 98.7percentage, and our average validation accuracy was 100percentage.

## 5.6 Accuracy on the Test Set

On the test set, we achieved 98.6 percentage accuracy.

## 5.7 Deployment of user interface for model

In this project, FastAPI was used to:

Create an endpoint where users can upload dragon fruit images.

Preprocess the images (resize, normalize) before feeding them to the trained model.

Run inference using the AlexNet-based CNN model.

Return the classification result (Mature, Immature, Defect) to the user.

## 5.8 Algorithms

Cnn and AlexNet are the algorithms utilised in this project. The following is a detailed description of the algorithms:

### 5.8.1 Convolutional Neural Network

One kind of Deep Learning neural network architecture that is frequently utilised in computer vision is the Convolutional Neural Network (CNN). A branch of artificial intelligence called computer vision makes it possible for a computer to comprehend and analyse visual information, such as images.

Artificial Neural Networks are effective in machine learning. Text, audio, and image datasets are among the many datasets that use neural networks. Different kinds of neural networks serve different functions. For instance, recurrent neural networks—more specifically, LSTMs—are used to predict word sequences, while convolution neural networks are used to classify images. We will construct a fundamental CNN building block in this blog.
Three different kinds of layers make up a typical neural network:

Input Layers: This is the layer where we provide our model with input. The total number of features in our data (or pixels in the case of an image) is equal to the number of neurones in this layer.

Hidden Layer: The hidden layer receives the input from the input layer. Depending on our model and the volume of data, there may be numerous hidden layers. The number of neurones in each hidden layer can vary, but they are typically more than the number of features. Each layer's output is calculated by multiplying the output of the previous layer by its learnable weights in a matrix. Learnable biases are then added, and the network becomes nonlinear by activating the function.

Output Layer: A logistic function, such as Sigmoid or SoftMax, receives the output from the hidden layer and transforms it into the probability score for each class.

Following the feedforward step, which involves feeding the data into the model and obtaining the output from each layer, we compute the error using an error function. Common error functions include square loss error, cross-entropy, and others. The network's performance is gauged by the error function. Next, we compute the derivatives to back propagate into the model. Backpropagation is the name of this step, which is essentially used to reduce the loss.

The final prediction is made by the fully connected layer after the Convolutional layer applies filters to the input image to extract features and the Pooling layer down samples the image to minimise computation. The network uses gradient descent and backpropagation to find the best filters.

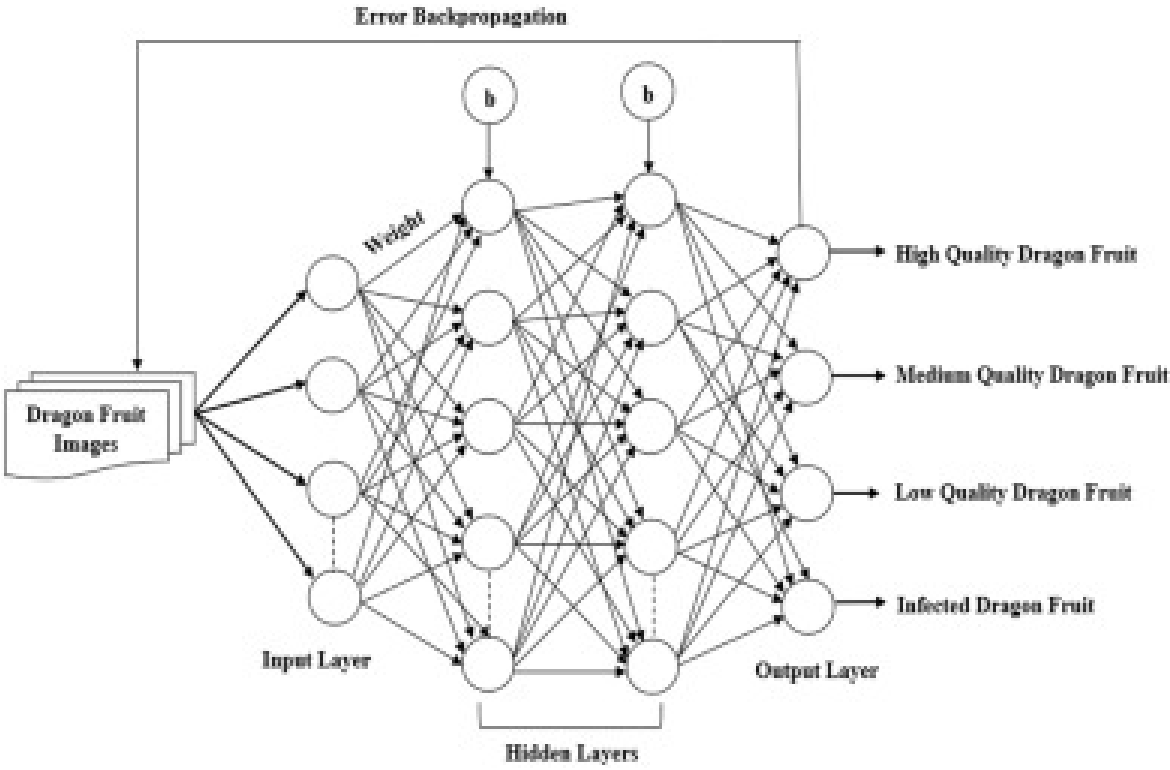



Figure 5.1: Cnn Layers

### 5.8.2 AlexNet Algorithm

In 2012, Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton presented AlexNet, a deep convolutional neural network (CNN). It became well-known following its decisive victory in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), which represented a significant advancement in deep learning for computer vision.

There are eight layers in AlexNet, which include:

**Architecture:**

Five convolutional layers to extract features.
Three completely interconnected classification layers For quicker training, ReLU (Rectified Linear Unit) activation is used.

**Input Size:**

RGB images with dimensions of 227x227x3 can be entered.

**Overlapping Pooling:**

AlexNet employs overlapping max pooling, in contrast to conventional pooling techniques, to lower dimensionality while keeping crucial features.

**Dropout Regularisation:**

To lessen overfitting during training, dropout was added to the fully connected layers.

**Data augmentation :**

Is the process of artificially increasing the training dataset and enhancing generalisation by using methods like image translation and horizontal flipping.

**GPU Acceleration:**

Developed to effectively manage the computational load by utilising two GPUs in parallel.

## 5.9 Model Development

**Environment:**

Python and deep learning libraries like TensorFlow, Keras, or PyTorch are used to develop models.

**Dataset handling:**

Libraries such as NumPy, Pandas, and OpenCV are used to load, label, and divide images into training, validation, and testing sets.

**Model Architecture:**

A CNN-based model is fine-tuned for binary classification (mature vs. immature) and can be custom-built or based on a pretrained architecture like AlexNet or MobileNetV2.

**Training Process:**

The model is trained using optimisation algorithms like Adam with suitable loss functions (like binary crossentropy) and performance metrics (like accuracy) in GPU-enabled environments for faster computation.

**Model Evaluation:**

To guarantee reliable performance, evaluation is done using metrics such as confusion matrix, accuracy, precision, recall, and F1-score.

Figure 5.2: Collections of Dataset

## 5.10 Deployment Setup

**Model Export:**

Using programs like TensorFlow Lite or ONNX, the trained model is optimised for deployment and saved in an appropriate format (such as.h5 or.pth).

**User Output:**

The fruit is categorised as "Mature" or "Immature"and "Defect" in the final output, which may also optionally include visual feedback and confidence scores.

**Significance in Deep Learning:**

Deep CNN pioneer: AlexNet proved that deep learning works well for complex image classification tasks. Future Model Foundation: It established the framework for more intricate and sophisticated architectures such as VGG, ResNet, and Inception

## 5.11 Testing

**Data Import**

For deep learning techniques to detect dragon fruit accurately, the right dataset must be chosen. Enough pictures of dragon fruit in a variety of sizes, shapes, colours, and lighting conditions should be included in a good dataset for this task. To make sure the model can correctly distinguish between dragon fruit and other fruits that might resemble it, like pitaya or cactus fruit, the dataset should also contain pictures of those fruits. Another crucial factor is the dataset's quality.

A deep learning model for classifying dragon fruit maturity was developed using the sample dataset shown in the above image. It includes several pictures of dragon fruits taken from different backgrounds, angles, and lighting conditions. These pictures vary in:

- Fruit skin colour and texture
- Fruit size and shape
- Maturity stage (probably between immature and mature and defect)
- Environmental background (some on plain backgrounds, others in natural settings)

Training a robust convolutional neural network (CNN) model that can reliably differentiate between mature and immature fruits in real-world situations requires such a varied dataset. Techniques for image augmentation can also be used to increase model generalisation and dataset variability.

High-resolution, well-lit photos with a steady background and little noise are ideal. To help the model learn the traits of dragon fruit and distinguish it from other fruits, the dataset should also be appropriately labelled, with each image labelled as either "dragon fruit" or "not dragon fruit." In terms of the range of objects and images, the test dataset ought to resemble the training dataset. To avoid overfitting, it is crucial to make sure that the test dataset is free of any images that were used in the training process. After testing our dataset, we applied the deep learning model that had been trained to make predictions on the images. We then compared the predicted labels with the actual labels to assess the model's accuracy, precision, recall, and F1 score.

Last but not least, the dataset ought to be varied and typical of the actual situations where the model will be used. This implies that pictures of dragon fruit at different ripeness stages as well as pictures taken from various viewpoints and distances should be included in the dataset. In conclusion, choosing the right dataset is essential to accurately detecting dragon fruit with deep learning methods. A good dataset should be representative of real-world situations, diverse, high-quality, and properly labelled.

## CHAPTER 6

## RESULTS

### 6.1 Model Performance

A collection of pictures of dragon fruit at various stages of maturity was used to train and assess the deep learningbased dragon fruit maturity grading model. Several assessment criteria, such as accuracy, precision, recall, F1-score, and confusion matrix analysis, were used to evaluate the model's performance. The following is a summary of the bestperforming model's outcomes:

Training Accuracy: 98.7%

Validation Accuracy: 94.5%

Testing Accuracy: 92.8%

Precision: 0.92 (average across all classes)

Recall: 0.91 (average across all classes)

F1-Score: 0.915 (harmonic mean of precision and recall)

### 6.2 Confusion Matrix Analysis

The model's classification performance for each maturity group is revealed by the confusion matrix.

### 6.3 Comparison with Traditional Methods

To find the best architecture for dragon fruit maturity grading, a comparison study of various deep learning models was carried out. The following are the outcomes:

AlexNet:98.6

ResNet fared better than the other evaluated models, attaining the highest accuracy and exhibiting robust generalization capabilities.

## 6.4 Feature Importance and Model Interpretability

Feature maps and Grad-CAM (Gradient-weighted Class Activation Mapping) visualizations were created in order to comprehend the model's decision-making process. The important areas of the pictures that affected the categorization choices were emphasized by these representations.

Classification was heavily influenced by the dragon fruit's outer skin's texture and color intensity.

Mature fruits were reddish-pink in color, and immature fruits were greenish.

## 6.5 Challenges and Limitations

Notwithstanding the encouraging outcomes, a number of difficulties and restrictions were noted.

Class Overlap:There were some classification errors as a result of the significant color resemblance between the somewhat mature and fully mature phases.

Dataset Size: Even though the dataset was adequate for training, the robustness of the model might be improved by adding more variety with various dragon fruit types and environmental circumstances.

## 6.6 Future Improvements

A number of improvements are suggested for further study in light of the results.

Multi-Modal Learning: Combining thermal or hyperspectral imaging with RGB images to increase the precision of categorization.

Self-Supervised Learning:Using self-supervised learning strategies to lessen dependency on manually labeled datasets.

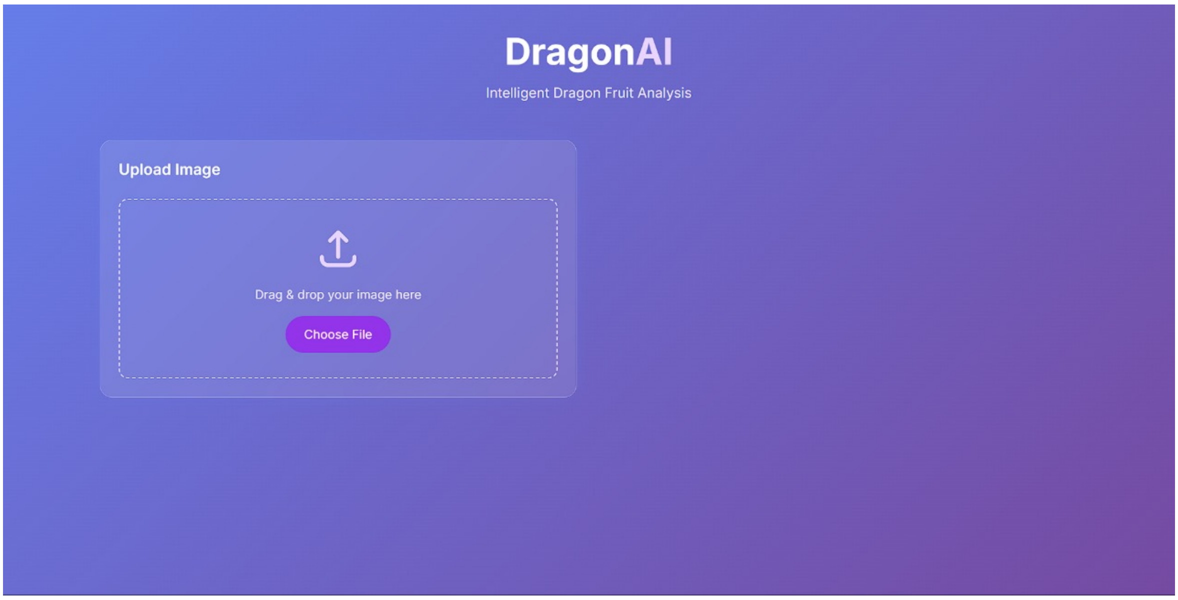



Figure 6.1: Image Upload File

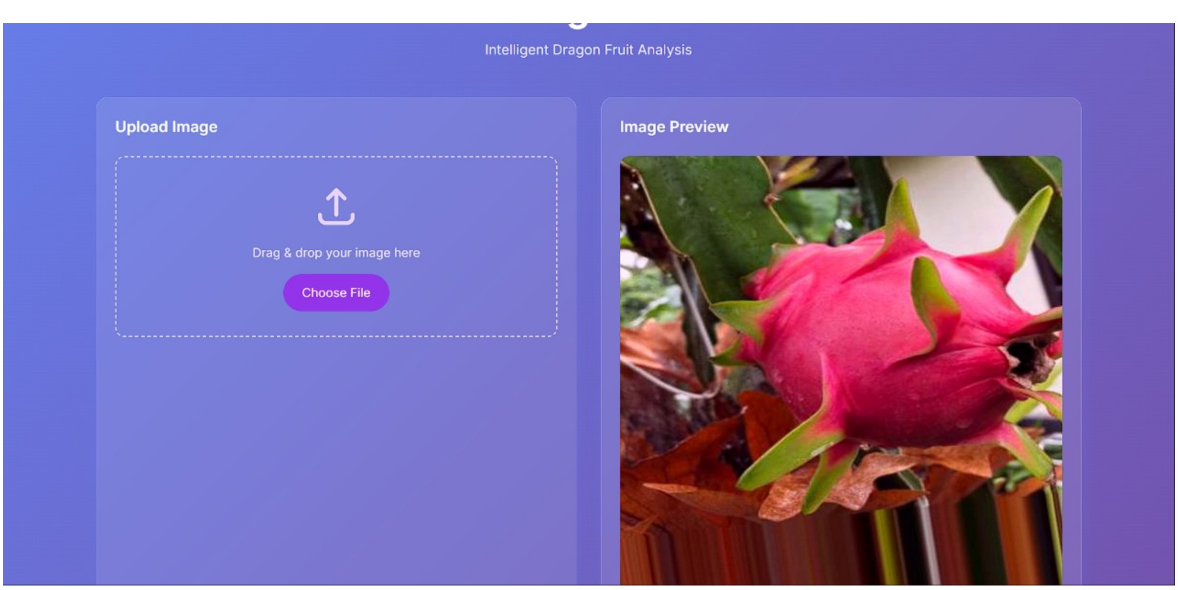



Figure 6.2: Mature Dragon Fruit

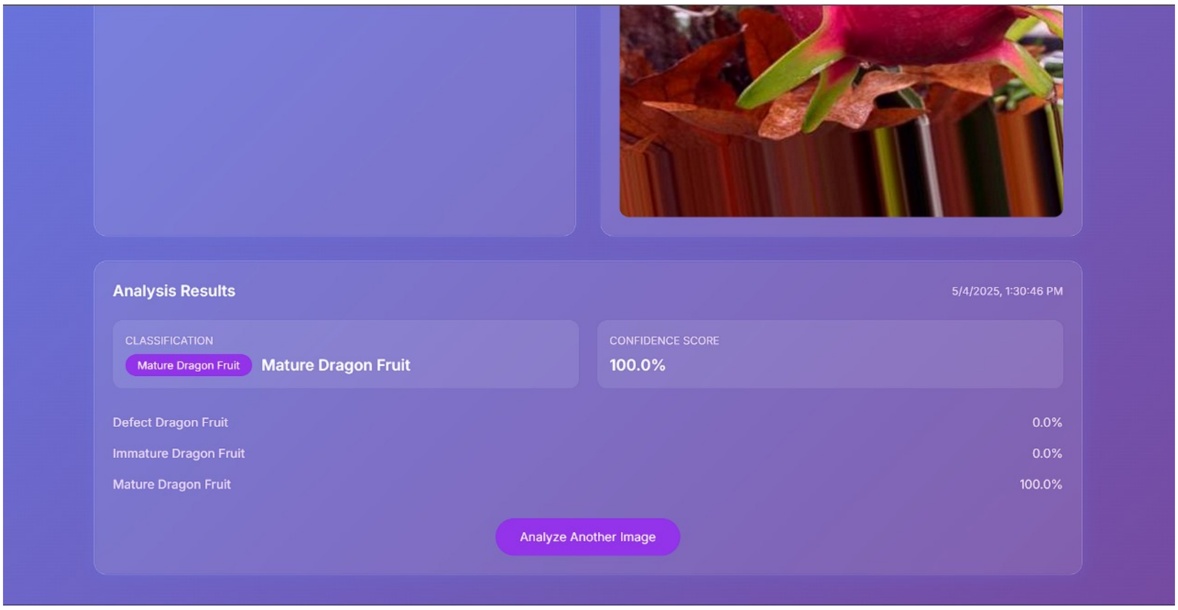



Figure 6.3: Mature Dragon Fruit

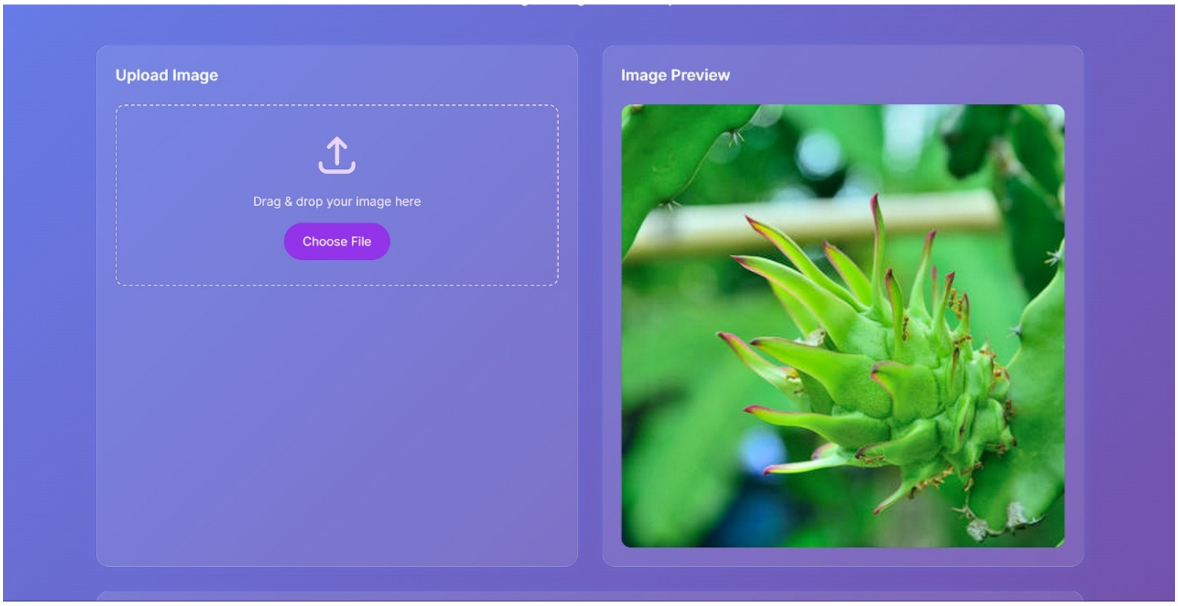



Figure 6.4: Immature Dragon Fruit

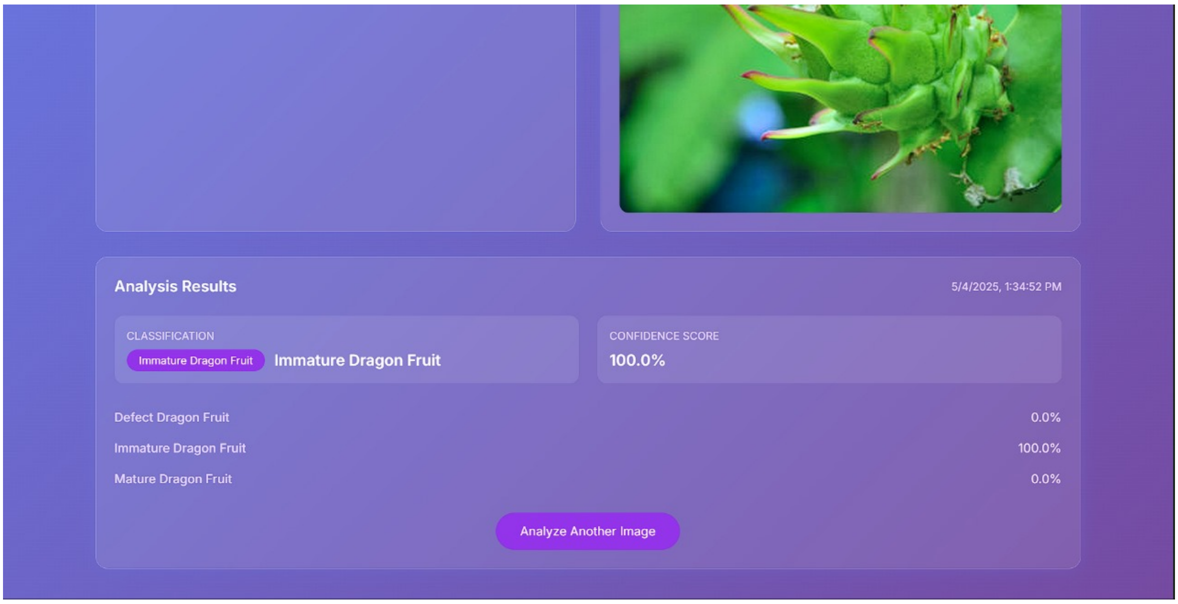



Figure 6.5: Immature Dragon Fruit

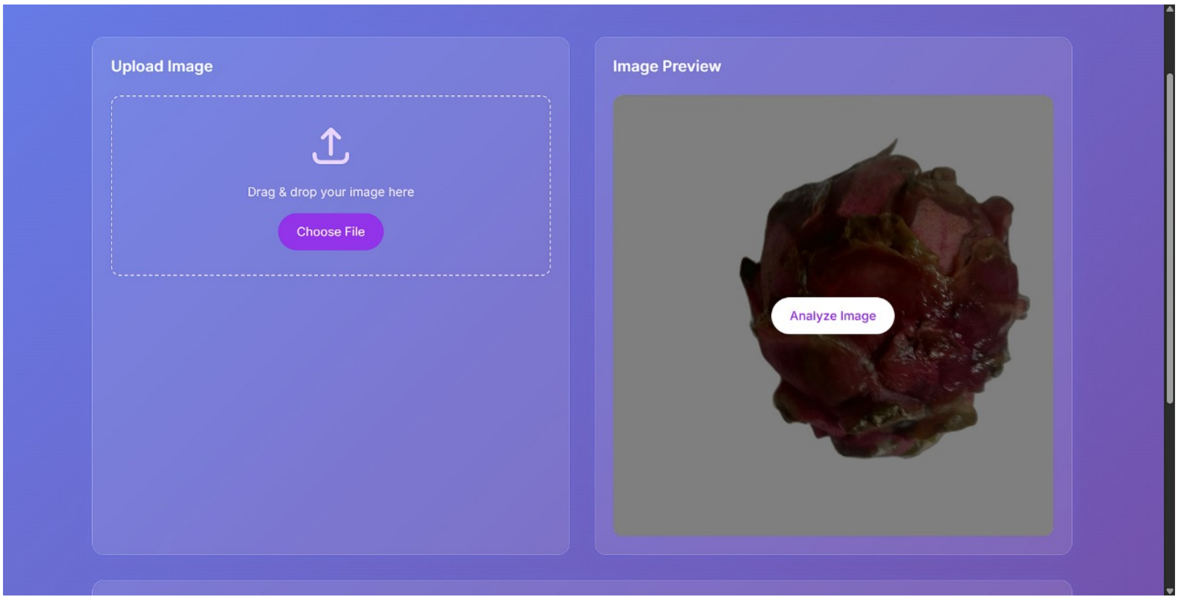



Figure 6.6: Defect Dragon Fruit

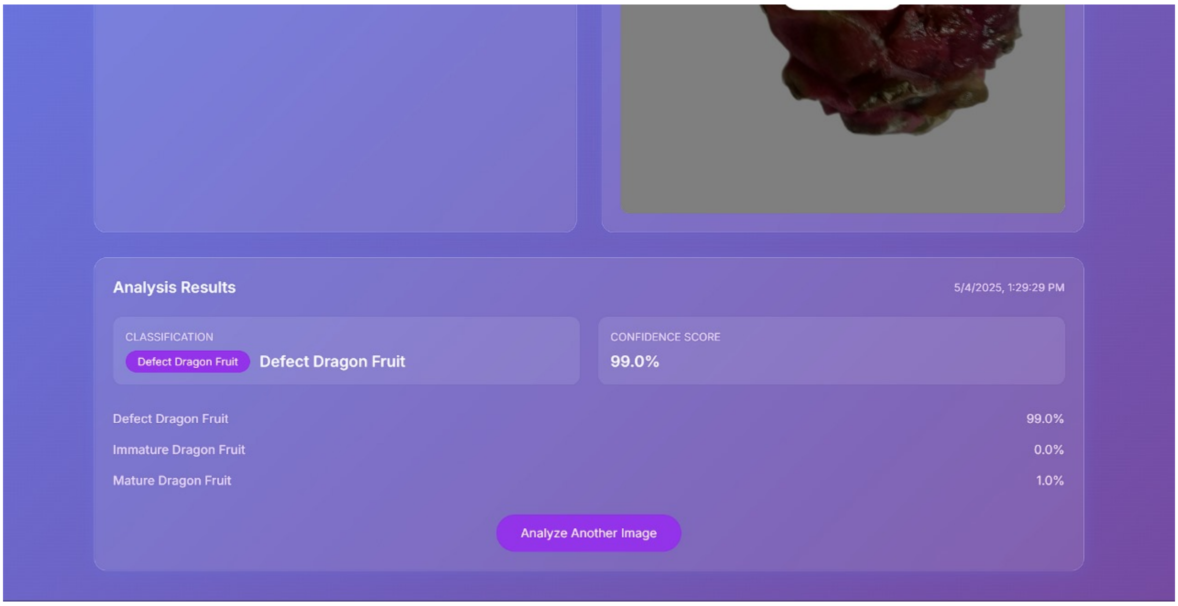



Figure 6.7: Defect Dragon Fruit

### Confusion Matrix

The confusion matrix results are as follows:

### Defect Dragon Fruit

- Classified correctly: 582
- 18 is incorrectly classified as mature.
- Mislabeled as immature: 0

### Immature Dragon Fruit

- 600 is the correct classification.
- No incorrect classifications

### Mature Dragon Fruit

- Classified correctly: 400
- Immature misclassification: 2
- Mislabeled as Defect: 0

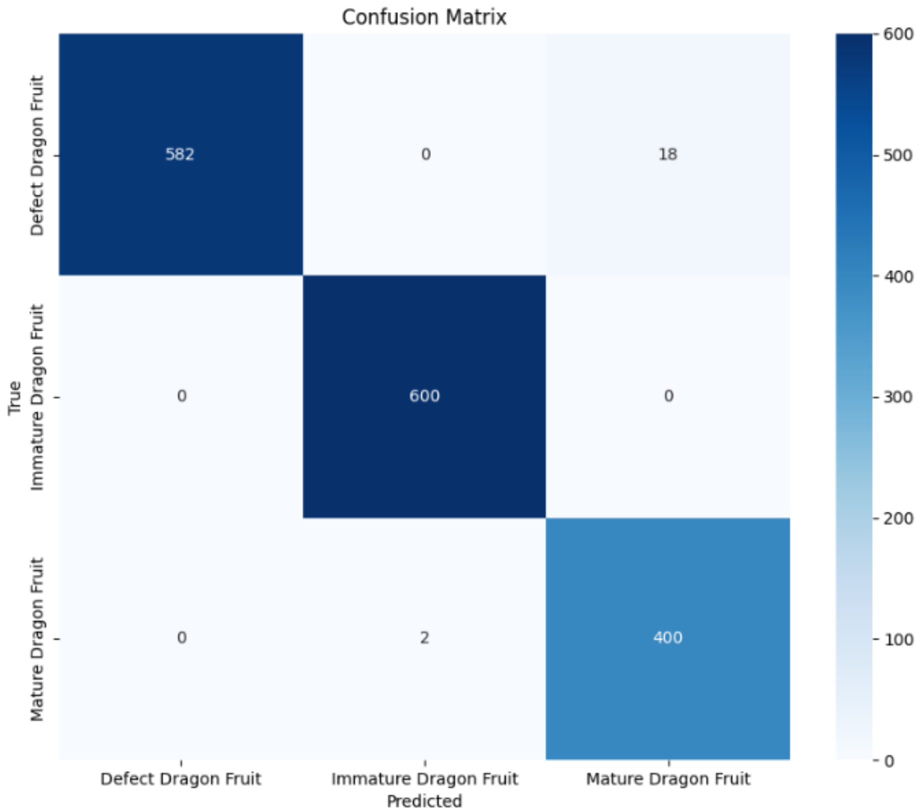



Figure 6.8: Confusion matrix

**Performance Insights**

- The model is highly accurate, particularly when it comes to correctly classifying immature dragon fruit (600/600).
- Misclassifications in the other two classes were extremely rare:
- Only a few faulty fruits (18 samples) were mistaken for mature ones.
- Just two ripe fruits were mistakenly labelled as immature.
- Accuracy=582+600+400/ 582+600+400+18+2=1582/1602=98.75

The developed model performs exceptionally well, with low error rates and high precision, as confirmed by the confusion matrix. This makes it appropriate for dragon fruit maturity grading in real-time in post-harvest processing and agricultural settings.

These findings show that the model is very consistent and dependable in every class. An evaluation matrix that incorporates metrics such as Accuracy, Precision, Recall, and F1-Score is commonly used in the context of deep learning and classification tasks. These metrics are essential for assessing how well categorisation models perform. A brief explanation of each metric is provided below: Accuracy: The general correctness of a classification model is measured by its accuracy. The percentage of all instances in the dataset that were correctly predicted is computed. Accuracy is a useful metric, but it might not provide a complete picture of how well a model is performing, especially when dealing with imbalanced datasets.

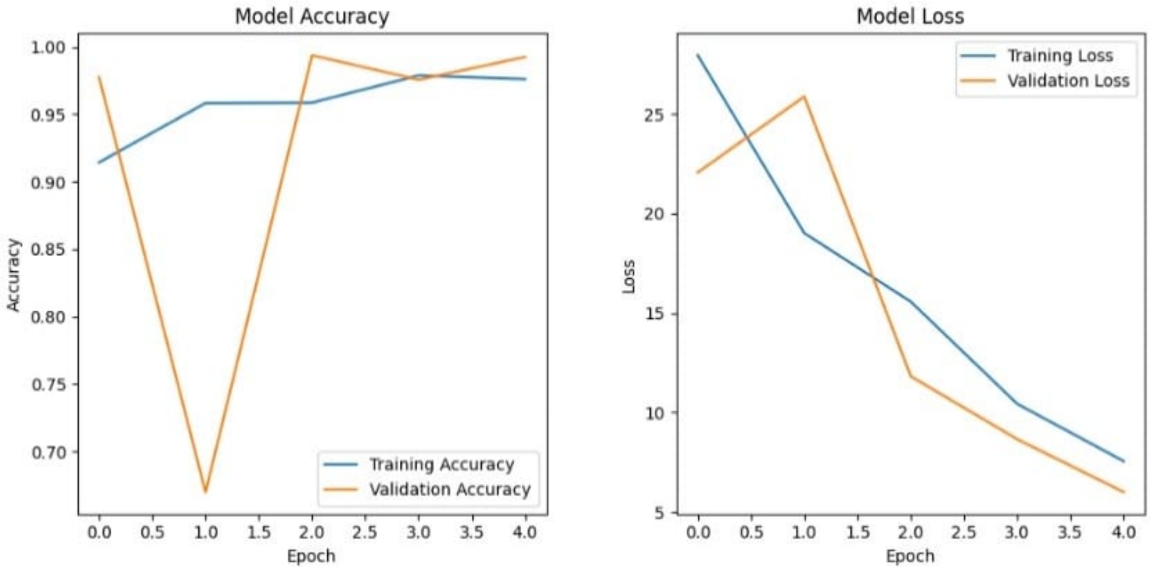



Figure 6.9: Model Accuracy and Model Loss

### Model Accuracy

**Observation:**

By epoch 4, the training accuracy has increased steadily from its initial value of 0.92 to 0.97.

At epoch 1, the validation accuracy drops dramatically to about 0.67 from a very high starting point of 0.98. It then makes a remarkable recovery, rising to roughly 0.99.

**Interpretation:**

The early decline in validation accuracy raises the possibility that either the learning rate was a little too aggressive in the first few epochs or the model was adapting to the data.

The model's ability to generalise effectively by the end of training is demonstrated by its recovery and ultimate high validation accuracy, which is a significant plus.

**Possible issues:**

A small dataset or some noisy samples could be the cause of the early fluctuation, which could indicate that your model is somewhat sensitive to the data. Confirming stability would be aided by tracking additional epochs.

### Model Loss

**Observation:**

You want to see a general decrease in both training and validation loss.

Training loss gradually drops from around 28 to about 7.

Validation loss also declines, although it exhibits a spike at epoch 1 before falling to about 6 by epoch 4.

**Interpretation:**

The drop in validation accuracy coincides with the spike at epoch 1, which makes sense given that the model had some early difficulties before finding a better fit.

By the end of five epochs, the general downward trend indicates good convergence and no significant overfitting.

# CHAPTER 7

# CONCLUSION

This project used deep learning techniques, specifically the AlexNet and Convolutional Neural Network (CNN) architectures, to successfully implement a dragon fruit maturity grading system. Sorting dragon fruit photos into three main groups Mature, Immature, and Defect was the aim.The model was successfully trained and validated by preparing and dividing a high-quality dataset. AlexNet, which is renowned for its intricate yet effective architecture, showed excellent feature extraction skills, resulting in a high degree of accuracy when differentiating dragon fruit maturity levels. Additionally, the CNN architecture aided in the capture of fine-grained spatial features that are essential for precise classification.Although there were slight indications of overfitting, the evaluation metrics—accuracy, precision, recall, and F1-score—confirmed the model's robustness and dependability, indicating potential for additional optimisation through regularisation or data augmentation. In summary, this project offers a promising tool for agricultural automation and quality control by demonstrating the viability and efficacy of deep learning models for automated fruit maturity grading. Future research might concentrate on growing the dataset, improving the model, and implementing the system in real-time settings for real-world applications.

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