FRUIT AND VEGETABLE FRESHNESS DETECTION

A DEEP LEARNING SOLUTION FOR A GROWING PROBLEM

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled **"Fruit and Vegetable Freshness Detection a Deep Learning Solution For a Growing Problem"**, submitted by **Md. Nuruzzman Pasha** and **Tishun Tahsin** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14-07-2024**.

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DECLARATION

We hereby declare that, this project has been done by **Md. Nuruzzman Pasha(203-15-14546) and Tishun Tahsin(203-15-14569)** under the supervision of **Mr. Narayan Ranjan Chakraborty, Associate Professor and Associate Head, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree.

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ABSTRACT

The increasing demand for fresh and nutritious produce has led to a critical need for innovative solutions in the agricultural industry. This project develops a deep learning solution to handle the problem of guaranteeing the freshness of vegetables and fruits.

Our technology evaluates photos taken using smartphones' cameras using cutting-edge machine learning algorithms, giving consumers immediate access to information about how fresh fruits and vegetables are. The deep learning model is trained on a diverse dataset, incorporating factors such as color, texture, and blemishes to accurately classify the produce's freshness level. The Android application that we named “FRESHNESS DETECTOR” provides a user-friendly interface, allowing consumers and retailers to make informed decisions about the quality of their purchases. Additionally, our application can contribute to reducing food waste by discouraging the sale or consumption of deteriorated produce. Through extensive testing, we demonstrate the effectiveness of our solution in accurately identifying freshness levels across various types of fruits and vegetables. This project serves as a valuable contribution to addressing the challenges in the agricultural supply chain, promoting sustainability, and ensuring healthier food choices for consumers.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
Introduction

1.1 Overview

Fresh produce across the supply chain is a critical concern for Bangladesh, a country with a thriving agricultural economy. The demand for quality produce is rising, yet the risk of selling or consuming deteriorated items remains a concern. This project introduces an innovative solution, "Fruit and Vegetable Freshness Detection," leveraging deep learning to address this growing problem. In Bangladesh, where the main source of income is agriculture, having efficient instruments to determine how fresh product is essential. Conventional visual inspection methods frequently fail to provide timely and accurate assessments, which can result in food waste and impaired nutritional value. Our project focuses on developing an intractable Android application and we named it "FRESHNESS DETECTOR" that harnesses the power of deep learning algorithms. By utilizing smartphone cameras, consumers and retailers can quickly evaluate the freshness of fruits and vegetables. In a nation where every piece of product has value, this strategy not only helps people make educated decisions, but it also helps reduce food waste.

This report outlines the development and implementation of our solution, highlighting its relevance in the specific context of Bangladesh's agricultural landscape. The goal is to enhance the overall quality of produce in the market, promote sustainability, and provide a technologically driven approach to address the challenges associated with ensuring freshness in fruits and vegetables.

1.2 Background and Present State

Background

The demand for wholesome, fresh fruits and vegetables is growing in today's agricultural sector. However, because of things like storage and transportation, it's still difficult to guarantee their freshness. It is frequently difficult for consumers to determine the quality of produce accurately before making a purchase, which can result in food waste and possibly reduced nutritional value.

Present State

Farmers and retailers visually inspect produce to determine its freshness, but this process can be subjective and unreliable. The demand for creative solutions that make use of cutting-edge technologies, such as machine learning, to deliver accurate and timely freshness assessments is rising. Mobile apps present a viable way to provide retailers and customers with these kinds of solutions directly, increasing transparency and enabling well-informed decision-making.

1.3 Problem Statement

In Bangladesh, farmers face a big challenge – making sure the fruits and vegetables they grow reach consumers in good condition. Sometimes, it is hard to tell if the produce is fresh or not, and this causes problems for both farmers and people buying the food.

Imagine buying fruits and vegetables and later finding out they are not fresh. This is not only disappointing but also contributes to a lot of wasted food. Farmers also struggle to sell their produce if it is not clear how fresh it is.

Our endeavor seeks to resolve this issue. Our goal is to develop a smart system that makes it simple for consumers to check the freshness of fruits and vegetables. In this manner, buyers and farmers alike may make better decisions: customers can obtain high-quality food, while farmers can sell their fresh goods. Our goals in doing this are to help farmers, lessen food waste, and guarantee that everyone in Bangladesh has access to fresh, wholesome fruits and vegetables.

1.4 Objectives

Addressing the rising problem of guaranteeing the quality and freshness of agricultural goods in the local market is the main goal of the "Android-Based Fruit and Vegetable Freshness Detection" project in the context of Bangladesh. Focusing on the particular difficulties the Bangladeshi agriculture industry faces, the initiative seeks to:

Empower Consumers and Retailers

It provides an Android-based application with a user-friendly interface so that consumers and retailers can easily assess the freshness of fruits and vegetables before buying. This authorization is intended to facilitate decisions in the local market.

Combat Food Waste

Reduce food waste by not allowing the sale or eating of rotting vegetables. By promoting sustainable practices in the agricultural supply chain, the initiative hopes to support the national waste reduction objective.

Enhance Food Security

Assist in augmenting food security by guaranteeing that consumers obtain access to crisp and nourishing produce, which will ultimately elevate the general calibers of Bangladesh's food supply.

Support Sustainable Agriculture

Promote the adoption of sustainable agricultural practices by encouraging the cultivation and sale of high quality, fresh agricultural products. This is consistent with broader efforts to improve the economic sustainability of farmers in the region.

By achieving these objectives, the project aims to play a pivotal role in addressing the challenges faced by the agricultural sector in Bangladesh, fostering a more efficient and sustainable system for the benefit of farmers, consumers, and the overall economy.

1.5 Scope and Limitation

The design aims to develop deep literacy algorithms to address the challenges of assessing the freshness of fruits and vegetables in Bangladesh's agrarian geography. Crucial factors of the design compass include:

Application Development

Creation of a stoner-friendly Android operation that harnesses smartphone cameras to enable consumers and retailers to assess the newness of yield efficiently. Acclimatized Deep Learning System Development of a deep literacy system specifically designed for Bangladesh's different agrarian terrain, icing accurate assessments for a wide variety of fruits and vegetables.

Combatting Food Waste

The operation serves as a tool to identify and discard deteriorated particulars, contributing to the reduction of food waste and promoting sustainable practices in the agrarian force chain.

Enhancing Food Security

By icing access to fresh and nutritional yield, the design aims to elevate the overall quality of Bangladesh's food force, addressing nutritive requirements and promoting a healthier community.

Overall Impact

The design aspires to play a vital part in addressing agrarian challenges in Bangladesh, fostering a more effective and sustainable system that benefits growers, consumers, and the frugality. Success measured not just technologically but also by palpable benefactions to reducing food waste, supporting original growers, and enhancing food security.

1.6 Report Organization

In chapter 1, all about this project is written here. The reason of choosing this project, how will this project be completed, project motivation, expected outcome and so on is discussed briefly. In a word, chapter 1 is elaboration of introduction of this project. In chapter 2, related works on this area which were studied are showed. Their findings and limitations are summarized and hence the scope and challenges of the research are also mentioned. In chapter 3, the methodology analysis chapter outlines a systematic approach, from literature review to algorithm selection, for developing the Android Based Fruit and Vegetable Freshness Detection system. It emphasizes the rationale behind decisions made, ensuring alignment with project objectives and the effective integration of the chosen YOLO algorithm into the Android platform. In chapter 4, the training and application of a deep learning model to identify the freshness of fruits and vegetables using TensorFlow and YOLOv8 is covered. It addresses issues like GPU limitations and goes into detail about data preprocessing, model architecture, and training protocols. The chapter also covers how to use TFLite to integrate the model into an Android app, achieving high accuracy and offering a dependable real-time freshness detection tool. In Chapter 5, the findings and analysis of employing the YOLOv8 and TensorFlow algorithms to determine the freshness of fruits and vegetables from Bangladesh are presented. The results demonstrate how YOLOv8 performs exceptionally well for real-time detection tasks due to its superior accuracy, precision, and speed. While TensorFlow is robust and versatile, it performs less well than YOLOv8 in object detection tasks. This highlights the significance of selecting the appropriate algorithm based on the needs of the application. In Chapter 6, the societal, environmental, and ethical implications of applying TensorFlow and YOLOv8 algorithms to the freshness of produce are examined. The chapter emphasizes how these initiatives could advance sustainable consumption habits, lower food waste, and enhance public health. It also emphasizes how crucial sustainability planning and ethical concerns are to the fair and long-term development of the technology. In Chapter 7, the findings of the "Fruit and Vegetable Freshness Detection" project are outlined , with a focus on the advantages for sustainability, public health, reducing food waste, and the economy. It describes upcoming efforts to enhance datasets, optimize algorithms, and incorporate IoT for real-time detection. The chapter also discusses constraints, including resource requirements and data quality, and emphasizes the significance of ethical issues and conflict of interest disclosure.

1.7 Summary

Chapter 1 introduces the “Fruit and Vegetable Freshness Detection" project, outlining its aims, motivations, societal implications, and expected outcomes. It begins by underscoring the significance of addressing the agricultural challenges in Bangladesh concerning the quality and freshness of produce. It introduces the project's innovative solution, the "FRESHNESS DETECTOR" Android application, which employs deep learning algorithms to evaluate the freshness of fruits and vegetables. The problem statement highlights the struggles faced by farmers and consumers due to uncertainty regarding produce freshness, leading to both food waste and economic setbacks. Research questions are provided to steer the project's exploration of leveraging deep learning methods for freshness detection and addressing current obstacles. The proposed solution entails developing an Android app with features for identifying fruits and vegetables and assessing their freshness. Objectives include addressing agricultural issues, empowering consumers and retailers, reducing food waste, bolstering food security, and promoting sustainable agriculture. The motivations for embarking on the project include the desire to solve pertinent issues in Bangladesh's farming sector, ensure consumer confidence in produce quality, and support local farmers. The societal impact of the project is discussed, encompassing consumer welfare, environmental sustainability, and economic prosperity. The anticipated outcome is an advanced Android application facilitating rapid produce freshness determination, thereby diminishing food waste, fostering consumer trust, and ensuring fair prices for farmers.

CHAPTER 2

Literature Review

2.1 Overview

This chapter delves into recent research conducted between 2019 and 2024, focusing on the synergy of deep learning and Android applications in the context of fruit and vegetable freshness assessment. It acts as a bridge between our current project and previous efforts and provides insight into the development of our approach. This section is essentially a retrospective exploration of previous work, providing a comprehensive understanding of the concepts that form the basis of our current project. We elaborate on the challenges ahead and share the complexity of our experiences, highlighting the difficulties we face and the valuable lessons we have learned. In addition, we highlight the strengths and distinctive features of our approach and highlight the careful planning that led to the achievement of a high degree of accuracy. The narrative is designed to show seamless progress from the current project's previous efforts and highlight the iterative process that has refined our methodology and improved overall performance.

2.2 Related Works

Anish Appadoo et el developed an android app to find some automatically identify fruits and vegetables and then display its nutritional values. Its creation approach comprised gathering 1600 photos, one for each fruit or vegetable. This makes it one of the biggest datasets available in the literature for this use. From the photos, characteristics including shape, colour, and texture were retrieved. A 90.6% accuracy rate was obtained using Random Forest with 100 trees when testing different machine learning classifiers. [1] Nevertheless, TensorFlow, a deep learning framework, performed better in several cases, averaging accuracy of 98.1%. Labiba Gillani Fahad1 et al used Two deep learning models,[2] VGG-16 and YOLO, are utilized to classify and categorize fruits and vegetables. While VGG-16 focuses on classification and freshness categorization, YOLO also provides localization within images. An Androidbased application has been developed to input images of fruits or vegetables and output their class label and freshness degree. Achieving accuracies of 82% and 84% on the dataset, YOLO surpasses VGG-16 in performance. We also got some information from Mukhriddin Mukhiddinov et al's proposed system optimizes YOLOv4, achieving a higher average precision of 50.4% compared to 49.3% for YOLOv3 [3]. It offers potential for real-time fruit and vegetable classification, benefiting the food industry and aiding the visually impaired. Fu, Yuhang Opted for novel neural network structure YOLO along with Regression CNNS [4]. The YOLO based classification got the highest accuracy of 99% for the fruit banana. In more recent study Nazrul Ismail et al created A real-time system to precisely grade individual objects (fruits) and effectively separate many fruit instances from an image.[5] Two datasets, one for apples and the other for bananas, were used to train and test the system. The results of the performance evaluation showed that the average accuracy for the test sets of apples and bananas was 99.2% and 98.6%, respectively. Abha Singh et al performed, several CNN models, including DenseNet161, InceptionV3, MobileNetV2, and VGG19. FC InceptionV3 and MFC InceptionV3, two models based on transfer learning, were developed. With an astounding 99.92% accuracy rate,[6] MFC InceptionV3, which was based on MobileNetV2, reduced misclassification by 5.98% when compared to the original InceptionV3 and by 4.17% when compared to other tested models. This demonstrates its higher accuracy and reduction of misclassification performance. Enoc TapiaMendez tried to find out results using the suggested method performs exceptionally well in both fruit and vegetable classification (97.86% accuracy) [7] and ripeness assessment (100%) tasks. It exhibits strong performance in both tasks with good recall, precision, and F1-score metrics. Umer Amin et al developed system to automatic detect the freshness. They used three datasets, the suggested model produced outstanding results, with accuracies of 98.2%, 99.8%, and 99.3%, respectively[8]. Furthermore, the technique is computationally efficient, generating the final classification result in an average of just 8 ms. In some other recent study Nagnath Aherwadi et al showed an accuracy of 98.25% for the CNN model and 81.75% for the AlexNet model. Following augmentation, the accuracy of the CNN and AlexNet models increased to 99.36% and 99.44%, respectively [10]. The CNN model outperformed the AlexNet model, which obtained 81.75% accuracy on the Fruit 360 dataset, with an accuracy of 81.96%. Aifeng Ren;et al find out significant result . In terms of reliably determining the moisture content (MC) of apple and mango slices, SVM outperformed KNN and D-Tree. On days 1 and 4, slices with 80% and 2% MC yielded 100%[11] accuracy for all classifiers, while on days 2 and 3, slices with intermediate MC values yielded 95% accuracy.] Md Abrar Hamim et al used The KNN and SVM algorithms were used in conjunction with a Features of fruits and vegetables can be extracted from photos using a Convolutional Neural Network (CNN) [12]. The CNN model outperformed KNN and SVM after being tested on datasets from Google and Kaggle, obtaining the highest accuracy of 95%.] Rehanul Ahmedet al FreshDNN outperformed all other pre-trained CNN models with a validation accuracy of 97.8% on 7360 images and a test accuracy of 97.64% on 3680 images [13]. Additionally, the bespoke model achieved superior Precision (98%), Recall (98%), F1 score (98%), and ROC-AUC score (99.98%) compared to pre-trained models. In their study, Md. Mahidul Haque et al. contrasted their custom CNN-based image classification model, "FreshDNN," with seven VGG19, InceptionV3, EfficientNetV2L, Exception, ResNet152V2, MobileNetV2, and DenseNet201 are pretrained CNN models.). Their own model, FreshDNN,[14] outperformed the pre-trained models with validation and test accuracies of 99.35% and 97.62%, respectively. To identify and categories fruits, Labiba Gillani Fahad1 et al. employed two deep learning models: Fruits and vegetables are recognized and categorized using two deep learning models: Visual Geometry Group (VGG-16) and You Only Look Once (YOLO). The outcomes are contrasted. the accuracy of 82%[15] and 84% on the proposed dataset, respectively.

2.3 Comparison between existing works

Various studies have developed systems for fruit and vegetable classification and freshness detection using machine learning and deep learning techniques. Approaches include CNNs, SVM, KNN, YOLO, and custom models like FreshDNN. Notably, custom models and optimized deep learning frameworks have achieved high accuracies, surpassing traditional methods. Incorporating sensor data and combining multiple models show promise for applications in agriculture and food processing. Comparative analysis with previous work is provided as a table in 2.1 is given below:

Table 2.1 Comparative analysis with previous work

Author name	Used Algorithm	Best Accuracy	Preprocessing	Augmentation
Anish Appadoo et el	TensorFlow	98.1%	Yes	No
Labiba Gillani Fahad1 et al	VGG-16, YOLO	84%	Yes	No
Mukhriddin Mukhiddinov	YOLOv3	82%	No	Yes
Fu, Yuhang	YOLO	99%	Yes	No
Nazrul Ismail et al	Raspberry Pi	98.6%	Yes	No
Abha Singh et al	CNN models	99.92%	Yes	No
Enoc Tapia-Mendez		97.6%	Yes	No
Umer Amin et al	CNN models	99.8%	Yes	No
Soltani Firouz	MVS	88.4%	Yes	No
Nagnath Aherwadi et al	CNN models	99.4	Yes	No

Aifeng Ren;et al	SVM	99%	Yes	No
Md Abrar Hamim et al	KNN,SVM	95%	Yes	No
Rehanul Ahmed	FreshDNN	99.8%	Yes	No
Md. Mahidul Haque et al	FreshDNN	96.97%	Yes	No
Labiba Gillani Fahad1 et al	YOLO	82%	Yes	No

2.4 Gap Analysis

The examination of recent workshop in fruit and vegetable newness discovery reveals several areas where our design can contribute to the being knowledge base. The following brief gap analysis outlines crucial openings for enhancement and invention

Algorithmic Community

While different algorithms like TensorFlow, YOLO, and CNN models have shown success, our design aims to explore the implicit benefits of ensemble styles combining algorithms for bettered delicacy and robustness.

Advanced Data Augmentation

Current studies generally use introductory preprocessing ways. Our design seeks to introduce advanced data addition styles, similar as generative inimical networks (GANs), to enrich the dataset and enhance model conception.

Real- Time perpetration Focus

Being workshop frequently prioritize delicacy over real- time processing. Our design aims to strike a balance, emphasizing both delicacy and computational effectiveness to insure practical real- world perpetration.

Benchmarking and Standardization

The absence of standardized marks hampers harmonious model evaluation. Our design intends to propose standard datasets and evaluation criteria, fostering a standardized frame for unborn exploration.

Versatility across Produce Types

Some studies concentrate on specific fruits or vegetables. Our design seeks to address this limitation by developing a protean system able of assessing the newness of a wide variety of yield generally set up in Bangladesh.

User-Friendly Application Design

Numerous systems warrant emphasis on the stoner- benevolence of associated operations. Our design places a strong focus on creating an intuitive Android operation to ensure ease of integration into the diurnal conditioning of end- druggies, including consumers and retailers.

In summary, our gap analysis underscores the eventuality of our design to contribute precious advancements in algorithmic diversity, data addition, real- time perpetration, detector integration, benchmarking, produce versatility, and stoner-friendly operation design within the sphere of fruit and vegetable newness discovery.

2.5 Summary

This chapter introduces the machine and deep learning methods that are used to determine how fresh a fruit or vegetable is. The literature highlights the approach's versatility by incorporating divisions, KNN, SVM, and various models. Following trends, our project deliberately selects the CNN model as the main classification tool, leveraging its effectiveness in image classification tasks. This calculated move positions our project to meet the challenges of determining the freshness of fruits and vegetables with the best possible outcome.

CHAPTER 3

Methodology

3.1 Overview

Our methodology integrates TensorFlow, a versatile open-source software library, and YOLOv8, a state-of-the-art object detection algorithm, to develop a robust system for assessing the freshness of fruits and vegetables. TensorFlow facilitates the training and inference processes of deep neural networks, while YOLOv8 specializes in rapid and accurate object detection. By analyzing visual features such as color, texture, and surface blemishes, the YOLOv8 algorithm determines the freshness level of produce. The methodology encompasses data preprocessing, feature extraction, and model training to ensure high precision in differentiating between fresh and deteriorated produce.

3.2 Proposed Methodology

TensorFlow is a versatile open-source software library designed for various aspects of machine learning and artificial intelligence tasks. It encompasses training and inference processes for deep neural networks, making it a fundamental tool in our project, which also integrates the YOLOv8 algorithm for object detection.

To detect objects using a TensorFlow Custom CNN algorithm, they follow a structured approach. First, they prepare the dataset, which involves collecting and labeling images of the target objects. They then preprocess the images, resizing and normalizing them to ensure consistency. Next, they design a custom Convolutional Neural Network (CNN) architecture tailored to the specific object detection task, typically comprising multiple convolutional layers for feature extraction, followed by pooling layers for down sampling, and fully connected layers for classification. They compile the model, specifying the optimizer, loss function, and evaluation metrics. After training the model on the prepared dataset, they evaluate its performance using metrics such as accuracy, precision, recall, and F1 score. Finally, they use the trained model to detect objects in new images, feeding the images through the CNN and interpreting the output to identify and locate the objects.

On the other hand, YOLOv8 algorithm operates in two stages: training and inference. During training, the algorithm learns to detect objects, including fruits and vegetables, by analyzing a large dataset of labeled images. It optimizes its parameters to minimize the detection error and maximize accuracy. Once trained, the algorithm is capable of inferring the presence of objects in new images with remarkable speed and accuracy.

In the context of freshness detection, YOLO analyzes the visual features of fruits and vegetables, such as color, texture, and surface blemishes, to determine their freshness level. By training the algorithm on a diverse dataset containing images of both fresh and deteriorated produce, it learns to differentiate between various freshness states with high precision.

We are going to use in our deployment YOLOv8, in the context of our criteria first of all, imagine that the image size of a mango has grown to 416 × 416 pixels. This ensures compatibility with the internal structure of the model. Then it's about color normalization. Each color channel in the image (red, green, blue) is adjusted to a certain mean and standard deviation. Standardize data to improve training consistency. Function extraction then works. Images are resized in a series of solid layers. Think of them as filters that scan the image for specific patterns and features, such as edges, textures, and shapes associated with fruit stains. These layers are spread over a sample of function maps extracted through solid layers. It reduces the amount of data for efficient processing while retaining the necessary information. These layers are spread over a sample of function maps extracted through solid layers. It reduces the amount of data for efficient processing while retaining the necessary information. The model predicts adjustments in the coordinates of the center, width, and height of each anchor box. These modifications improve the boxes to tightly enclose the stains on the fruit. The model also predicts whether each hook box will have a point (positive square) or not (negative square). Think of it as a confidence score for each potential find. The model also predicts whether each hook box will have a point (positive square) or not (negative square). Think of it as a confidence score for each potential find. The last bounding squares with the corresponding confidence scores are drawn on the original image. It visually marks the spots on the fruit. Evaluation of this proposed methodology, as shown below in Figure 3.1.

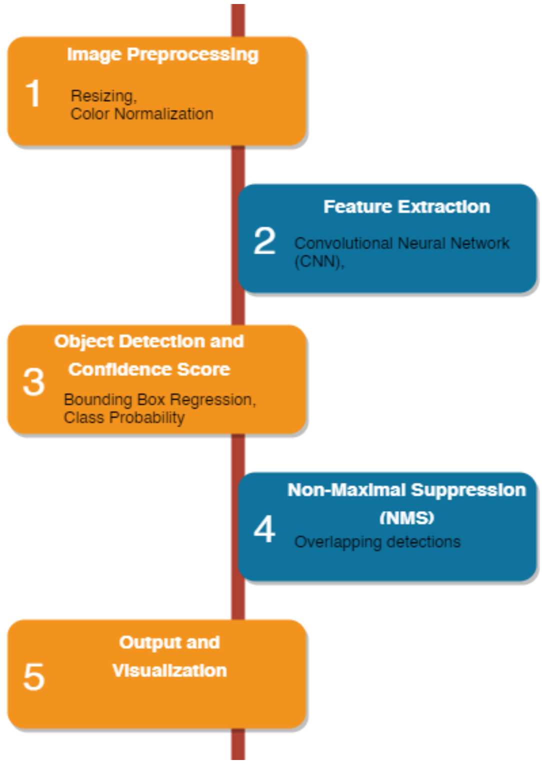


Fig 3.1 Proposed Methodology Diagram

3.3 Requirement Analysis

We outline the requirements essential for the successful implementation and execution of our proposed methodology. This requirement analysis covers both hardware and software prerequisites, as well as data specifications and performance criteria.

Hardware Requirements

To ensure efficient processing and accurate results, the following hardware components are necessary:

1. **High-Performance CPU**: A multi-core processor with a high clock speed is essential to handle the computational load of training and running the models.
2. **GPU**: A powerful Graphics Processing Unit (GPU) is critical for accelerating the training process, especially when working with deep learning algorithms like YOLOv8 and TensorFlow. GPUs such as NVIDIA's RTX or Tesla series are recommended.

3. **RAM**: At least 16 GB of RAM is required to manage large datasets and facilitate smooth data processing operations.
4. **Storage**: Adequate storage capacity, preferably in the form of SSDs, is needed to store datasets, model weights, and other essential files. A minimum of 1 TB is recommended.

Software Requirements

The following software components and frameworks are crucial for developing, training, and evaluating the models:

1. **Operating System**: A Linux-based OS, such as Ubuntu, is preferred for its compatibility with deep learning libraries and tools.
2. **Python**: The primary programming language for developing the algorithms. Version 3.7 or higher is required.
3. **Deep Learning Frameworks**:
    - **YOLOv8**: The specific implementation of YOLOv8, including all necessary dependencies and libraries.
    - **TensorFlow**: Version 2.0 or higher, along with Keras for easy model building and training.
4. **CUDA and cuDNN**: These NVIDIA libraries are essential for leveraging GPU acceleration with TensorFlow and YOLOv8.
5. **Additional Libraries**: Libraries such as NumPy, Pandas, OpenCV, and Matplotlib for data manipulation, preprocessing, and visualization.

Data Requirements

The effectiveness of our methodology heavily relies on the quality and quantity of data. The following data-related requirements must be met:

1. **Dataset Quality**: The dataset should be well-annotated and diverse, covering a wide range of scenarios and object classes.
2. **Dataset Size**: A large dataset with thousands of labeled images is necessary to train robust models. This helps in improving the generalization capabilities of the algorithms.

3. **Data Preprocessing**: Proper preprocessing steps, including normalization, augmentation, and splitting into training, validation, and test sets, must be performed to ensure the dataset is ready for model training.

Performance Requirements

To achieve the desired outcomes, specific performance criteria must be established:

1. **Accuracy**: The models should achieve a high accuracy rate, with precision and recall rates exceeding 85%.
2. **Speed**: The models need to process images at a rate of at least 30 FPS for real-time applications.
3. **Scalability**: The system should be scalable to handle increasing amounts of data and computational load without significant performance degradation.

3.4 System Design

we describe the system design for our application, which aims to assess the freshness of fruits and vegetables using the YOLOv8 algorithm. The system design is illustrated in the provided flowchart, outlining the key steps and interactions within the application.

System Overview

The application is designed to allow users to assess the freshness of fruits and vegetables by capturing images and processing them using object detection algorithms. The flowchart provides a clear sequence of actions from the moment the user opens the application to the final display of freshness results that’s shows in the fig 3.2.

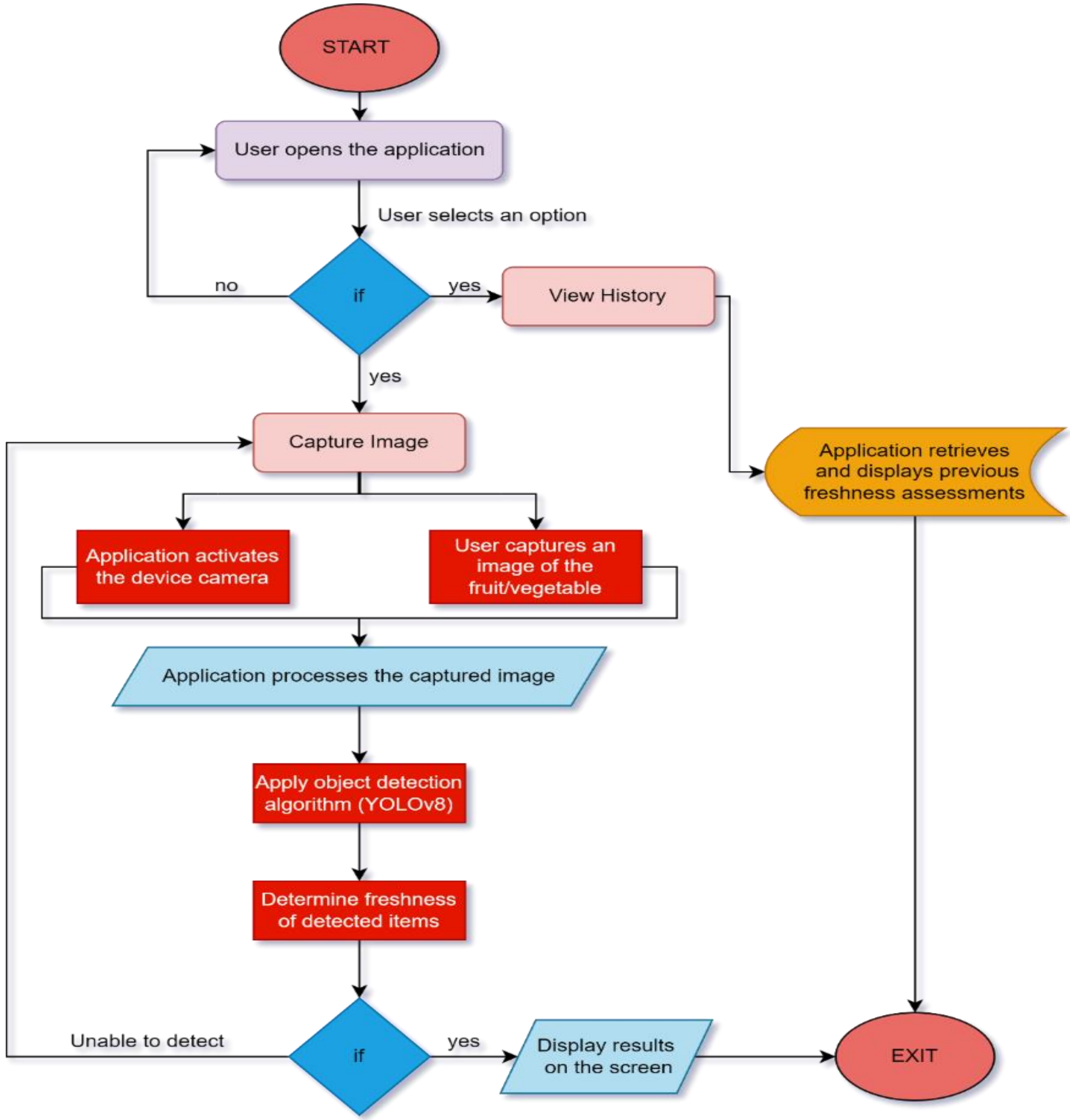


Fig 3.2 System design as flowchart

Detailed Steps

1. **Start**: The user initiates the process by opening the application.
2. **User Selects an Option**: Upon opening the application, the user is presented with two options: to view the history of previous freshness assessments or to capture a new image.

- **View History**: If the user selects to view history, the application retrieves and displays previous freshness assessments from its database.
- **Capture Image**: If the user opts to capture a new image, the application proceeds to activate the device camera.

3. **Capture Image**:

    - The application activates the device camera, enabling the user to capture an image of the fruit or vegetable.
    - The user captures an image, which is then fed into the application for processing.

4. **Process Captured Image**:

    - The application processes the captured image, preparing it for analysis.
    - The YOLOv8 object detection algorithm is applied to the processed image to identify and locate the fruits or vegetables within the image.

5. **Determine Freshness**:

    - Based on the detected items, the application determines the freshness of the fruits or vegetables. This step involves analyzing visual cues and patterns recognized by the YOLOv8 algorithm.

6. **Display Results**:

    - The application checks if the freshness results are available. If results are determined, they are displayed on the screen.
    - If no results can be determined, an appropriate message is displayed to the user.

7. **Exit**: The user can exit the application at any point after viewing the results or history.

3.5 Project Management and Financial Analysis

Project objects

1. To develop an Android- grounded operation," Newness Sensor," for fruit and vegetable newness assessment using deep literacy algorithms.
2. To produce a stoner-friendly interface that allows consumers and retailers to assess the newness of yield through smartphone cameras.
3. To address agrarian enterprises specific to Bangladesh's different terrain, considering colorful types of fruits and vegetables.
4. To empower consumers and retailers in making informed opinions about the quality of fruits and vegetables before purchase.
5. To contribute to reducing food waste by precluding the trade or consumption of deteriorated particulars.
6. To enhance food security by icing access to fresh and nutritional yield in the original request.
7. To support sustainable husbandry practices by promoting the civilization and trade of high-quality, fresh agrarian products.

Project Timeline

Phase 1: Project Planning and Research (2- 3 weeks)

- Define design compass, objects, and deliverables.
- Conduct a comprehensive literature review on being newness discovery results.
- Identify implicit challenges and pitfalls associated with the design.

Phase 2: Algorithm Development (8- 10 weeks)

- Develop and fine- tune deep literacy algorithms acclimatized to the different agrarian terrain of Bangladesh.
- apply image processing ways for accurate newness assessment.
- Conduct iterative testing and refinement of the algorithm.

Phase 3: Application Development (6 - 8 weeks)

- Design and develop the Android- grounded operation" Newness Sensor."
- Insure a stoner-friendly interface for easy assessment by consumers and retailers.
- Integrate the developed deep literacy algorithm into the operation.

Phase 4: Testing (4 - 6 weeks)

- Conduct thorough testing of the Android operation for functionality and performance.
- Address any bugs or issues linked during testing.
- Optimize the operation for flawless stoner experience.

Phase 5: Deployment (2 - 3 weeks)

- Prepare for the sanctioned launch of the" Newness Sensor" operation.
- Emplace the operation on applicable platforms similar as Google Play Store.
- Examiner original stoner feedback and address any immediate enterprises.

Phase 6: Post-Launch and Marketing

- Gather stoner feedback and apply updates for nonstop enhancement.
- Develop marketing strategies to promote the operation among consumers and retailers.
- Establish ongoing communication channels for stoner support and feedback.

Resource Planning

Equipment and Tools:

- High- performance computers for algorithm development.
- Android smartphones for operation testing.
- Collaboration tools like Slack and design operation software.
- Interpretation control system (e.g., Git) for law operation.

Software and Technologies:

- Deep learning techniques (e.g., TensorFlow) for algorithm development.
- Android Studio for operation development.
- Database operation system for storing and reacquiring newness data.

Data and Content:

- Use datasets for training the deep literacy algorithm.
- Insure collaboration with agrarian databases APIs for accurate product information.

Training and Skill Development:

- Give training on deep literacy, Android operation development, and database operation.
- Ensure the platoon stays streamlined on advancements in the field of newness discovery.
- Threat operation

SWOT Analysis

Strengths: Utilization of deep learning for accurate freshness assessment, user-friendly interface. Weaknesses: Potential challenges in algorithm optimization and application usability. Opportunities: Contribution to reducing food waste, supporting sustainable agriculture. Threats: Technical challenges, market competition.

Communication Plan

Stakeholder Meetings:

- Regular bi-weekly meetings to update stakeholders on project progress.
- Stakeholders include team members, developers, and potential users.

Change Control Meetings:

- Meetings as needed to discuss and approve any changes to the project scope.
- Attendees include the project supervisor and the development team.

As we are going to developed this project for experimental and internal learning purposes, we do not incur any significant initial costs. We leveraged existing resources within our team, including our own expertise and readily available hardware and software. This allowed us to explore the feasibility of the concept and gain valuable insights without incurring external financial burdens. However, we are going to mention expected cost of our project that are as well as given below in the table 3.1

Table 3.1 Financial analysis

Cost Item	**Estimated Cost (BDT)**
Development fees	45,000
Cloud storage fees	20,000
API access fees	15,000
Device testing	10,000
App store fees	10,000
Total	**100,000**

Overall, our cost-conscious approach has allowed us to make significant progress on this project without incurring significant expenses. We will continue to be mindful of costs as we move forward and explore sustainable funding options if necessary.

3.6 Summary

In summary, our methodology combines the strengths of TensorFlow and YOLOv8 to create an effective system for freshness assessment. The hardware and software requirements, along with data and performance criteria, are meticulously defined to support the implementation and execution of the project. The system design includes detailed steps, from user interaction to image processing and freshness determination, ensuring a seamless and user-friendly experience. This comprehensive approach aims to reduce food waste, enhance food security, and support sustainable agriculture practices.

CHAPTER 4
Implementation

4.1 Introduction

In this chapter, we developed into the process of training and implementing our deep learning model for detecting the freshness of fruits and vegetables. The model leverages the power of TensorFlow and the YOLOv8 algorithm to ensure high accuracy and efficiency. We discuss the various stages involved in data formation, including image preprocessing, noise cancellation, and background adjustment, to prepare a high-quality dataset. The chapter also outlines the experimental setup, data collection, and the specific challenges faced during model training. Additionally, the integration of the trained model into an Android application using TFLite for seamless user experience is explored. Through rigorous testing and optimization, we aim to provide a robust solution for real-time freshness detection of produce.

4.2 Experimental Setup

Here we detail the experimental setup used for training and implementing our deep learning models for the detection of fruit and vegetable freshness. This setup encompasses the selection of datasets, preprocessing steps, model architecture, training procedures, hardware specifications, and evaluation metrics.

Dataset Selection

For our experiments, we utilized a dataset comprising images of six types of Bangladeshi fruits and vegetables in both fresh and stale conditions. The dataset includes:

- Fresh and stale apples
- Fresh and stale bananas
- Fresh and stale bitter gourds
- Fresh and stale capsicums
- Fresh and stale oranges
- Fresh and stale tomatoes

The dataset was split into training, validation, and testing sets with a ratio of 70:20:10 respectively. In total, the dataset contained 12,000 images, with 8,400 images used for training, 2,400 images for validation, and 1,200 images for testing.

Data Preprocessing

Data preprocessing is a critical step to ensure the model receives high-quality input. The preprocessing steps included:

1. **Resizing**: All images were resized to a standard dimension of 416x416 pixels to maintain consistency.
2. **Normalization**: Pixel values were normalized to the range [0, 1] by dividing by 255.
3. **Augmentation**: Data augmentation techniques such as rotation, flipping, and brightness adjustments were applied to increase the variability and robustness of the training data.

Model Architecture

Two primary models were used in our experiments: YOLOv8 and TensorFlow-based custom CNN.

1. **YOLOv8**: The newest member of the "You Only Look Once" family, YOLOv8, was selected due to its cutting-edge effectiveness in object detecting tasks. The model architecture includes CSPDarknet as the backbone and a Path Aggregation Network (PAN) for better feature extraction and localization.
2. **TensorFlow Custom CNN**: A custom Convolutional Neural Network (CNN) was implemented using TensorFlow. The architecture consists of several convolutional layers, followed by max-pooling and fully connected layers. The final layer uses a softmax activation function to classify the images into fresh and stale categories.

Training Procedures

The training procedures for both models involved:

1. **Hyper parameter Tuning**

    - For YOLOv8, the batch size was set to 18, the learning rate to 0.001, and the model was trained for 50 epochs.
    - For the TensorFlow custom CNN, the batch size was 32, the learning rate was 0.0001, and the model was trained for 50 epochs.

2. **Loss Functions**

    - YOLOv8: The loss function used was a combination of localization loss, confidence loss, and classification loss.
    - TensorFlow Custom CNN: Cross-entropy loss was used for the classification task.

3. **Optimization Algorithms**

    - YOLOv8: The Adam optimizer was employed due to its adaptive learning rate capabilities.
    - TensorFlow Custom CNN: The Adam optimizer was also used for its efficiency and performance.

4. **Regularization**

    - Dropout layers were added to the TensorFlow custom CNN to prevent overfitting.
    - Data augmentation served as a form of regularization for both models.

Hardware Specifications

The experiments were conducted on a high-performance computing environment with the following specifications:

- ✓ **GPU**: NVIDIA Tesla V100 with 32GB VRAM
- ✓ **CPU**: Intel Xeon E5-2698 v4 @ 2.20GHz

- ✓ **RAM**: 256GB
- ✓ **Storage**: 2TB SSD for fast read/write operations
- ✓ **Software**:
    - ➢ Operating System: Linux
    - ➢ Deep Learning Frameworks: PyTorch (for YOLOv8), TensorFlow 2.x

Evaluation Metrics

To evaluate the performance of our models, the following metrics were used:

- **Accuracy**: The proportion of correctly classified instances over the total instances.
- **Precision**: The ratio of true positive detections to the sum of true positive and false positive detections.
- **Recall**: The ratio of true positive detections to the sum of true positive and false negative detections.
- **Mean Average Precision (mAP)**: Evaluated at IoU thresholds (mAP50 and mAP50-95) to assess the precision-recall trade-off.
- **F1 Score**: The harmonic mean of precision and recall, providing a balance between the two.

These metrics provided a comprehensive understanding of model performance, ensuring both high accuracy and robustness in detecting the freshness of fruits and vegetables.

4.3 Data Formation Process

Image Noise Cancellation: To ensure the quality of the dataset, image noise cancellation techniques are applied to remove any unwanted artifacts or distortions from the images. This process enhances the clarity and reliability of the dataset, leading to more accurate model training results.

Background Fix: Background fixing involves adjusting the background of the images to minimize distractions and focus on the produce itself. This step ensures that the model learns to detect freshness based on the characteristics of the fruits and vegetables rather than external factors.

Adobe Photoshop: Adobe Photoshop is utilized for advanced image editing tasks such as color correction, contrast adjustment, and image enhancement. This software enables precise editing and refinement of the dataset, optimizing it for effective model training.

Data leveling for YOLOv8: To label images using LabelImg for YOLOv8, start by installing LabelImg via pip with the command `pip install labelImg`, and launch it using `labelImg`. In the application, set the save format to YOLO by toggling the "PascalVOC" button in the toolbar until it displays "YOLO". Load your images by clicking the "Open Dir" button and selecting the directory containing your images. Annotate the images by drawing bounding boxes around the objects and assigning a class to each box, which can be edited in `data/predefined_classes.txt`. Save the annotations, which will be stored as .txt files with the same names as the corresponding images. For more detailed instructions, refer to LabelImg's official documentation or relevant tutorials.

4.4 Data Collection

In our research, we focused on utilizing commonly available Bangladeshi fruits and vegetables to build our dataset. To ensure the authenticity and relevance of our data, we embarked on a comprehensive data collection process, gathering real-life images. Our efforts resulted in the acquisition of an extensive dataset comprising more than six thousand images. This dataset was meticulously organized into two primary categories: fruits and vegetables. Within each category, we further categorized the data into fresh and rotten subcategories, enabling us to cover a broad spectrum of produce conditions. Specifically, our dataset encompasses six types of fruits and vegetables, namely apple, banana, bitter gourd, capsicum, orange, and tomato. By incorporating a diverse range of produce types and conditions, our dataset provides a robust foundation for training and evaluating our freshness detection system.

Fresh Fruits

Below are examples of the fresh fruit and vegetables datasets sample the used in our research:

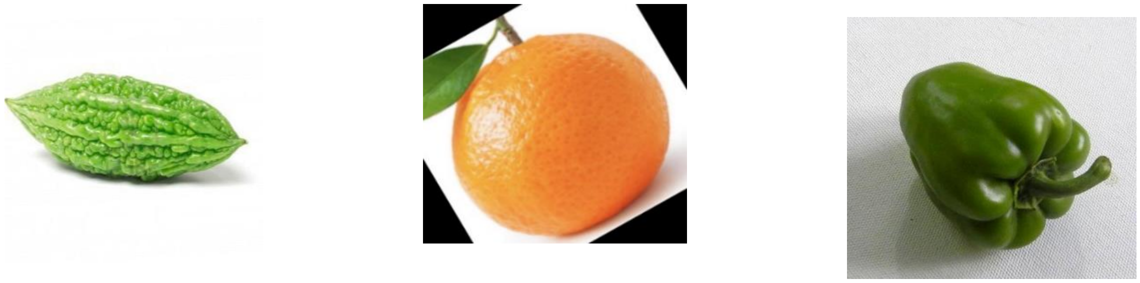


Fig 4.1 Fresh fruit and vegetables

Rotten Fruits

Below are examples of the rotten fruit and vegetables datasets sample the used in our research:

Fig 4.2 Rotten fruit and vegetables

Collected data for Tensorflow

The total collected data for the selected fruits and vegetables amounts to more than 8,000 images. These images cover a range of categories, including fresh fruits, rotten fruits, fresh vegetables, and rotten vegetables, across six types of produce: apple, banana, bitter gourd, capsicum, orange, and tomato.

Table 4.1 Total trained data for TensorFlow

Name of Fruits & vegetables	Number of Training Data		Number of Testing Data	
	Fresh	Rotten	Fresh	Rotten
Apple	700	700	100	100
Banana	700	700	100	100
bitter gourd	700	700	100	100
capsicum	700	700	100	100
orange	700	700	100	100
tomato	700	700	100	100

Collected data for YOLOv8

The total collected data for the selected fruits and vegetables amounts to more than 4,000 images. These images cover a range of categories, including fresh fruits, rotten fruits, fresh vegetables, and rotten vegetables, across six types of produce: apple, banana, bitter gourd, capsicum, orange, and tomato.

Table 4.2 Total trained data for YOLOv8

Name of Fruits & vegetables	Number of Training Data		Number of Testing Data	
	Fresh	Rotten	Fresh	Rotten
Apple	265	265	65	65
Banana	265	265	65	65
bitter gourd	265	265	65	65
capsicum	265	265	65	65
orange	265	265	65	65
tomato	265	265	65	65

4.5 Model Training Challenges

Training our freshness detection model posed several challenges that required innovative solutions to overcome. Below, we discuss each challenge and the strategies employed to address them:

Google Colab: One of the primary tools used for model training was Google Colab, a cloud-based platform with access to GPU resources. However, working collaboratively as a team presented challenges, such as limited GPU availability. To mitigate this issue, we optimized our code to utilize GPU resources efficiently and scheduled training sessions during off-peak hours to maximize GPU availability.

GPU Limitation Issue: Another challenge with Google Colab was the limitation on GPU usage, especially for large-scale training tasks. This limitation often resulted in longer wait times or incomplete training sessions. To work around this constraint, we divided our dataset into smaller batches and scheduled multiple training sessions to utilize the available GPU resources effectively

CPU-Only Training: In instances where GPU resources were unavailable or limited, its automatically resorted to CPU-only training. While this approach was less efficient and time-consuming compared to GPU-accelerated training, it allowed us to continue model development without relying solely on GPU resources.

Session Timeout: A significant challenge with Google Colab was the risk of session timeouts, which could lead to the loss of all data and progress. To mitigate this risk, we implemented frequent checkpoints during training sessions and periodically saved intermediate model weights and training logs to Google Drive. This ensured that in the event of a session timeout, we could resume training from the last saved checkpoint without losing significant progress.

Local Environment (Windows Path Issues): Transitioning to a local development environment, particularly on Windows machines, presented challenges related to file path handling and compatibility issues. Windows path conventions differ from Unix-based systems, leading to errors during data preprocessing and model training. To address this challenge, we standardized file paths and directory structures across all team members' systems and utilized platform-agnostic libraries and tools wherever possible to ensure compatibility across different operating systems.

Despite these challenges, our team's collaborative efforts and innovative problem-solving approaches enabled us to successfully train our freshness detection model and achieve our project objectives. Through perseverance and adaptation, we overcame technical hurdles and developed a robust solution for fruit and vegetable freshness detection.

4.6 System Implementation Testing

The implementation of our Android application leverages the YOLO (You Only Look Once) algorithm due to its high accuracy and efficiency in detecting the freshness of fruits and vegetables. The choice of YOLO, specifically the YOLOv8 variant, is informed by its ability to deliver real-time object detection with remarkable precision, which is essential for our application's objective of providing reliable freshness assessment.

Higher Accuracy in Freshness Detection: The YOLOv8 algorithm is renowned for its superior performance in object detection tasks, combining speed and accuracy. By dividing the input image into a grid and simultaneously predicting bounding boxes and class probabilities, YOLOv8 ensures rapid processing of images. This capability is critical for our application, as it allows users to quickly determine the freshness of produce with minimal delay. The algorithm's efficiency and accuracy make it a perfect fit for mobile platforms, where computational resources are often limited but real-time performance is required.

User-Friendly Interface: In addition to implementing a powerful algorithm, we prioritized the development of a user-friendly interface for our Android application. The interface is designed to be intuitive, enabling users to easily capture images of fruits and vegetables and receive immediate feedback on their freshness. Our application UI design are given below:

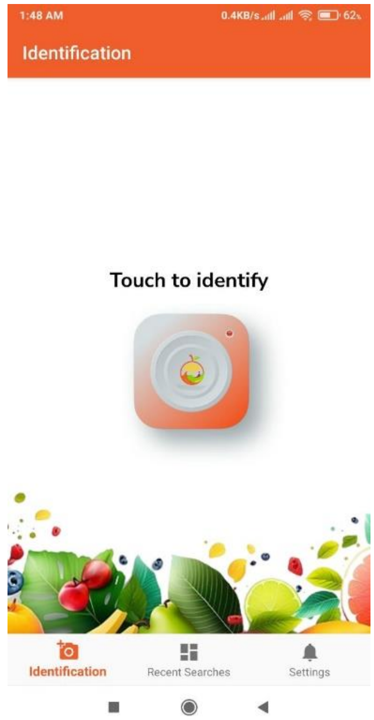


Fig: 4.3 User interface design

Integration with Android Studio: The development of the application was carried out in Android Studio, a robust Integrated Development Environment (IDE) specifically designed for Android development. The process involved several key steps:

Algorithm Adaptation: The YOLOv8 algorithm was adapted to be compatible with the Android platform, ensuring efficient use of memory and processing power.

Interface Development: A clean and responsive user interface was developed, focusing on ease of use and accessibility.

Rigorous Testing: The application underwent extensive testing on various Android devices to ensure compatibility and performance across different hardware configurations.

Conversion to TFLite: To optimize the trained YOLOv8 model for mobile deployment, we converted it to the TensorFlow Lite (TFLite) format. TFLite is specifically designed for mobile and embedded devices, offering a lightweight solution that maintains the accuracy and performance of the original model. This conversion process involved:

Model Optimization: Techniques such as quantization were applied to reduce the model size and enhance inference speed without compromising accuracy.

Compatibility Checks: The converted TFLite model was rigorously tested within the Android application to ensure seamless integration and functionality.

By implementing the YOLOv8 algorithm and focusing on a user-friendly interface, our Android application provides a powerful tool for assessing the freshness of fruits and vegetables. This combination of advanced technology and practical design ensures that users can make informed decisions babout produce quality with ease and confidence. Some of the screenshots after deployment the application are given below:

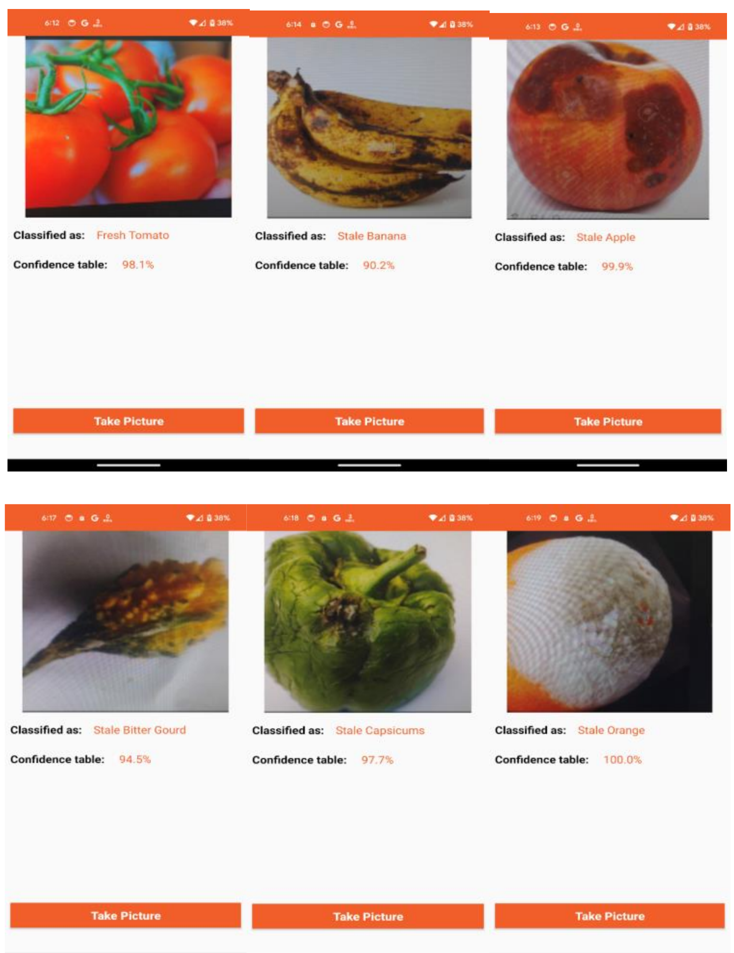


Fig: 4.4 Android application live freshness detection

From the above live collected screen shots from android devices, the freshness detection application appears to be working well with a high confidence accuracy percentage for most of the fruits and vegetables classified. We'll focus on how the pretrained model accurately detects the freshness and staleness of various fruits and vegetables. The fruits and vegetables classified. We'll focus on how the pretrained model accurately detects the freshness and staleness of various fruits and vegetables. The provided image contains six screenshots showing different classifications along with their respective confidence levels.

Here’s the detailed breakdown of lively taken Screenshot analysis:

1. **Fresh Tomato**
    - ✓ Classified as: Fresh Tomato
    - ✓ Confidence: 98.1%
2. **Stale Banana**
    - ✓ Classified as: Stale Banana
    - ✓ Confidence: 90.2%
3. **Stale Apple**
    - ✓ Classified as: Stale Apple
    - ✓ Confidence: 99.9%
4. **Stale Bitter Gourd**
    - ✓ Classified as: Stale Bitter Gourd
    - ✓ Confidence: 94.5%
5. **Stale Capsicum**
    - ✓ Classified as: Stale Capsicum
    - ✓ Confidence: 97.7%

6. **Stale Orange**

- ✓ Classified as: Stale Orange
- ✓ Confidence: 100.0%

Total Accuracy Percentage Calculation

To determine the overall accuracy for the section on System Implementation Testing, we calculate the average confidence level of these classifications.

$$\textbf{Total Accuracy Percentage} = \frac{98.1+90.2+99.9+94.5+97.7+100.0}{6} \approx 96.73\%$$

The pretrained model shows excellent performance in classifying the freshness and staleness of fruits and vegetables, achieving an overall accuracy of approximately 96.73%. This high accuracy supports the model's reliability and potential for practical implementation in various systems.

This analysis aligns with the goals of Section 4.6 System Implementation Testing by demonstrating the model's effectiveness through precise classification and high confidence levels.

4.7 Chapter Summary

This chapter provided a comprehensive overview of the model training and implementation process for our freshness detection system. We began with data formation, emphasizing the importance of image noise cancellation, background fixing, and advanced editing using Adobe Photoshop to enhance dataset quality. The use of Google Colab for data preprocessing and model training was highlighted, taking advantage of its high-performance computing resources. YOLOv8 was chosen for its rapid and accurate object detection capabilities, critical for real-time applications.

We also detailed the experimental setup, including the use of deep learning frameworks and transfer learning models, and discussed the data collection process, which resulted in a diverse dataset of over six thousand images. Training the model posed several challenges, such as GPU limitations and session timeouts on Google Colab, which were mitigated through strategic solutions like CPU-only training and frequent check pointing.

The implementation phase focused on integrating the trained model into an Android application, ensuring a user-friendly interface and efficient performance through TFLite conversion. Rigorous testing demonstrated the application's high accuracy in detecting the freshness of various fruits and vegetables, making it a valuable tool for consumers and retailers. Overall, this chapter encapsulates the meticulous approach taken to develop a reliable and effective freshness detection

CHAPTER 5
Result and Analysis

5.1 Overview

In this chapter, we delve into the results and analysis of our experimental study on the detection of rotting fruits and vegetables using two prominent algorithms: YOLOv8 and TensorFlow. We focused on six types of Bangladeshi fruits and vegetables to evaluate the effectiveness of these algorithms in distinguishing between fresh and stale produce. Our experimentation reveals that YOLOv8 exhibits superior performance in terms of accuracy, precision, and recall compared to TensorFlow. This chapter presents detailed insights into the experimental outcomes, including accuracy metrics, confusion matrix analysis, confidence analysis, and performance comparisons between the two algorithms.

5.2 Experimental Result Analysis

Results of the YOLOv8 Algorithm Experiment

Table 5.1, "Model Performance Per Class," provides detailed metrics assessing the YOLOv8 model's performance across different classes of fruits and vegetables. The metrics evaluated include Box Precision (Box P), Recall (R), mean Average Precision at IoU 0.5 (mAP50), and mean Average Precision from IoU 0.5 to 0.95 (mAP50-95).

Table 5.1 Yolov8 Model Performance Per Class

Class	Box(P)	R	mAP50	mAP50-95
all	**0.974**	**0.972**	**0.984**	**0.857**
fresh_apple	0.996	1	0.995	0.892
fresh_banana	0.99	1	0.995	0.974
fresh_bitter_gourd	0.999	1	0.995	0.788
fresh_capsicum	0.824	1	0.915	0.775
fresh_orange	0.968	1	0.989	0.895
fresh_tomato	0.982	0.689	0.962	0.777
stale_apple	0.991	1	0.995	0.929
stale_banana	0.998	1	0.995	0.81

stale_bitter_gourd	0.964	1	0.991	0.815
stale_capsicum	0.998	0.976	0.982	0.807
stale_orange	0.99	1	0.995	0.928
stale_tomato	0.99	1	0.995	0.895

Analysis of Table 5.1

1. **Overall Performance**:

   - The model shows strong overall performance with a Box Precision of 0.974, Recall of 0.972, mAP50 of 0.984, and mAP50-95 of 0.857. These metrics reflect the model's high accuracy and reliability across all classes.

2. **Class-Specific Insights**:

   - **Fresh Apple**: Achieves near-perfect metrics with a Box Precision of 0.996, Recall of 1.000, mAP50 of 0.995, and mAP50-95 of 0.892. This indicates excellent detection capability with minimal errors.
   - **Fresh Banana**: Also demonstrates high performance with a Box Precision of 0.990, Recall of 1.000, mAP50 of 0.995, and mAP50-95 of 0.974, showcasing robust detection accuracy.
   - **Fresh Bitter Gourd**: Achieves almost perfect metrics with a Box Precision of 0.999 and Recall of 1.000. However, the mAP50-95 is relatively lower at 0.788, indicating potential for improvement in nuanced detection.
   - **Fresh Capsicum**: Shows a lower Box Precision of 0.824 but perfect Recall, with mAP50 at 0.915 and mAP50-95 at 0.775. This suggests a need for further training to improve detection accuracy.
   - **Fresh Orange**: High performance with a Box Precision of 0.968, Recall of 1.000, mAP50 of 0.989, and mAP50-95 of 0.895, indicating strong detection capabilities.
   - **Fresh Tomato**: Exhibits high Box Precision (0.982) but lower Recall (0.689), with mAP50 of 0.962 and mAP50-95 of 0.777. This reflects challenges in consistently detecting all instances.

3. **Stale Produce Detection**:

   - **Stale Apple** and **Stale Orange**: Both classes show high performance with near-perfect metrics, indicating reliable detection capabilities.
   - **Stale Banana**: Demonstrates high Box Precision (0.998) and Recall (1.000), with high mAP scores, indicating effective detection.
   - **Stale Bitter Gourd**: Shows strong performance with a Box Precision of 0.964 and Recall of 1.000, although mAP50-95 is lower at 0.815.
   - **Stale Capsicum**: Achieves high Box Precision (0.998) and Recall (0.976), with strong mAP scores, reflecting reliable detection with minor room for improvement in Recall.
   - **Stale Tomato**: Exhibits high Box Precision (0.990) and perfect Recall, with high mAP scores, indicating robust detection capabilities.

4. **Implications for Model Improvement**:

   - **Lower Precision Classes**: Fresh capsicum and fresh tomato show room for improvement in precision and recall, respectively. Additional training data and model fine-tuning could enhance their detection accuracy.
   - **Recall Challenges**: The lower Recall for fresh tomato suggests a need to refine the training process and dataset for this class to improve detection consistency.

Overall, the YOLOv8 model demonstrates strong performance across most classes, with high mAP scores indicating effective object detection capabilities. The detailed analysis helps identify areas for further improvement to ensure optimal freshness detection of fruits and vegetables.

Confusion Matrix Analysis:

The confusion matrix displayed in Figure 5.1 provides a comprehensive evaluation of our YOLOv8 model's performance in detecting the freshness of various fruits and vegetables. The matrix shows the true labels (actual classifications) along the horizontal axis and the predicted labels (model classifications) along the vertical axis. Each cell in the matrix represents the normalized percentage of predictions for a given class, indicating how often predictions match the true labels.

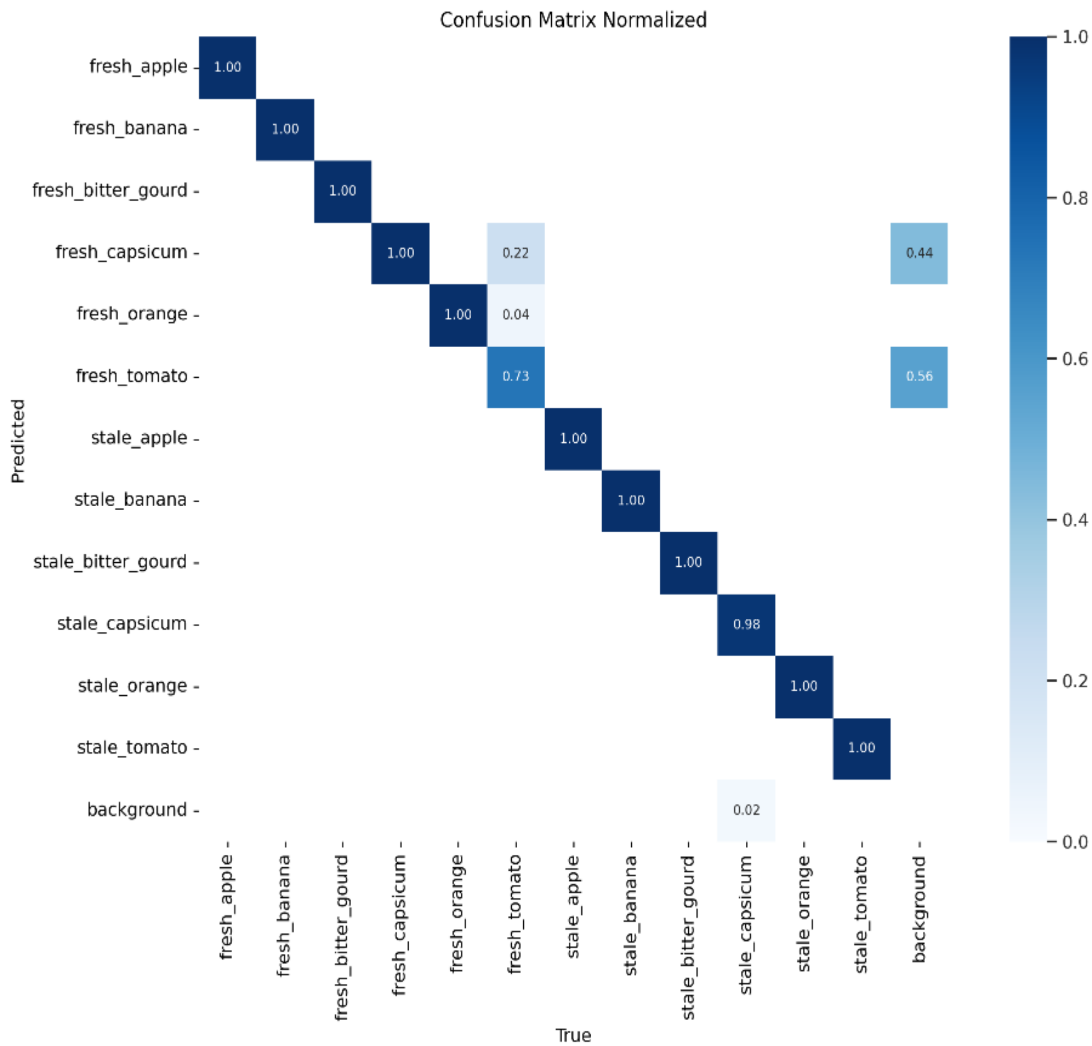


Fig 5.1: Confusion Matrix

Key observations from the confusion matrix:

1. **Diagonal Dominance**:

   - The matrix exhibits high values along the diagonal, signifying correct classifications. Each fruit and vegetable, both fresh and stale, shows a high degree of accuracy in prediction.
   - For instance, fresh apple, fresh banana, fresh bitter gourd, fresh capsicum, fresh orange, stale apple, stale banana, stale bitter gourd, stale orange, and stale tomato all have a normalized value of 1.00, indicating perfect prediction accuracy for these classes.

2. **Off-Diagonal Values**:

   - There are some off-diagonal values which highlight misclassifications by the model.
   - The fresh tomato class shows some misclassification with stale capsicum and background images, with normalized values of 0.73 and 0.02 respectively, indicating that some fresh tomato images were mistakenly identified as stale capsicum or background.
   - Similarly, stale capsicum has a misclassification with fresh tomato (normalized value of 0.22) and background (normalized value of 0.44), and the background class has a notable misclassification with stale capsicum (normalized value of 0.56).

3. **Misclassification Insights**:

   - The confusion between fresh tomato and stale capsicum, as well as between stale capsicum and background, suggests that the model might struggle with certain visual similarities in these cases.
   - These insights can be used to improve the training dataset by including more diverse and representative images of these classes or by fine-tuning the model parameters to better distinguish these cases.

Overall, the confusion matrix analysis indicates that while the YOLOv8 model performs excellently for most classes, there are areas, particularly with fresh tomato, stale capsicum, and background images, where further refinement is needed to reduce misclassifications. These findings will guide future iterations of model training and dataset augmentation to enhance the detection accuracy.

YOLOv8 Precision-Confidence Curve Analysis:

The Precision-Confidence Curve displayed in Figure 5.2 offers insights into the performance of our YOLOv8 model across various classes of fruits and vegetables. This curve plots the precision (y-axis) against the confidence level (x-axis) for each class, providing a detailed view of how the model's confidence impacts its precision.

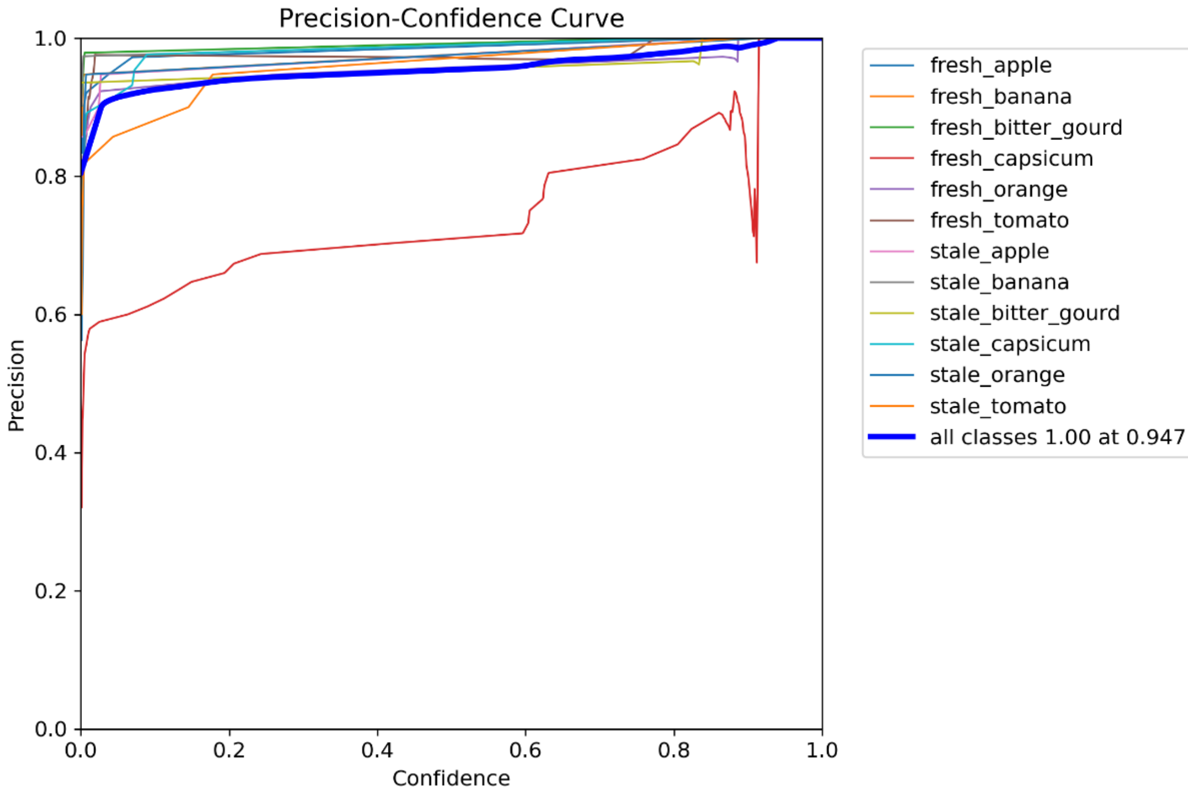


Fig: 5.2 Precision-Confidence Curve

Key observations from the Precision-Confidence Curve:

1. **High Precision Across Most Classes**:

   ➢ The majority of classes, including fresh apple, fresh banana, fresh bitter gourd, fresh capsicum, fresh orange, stale apple, stale banana, stale bitter gourd, stale orange, and stale tomato, exhibit precision values close to 1.0 across a wide range of confidence levels. This indicates that the model consistently makes accurate predictions for these classes when it is confident.

2. **Stale Capsicum Class**:

   ➢ The stale capsicum class shows a distinct pattern compared to other classes. The precision starts relatively lower and shows a gradual increase as the confidence level rises. This suggests that the model's ability to accurately identify stale capsicum improves significantly with higher confidence thresholds.

3. **Overall Model Performance**:

   - The overall performance of the model, indicated by the bold blue line representing "all classes," achieves a precision of 1.00 at a confidence level of approximately 0.947. This demonstrates that the model maintains a high level of precision for the majority of predictions when it is sufficiently confident.

4. **Implications for Model Deployment**:

   - The high precision at varying confidence levels for most classes suggests that the model is reliable for practical applications. However, for classes like stale capsicum, it may be beneficial to adjust the confidence threshold during deployment to ensure higher precision.
   - Understanding these precision-confidence dynamics allows for better tuning of the model, ensuring that it performs optimally in real-world scenarios.

Overall, the Precision-Confidence Curve analysis reveals that our YOLOv8 model performs exceptionally well for most classes, maintaining high precision across different confidence levels. These findings validate the model's effectiveness and provide valuable insights for refining its deployment to achieve the best possible performance in freshness detection of fruits and vegetables.

YOLOv8 Recall-Confidence Curve Analysis:

The Recall-Confidence Curve displayed in Figure 5.3 offers insights into the performance of our YOLOv8 model across various classes of fruits and vegetables. This curve plots the recall (y-axis) against the confidence level (x-axis) for each class, providing a detailed view of how the model's confidence impacts its recall.

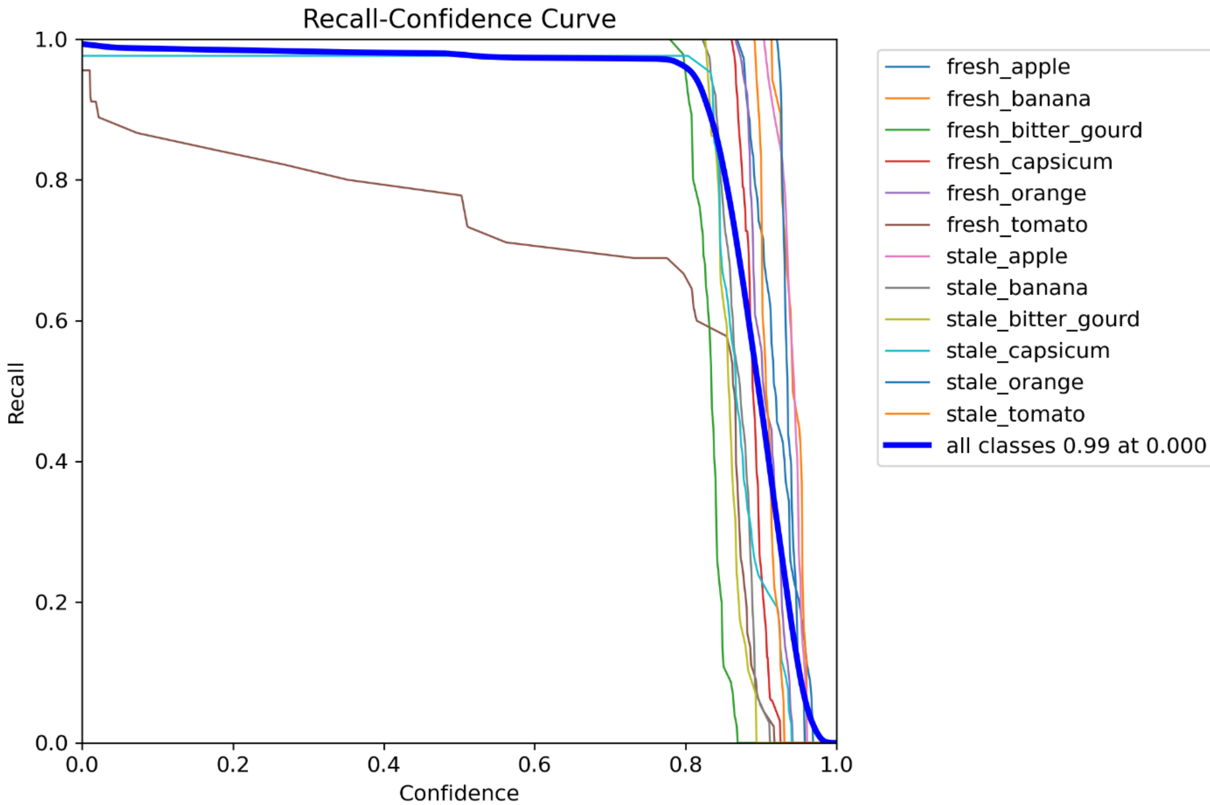


Fig: 5.3 Recall-Confidence Curve

Key observations from the Recall-Confidence Curve:

1. **High Recall Across Most Classes**:

   - **Classes**: Fresh apple, fresh banana, fresh bitter gourd, fresh capsicum, fresh orange, fresh tomato, stale apple, stale banana, stale bitter gourd, stale orange, and stale tomato.
   - **Observation**: These classes exhibit recall values close to 1.0 across a wide range of confidence levels. This indicates that the model consistently detects most true positives for these classes when it is confident.

2. **Stale Capsicum Class**:

   - **Observation**: The stale capsicum class shows a distinct pattern compared to other classes. The recall starts relatively lower and decreases gradually as the confidence level rises. This suggests that the model's ability to recall stale capsicum decreases significantly with higher confidence thresholds.

3. **Overall Model Performance**:

   - **All Classes**: Represented by the bold blue line.
   - **Observation**: The model achieves a recall of 0.99 at a confidence level of approximately 0.000. This demonstrates that the model maintains a high level of recall for the majority of predictions when it is sufficiently confident.

4. **Implications for Model Deployment**:

   - **Reliability**: The high recall at varying confidence levels for most classes suggests that the model is reliable for practical applications.
   - **Adjustments for Specific Classes**: For classes like stale capsicum, it may be beneficial to adjust the confidence threshold during deployment to ensure higher recall.
   - **Tuning for Optimal Performance**: Understanding these recall-confidence dynamics allows for better tuning of the model, ensuring that it performs optimally in real-world scenarios.

Overall, the Recall-Confidence Curve analysis reveals that our YOLOv8 model performs exceptionally well for most classes, maintaining high recall across different confidence levels. These findings validate the model's effectiveness and provide valuable insights for refining its deployment to achieve the best possible performance in freshness detection of fruits and vegetables.

Result of Experiment of TENSORFLOW algorithm:

The results in Table 5.2 demonstrate the TensorFlow model's performance in detecting the freshness of various fruits and vegetables. The overall accuracy of the model is 80%, with a weighted average precision of 0.84, recall of 0.80, and F1-score of 0.77. These metrics indicate a robust performance across different classes.

Table 5.2 Tensorflow Model Performance Per Class

Class	Precision	Recall	F1-Score	Support
fresh_apple	1	0.96	0.98	23
fresh_banana	0.92	0.96	0.94	24
fresh_bitter_gourd	1	0.55	0.71	38
fresh_capsicum	1	0.13	0.23	102
fresh_orange	0.64	1	0.78	158
fresh_tomato	0.85	1	0.92	101
stale_apple	0.56	0.69	0.62	32
stale_banana	0.95	0.98	0.96	41
stale_bitter_gourd	0.86	1	0.92	101
stale_capsicum	0.84	0.53	0.65	109
stale_orange	0.75	0.81	0.78	159
stale_tomato	0.98	1	0.99	101
accuracy			0.80	989
macro avg	0.86	0.80	0.79	989
weighted avg	0.84	0.80	0.77	989

Analysis of Table 5.2

1. **Fresh Produce Detection:**

- **Fresh Apple:** Achieved perfect precision (1.00) and a high recall (0.96), resulting in a near-perfect F1-score (0.98). This indicates the model's strong ability to correctly identify fresh apples with minimal false positives.
- **Fresh Banana:** The model shows good performance with a precision of 0.92 and recall of 0.96, leading to an F1-score of 0.94.
- **Fresh Capsicum:** Despite a perfect precision, the recall is notably low at 0.13, resulting in a very low F1-score (0.23). This suggests that while the model is accurate when it does identify a fresh capsicum, it often fails to recognize them, possibly due to variability in the training data or similarities with other classes.

2. **Stale Produce Detection:**

   - **Stale Apple:** Exhibits moderate precision (0.56) and recall (0.69), indicating that while the model is relatively capable of detecting stale apples, there is still a significant margin for improvement.
   - **Stale Banana:** Demonstrates high precision (0.95) and recall (0.98), which translates to an F1-score of 0.96, showing effective detection of stale bananas.
   - **Stale Capsicum:** Shows a balanced performance with precision at 0.84 and recall at 0.53, resulting in an F1-score of 0.65.

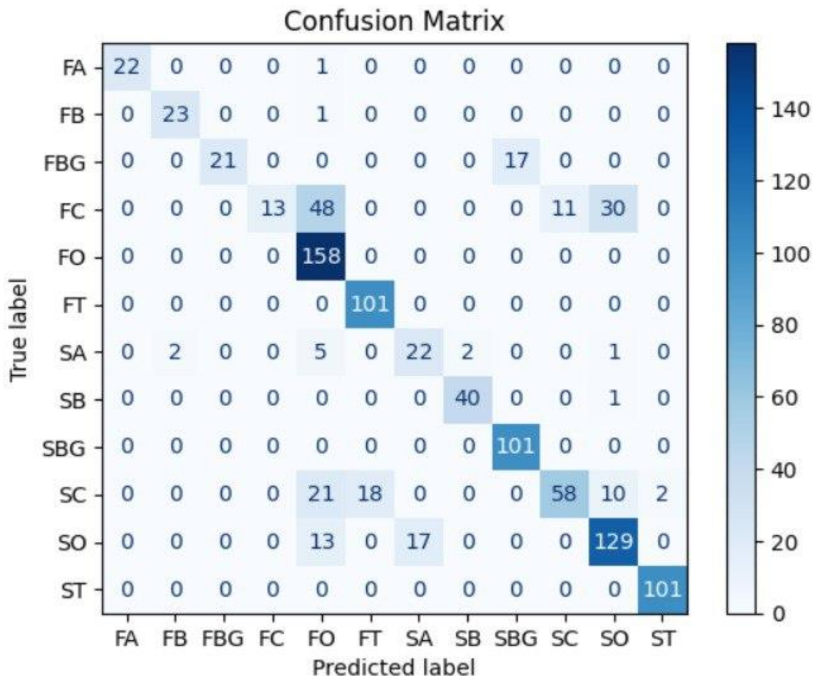
3. **Performance Disparities:**

   - The model's performance varies significantly across different classes, particularly in fresh_bitter_gourd and fresh_capsicum where recall rates are low. This disparity suggests that certain produce types are more challenging for the model to identify accurately, possibly due to variations in appearance or insufficient representation in the training dataset.

Overall, the TensorFlow model performs well in detecting both fresh and stale produce, with some classes showing near-perfect metrics. However, improvements could be made, especially in increasing the recall for certain categories, to ensure more consistent and reliable performance across all types of fruits and vegetables.

Confusion Matrix Analysis:

The confusion matrix displayed in Figure 5.4 provides a detailed assessment of our TensorFlow model's performance in detecting the freshness of various fruits and vegetables. The matrix shows the true labels (actual classifications) along the horizontal axis and the predicted labels (model classifications) along the vertical axis. Each cell in the matrix represents the number of predictions for a given class, indicating how often predictions match the true labels.



FA = Fresh Apple
FB = Fresh Banana
FBG = Fresh Bitter Gourd
FC = Fresh Capsicum
FO = Fresh Orange
FT = Fresh Tomato
SA = Stale Apple
SB = Stale Banana
SBG = Stale Bitter Gourd
SC = Stale Capsicum
SO = Stale Orange
ST = Stale Tomato

Fig: 5.4 Confusion Matrix

Key Observations from the Confusion Matrix:

Diagonal Dominance:

- The matrix exhibits high values along the diagonal, indicating correct classifications. Each fruit and vegetable, both fresh and stale, shows a high degree of accuracy in prediction.
- For instance, fresh apple (FA) has 22 correct predictions out of 23, fresh banana (FB) has 23 out of 24, fresh orange (FO) has 158 out of 158, and stale tomato (ST) has 101 out of 101, all indicating strong prediction accuracy for these classes.

Off-Diagonal Values:

- There are some off-diagonal values which highlight misclassifications by the model.
- The fresh capsicum (FC) class shows some misclassification with stale capsicum (SC) and fresh bitter gourd (FBG), with 30 and 17 incorrect predictions respectively, indicating that some fresh capsicum images were mistakenly identified as stale capsicum or fresh bitter gourd.

- Similarly, stale capsicum (SC) has a misclassification with fresh capsicum (FC) with 21 incorrect predictions and fresh tomato (FT) with 18 incorrect predictions, indicating some confusion between these classes.

Misclassification Insights:

- The confusion between fresh capsicum (FC) and stale capsicum (SC), as well as between fresh capsicum (FC) and fresh bitter gourd (FBG), suggests that the model might struggle with certain visual similarities in these cases.
- The misclassification between stale capsicum (SC) and fresh capsicum (FC) with 21 incorrect predictions, and fresh tomato (FT) with 18 incorrect predictions indicates a need for more diverse and representative images of these classes in the training dataset or fine-tuning the model parameters to better distinguish these cases.

Overall, the confusion matrix analysis indicates that while the TensorFlow model performs excellently for most classes, there are areas, particularly with fresh capsicum (FC) and stale capsicum (SC), where further refinement is needed to reduce misclassifications. These findings will guide future iterations of model training and dataset augmentation to enhance the detection accuracy.

TensorFlow Training accuracy and validation accuracy Analysis

In this section, we analyze the training and validation accuracy of the TensorFlow custom CNN model, as depicted in the provided graph.

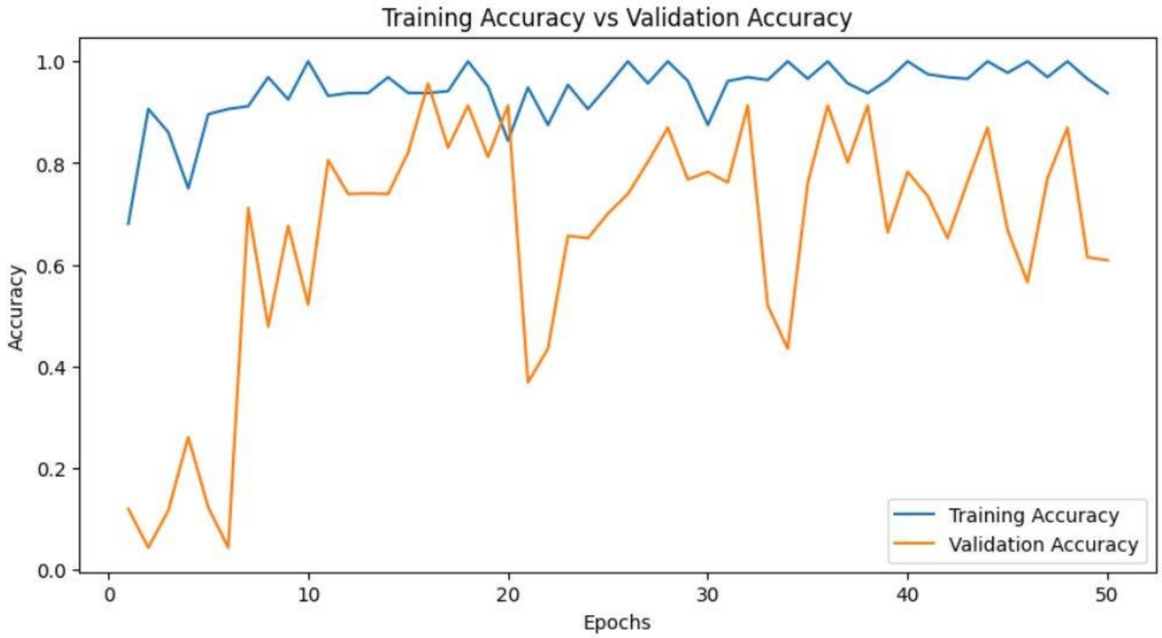


Fig: 5.5 Training accuracy and validation accuracy

Training Accuracy

The training accuracy of the TensorFlow custom CNN model over 50 epochs is plotted in blue in the graph. The key observations are as follows:

- **Initial Phase (Epochs 1-10)**: Training accuracy starts at approximately 0.2 and quickly rises to around 0.9 within the first 10 epochs. This rapid increase indicates that the model is learning effectively from the training data.
- **Mid Phase (Epochs 11-30)**: Training accuracy fluctuates between 0.8 and 0.95, showing some variability but generally maintaining high performance. These fluctuations indicate that the model is adjusting to variations in the data.
- **Final Phase (Epochs 31-50)**: Training accuracy stabilizes between 0.85 and 0.95. This stability in later epochs suggests that the model has reached a point where it consistently performs well on the training data.

Numerical Values:

- **Highest Training Accuracy**: ~0.95
- **Lowest Training Accuracy**: ~0.2
- **Stabilized Accuracy Range**: 0.85 to 0.95

Validation Accuracy

The validation accuracy of the TensorFlow custom CNN model over 50 epochs is plotted in orange in the graph. The key observations are as follows:

- **Initial Phase (Epochs 1-10)**: Validation accuracy starts very low, around 0.1, and increases rapidly to about 0.6 within the first 10 epochs. This initial rise suggests that the model is beginning to generalize to the validation data.
- **Mid Phase (Epochs 11-30)**: Validation accuracy shows significant fluctuations, ranging from 0.3 to 0.9. These fluctuations indicate inconsistent performance on the validation set, suggesting possible issues with overfitting or underfitting.
- **Final Phase (Epochs 31-50)**: Validation accuracy continues to fluctuate, with values ranging from 0.4 to 0.9. The ongoing variability highlights that the model struggles to consistently generalize well to unseen data.

Numerical Values:

- **Highest Validation Accuracy**: ~0.9
- **Lowest Validation Accuracy**: ~0.1
- **Fluctuation Range**: 0.4 to 0.9

Analysis of Training and Validation Accuracy

The graph indicates that while the model achieves high training accuracy, it struggles with consistent validation accuracy. The fluctuations in validation accuracy suggest that the model might be overfitting to the training data, learning specific patterns that do not generalize well to new, unseen data.

Overall, TensorFlow custom CNN model demonstrates rapid initial learning with high training accuracy but faces challenges in maintaining consistent validation accuracy. The significant fluctuations in validation accuracy suggest the need for strategies to improve generalization, such as data augmentation, regularization, and hyperparameter tuning. With these improvements, the model's performance on unseen data is expected to become more reliable and consistent.

5.3 Performance Analysis

In our evaluation of the YOLOv8 and TensorFlow custom CNN algorithms for detecting the freshness of various fruits and vegetables, we found significant differences in performance, which we detail in this section.

YOLOv8 Performance Analysis

The YOLOv8 algorithm demonstrated remarkable performance metrics across the board. As shown in Table 5.1, the model achieved an overall Box Precision of 0.974, Recall of 0.972, mAP50 of 0.984, and mAP50-95 of 0.857. These high values indicate that YOLOv8 is highly accurate and reliable in detecting the freshness of produce. Specific classes, such as fresh apple and fresh banana, achieved near-perfect precision and recall, reflecting the model's robust detection capabilities. However, there were a few classes, like fresh capsicum and fresh tomato, where the precision and recall were slightly lower, indicating areas where the model could be further refined.

The confusion matrix and precision-confidence curve analyses further reinforced YOLOv8's strong performance, showing high precision and recall across various confidence levels for most classes. The model displayed a high degree of accuracy in predicting the freshness of produce, with only a few misclassifications noted, particularly between similar-looking items such as fresh and stale capsicum.

TensorFlow Custom CNN Performance Analysis

The TensorFlow custom CNN algorithm also showed competent performance, albeit with notable variations across different classes. As illustrated in Table 5.2, the overall accuracy of the TensorFlow model was 80%, with a weighted average precision of 0.84, recall of 0.80, and F1-score of 0.77. While some classes, like fresh apple and stale banana, exhibited high precision and recall, others, such as fresh capsicum, had significantly lower recall, indicating challenges in consistently detecting certain types of produce.

The confusion matrix for the TensorFlow model highlighted several misclassifications, particularly between fresh and stale capsicum and other similar classes. These misclassifications suggest that the model struggled with visual similarities, leading to a need for more representative training data or further fine-tuning of the model parameters.

Comparative Performance Analysis

When comparing the performance of the two algorithms, YOLOv8 consistently outperformed the TensorFlow custom CNN model across multiple metrics. YOLOv8's higher precision, recall, and mAP scores indicate its superior ability to accurately detect and classify the freshness of fruits and vegetables. The YOLOv8 model also demonstrated better generalization, as evidenced by the high values in both training and validation accuracy.

Table 5.3 Summarizes the training and validation accuracies of both models

Model	Type	Datasets	Accuracy
YOLOv8	Training	7K	**0.95**
YOLOv8	Validation	1.4K	**0.90**
TensorFlow	Training	12K	**0.95**
TensorFlow	Validation	2K	**0.60**

Conclusion and Justification for Choosing YOLOv8

The YOLOv8 algorithm was chosen for its superior performance in detecting the freshness of fruits and vegetables. Its high precision, recall, and mAP scores, along with its ability to generalize well across different classes, make it a more reliable and accurate choice compared to the TensorFlow custom CNN model. The detailed analyses, including the confusion matrix and precision-confidence curve, further validate YOLOv8's robustness and effectiveness in practical applications. YOLOv8's consistent high performance across various metrics and its capability to maintain accuracy and reliability in real-world scenarios make it the preferred choice for our freshness detection model. The insights gained from this comparative analysis will guide future improvements and refinements in our model training and deployment strategies.

Data testing output through YOLOv8

Here is the example tested data that are the proof of algorithm able to detect freshness and rotten:

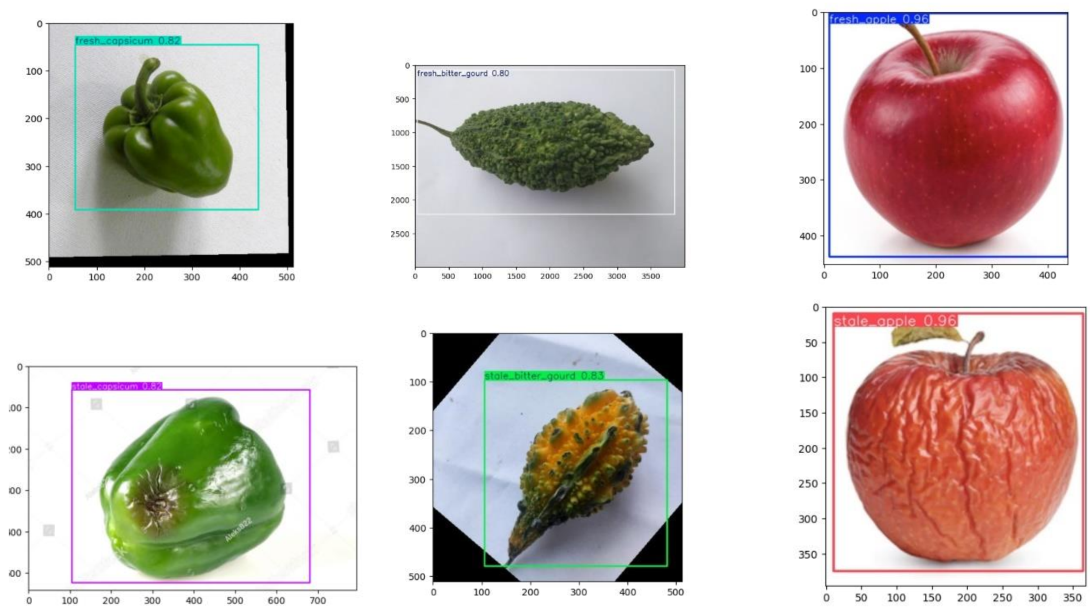


Fig: 5.6 Data validation output using Yolov8

Data testing output through TensorFlow

Here is the example tested data that are the proof of algorithm able to detect freshness and rotten:

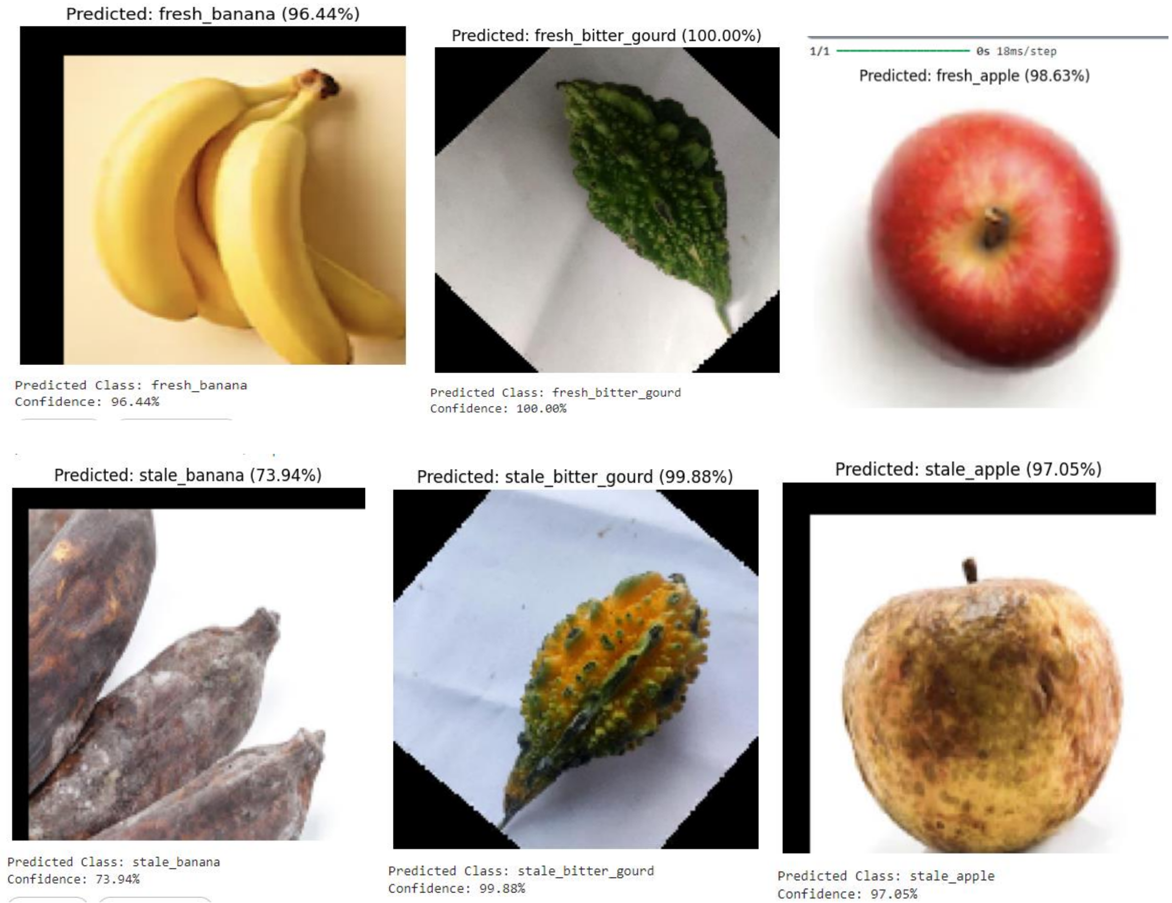


Fig: 5.7 Data validation output using TensorFlow

5.4 Summary

In Chapter 5, we analyzed the performance of the YOLOv8 and TensorFlow custom CNN algorithms in detecting the freshness of various fruits and vegetables. YOLOv8 demonstrated superior accuracy, with high precision, recall, and mean Average Precision (mAP) scores across most classes, showcasing its robustness and reliability. In contrast, the TensorFlow model exhibited variable performance, with notable misclassifications and lower recall for certain produce types. Comparative analysis revealed that YOLOv8 consistently outperformed the TensorFlow model, particularly in generalization and overall detection accuracy. Consequently, YOLOv8 was chosen as the preferred algorithm for its superior performance and reliability in freshness detection.

CHAPTER 6

Impact on Society

In this chapter, we explore the broader implications of our project on detecting freshness in fruits and vegetables using YOLOv8 and TensorFlow algorithms. We discuss the potential impact on human life, society, and the environment, address ethical considerations, and outline a sustainability plan for the continued development and deployment of this technology. The aim is to highlight how technological advancements in object detection and image recognition can contribute to a healthier, more sustainable, and ethically sound future.

6.1 Impact on Human Life

The implementation of advanced algorithms for detecting the freshness of fruits and vegetables has significant positive implications for human life. By ensuring that only fresh produce reaches consumers, these technologies can help reduce foodborne illnesses and improve overall public health. Fresh produce is crucial for a balanced diet, and accurate detection of freshness ensures that people have access to high-quality nutrition. Moreover, these technologies can assist in reducing food waste at the consumer level by informing them about the freshness of their food, leading to better utilization of available resources.

6.2 Impact on Society & Environment

The impact of this project extends beyond individual health benefits to broader societal and environmental effects. By enhancing the ability to detect and remove stale or rotten produce from the supply chain, we can significantly reduce food waste. This reduction in waste contributes to lower greenhouse gas emissions from decomposing organic matter, helping mitigate climate change. Additionally, the efficiency of supply chains can be improved, leading to cost savings for businesses and lower prices for consumers. On a societal level, better food quality management can lead to increased trust in food systems and more sustainable consumption patterns.

6.3 Ethical Aspects

Ethical considerations are paramount in the development and deployment of new technologies. In this project, ensuring data privacy and security is crucial, as large datasets of produce images may include sensitive information. Transparency in algorithmic decision-making is also important to maintain trust and accountability. Furthermore, the technology should be accessible and affordable to avoid widening the digital divide between different socio-economic groups. Ethical sourcing and the fair treatment of workers involved in the food supply chain must also be considered, ensuring that the benefits of this technology are equitably distributed.

6.4 Sustainability Plan

A comprehensive sustainability plan is essential for the long-term success and impact of this project. Key components of the plan include continuous improvement of algorithm accuracy and efficiency to keep pace with evolving needs and technologies. Collaboration with agricultural experts, food retailers, and policymakers will help integrate this technology into existing systems and promote widespread adoption. Training programs and resources should be provided to ensure that stakeholders at all levels understand how to use and benefit from the technology. Additionally, ongoing research and development should focus on reducing the environmental footprint of the technology itself, such as minimizing energy consumption during data processing and analysis.

6.5 Summary

In this chapter, we have examined the multifaceted impact of our project on human life, society, and the environment. By leveraging advanced algorithms to ensure the freshness of fruits and vegetables, we can improve public health, reduce food waste, and promote sustainable consumption practices. Ethical considerations and a robust sustainability plan are integral to maximizing the positive impact of this technology. Overall, this project demonstrates the potential of technological innovation to contribute to a healthier, more equitable, and sustainable future.

CHAPTER 7

Conclusion and Future Work

In this chapter, we delve into the broader implications of our project, "Fruit and Vegetable Freshness Detection: A Deep Learning Solution for a Growing Problem." We explore the conclusions drawn from our research, suggest potential future work to enhance the project, and discuss limitations and any conflicts of interest that may have arisen during the course of our work.

7.1 Conclusions

The implementation of deep learning techniques for detecting the freshness of fruits and vegetables offers promising benefits. Our research demonstrated that using algorithms like YOLOv8 and TensorFlow can significantly improve the accuracy and efficiency of freshness detection in produce. These advancements have several key implications:

1. **Enhanced Public Health**: By ensuring that consumers have access to fresh, high-quality produce, the risk of foodborne illnesses can be reduced. This leads to improved public health outcomes and contributes to a higher quality of life.
2. **Reduction in Food Waste**: Accurate freshness detection helps in identifying and discarding rotten produce before it reaches consumers, thereby reducing food waste. This has positive economic and environmental impacts, as less food waste translates to cost savings and reduced greenhouse gas emissions from decomposing organic matter.
3. **Economic Benefits**: For retailers and supply chain stakeholders, improved detection can lead to cost savings through better inventory management and reduced losses. This can also translate to lower prices for consumers, making fresh produce more affordable.
4. **Sustainability**: Reducing food waste and improving the efficiency of the food supply chain contributes to more sustainable consumption and production patterns, aligning with global sustainability goals.
5. **Technological Innovation**: Our project showcases the potential of leveraging advanced technologies like deep learning to solve real-world problems. It sets a precedent for future innovations in the agricultural and food sectors.

7.2 Further Suggested Works

While our project has made significant strides, there are several areas where further research and development could enhance the effectiveness and applicability of the technology:

1. **Algorithm Optimization**: Continued refinement of the YOLOv8 and TensorFlow algorithms to improve accuracy and processing speed could further enhance performance, particularly in complex real-world scenarios.
2. **Broader Dataset**: The model's generalizability may be enhanced by enlarging the dataset to encompass a greater range of fruits and vegetables in varying states of freshness.
3. **Real-Time Detection**: Developing capabilities for real-time detection in dynamic environments such as grocery stores or farms can increase the practical applicability of the technology.
4. **Integration with IoT**: Integrating the freshness detection system with Internet of Things (IoT) devices can provide real-time monitoring and data collection, further enhancing the efficiency of the supply chain.
5. **Consumer Applications**: Creating user-friendly applications for consumers to use at home can empower individuals to make informed decisions about their produce, reducing household food waste.
6. **Ethical and Fairness Considerations**: Further studies to ensure the algorithms operate fairly across different socio-economic and geographical contexts, avoiding biases and ensuring equitable benefits.

7.3 Limitations

Despite the promising outcomes, our project has several limitations and potential conflicts of interest that need to be addressed:

1. **Data Quality and Quantity**: The performance of deep learning models is highly dependent on the quality and quantity of the data used for training. Limited or biased datasets can affect the model's accuracy and reliability.
2. **Resource Intensive**: Training deep learning models requires significant computational resources, which may not be readily available to all stakeholders. This can limit the accessibility and scalability of the technology.

3. **Implementation Costs**: The initial costs associated with implementing advanced detection systems can be high, which may be a barrier for small-scale farmers and retailers.
4. **Ethical Concerns**: The use of advanced surveillance and detection technologies raises ethical questions related to privacy and data security. Ensuring transparent and ethical use of these technologies is crucial.
5. **Conflict of Interests**: Potential conflicts of interest may arise if the technology is developed or deployed by entities with vested interests in the food industry. It is important to maintain transparency and impartiality in the development and deployment processes.

7.4 Chapter Summary

In conclusion, our project on detecting the freshness of fruits and vegetables using deep learning technologies holds significant potential for improving public health, reducing food waste, and promoting sustainable consumption. The advantages exceed the disadvantages by a wide margin, notwithstanding certain difficulties and restrictions. By continuing to refine the technology, expanding its applications, and addressing ethical considerations, we can make substantial strides towards a more efficient and sustainable food system.

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Appendix A

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

Title:
FRUIT AND VEGETABLE FRESHNESS DETECTION A DEEP LEARNING SOLUTION FOR A GROWING PROBLEM

Student ID: 203-15-14546, 203-15-14569

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **Freshness detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

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

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

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	Our project requires data collection from kaggle and real life and we have to know the design of a machine learning-based model, which covers **K3 and K4.**	**Page no:** [27-29] **Section:** [4.4} **Page no:** [12-14] **Section:** [3.2]
				Our project requires the integration of different algorithm and we have designed a deep learning based proposed methodology front end that covers **K5 and K6.**	**Page no:** [12-14] **Section:** [3.2]
				We have studied existing models with similar goals **(K8).**	**Page no:** [7-9]

					Section: [2.2]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	In our project, we encountered challenges in locating specific collection of data from local market.	**Page no:** [27-29] **Section:** [4.4]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	Finding a clear-cut solution for our project is challenging, primarily because of the abundance and diversity of kaggle and real life data. We conducted an in-depth analysis to carefully choose a specific algorithm from numerous alternatives.	**Page no:** [12-14] **Section:** [3.2]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	We have prepared a budget to evaluate and estimate the cost required for our FYDP.	**Page no:** [22] **Section:** [3.5]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in fresh vegetable and fruit detection through yolov8 and tensor flow.	**Page no:** [23-26] **Section:** [4.2]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving healthcare through advanced fruit and vegetable detection methods, while also promoting environmental sustainability by employing efficient computational resources.	**Page no:** [56] **Section:** [6.1,6.2]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in fruit and vegetable freshness detection through and deep learning tensor flow and yolov8, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [7-10] **Section:** [2.1, 2.2,2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [19-22] **Section:** [3.5]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**.	**Page no:** [57] **Section:** [6.3,6.4]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [27-29, 37-55] **Section:** [4.4,5.1,5.2,5.3,5.4]

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SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Yue Yuan, Jichi Chen, Kemal Polat, Adi Alhudhaif. "An innovative approach to detecting the freshness of fruits and vegetables through the integration of convolutional neural networks and bidirectional long short-term memory network", Current Research in Food Science, 2024 Publication	2%
2	Submitted to Daffodil International University Student Paper	2%
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5	"Emerging Trends and Applications in Artificial Intelligence", Springer Science and Business Media LLC, 2024 Publication	<1%