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**ASSIGNMENT COVER SHEET**

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| PROGRAMME | : | Master of Business Analytics | | |
| SUBJECT CODE AND TITLE | : | PRJ5158 CAPSTONE PROJECTS II | | |
| ASSIGNMENT TITLE | : | Reducing Food Waste through AI: Automated Fruit Classification for Informed Decision Making | | |
|  |  |  | | |
| LECTURER | : | Dr Muaadh Mukred | ASSIGNMENT DUE DATE: | 26/02/2025 |

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| **Tool** | **Purpose** | **Prompts** | **Sections where AI output was used / Outcome(s) in the submission** |
| ChatGPT | Structuring the essay | “Outline a structure for an essay on AI in fruit classification.” | The structure of this project is generated by AI for references. |
| Grammarly | Checking grammar | N/A | The grammar for whole document was checked using Grammarly. |
| ChatGPT | Integration purpose | “How to integrate deep learning model and SHAP analysis heatmap into PowerBI” | The deployment plan and code are suggested by AI for references. |

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**REDUCING FOOD WASTE THROUGH AI:**

**AUTOMATED FRUIT CLASSIFICATION FOR INFORMED DECISION MAKING**

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Research Project Submitted in Fulfilment of the Requirement

of

MASTER OF BUSINESS ANALYTICS

SUNWAY BUSINESS SCHOOL

MALAYSIA

26th February 2025

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# **ABSTRACT**

**Purpose:** This research addresses the critical issue of food waste in the fruit supply chain by leveraging advanced AI techniques for automated fruit classification. Despite advancements in AI-driven fruit classification, existing models often operate as “black boxes”, limiting transparency and stakeholder trust. This study proposes an explainable AI (XAI) framework for fruit classification using YOLOv8, a deep learning model enhanced by SHapley Additive Explanations (SHAP) for improved interpretability.

**Methodology:** Following the CRISP-DM framework, the study encompasses data acquisition, preprocessing, modeling, and deployment. A publicly available dataset containing 12,335 images of fresh and rotten fruits was used for training and evaluation. The YOLOv8 model was trained and evaluated, followed by SHAP analysis to identify key visual features influencing model predictions. The final model was deployed through a Power BI dashboard.

**Findings:** Experimental results show that YOLOv8 achieves high classification accuracy, confirming its effectiveness for real-world deployment. SHAP analysis provided key insights into feature importance, revealing that color and texture were the most influential factors in fruit classification. The integration of Power BI visualization allows stakeholders to make data-driven decisions regarding inventory management, purchasing, and quality control.

**Contributions:** This research contributes to operational efficiency and food waste reduction, aligning with Sustainable Development Goal (SDG) 12.3 on responsible consumption and production. By integrating YOLOv8 with XAI techniques, this study enhances AI transparency and stakeholder trust, facilitating real-world adoption in food supply chains. Furthermore, the proposed framework is scalable and adaptable to other perishable goods, offering broader applications in sustainability-focused AI solutions.

**Keywords**: Explainable AI, Deep Learning, YOLOv8, SHAP, Fruit Classification, Food Waste Reduction, Machine Learning, Power BI, Transparency, Sustainability

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# **List of Abbreviation**

|  |  |
| --- | --- |
| **Abbreviation** | **Meaning** |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| BI | Business Intelligence |
| CBS | Convolution, Batch Normalization, and SiLu activation functions |
| CNN | Convolutional Neural Network |
| CPI | Consumer Price Index |
| CRISP-DM | CRoss-Industry Standard Process for Data Mining |
| CSP | Cross Stage Partial |
| CT | Computed Tomography |
| DeepLIFT | Deep Learning Important FeaTures |
| DFL | Distribution Focal Loss |
| EDA | Exploratory Data Analysis |
| ETL | Extract-Transform-Load |
| FAO | Food and Agriculture Organization |
| FIFO | First-In-First-Out |
| FN | False Negative |
| FP | False Positive |
| FPN | Feature Pyramid Network |
| GAN | Generative Adversarial Networks |
| GPU | Graphical Processing Unit |
| HSI | Hyperspectral Image |
| KNN | k-nearest neighbors algorithm |
| KPI | Key Performance Index |
| LIME | Local Interpretable Model-agnostic Explanations |
| mAP | mean Average Precision |
| MATLAB | Matrix Laboratory |
| ML | Machine Learning |
| MLP | Multilayer Perceptron |
| NAS | Neural Architecture Search |
| NLP | Natural Language Processing |
| NMS | Non-Maximum Suppression |
| NN | Neural Network |
| PCA | Principal Component Analysis |
| R-CNN | Region-based Convolutional Neural Network |
| RGB | Red, Green, Blue, ie the primary colors in additive color synthesis |
| RNN | Recurrent Neural Network |
| SDG | Sustainable Development Goals |
| SHAP | SHapley Additive exPlanations |
| SVD | Singular Value Decomposition |
| SVM | Support Vector Machine |
| TN | True Negative |
| TP | True Positive |
| UN | United Nations |
| VGG | Visual Geometry Group |
| VRAM | Video Random-Access Memory |
| XAI | Explainable AI |
| YOLO | You Only Look Once |

# **INTRODUCTION**

## **1.0 Introduction**

This section provides an overview of the study, followed by a detailed problem statement. It outlines the research objectives as well as research questions. This chapter ends with discussing the scope of research.

## **1.1 Background of Study**

Sustainable Development Goal (SDG) 12.3 is one of the initiatives made by the United Nations (UN) to reduce food waste and food loss. The initiative aimed to halve per capita global food waste at the retail and consumers levels and reduce food losses in the overall supply chains by 2030 (Jacob-John et al., 2023). However, according to the Food and Agriculture Organization (FAO) in 2022, approximately one-third of all food produced for human consumption is wasted worldwide, occurring at various stages of the supply chain, from farms to retail and consumers.

Food waste refers to edible food discarded at the retail and consumer levels, often due to expiration dates, blemishes, overstocking or improper storage (City et al., 2012). On the other hand, food loss is defined as the food discarded in the early supply chain where it can be during production, storage, processing and distribution (Ishangulyyev et al., 2019). In measuring the loss of the food in the supply chain, there are indicators that are used which are Food Loss Index and Food Waste Index.

Food security and food waste are complex issues that are linked to each other. Crush & Frayne (2011) explained food security as a concept that reflects the human or people normative sensitivities about hunger, disparities in food access and production capabilities and the power differentials in the food system. In Malaysia, particularly in the fresh fruits produce, it has seen a slow growth over the years. The factors that lead to this include cheaper imports, lack of government support particularly in Research & Development and higher cost of production (Arshad, 2017). Thus, addressing the issue of food waste is a critical component of improving food security. As Malaysia has produced lesser fresh fruits, it is important to improve the efficiency and quality of the fruit produced to reduce food waste.

Figure 1.1 shows the global total amount of fruit waste in the supply chain from 1961 to 2021. This data only shows the total amount of waste in the supply chain and does not include the waste thrown by the end consumers. There is a consistent upward trend in fruit waste and by the year 2021, the fruit waste has gone over 70 million tonnes. Between the year 1961 and 2021, there has been a sevenfold increase in fruit waste in the supply chain, increasing from approximately 10 million tonnes to over 70 million tonnes which is very alarming.

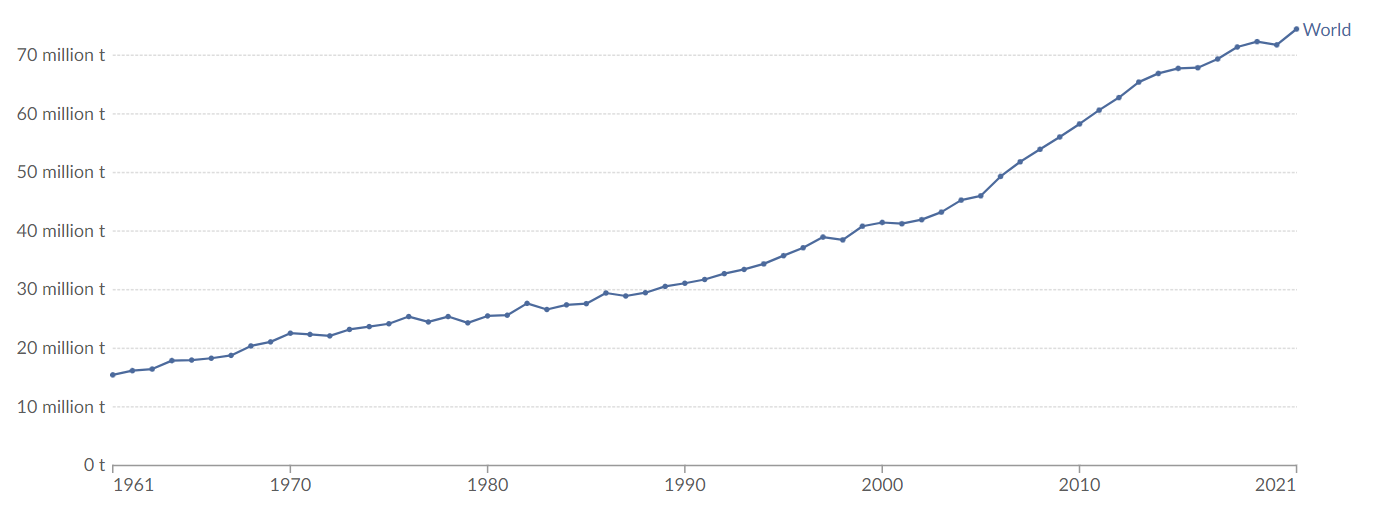


Figure 1.1: Fruit Waste in Supply Chain, 1961-2021

Sources: UN Food and Agriculture Organization (FAO)

In areas where food quality is essential such as the hospitality industry, which includes restaurants, hotels and food services, getting the right method of classifying fresh fruits is very crucial. Fruits are staple in many hospitality settings and getting the right freshness of fruits is important to maintain quality and customer satisfaction. However, fruits are commonly known as a highly perishable food, making them susceptible to spoilage, leading to significant waste if it is not managed properly.

When it comes to food waste, fruits are one of the types of foods that should be focused on. First of all, fruits have high perishability, implying that they have shorter shelf lives compared to other food products (Kirci et al., 2022). Therefore, it may be useful to determine a fruit’s freshness earlier. Factors such as its high water content, fragile structure and the environment’s temperature make fruits more susceptible to spoil.

Fruits’ high water content make them prone to desiccation, mechanical injury and bacterial growth (Kader, 2002). Desiccation or wilting from water loss (transpiration), not only affects its appearance but also reduces nutrients like vitamin C (Zhang & Bartels, 2018). Fragility increases the risk of mechanical injury during handling, compromising structure and promoting microbial growth (Ladaniya, 2008). With high water activity (Aw), fruits provide an ideal environment for microbes which accelerates spoilage (Barth et al., 2009). Temperature also influences perishability as higher temperatures boost ethylene production which in turn speeds up ripening, while lower temperatures slow it down (Ebrahimi et al., 2022). Improper cold storage can cause chilling injury, damaging tissues and increasing vulnerability to microbes (Patel et al., 2016) while warmer temperatures further promote spoilage through faster microbial growth (Barth et al., 2009).

Aside from the high perishability of fruits, the wasting of fruits has significant implications from an economic standpoint due to their high economic value along with its impact on consumer price index, consumer preference and consumer spending. Fruits have high economic value due to its overall high cost and demand. With external factors such as pests, diseases and environmental changes, the cost of the production of fruits may increase. If these higher cost fruits were to spoil, it would result in a higher degree of financial losses due to the amount of resources invested to produce them (Fatemi et al., 2024). Furthermore, exotic and off-season fruits need to be considered as they drive higher market prices. If these fruits were to spoil, it would also result in a higher degree of financial losses.

Consumer Price Index (CPI) is a measure of the average change over time of the prices paid by consumers for goods and services. Fruits are an essential aspect to calculate the CPI of the food basket, meaning that a reduction in food waste would lead to an increase in CPI (Aschemann-Witzel et al., 2020). Since fruits are generally sensitive to perishability and changing weather conditions, their prices are very volatile, due to the spoilage of fruits. As spoiled fruits are wasted, there is a loss of supply, which leads to an increase in their price to compensate for this loss of supply. As a result, the volatility is reflected in the CPI, as it will cause CPI fluctuation (Kim, Rundle-Thiele, & Knox, 2019). Additionally, as mentioned earlier, an increase in fruit prices is caused by the spoilage of fruits, which, in turn, contributes to inflation. As an effect of poor handling and classification of fruits, the overall costs of fruits increases, resulting in the price to increase as well. Minimizing fruit waste would also minimize the cost of fruits, reducing inflationary pressures (Abeliotis & Lasaridi, 2023). Furthermore, the prices of various off-season fruits will sharply increase due to its low supply and high demand. As a result of this spike in price, there will be fluctuations in CPI throughout the year (Fatemi et al., 2024).

Consumer spending may be defined as the total amount of money households spend on goods and services (Aschemann-Witzel et al., 2020). The spoilage of fruits would significantly affect consumer spending. Affordability and accessibility of fruits is one aspect of consumer spending that would be affected since suppliers would need to increase the prices of their fruits as a result of fruit wastage. Consequently, these fruits are less affordable and accessible to consumers, especially for lower-income households (Fatemi et al., 2024). Due to this price hike and knowing that these fruits have the tendency to spoil in the short-term, consumer confidence for these fruits would likely decrease. As a result of low consumer confidence, consumers are discouraged from purchasing these fruits in the future, resulting in lower consumer spending (Abeliotis & Lasaridi, 2023). Furthermore, if prices were to increase due to spoilage of fruits, it would reduce the amount of return purchases. If consumers know that these fruits are not high-quality and the prices are high, they are very unlikely to continue purchasing these fruits (Salan & Hossain, 2024). These suppliers should aim to gain the consumers’ trust by providing them with high-quality fruits and selling them for affordable prices.

Consumer preference may be defined as a consumer’s or household’s tastes and choices regarding goods and services (Herz et al., 2022). There are many factors that influence their preferences such as income level, personal tastes and the quality of the goods or services (Veer, 2018). Consumer preference is a driving factor that justifies why classification of fruits is beneficial. In the context of fruits, consumer preference is influenced by factors such as appearance, quality, freshness and taste (Marques et al., 2021).

When consumers choose the fruits they want to purchase, they have the tendency to select the fruits that are the most visually appealing and avoid the fruits that have scratches or bruising. Although these less appealing fruits are still ripe and edible, consumers would gravitate more to the more appealing options (Marques et al., 2021). Additionally, generally speaking, consumers prefer fresher fruits, with characteristics such as firmness, vibrance and smoothness (lack of visible defects) indicating their freshness. Based on these characteristics, consumers would have the perception that these fruits are higher quality, taste better, and have higher nutritional value (Marques et al., 2021). Relating to the unappealing characteristics of fruits, consumers may view these characteristics as ones that are related to spoiled fruits or on the verge of spoiling. Therefore, they will have the tendency to avoid purchasing these fruits, as they may perceive it as a waste of their money (Liu et al., 2019). To address the issues above, the use of an image recognition system is the way forward improving efficiency and reducing food waste.

## **1.2 Problem Statement**

Fruit classification plays a crucial role in ensuring quality control and minimizing food waste in the food industry. However, traditional manual inspection methods are increasingly inefficient and unsustainable due to human errors, time constraints, and high labor costs (Jia et al., 2023). As businesses scale up, traditional classification methods struggle with large inventory volumes, leading to delays, misclassifications, and inconsistencies in quality control (Chen, 2024). Furthermore, variations in lighting conditions, bruising, and natural imperfections make manual classification subjective and inconsistent. Previous machine learning-based approaches, such as k-NN and SVM, require extensive feature engineering and fail to generalize well across diverse fruit datasets (Huynh et al., 2022). Even deep learning models, such as CNNs, have limitations in real-time object detection due to their computational complexity (Dewi et al., 2023). Without an automated, high-speed, and scalable classification system, businesses face difficulties in optimizing workflow and reducing food waste. To address these challenges, this study proposes training and optimizing a YOLOv8-based deep learning model to enhance classification accuracy and performance. YOLOv8 has been selected due to its anchor-free design, improved feature fusion, and real-time detection capabilities, which outperform previous YOLO versions and CNN-based models (Kulkarni et al., 2024). Model performance will be evaluated using precision, recall, F1-score, and mean Average Precision (mAP) to ensure high reliability and promote adoption among stakeholders (Shrawne et al., 2024).

Despite advancements in deep learning, interpretability remains a major concern. Most AI-driven classification models function as black boxes, meaning their decision-making process is opaque, making it difficult for users to trust and validate predictions (Singh, et al., 2024). This lack of transparency has significant consequences across industries, including food supply chains, where misclassifications can lead to unnecessary waste, financial losses, and inefficiencies in inventory management. In critical sectors like healthcare, similar challenges persist, where black-box models provide highly accurate disease predictions but fail to offer interpretable explanations, leading to skepticism and limited adoption (Marey et al., 2024; Zhang et al., 2022). In the food industry, misclassifications such as labeling fresh fruits as rotten or vice versa can lead to supply chain disruptions and economic loss (Mavani et al., 2022). To overcome this issue, this study integrates SHAP (SHapley Additive exPlanations), an explainable AI (XAI) technique, to identify key visual features influencing fruit classification decisions. By doing so, stakeholders can better understand model outputs, reduce uncertainty, and build trust in AI-based automation, thereby facilitating its broader adoption in the food industry (Ponce-Bobadilla et al., 2024).

Additionally, AI model output alone may not be sufficient for real-world decision-making without an intuitive and actionable interface. To bridge the gap between AI predictions and stakeholder usability, a Power BI-based visualization dashboard will be developed. Power BI has been shown to enhance decision-making processes by transforming complex datasets into clear, interactive visual insights (Devineni, 2024). By integrating this dashboard, stakeholders, including retailers, suppliers, and inventory managers are able to monitor classification results, track model performance, and optimize inventory decisions. Prior studies have demonstrated that AI-driven data visualization improves operational efficiency in food supply chains, enhances resource allocation, and reduces overall waste (Jiang et al., 2022; Hilliard et al., 2023). This integration of YOLOv8 for real-time classification, SHAP for interpretability, and Power BI for visualization aims to provide a robust, scalable, and transparent solution for minimizing fruit waste and improving food industry efficiency.

## **1.3 Research Objectives**

The objectives of the research of this study are discussed below.

**RO1:** **To train a YOLO-based deep learning model for classifying fresh and rotten fruits**

This objective aims to develop a YOLO-based deep learning model to classify fresh and rotten fruits by evaluating its performance using metrices such as precision, recall, F1-score, and mean Average Precision (mAP) at varying thresholds. These evaluation metrics ensure that the AI model is accurate and efficient in classifying fruits, allowing for consistent and reliable identification of fruit freshness.

**RO2: To enhance model interpretability using SHapley Additive exPlanations (SHAP)**

This objective aims to improve the transparency of AI models by implementing Shapley Additive Explanations (SHAP) to identify key visual features that influence the classification of both fresh and rotten fruits. By providing rationale behind the model’s decision-making process, this approach enhances trust and reliability in AI-driven fruit classification among stakeholders.

**RO3: To develop an interactive Power BI dashboard that provides visualization of classification outputs**

This objective focuses on creating a Power BI dashboard that displays classification results, model performance and key insights. By offering clear and interactive visualizations, the dashboard enables stakeholders to monitor fruit freshness and make informed decisions which ultimately reduces food waste.

## **1.4 Research Questions**

The specific questions of this study are discussed below.

RQ1: How accurately can a YOLO-based deep learning model classify fresh and rotten fruits?

RQ2: How can SHAP be used to enhance the interpretability of the model’s classification decisions?

RQ3: How can an interactive Power BI dashboard be developed to display model outputs?

## **1.5 Scope of Research**

This project focuses on training a YOLO-based deep learning model to monitor fruit freshness and to classify as fresh or rotten fruits. The performance of the model is evaluated using precision, recall, F1-score, mean Average Precision 0.5 and mean Average Precision 0.5:0.95. To make the model’s decision-making process more explainable, SHAP, which is an explainable AI tool, will be used to identify key visual features that influence classification decisions. In addition, a Power BI dashboard will be developed to provide visualization of model outputs and insights to help stakeholders monitor fruit freshness and reduce food waste. The dataset consists of 12,335 fruit images which are then annotated and used for training and evaluation. The implementation is conducted using Python, Yolov8 for model training and testing, SHAP for interpretability, and Power BI for visualization purposes.

# **LITERATURE REVIEW**

## **2.0 Introduction**

This chapter presents a literature review, beginning with the introduction of image processing and the use of machine learning for image classification. It covers the evolution of deep learning, its application in classifying fruit types and freshness, the YOLO model, explainable AI, and dashboard visualization.

## **2.1 Image Processing**

Image processing is a technique that involves improving and analyzing images to extract useful information for various applications (Masood et al., 2016). It plays an important role in enhancing the quality of input data which facilitates the process of classification, detection and segmentation of images (Udawant et al., 2019). There are several image processing techniques which are instrumental such as image restoration, filtering, segmentation, and feature extraction (Prabu & Gnanasekar, 2021).

Image restoration methods which include denoising, deblurring and super-resolution, make sure that the original structure of degraded images is recovered, hence making it suitable for further analysis (Bhagya & Perumal, 2024). Besides, filtering is another fundamental pre-processing step that enhances the quality of an image by removing noise and preserving important features like edges. This technique includes convolution and edge detection which emphasize crucial details like texture and contours (Flores-Vidal et al., 2022). The next step in image processing is segmentation which involves dividing an image into meaningful regions using methods such as thresholding and clustering. This process involves separating objects from the background, improving object detection and classification (Qiao, 2024).

Segmentation is critical in image analysis, especially in medical imaging because it aids in identifying and detecting regions of interest which in turn allows for accurate disease diagnosis and improves overall diagnostic precision (Hephzibah et al., 2022). Feature extraction is another essential step where relevant information such as color, shape, and texture are explored for model training. Data augmentation techniques like flipping, rotating, brightness adjustment and noise addition are applied to increase data diversity which helps the model to learn better, make more accurate predictions, prevent overfitting and improve robustness of deep learning models (Jain & Varshney, 2024). Feature extraction is important for tasks like object classification and pattern recognition as it reduces computational complexity and enhances model performance across various applications like medical imaging, facial recognition and traffic monitoring (Rajakumar et al., 2023).

In the context of fruit classification, image processing techniques are important to improve the quality of images and extracting relevant features required for accurate classification. Filtering and segmentation improve fruit images by reducing noise and highlighting key visual features such as texture, color, and shape. Feature extraction and data augmentation techniques enhance the model further to distinguish fresh and rotten fruits better under varying conditions. In this research, these techniques serve as the foundation for training deep learning models, making sure that classifications are accurate and reliable.

## **2.2 Machine Learning in Image Processing and Classification**

Machine learning, which is commonly abbreviated as ML, has greatly improved automated image processing by performing tasks like feature extraction, classification and pattern recognition that required human effort previously. Principal Component Analysis (PCA) and Singular Value Decomposition (SVD) are early methods that provided a foundation for facial recognition and fingerprint identification. These methods automated identification processes, minimizing human involvement and increasing efficiency (Jaya & Latha, 2021). As ML advanced, it began to solve tougher challenges across a wide range of fields. Goldenberg et al. (2019) revealed that ML improved prostate cancer diagnostics by organizing clinical workflows, automating diagnostic imaging and planning surgeries. Similarly, Abdullah et al. (2021) found that deep learning models, especially Convolutional Neural Networks (CNNs) have helped healthcare systems by automating feature extraction from CT images for cancer detection.

Beyond healthcare, ML has also impacted non-clinical fields positively. Tropea and Fedele (2019) found that combining traditional classifiers like Support Vector Machines (SVM) and k-Nearest Neighbours (k-NN) with CNNs increased accuracy in real-time applications such as autonomous vehicles and surveillance systems. Additionally, Dong et al. (2020) showed that hybrid models, combining CNNs with Random Forest classifiers improved satellite image classification for land-use analysis and environmental management. In biological research, ML has automated microscopy analysis. Owoeye and Ojo-Omoniyi (2022) demonstrated how deep learning improved edge detection and feature extraction from microscopy datasets, uncovering insights beyond human analytical abilities.

Feature selection is also essential in ML as it improves model accuracy by focusing on relevant data. Chen et al. (2020) emphasized that using Random Forests for feature selection enhances classification, especially in complex datasets. Tasnim and Habiba (2021) revealed how feature selection enhances the performance of predictive models which shows that combining techniques like PCA with Random Forest improves diagnostic accuracy, particularly in heart disease prediction. Ensemble learning has further boosted ML’s performance. Doreswamy et al. (2020) reported that combining feature selection with ensemble classifiers significantly improved network anomaly detection indicaing how versatile ML is across various domains.

Nevertheless, interpretability remains a challenge particularly in healthcare where transparency is patients’ utmost priority. Bhattacharya and Datta (2023) stressed the importance of using interpretable models like decision trees and rule-based methods to maintain trust in clinical diagnostics. Oleiwi et al. (2023) also addressed the challenge of data sparsity, demonstrating that algorithms like Random Forests and Logistic Regression perform well even with limited data which ensures reliable real-world outcomes.

The rise of advanced machine learning models has transformed image processing across industries (Gowda et al., 2024). Early research focused on automating classification, segmentation and feature extraction, but the emergence of CNNs brought significant improvements in accuracy and scalability (Sharma et al., 2022). Current trends suggest that hybrid models combining the strengths of deep learning with the interpretability of traditional algorithms will keep ML models effective and understandable (Sharma et al., 2018). With continuous advancements, ML drives innovation across various sectors like healthcare, transportation and environmental monitoring, expanding the possibilities for visual data analysis (Ahmed at al., 2024).

In this study, machine learning plays a major role in automating fruit classification by enabling efficient extraction of features from images, segmentation, and pattern recognition. Advancements in machine learning enhance the ability to classify fresh and rotten fruits accurately. In addition, the integration of explainable AI techniques makes sure the decision-making process is transparent to address trust issues. By using these machine learning models, this study aims to develop an accurate and efficient fruit classification system to reduce food waste.

## **2.3 Evolution of Deep Learning Models**

Deep learning evolved from its early stage where it used to train simple artificial neural networks (ANNs) to develop complex and deep architectures that drive today’s artificial intelligence (AI) applications. Neural networks were initially limited to shallow models such as Multi-Layer Perceptrons (MLPs). However, these models struggled with complex tasks due to insufficient computing power and small datasets (Young et al., 2018). The application of deep learning in image classification is a significant achievement. Young et al. (2018) found that AlexNet’s win in the 2012 ImageNet competition demonstrated the potential of deep networks to excel and perform well in large-scale visual tasks. Sun et al. (2018) explored that after the success of AlexNet, deeper models such as VGGNet and ResNet were introduced, and it demonstrates that performance can be improved by increasing network depth using techniques like residual connections. Miikkulainen et al. (2019) revealed that GANs were introduced later, and it enabled the production of new data through adversarial training rather than relying on the modelling of the already available existing datasets. Nevertheless, the advancement of deep learning also brought challenges, including overfitting, vanishing gradients and the need for large datasets. Innovations such as normalization, regularization and Residual Networks (ResNet) mitigate these issues which allowed the effective training of deeper models (Fan et al., 2019).

The return of deep learning began with the availability of enhanced GPUs and large datasets which allowed training of deeper networks that achieved superior performance across various tasks such as natural language processing (NLP), computer vision and speech recognition (Janiesch et al., 2021). As time goes by, new deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Generative Adversarial Networks (GANs) were developed. CNNs performed well in processing spatial data whereas RNNs performed well in sequential tasks like text and speech processing (Dong et al., 2021).

The introduction of CNNs were instrumental in image classification as it automated the feature extraction task through convolutional layers (Wang et al., 2020). Jia et al. (2021) explained that CNNs are designed to learn spatial hierarchies from image data where the image is broken down into hierarchical layers. Low-level features are learned in early layers whereas higher level abstract patterns are learned in deeper layers. Furthermore, Balasubramaniam and Pasricha (2022) discovered that object detection for autonomous vehicles is strongly related to deep learning models like Convolutional Neural Networks (CNNs). These real-world deployments enable the recognition of pedestrians, other vehicles and road signs in real-time which ensures the safe operation of automated navigation. The researchers of the study reported that this is important as deep learning algorithms can significantly enhance accuracy and responsiveness during driving, even under dynamic conditions.

Over the years, deep learning has evolved significantly in image classification. Early developments were focused on optimizing hyperparameters and network architectures that address the challenges of manual tuning (Sun et al., 2019). Wang et al. (2020) emphasized that when the model is refined repetitively, it will perform well even with limited labelled data.

Jena et al. (2021) discovered that deep learning became more advanced through hybrid models where deep learning models were combined with other machine learning techniques for specialized applications. In the study, the researchers explored the integration of deep learning with autoencoders to enhance feature extraction by leveraging both spatial and latent representations. In areas such as hyperspectral image (HSI) classification, where labelled data is scarce, researchers have employed few-shot learning and transfer learning to boost model’s accuracy (Jia et al., 2021). Transfer learning enables CNNs pre-train on large datasets to adapt to new tasks, reducing the need for extensive labelled data. This adaptability has further expanded the application of deep learning to fields with diverse data constraints, such as environmental monitoring and security systems (Borowiec et al., 2022).

The evolution of deep learning has transformed image classification, making it possible to handle large-scale visual tasks with high accuracy. Developing from shallow networks to deep architectures like CNNs has allowed models to learn directly from data and automate feature extraction. Innovations such as hybrid models, evolutionary algorithms and transfer learning have enhanced the capabilities of deep learning, allowing it to adapt to new challenges and datasets. As research progresses in future, Dong et al. (2021) revealed that the focus will shift toward lightweight architectures and explainable AI (XAI) to enhance the interpretability and efficiency of image classification models.

In this research of fruit classification, advancements in deep learning are significant as it improves the accuracy and precision of the classification. The evolution of deep learning from shallow networks to deep architectures like CNNs allowed automated feature extraction, facilitating the classification process. These advancements and evolution enable the fruit classification model to distinguish both fresh and rotten fruits effectively, ensuring reliable and consistent results.

### **2.3.1 Deep Learning Used for Classifying Fruits Type**

Deep learning techniques have proven effective in automating fruit classification tasks which are traditionally reliant on manual labor. Studies have showcased the success of convolutional neural networks (CNNs) in accurately identifying fruits based on visual features. For example, Altaheri et al. (2019) used a fine-tuned VGG-16 model for robotic date fruit harvesting, achieving 99% accuracy on an in-house dataset. Saranya et al. (2020) highlighted the superiority of CNNs over traditional machine learning models like KNN and SVM, demonstrating better accuracy and efficiency using a public dataset of fruits. Rojas-Aranda et al. (2020) adapted a CNN model based on MobileNetV2, incorporating features like RGB color and histograms for fruit classification in retail environments, achieving 95% accuracy even with fruits inside plastic bags. Similarly, Joseph, Kumar & Mathew (2021) used the Fruits 360 dataset to develop a CNN model, achieving 94.35% accuracy across 131 fruit classes. A recent study by Dewi et al. (2024) applied Neural Architecture Search (NAS) to optimize neural networks for fruit detection, achieving a mean Average Precision (mAP) of 99.98% across 15 fruit types. The automated design and tuning of network architectures through NAS outperformed previous models, highlighting its potential to refine deep learning solutions for practical deployment.

It can be deduced that deep learning has proven to be very effective in detecting fruit freshness with high accuracy. Techniques like MobileNetV2 and Neural Architecture (NAS) can improve accuracy, making it easier to identify fresh fruits from rotten ones. These deep learning models will be the key to developing an AI-powered model that ensures better and more reliable fruit classification, leading to decreased food waste.

### **2.3.2 Deep Learning Used for Classifying Fruits Freshness**

The classification of fresh and rotten fruits using deep learning has been extensively explored, with various models achieving significant accuracy improvements. Convolutional Neural Networks (CNNs) have been widely used due to their feature extraction capabilities, while YOLO-based object detection models offer real-time classification benefits. However, the trade-off between accuracy, computational efficiency, and interpretability remains a critical challenge.

Turaev et al. (2020) evaluated VGG19 and ResNet18, concluding that VGG19 performed best on original images, whereas ResNet18 excelled when trained on augmented datasets. This suggests that model performance can be dataset-dependent, highlighting the need for robust pre-processing techniques. Similarly, Chakraborty et al. (2021) achieved 99.61% accuracy using CNN with MobileNetV2, reinforcing the effectiveness of lightweight deep learning architectures for classification tasks.

To further mitigate misclassification, Meshram et al. (2021) introduced “MNet: Merged Net” based on InceptionV3, achieving 99.92% accuracy, demonstrating the potential of ensemble and hybrid architectures. In contrast, Raj et al. (2021) compared CNN, YOLO, and MATLAB-based color detection, revealing that YOLO (85%) outperformed MATLAB (74%) and CNN (63%), highlighting YOLO’s strength in real-time classification.

Other studies focused on transfer learning and feature enhancement. Kazi & Panda (2022) reported over 99% accuracy with ResNet50 and AlexNet, emphasizing the power of pre-trained models. Similarly, Amin et al. (2023) leveraged transfer learning with AlexNet, achieving up to 99.8% accuracy, showcasing the ability of deep networks to generalize across datasets.

Regarding object detection, Chen et al. (2022) improved YOLOv3, attaining 88% accuracy, demonstrating its adaptability for external fruit quality assessment. Further refinements were introduced by Mukhiddinov et al. (2022), who enhanced YOLOv4 with the Mish activation function, achieving an average precision of 50.4%, which, while lower than CNN-based models, was optimized for real-time processing in industrial applications.

Beyond classification, Sultana et al. (2023) focused on flaw detection, where VGG16 yielded 96.04% accuracy, and Sofana Reka et al. (2024) combined CNNs with Random Forest, achieving 95% accuracy, illustrating the potential for integrating deep learning with traditional machine learning techniques to improve fruit shelf-life prediction.

These studies highlight the diverse deep learning strategies employed for fruit freshness classification, each with distinct advantages and trade-offs. While CNN-based models consistently achieve high accuracy, YOLO models provide real-time efficiency. However, most prior studies do not address explainability, making interpretability a key gap that this research aims to bridge using SHAP. Table 2.1 summarizes the comparative analysis of deep learning models for fruit freshness classification.

Table 2.1: Comparative Analysis of Deep Learning Models for Fruit Freshness Classification

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Study** | **Model/Technique Used** | **Performance** | **Key Strengths** | **Limitations** |
| Turaev et al. (2020) | VGG19, ResNet18 | VGG19 best on original, ResNet18 on augmented | Strong feature extraction | Requires large datasets |
| Chakraborty et al. (2021) | CNN with MobileNetV2 | 99.61% | Lightweight, efficient | Less robust to complex variations |
| Meshram et al. (2021) | MFC\_InceptionV3 (“MNet: Merged Net”) | 99.92% | Reduces misclassification | High computational cost |
| Raj et al. (2021) | CNN, YOLO, MATLAB color detection | YOLO: 85%, MATLAB: 74%, CNN: 63% | YOLO effective for real-time | CNN performs poorly on small datasets |
| Kazi & Panda (2022) | ResNet50, AlexNet | Over 99% | Transfer learning improves performance | Requires pre-training |
| Chen et al. (2022) | Improved YOLOv3 | 88% | Object detection for external quality | Lower accuracy vs. CNN |
| Mukhiddinov et al. (2022) | Enhanced YOLOv4 with Mish activation | Average precision of 50.4% | Real-time classification for industries | Lower AP vs. other YOLO versions |
| Amin et al. (2023) | AlexNet with transfer learning | Up to 99.8% | High generalization | Needs large datasets |
| Sultana et al. (2023) | VGG16 for flaw detection | 96.04% | Strong defect detection | Not real-time |
| Sofana Reka et al. (2024) | CNNs (VGG16) & Random Forest | 95% (VGG16 for classification) | Hybrid approach enhances prediction | Requires manual feature selection |

In this study, deep learning techniques will be used to classify fresh and rotten fruits with high accuracy and reliability. CNN and YOLO models have proven effective and reliable in previous studies, hence, this study focuses on improving classification performance by leveraging advanced deep learning methods. By making sure fruits are correctly classified, it helps to reduce food waste and improve quality control in real-world applications.

## **2.4 You Only Look Once (YOLO) Model**

YOLO is a real-time object detection algorithm that predicts bounding boxes and class probabilities in a single network pass, making it highly efficient compared to traditional detection methods. Unlike region-based CNNs (R-CNN), which require multiple passes, YOLO divides an image into an s × s grid and assigns predictions based on detected object locations. Studies by Tang et al. (2023), Zhang et al. (2022) and Zhou et al. (2022) highlight this approach, while Egi et al. (2022) and Gao et al. (2022) emphasize the direct regression capabilities of YOLO models.

Studies have demonstrated the power of YOLO for fruit classification and ripeness detection. Liu et al. (2022) improved YOLOv3 for pineapple detection by integrating DenseNet into the Darknet53 backbone, achieving an average precision of 97.55%, highlighting how network enhancements improve detection accuracy. Gai et al. (2021) conducted a study comparing different deep learning algorithms within the YOLO framework and found that the improved YOLOv4 achieved higher accuracy than other versions in detecting cherry fruits.

Similarly, Wang et al. (2022) optimized YOLOv5 for apple stem detection, using transfer learning and pruning techniques to reduce model complexity by 71% while maintaining a mean Average Precision (mAP) of 93.89%. This study underscores YOLO’s ability to balance model efficiency and detection precision, making it a strong candidate for real-world agricultural applications. In a related study, Zhang et al. (2023) developed a YOLOv5-based algorithm for tomato detection and ripeness classification, achieving 82.4% accuracy for unoccluded tomatoes, a recall rate of 90.9%, and a 3D pose classification accuracy of 96.9%. This further demonstrates YOLO’s adaptability across different fruit types and environmental conditions. YOLOv7 has been employed in another study to detect pomegranate fruits at different growing stages and classify them into five categories which are ripe, mid-growth, early-fruit, flower, and bud. The research achieved a recall of 0.888, a precision of 0.916, an mAP@0.5 of 0.943, and an mAP@0.5:0.95 of 0.824 (Nergiz, 2023).

Despite these improvements, YOLO models still face challenges, particularly in detecting small, occluded, or low-contrast objects. While newer YOLO versions, for example, YOLOv8 introduces anchor-free designs, improved feature fusion, and better generalization, their adoption in fruit classification with explainable AI remains underexplored. This study aims to address these gaps by integrating YOLOv8 with SHAP to improve classification transparency, making accurate predictions more interpretable for stakeholders.

## **2.5 Explainable AI (XAI)**

All the reviewed studies demonstrate that deep learning models can effectively classify fruits and assess their freshness with relatively high accuracy. However, these models operate as “black boxes”, meaning they provide results or make decisions without explaining the underlying processes (von Eschenbach, 2021). This lack of transparency can reduce trust, particularly when these models are used for critical decision making (Zhang et al., 2023). This research gap highlights the need for more studies exploring the use of explainable AI in fruits classification to enhance decision-making. To improve the model interpretability to distinguish between fresh and rotten fruits, it is crucial to identify the key features influencing its classification decisions. Therefore, this research aims to address this by employing an explainable AI technique known as Shapley Additive Explanations (SHAP), which clarifies how deep learning models make predictions by attributing the contribution of each feature, thus enhancing transparency (Bhargava & Gupta, 2022; Jain et al., 2023).

Developed by Lundberg and Lee (2017), SHAP integrates various approaches from the additive feature acknowledgment class, like LIME (Ribeiro et al., 2016) and DeepLIFT (Shrikumar et al., 2017). Adadi and Berrada (2018) provided illustrations of several XAI techniques, with SHAP being one of the methods covered. SHAP architecture has also been effectively applied in different contexts such as text analysis and image classification (Shrikumar et al., 2017). Recent studies demonstrate SHAP’s versatility across different fields. Walia et al. (2022) used kernel SHAP to identify key features in detecting forged images, improving model credibility. Aldughayfiq et al. (2023) discovered that LIME and SHAP are useful tools for identifying the particular regions and features in input retinoblastoma images that significantly influence the model’s predictions, providing important insights into the decision-making process of the deep learning model. Yang et al. (2024) applied a SHAP-based framework to urban cellular automata (CA) models to enhance feature selection, integrate analysis across modules and reveal spatial patterns. This approach improved model accuracy by 3%, highlighting critical factors like road proximity in industrial areas. Compared to LIME, SHAP offers several advantages. It provides a consistent and fair measure of feature importance across different instances, grounded in cooperative game theory (Younisse et al., 2022). Unlike LIME, which focuses on local explanations and may vary significantly, SHAP allows for both local and global insights, making it more robust and effective at capturing feature interactions (Salih et al., 2023). Its comprehensive approach improves understanding and trust in machine learning models across various applications (Vimbi et al., 2024).

By rendering model explanations in a format that is easily understandable to humans, XAI allows users to intuitively grasp AI decisions without requiring specialized knowledge in machine learning or statistics. Additionally, XAI addresses ethical considerations by promoting fairness, accountability, and trustworthiness in AI applications. By providing clear explanations for AI-driven decisions, XAI helps mitigate biases and ensures that AI systems align with ethical and societal norms. Overall, XAI plays a critical role in fostering human understanding, improving transparency, and supporting the responsible deployment of AI technologies across various domains (Dewangan & Gupta, 2024).

However, explainable AI has been limited in its application to fruit classification, making decision-making in this context less transparent. To address this research gap, this study aims to integrate SHAP with the YOLOv8 model to classify fresh and rotten fruits while providing SHAP-based explanations for the model’s predictions.

## **2.6 PowerBI and Ability to Visualize Data**

In today’s data-intensive world, dashboard visualization is an important element in businesses as it provides a single view into operations and offers real-time insights to support data-driven decision-making. Dashboards play a key role in displaying interactive and easy-to-understand key performance indicators (KPIs). By consolidating and arranging data in one place, dashboards allow users to track and respond to various metrics efficiently. Dashboards facilitate decision-making by visually summarizing business processes and simplifying complex information with clear, straightforward and interactive graphics. Managers can leverage Power BI to analyze data from multiple sources seamlessly and translate it into meaningful insights for better decision making (Goncalves et al., 2023). A dashboard is a graphical interface that interprets real-time data from various systems that are stored in a data warehouse using extract-transform-load (ETL) processes. Becker and Gould (2019) found that Power BI offers enhanced visual capabilities such as slicers and cross-highlighting improving the way users interact with the data. The researchers also study that organizations can strategically use dashboards to align performance with business goals and objectives to optimize decision-making processes.

Current literature increasingly emphasizes the integration of data visualization with machine learning (ML) techniques for enhanced decision-making. Visualization serves as a bridge between complex ML models and end-users as it transforms intricate data outputs into understandable visual formats. According to Yuan et al. (2021), effective visualization of machine learning results can help stakeholders discover patterns and insights. This is particularly vital in sectors such as healthcare, finance, and supply chain management, where real-time insights can significantly influence operational efficiency and strategic planning. Furthermore, machine learning algorithms can be utilized to dynamically update dashboard visualizations based on real-time data inputs. This ensures that users are always presented with the most current and up-to-date insights. For instance, Taylor et al. (2024) demonstrated how integrating predictive analytics with dashboards enables organizations to forecast future trends and make proactive decisions, thus enhancing their competitive advantage. This predictive capability aligns perfectly with the goal of providing timely insights for better decision-making.

Best practices for a good dashboard include: -

1. **Interactivity and filters:** Dashboards should include dynamic elements such as filters and live previews to allow users to explore data and get immediate insights (Goncalves et al., 2023).
2. **Alerts and Notifications:** Timely alerts make sure managers take actions and respond to any issues quickly (Becker & Gould, 2019).
3. **Accessibility and Collaboration:** Dashboards should be easy for relevant stakeholders to access as it fosters collaboration across departments and align with business objectives (Thomas, 2024).

Dashboards have become an integral part of business today. They help organizations monitor performance and make informed decisions. Visualization tools like Power BI portray how interactive dashboards can seamlessly integrate data and deliver business insights to stakeholders in a clear and effective manner. Desai et al. (2021) utilized Power BI in their research to improve business intelligence and data visualization within the realm of sentiment analysis. Similarly, another study investigated a business intelligence solution that employed Power BI to integrate, analyze, and visualize data, allowing managers to make informed sales decisions through intuitive reports and dashboards. This case study illustrated the advantages of business intelligence tools, emphasizing their capability to develop an integrated data system within data warehouses that supports rapid, clear and easily interpretable analyses with real-time updates (Goncalves et al., 2023).

In this research, Power BI has a significant role in visualizing the classification results of fresh and rotten fruits, making the model’s performance and insights to be easily accessible to stakeholders. Integration of Power BI to visualize classification outputs allow users to monito fruit freshness, analyze model accuracy and make informed decisions in real-world situations.

# **METHODOLOGY**

## **3.0 Introduction**

This chapter begins by introducing the research design, followed by the methodology framework. It then explains how the methodology framework is adapted to the proposed framework, providing a detailed explanation of each phase within the framework.

## **3.1 Research Design**

This research adopts a positivist paradigm, emphasizing objectivity and the use of observable data which aligns with the focus on empirical evidence derived from the performance and interpretability metrics of machine learning techniques (Alharahsheh & Pius, 2020). A quantitative approach has been employed (De Beuckelaer & Wagner, 2007), leveraging measurable data to classify fruits using a deep learning model while analyzing feature importance through SHAP (SHapley Additive exPlanations). The methodology is both experimental and applied meaning that this research will conduct experiments to train and evaluate the model, addressing the practical challenge of fruit classification and interpretability of the model’s prediction. By focusing on real-world issues related to food waste in the agricultural sector, this study aims to contribute meaningful insights that can enhance decision-making and operational efficiency.

## **3.2 Methodology Framework**

The methodology for this project follows the CRoss-Industry Standard Process for Data Mining (CRISP-DM), which provides a structured framework for data mining projects. As illustrated in Figure 3.1, it consists of six key phases which are Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation and Deployment. The process starts with developing a clear understanding of the business problem and how data mining can help address it. It sets the objectives and requirements from a business perspective (Peker & Kart, 2023). Next, the data is collected, explored and understood to identify patterns, detect anomalies and gain insights. In the Data Preparation phase, the data is cleaned, transformed and prepared for analysis. This phase often involves dealing with missing values and outliers as well as ensuring the data is in a suitable format for modeling (Schröer et al., 2021). The Modeling phase involves selecting and applying appropriate algorithms to create models that can generate valuable predictions or classifications. These models are then assessed during the Evaluation phase to ensure they meet the desired performance criteria and address the original business objectives. Finally, the Deployment phase involves implementing the results into practical use, such as integrating the model into existing systems or creating dashboards for decision-making. CRISP-DM is iterative, meaning insights from any stage can lead to refinement or a return to earlier steps, making it a flexible and adaptable approach to data analysis. Several researchers have applied CRISP-DM in different contexts such as credit classification (Darmawan, 2020), mood classification (Thoyyibah et al., 2022) and fraud detection (Pahuja & Kamal, 2023). Rahmadi et al. (2023) also applied the CRISP-DM framework in their research on crop prediction, utilizing its structured and iterative approach to develop effective machine learning models for forecasting crop yields. Another study by Antunes et al. (2024) utilized the CRISP-DM methodology, covering all phases from data preparation to deployment, to identify aromatic herbs using deep learning techniques.



Figure 3.1: CRISP-DM Framework

## **3.3 Modified CRISP-DM Framework**

CRISP-DM is well-suited for this project as it integrates business aspects that are essential for a comprehensive understanding of the project’s objectives. The Figure 3.2 illustrates the adapted CRISP-DM approach applied to the classification of fruits by adding an explainable AI component. This modified CRISP-DM framework ensures not only high-performing models but also transparency and interpretability which are essential for building trust in AI solutions. Hence, the adapted CRISP-DM in this research includes phases such as business understanding, data acquisition, data preparation, modelling, evaluation, Explainable AI (XAI) and deployment.

A diagram of a flowchart

AI-generated content may be incorrect.

Figure 3.2: Modified CRISP-DM Framework

### **3.3.1 Business Understanding**

In the fruit industry, ensuring the quality of produce is critical for maintaining customer satisfaction, reducing waste and maximizing profitability. However, the process of assessing fruit freshness typically relies on manual inspection, which can be time-consuming, costly and prone to human error. With the rise of AI and machine learning, businesses have started adopting automated classification models to enhance efficiency in quality control. By integrating AI-driven classification models into the quality control process, businesses can not only enhance operational efficiency but also achieve more consistent and accurate fruit assessments, minimizing human error and reducing both waste and costs. Despite their high accuracy, many existing models function as “black boxes,” offering little to no explanation of how they make their predictions. This lack of transparency can hinder trust, prevent widespread adoption and lead to operational inefficiencies as businesses may hesitate to rely on systems they cannot understand or validate.

### **3.3.2 Data Acquisition**

This research utilizes a publicly available dataset to train and evaluate the image recognition model for classifying fresh and rotten fruits (Sultana et al., 2022). This dataset was selected due to its comprehensive representation of various fruits and conditions, providing a strong foundation for developing a reliable model for fresh and rotten fruit classification.

The dataset consists of 12,335 images that are created using data augmentation techniques such as rotation, flipping, zooming, and shearing to enhance data variety. There are sixteen types of fruit classes in this dataset, namely fresh apple, rotten apple, fresh banana, rotten banana, fresh orange, rotten orange, fresh grape, rotten grape, fresh guava, rotten guava, fresh jujube, rotten jujube, fresh pomegranate, rotten pomegranate, fresh strawberry and rotten strawberry. Each image has been labeled by domain experts from an agricultural institute to ensure accurate classification. The distribution of images across categories include fresh and rotten for each fruit is shown below.

Table 3.1: Distribution of Images across Categories

|  |  |  |
| --- | --- | --- |
| **Category** | **Fruits** | **No. of Images** |
| **Fresh** | Apple | 734 |
| Banana | 740 |
| Orange | 796 |
| Grape | 800 |
| Guava | 797 |
| Jujube | 793 |
| Pomegranate | 797 |
| Strawberry | 737 |
| **Total** | | 6,194 |
| **Rotten** | Apple | 738 |
| Banana | 736 |
| Orange | 796 |
| Grape | 746 |
| Guava | 797 |
| Jujube | 793 |
| Pomegranate | 798 |
| Strawberry | 737 |
| **Total** | | 6,141 |
| **Grand Total Number of Images in Dataset** | | 12,335 |

Sultana et al. (2023) demonstrated the effectiveness of deep learning models in classifying fresh and rotten fruits, providing a solid benchmark for the current research. The performance of the VGG16 model, achieving an accuracy of 96.04%, serves as an aspirational target for the model being developed in this study.

### **3.3.3 Data Preprocessing**

There is a need to annotate all the images in the dataset since this research will be done by using YOLO model. YOLO, as a real-time object detection model, requires precise annotation of images. Annotating each fruit with bounding boxes and corresponding labels allows YOLO to accurately detect and classify fruits in images based on their visual features and spatial location within the frame. YOLO is a supervised learning model, meaning it learns from labeled data (Vijayakumar & Vairavasundaram, 2024). Annotation provides the necessary labels and bounding box coordinates that tell the model what objects to look for in images and where they are located. By providing annotated examples, the model learns to identify features that distinguish one class from another (Saqib et al., 2024), in this case, fresh fruits and rotten fruits. Roboflow is a popular open-source annotation tool that can manually draw bounding boxes around objects in the images and assign labels to them. Once images are labeled, the dataset will be split into three sets to train, validate and evaluate the model:

1. Training set: 80% of the total images, used to train the model.
2. Validation set: 10% of the total images, used to tune hyperparameter and prevent overfitting.
3. Test set: 10% of the total images, used to assess the final model performance.

The 80:10:10 split is commonly used in machine learning research to ensure a balanced approach that allows the model to train on a sufficient amount of data while preserving unseen data for validation and testing (Xu & Goodacre, 2018). This helps mitigate the risk of overfitting and ensures that the model can generalize new data. According to Xu & Goodacre (2018) and Tan et al. (2021), this splitting strategy ensures that the model is effectively trained, validated, and tested, confirming its robustness and ability to generalize to unseen data. Maintaining a balance among these subsets is essential for reliably estimating model performance (Picon et al., 2019). A sufficiently large training set is critical for developing a model with strong generalization capabilities. The validation set serves to assess the model’s performance on previously unseen data, aiding in the fine-tuning of its parameters. Finally, the test set must remain entirely separate from both the training and validation sets to provide an accurate measure of the model’s performance on unseen data.

### **3.3.4 Exploratory Data Analysis (EDA)**

**3.3.4.1 Dataset Overview**

The dataset consists of images of various fruits categorized into two main classes which are fresh and rotten. The dataset includes multiple fruit types, such as apples, bananas, grapes, guavas, jujubes, oranges, pomegranates, and strawberries. The total number of images in the dataset is 12,335, distributed across training, validation, and test sets in an 80:10:10 ratio. Specifically, the dataset is structured as 9,871 images for train, 1,227 for validation and 1,237 for test. Ensuring a well-balanced dataset across these splits is crucial for achieving a high-performing classification model.

The dataset used for training the YOLOv8 model in this research comprises 12,335 images. While this may seem modest compared to larger datasets, it aligns well with the sample sizes used in recent literature, which have demonstrated the feasibility of training robust YOLOv8 models with similar or slightly smaller datasets. For example, Gu et al. (2024) applied YOLOv8 for apple classification and recognition, achieving high detection accuracy with an optimized dataset of 20,705 images. Similarly, Aishwarya and Kumar (2023) utilized 18,074 images for classifying banana ripeness, with YOLOv8 reaching an impressive accuracy of 96.3%. In another study, an apple dataset of 1,500 images, divided into categories such as good apples, rotten apples, unripe apples, and diseased apples, was used to train a YOLOv8 model. Despite the dataset size being relatively modest, the enhanced YOLOv8 model achieved an accuracy of 87.3%, surpassing the original model by 3.5% in mean average precision (mAP) (Zhang et al., 2024). Studies have shown that even datasets with smaller sample sizes can still lead to robust models, especially with well-annotated and representative data. Moreover, Gamani et al. (2024) expanded their dataset to include 1,386 training images, 87 validation images, and 86 test images, all focusing on ripe and unripe strawberries. YOLOv8n achieved an accuracy of 80.9% in detecting these strawberries. This further supports that YOLOv8 can perform effectively with datasets of this size when the data is well-prepared and the model is fine-tuned.

**3.3.4.2 Dataset Visualization**

To better understand the dataset, this section presents sample images of fresh and rotten fruits. The dataset consists of 16 fruit classes, each classified into fresh and rotten categories. Table 3.2 and 3.3 illustrate representative images of fresh and rotten fruits from the dataset. These images demonstrate key visual differences such as color changes, texture variations and structural differences. Rotten fruits often exhibit dark spots or discoloration and may shrink or develop a mushy texture. Fresh fruits appear smooth, whereas rotten fruits may show wrinkling or mold.

Table 3.2: Fresh Fruit Samples

|  |  |  |  |
| --- | --- | --- | --- |
| **Fruit Name** | **Sample Image** | **Fruit Name** | **Sample Image** |
| **Fresh Apple**  **(Class 0)** | A close-up of a red apple  AI-generated content may be incorrect. | **Fresh Jujube**  **(Class 4)** | A yellow fruit on a white surface  AI-generated content may be incorrect. |
| **Fresh Banana**  **(Class 1)** | A yellow banana on a white surface  AI-generated content may be incorrect. | **Fresh Orange**  **(Class 5)** | An orange on a white surface  AI-generated content may be incorrect. |
| **Fresh Grape**  **(Class 2)** | A close-up of a bunch of grapes  AI-generated content may be incorrect. | **Fresh Pomegranate**  **(Class 6)** | A close up of a pomegranate  AI-generated content may be incorrect. |
| **Fresh Guava**  **(Class 3)** | A close-up of a lime  AI-generated content may be incorrect. | **Fresh Strawberry**  **(Class 7)** | A close up of a strawberry  AI-generated content may be incorrect. |

Table 3.3: Rotten Fruit Samples

|  |  |  |  |
| --- | --- | --- | --- |
| **Fruit Name** | **Sample Image** | **Fruit Name** | **Sample Image** |
| **Rotten Apple**  **(Class 8)** | A red apple with a large spot on it  AI-generated content may be incorrect. | **Rotten Jujube**  **(Class 12)** | A brown apple on a white surface  AI-generated content may be incorrect. |
| **Rotten Banana**  **(Class 9)** | A rotten banana on a white surface  AI-generated content may be incorrect. | **Rotten Orange**  **(Class 13)** | A peeled orange on a white surface  AI-generated content may be incorrect. |
| **Rotten Grape**  **(Class 10)** | A group of green grapes  AI-generated content may be incorrect. | **Rotten Pomegranate**  **(Class 14)** | A close up of a fruit  AI-generated content may be incorrect. |
| **Rotten Guava**  **(Class 11)** | A rotten apple on a white surface  AI-generated content may be incorrect. | **Rotten Strawberry**  **(Class 15)** | A group of red fruit  AI-generated content may be incorrect. |

Figures 3.3 and 3.4 illustrate sample images from the dataset with YOLO-generated bounding box annotations, showcasing how the model learns to detect and classify fruits. Figure 3.3 presents an image containing multiple fruits, each labeled with a bounding box and its corresponding class. Figure 3.4 displays an image with a single fruit, ensuring that the model can correctly classify individual fruits.

A group of apples with yellow squares

AI-generated content may be incorrect.

Figure 3.3: Example of Annotated Fresh Fruit Images

A rotten orange with a black and white background

AI-generated content may be incorrect.

Figure 3.4: Example of Annotated Rotten Fruit Images

**3.3.4.3 Data Quality Assurance**

To ensure data completeness and consistency, an analysis was conducted on the number of images and their corresponding annotation files across all dataset splits. The results in Table 3.4 confirmed that each image in the dataset has a corresponding annotation file, with no missing labels detected. This ensures that the YOLO model can be trained effectively without issues related to missing annotations.

Table 3.4: Number of Images and Their Corresponding Annotation Files

|  |  |  |
| --- | --- | --- |
| **Datasets** | **Images** | **Labels** |
| **Train** | 9871 | 9871 |
| **Valid** | 1227 | 1227 |
| **Test** | 1237 | 1237 |

The dataset is structured according to best practices for classification, with separate folders for images and labels in each split for train, validation, and test. Each image is accompanied by a label file containing annotation details, ensuring a well-organized dataset that facilitates efficient model training and performance evaluation.

Additionally, each image includes annotations in the form of bounding boxes that mark the exact location of the fruit. These bounding boxes are crucial for training the YOLO model to accurately detect and classify fresh and rotten fruits. The variation in bounding box sizes and numbers across images reflects different classification challenges, which the model must learn to handle effectively. These quality checks confirm that the dataset is reliable, well-structured, and suitable for training a robust fruit classification model. This ensures a structured workflow for model training and minimizes errors due to inconsistent labeling.

**3.3.4.4 Image Resolution Analysis**

Maintaining consistent image resolution is vital for efficient model training. During the exploratory data analysi, the resolution of all images was assessed to ensure uniformity. As shown in Figure 3.5, the analysis revealed that 12,334 images had a resolution of 1020×1020 pixels, while only one image had a resolution of 1040×780 pixels. To ensure consistency, all images were resized to 800×800 pixels before training using the imgsz=800 parameter. Standardizing image sizes improves the efficiency of batch processing and enhances classification performance.

In prior experiments and literature, resizing images to 800×800 pixels has been shown to offer a good balance between computational efficiency and model performance. For example, Yue et al. (2024) and Wu et al. (2024) used 800×800 pixel images for object detection tasks with YOLOv8, demonstrating that this resolution supports multi-scale and dense target detection without significant performance degradation. However, choosing an image resolution of 800×800 pixels is not without trade-offs. While reducing the resolution can lead to faster training times and lower computational resource requirements, it may also reduce the model’s ability to capture fine-grained details. A study by Yan et al. (2021) examined the effects of image resolution on convolutional neural networks. The authors demonstrated that while higher resolutions can enhance accuracy by capturing finer details, they also lead to increased computational, storage, and bandwidth costs. They proposed a dynamic resolution mechanism that adjusts image resolution during inference to optimize the trade-off between accuracy and efficiency. This finding highlights the importance of balancing image resolution with computational constraints to ensure efficient model performance. Therefore, the decision to use 800×800 pixels strike a balance between achieving satisfactory detection accuracy and maintaining a manageable computational load, ensuring that the model performs efficiently in real-world applications.

A purple square with numbers and a white background

AI-generated content may be incorrect.

Figure 3.5: Image Resolution Frequency

**3.3.4.5 Bounding Box Distribution Analysis**

Bounding box distribution plays a crucial role in object detection performance by providing insights into the number of objects present in each image. As illustrated in Figure 3.6, the distribution of bounding boxes is highly skewed, with most images containing fewer than five bounding boxes. However, there are some images that contain more than 20 bounding boxes, reflecting a more complex distribution. This discrepancy may arise from images containing multiple fruits, such as 20 apples in a single image, or from fruits like grapes, which are often displayed in bunches and annotated individually, resulting in a higher count of bounding boxes.

While images with more than 20 bounding boxes could pose a challenge for the model due to increased complexity and potential for occlusion or overlap, no specific preprocessing was applied to reduce the number of bounding boxes in these cases. The YOLOv8 model is designed to handle such complexity by efficiently detecting multiple objects in a single image. The model utilizes anchor boxes, which are predefined bounding boxes of various sizes and aspect ratios, to predict multiple objects within a grid cell (Redmon et al., 2016; Bochkovskiy et al., 2020). Additionally, non-maximum suppression (NMS) is employed to eliminate redundant or overlapping bounding boxes, ensuring that the final detection is accurate and reflects only the most relevant objects in a scene. This approach enables the model to handle densely packed or clustered objects, even in cases of overlap, thereby maintaining detection accuracy (Babar, 2024).

A green and white graph

AI-generated content may be incorrect.

Figure 3.6: Number of Bounding Boxes Per Image

**3.3.4.6 Bounding Box Size Analysis**

Bounding box size significantly influences the ability of object detection models to accurately classify fruits. According to the analysis in Figure 3.7, the majority of bounding boxes are relatively small, and as the size of the bounding box increases, the frequency of larger boxes decreases. This pattern suggests that smaller fruits or densely packed fruits are more common in the dataset, which could impact detection accuracy. For instance, grapes may be annotated with many small bounding boxes due to their size and the way they are grouped or clustered in images.

The natural characteristics of fruits, such as size, shape, and packing style, play a crucial role in how bounding boxes are generated and how well the model performs. Smaller fruits that cluster closely pose challenges for accurate detection, as models may struggle to differentiate individual items within dense groupings. Conversely, larger fruits with distinct features and spacing are more readily detected.

YOLOv8 addresses these challenges through several key features that enhance its ability to detect objects of varying sizes. Unlike earlier YOLO versions that relied on predefined anchor boxes, YOLOv8 adopts an anchor-free approach, allowing it to directly predict object locations without predefined bounding boxes. This enhances its flexibility in detecting both small, densely packed fruits and larger fruits more effectively. To further enhance detection accuracy and robustness, Su et al. (2024) introduce adaptive anchor box generation and multi-scale feature fusion, improving the model’s ability to handle diverse object scales effectively.

Additionally, YOLOv8 employs a Feature Pyramid Network (FPN), which enables multi-scale detection. This allows the model to extract features from different layers of the network, with higher-resolution layers capturing fine-grained details for smaller objects like grapes, and lower-resolution layers capturing broader features for larger fruits. This multi-scale approach helps improve the accuracy of detection for both small and large fruits. To further enhance YOLOv8’s small object detection capabilities, Wang et al. (2024) propose the use of a bidirectional Feature Pyramid Network (BiFPN), which improves accuracy while maintaining efficiency by enabling better information flow across different feature levels.

A red graph with white background

AI-generated content may be incorrect.

Figure 3.7: Bounding Box Size Distribution

Figure 3.8 demonstrated the bounding box aspect ratio distribution chart. It provides valuable insights into the shape characteristics of detected objects in the dataset. The distribution is right-skewed, with most bounding boxes having an aspect ratio close to 1, indicating that the majority of objects are nearly square in shape. However, a small subset of bounding boxes exhibits significantly higher aspect ratios, likely representing elongated objects such as bananas or clustered grapes. The presence of a long tail suggests extreme values where some objects have a much greater width relative to their height. While this variability in aspect ratios is typically an important factor for object detection models, in this case, the observed distribution aligns with the natural characteristics of the dataset. Therefore, no adjustments have been made.

A graph of a line graph

AI-generated content may be incorrect.

Figure 3.8: Bounding Box Aspect Ratio Distribution

**3.3.4.7 Class Distribution Analysis**

Class distribution analysis visualized in Figure 3.9, reveals a generally balanced representation of fresh and rotten fruit classes across the dataset. While minor variations in sample counts exist between specific fruit types, the overall distribution demonstrates a reasonable degree of parity, with counts ranging approximately between 730 and 800 instances per class. Notably, classes such as “FreshGrape,” “FreshOrange,” “RottenGrape,” and “RottenOrange” exhibit slightly higher representation, while “FreshApple,” “FreshBanana,” and several rotten fruit categories possess marginally lower counts. However, these discrepancies are relatively small and unlikely to introduce significant bias during model training as previous studies have shown that moderate class imbalances typically do not degrade model performance (Narwane & Sawarkar, 2021) and that class-wise difficulty is often more critical than mere class size (Sinha et al., 2020). Furthermore, research on energy aligning techniques (Zhao et al., 2021) and class balancing strategies (Chen et al., 2022) suggest that even when biases emerge from imbalanced distributions, they can be effectively mitigated. Similarly, studies on overfitting in neural networks indicate that moderate class imbalances are generally manageable through proper regularization (Li et al., 2020).

**A graph of different colors of fruit

AI-generated content may be incorrect.**

Figure 3.9: Distribution of Fresh and Rotten Fruits per Type

**3.3.4.8 Feature Correlation Analysis**

The correlation matrix and heatmap presented in Figure 3.10 and 3.11 provide insights into the relationships between different image features used for fruit classification. Notably, MeanColorIntensity, Brightness, and MeanGreen exhibit strong positive correlations (above 0.94), indicating that as one increases, the others also rise significantly. Similarly, MeanRed and MeanGreen are moderately correlated (0.63), suggesting a connection between these color intensities. Conversely, BoundingBoxSize shows weak negative correlations with most features, such as MeanColorIntensity (-0.13), MeanRed (-0.21), and Brightness (-0.15), implying that fruit size does not strongly influence color characteristics. Additionally, AspectRatio has minimal correlation with other features, indicating that fruit shape does not significantly impact brightness or color intensity. These findings suggest that while color-related features are interdependent, some variables like AspectRatio and BoundingBoxSize may be less relevant for classification, allowing for feature selection to improve model efficiency.

However, since YOLOv8 is a deep learning-based object detection model, these correlations do not directly impact its training process. Unlike traditional machine learning models that rely on explicit feature selection, YOLOv8 automatically extracts and prioritizes the most relevant features through its convolutional layers. The model processes images in RGB format, inherently capturing color variations, brightness, and shape details without being affected by feature redundancy. While the high correlation among color-related features may indicate redundancy in classical modeling, YOLOv8 learns hierarchical patterns, making manual feature selection unnecessary. Additionally, the weak correlation between BoundingBoxSize, AspectRatio, and color features suggests that shape and size are independent of color intensity, but YOLOv8 can still leverage these spatial characteristics for accurate classification (Yaseen, 2024). Therefore, rather than focusing on feature correlation, improving model performance should emphasize high-quality image data, augmentation techniques, and hyperparameter tuning.

**A screenshot of a computer

AI-generated content may be incorrect.**

Figure 3.10: Feature Correlation Matrix

**A diagram of heatmap

AI-generated content may be incorrect.**

Figure 3.11: Feature Correlation Heatmap

**3.3.4.9 Color Distribution Analysis**

Analysis of color distribution revealed an observable difference in brightness between fresh and rotten fruits within the dataset. As illustrated in Figure 3.12, the histogram of mean brightness values demonstrates a broader distribution for fresh fruits, with a peak in the higher brightness range approximately 160-180. This suggests a greater variability in the brightness of fresh produce, likely reflecting natural variations in ripeness, lighting conditions, and potentially, fruit type. Conversely, the brightness distribution for rotten fruits exhibits a more concentrated pattern, clustering towards lower-to-mid range values around 120-160 and peaking around 150-160. This observation aligns with the expected visual characteristic of rotten fruits appearing darker or duller. While a degree of overlap exists between the two distributions, particularly in the mid-range, the higher peak brightness observed for fresh fruits indicates that this metric may serve as a useful, albeit imperfect, discriminator in classification models.

**A graph of a red and green graph

AI-generated content may be incorrect.**

Figure 3.12: Color distribution Analysis

**3.3.4.10 Summary of Exploratory Data Analysis**

The exploratory data analysis confirms that the dataset is well-structured, balanced, and suitable for training a robust fruit classification model using YOLOv8. Data preprocessing steps including image resizing and annotation verification ensure consistency and quality. The insights gained from bounding box distribution, aspect ratios, and feature correlations will aid in optimizing model training for accurate fresh and rotten fruit classification.

### **3.3.5 Modelling**

**YOLOv8**

YOLOv8 builds upon its predecessors by introducing several architectural and performance enhancements, making it particularly well-suited for real-time fruit classification. It retains the Cross Stage Partial (CSP) architecture from YOLOv5 while integrating C2F (CSP-Fast) blocks, which improve feature extraction and learning efficiency (Sohan et al., 2024). Additionally, YOLOv8 eliminates the 1×1 CBS convolution structure and replaces the previous C3 module with the C2F block, allowing for better gradient flow and enhanced image analysis capabilities (Vijayakumar & Vairavasundaram, 2024). These optimizations improve inference speed and detection accuracy, addressing key limitations of earlier YOLO models.

Recent studies have demonstrated the effectiveness of YOLOv8 for fruit detection and classification tasks. Xiao et al. (2023) compared YOLOv8 and CenterNet, finding that YOLOv8 achieved 99.5% accuracy with a detection time of just 2.9ms, making it ideal for real-time agricultural applications. Similarly, Qiu et al. (2024) developed the GSE-YOLO network, based on YOLOv8n, to assess pitaya maturity across four stages, achieving 85.2% accuracy while reducing false detections in complex environments. Meanwhile, Wang et al. (2024) introduced an improved YOLOv8+ model for strawberry ripeness classification, achieving 97.81% accuracy, demonstrating YOLOv8’s ability to generalize across various fruit types and conditions. These studies highlight YOLOv8’s potential to enhance precision agriculture and automate quality control processes.

While various deep learning models, including CNNs and other object detection frameworks, have been used for fruit classification, YOLOv8 offers a superior balance between speed, accuracy, and computational efficiency (Khalili & Smyth, 2024). Table 3.5 compares YOLOv8 with alternative deep learning models commonly used in object detection and classification tasks. It is important to note that the accuracy and inference speed values are approximately and may vary based on specific implementations and datasets.

Table 3.5: Comparison of YOLOv8 with Alternative Models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Accuracy** | **Inference Speed (ms/frame)** | **Strengths** | **Limitations** |
| **CNN (ResNet50. MobileNetV2, AlexNet)**  (Kazi & Panda, 2022) | 95-99% | 50-100ms | Strong feature extraction, transfer learning | Slow inference, not optimized for real-time detection |
| **Faster R-CNN** (Ezzeddini et al., 2024) | 90-97% | 100-200ms | High precision, region-based detection | Computationally expensive, slow for real-time applications |
| **EfficientDet** (Tan et al., 2020) | 92-98% | 15-50ms | Optimized detection with scaling | Requires extensive hyperparameter tuning |
| **YOLOv5** (Casas et al., 2024) | 85-97% | 5-10ms | High-speed detection, well-optimized | Limited feature extraction compared to YOLOv8 |
| **YOLOv8** (Keylabs, 2024) | 97-99.5% | 2.9-5ms | Real-time detection, anchor-free, robust feature extraction | Higher computational cost than YOLOv5 |

After evaluating various models, YOLOv8 was selected for this research due to its high-speed processing, superior accuracy, and real-time object detection capabilities (Ali & Zhang, 2024; Bilous et al., 2024). Compared to CNN-based models, YOLOv8 eliminates the need for exhaustive feature extraction while maintaining high classification accuracy (Hawaldar et al., 2024). Unlike Faster R-CNN and EfficientDet, YOLOv8 achieves faster inference speeds, making it more practical for real-time applications (Liu et al., 2024). Its anchor-free design and mosaic augmentation improve object recognition under varying conditions, addressing challenges such as occlusions, uneven lighting, and fruit deformities (Qi & Wang, 2024). Additionally, YOLOv8 outperforms YOLOv5 by offering enhanced detection accuracy and faster inference while reducing computational complexity (Bilous et al., 2024). The model’s ability to handle multiple object detections simultaneously ensures that each fruit is accurately classified as fresh or rotten, making it ideal for automated fruit quality assessment in agricultural and retail industries. By integrating YOLOv8 with SHAP, this research aims to improve both classification accuracy and interpretability, addressing the limitations of black-box AI models in food quality assessment.

### **3.3.6 Evaluation Metrics**

To evaluate the model performance of YOLO model, several evaluation metrics are proposed to be used. Precision (1) is the measure of exactness which is the accuracy of prediction of true positive (TP) over all the predicted positives. Recall (2) assesses the completeness of the model, measuring the proportion of true positive predictions relative to all actual positive instances. F-Measure (3) represents the harmonic mean of precision and recall, providing a single metric to evaluate the balance between the two.

To gain further insights into the model’s performance, a confusion matrix will be presented. This matrix provides a visual representation of the classification results, summarizing the true positives (TP), false negatives (FN), false positives (FP), and true negatives (TN). By examining the confusion matrix, this study can identify specific areas where the model excels or struggles, which can inform future improvements (Naidu et al., 2023).

|  |  |
| --- | --- |
|  | *(1)* |
|  | *(2)* |
|  | *(3)* |

In this case, the TP, FN, FP and TN are described below.

True Positive (TP) is where the model predicts the fresh fruits as fresh.

False Negative (FN) is where the model predicts the fresh fruits as rotten.

False Positive (FP) is where the model predicts the rotten fruits as fresh.

True Negative (TN) is where the model predicts the rotten fruits as rotten.

Additionally, the Mean Average Precision (mAP) is a crucial metric in object detection, particularly for evaluating YOLO models. It quantifies the model’s ability to accurately identify objects across different classes and scales by averaging precision over various recall levels. This metric provides a comprehensive evaluation, reflecting the trade-off between precision and recall across multiple object categories. Average Precision (AP) is first calculated for each class, and mAP is the mean of the AP scores for all classes. In YOLOv8, mAP can be computed at a specific Intersection over Union (IoU) threshold (e.g., mAP@0.5) or across a range of thresholds (e.g., mAP@0.5:0.95). The Intersection over Union (IoU) measures the overlap between the predicted bounding box and the actual bounding box. A high IoU indicates that the predicted bounding box closely matches the actual object’s location, signaling precise detection. This metric is essential for evaluating the performance of object detection models, as it helps determine how accurately the model locates objects within an image.

### **3.3.7 SHapley Additive exPlanations (SHAP)**

This research aimed at investigating the interpretability and transparency of the model by employing XAI techniques specifically Shapley Additive Explanations (SHAP). SHAP is a method that helps users understand how the AI model makes its decisions by identifying which features are most influential in determining whether the fruit is classified as fresh or rotten. Interpretability is crucial as it allows stakeholders to see beyond the model’s prediction and understand the rationale behind them. By visualizing the contribution of each feature to the final decision, SHAP provides a clear and detailed explanation of the model’s inner workings. This step not only enhances trust and transparency but also supports more informed decision-making, especially in critical applications where understanding the factors influencing an outcome is essential. The trained model and an image will be given to the SHAP deep explainer to understand how the model makes its predictions. The explainer calculates SHAP values, which show which parts of the image influenced the model’s decision the most. After that, a SHAP image plot is used to highlight these important parts. In the plot, red areas show the parts of the image that positively influenced the model’s decision, making it more likely to choose a specific class, while blue areas show parts that had a negative influence (Temenos et al., 2023).

Figure 3.13 is an example of SHAP output from Wang et al. (2024). The researchers explain that images of three fruits including oranges, apples, and lemons were captured by the camera and used for prediction, with the resulting SHAP value heatmaps displayed. The model used to predict their shapes highlights red areas that enhance recognition and blue areas that impede it. Oranges and lemons, both from the Brassicaceae family, share similar characteristics. Some areas of the lemons are highlighted in light red, indicating a similarity to oranges.

A screenshot of a computer screen

AI-generated content may be incorrect.

Figure 3.13: Example of SHAP Output Using Fruits

### **3.3.8 Deployment**

The deployment phase of this research involves integrating the developed AI model and its interpretative insights into a user-friendly platform using Power BI. This approach ensures that stakeholders can easily access and utilize the classification model results and the SHAP output for enhanced decision-making in fruit quality management.

The first step in deployment will involve importing the classification model into Power BI. This will enable stakeholders such as farmers, suppliers and restaurant owners to interact with the model’s predictions directly. By setting up a dynamic dashboard, users will be able to input images of fruits and receive immediate classification results whether the fruits are fresh or rotten, thereby facilitating prompt decision-making.

To enhance the interpretability of the model’s predictions, the SHAP output will be incorporated into the Power BI dashboard. SHAP values provide insights into the factors influencing the model’s decisions, highlighting the most significant features that affect fruit classification. This transparency is essential for building trust in AI applications among stakeholders, as it allows them to understand the rationale behind each prediction.

Key performance indicators (KPIs) will also be included to summarize the model’s accuracy and reliability, providing users with confidence in the system’s effectiveness. The deployment of the model through Power BI also allows for monitoring of fruit quality. Users will be able to upload images and instantly receive feedback on the quality classification. This feature supports continuous assessment and enhances the operational efficiency of inventory management, purchasing decisions and quality control practices.

As the technology matures, future updates to the Power BI dashboard may include the integration of additional food products for classification and the incorporation of real-time data streams from supply chain operations. Moreover, stakeholders can provide feedback on the model’s performance, which can be utilized for iterative improvements and model retraining, ensuring the system remains up to date with evolving market needs. This would further expand the model’s applicability and provide stakeholders with a comprehensive tool for managing food quality and reducing waste across various sectors.

# **RESULT AND ANALYSIS**

## **4.0 Introduction**

This chapter presents the results derived from the training, validation, and testing of the YOLOv8 model for automated classification of fresh and rotten fruits. It also includes SHAP analysis for model interpretability along with the implementation of a Power BI dashboard to visualize the classification outcomes.

## **4.1 Model Training Performance**

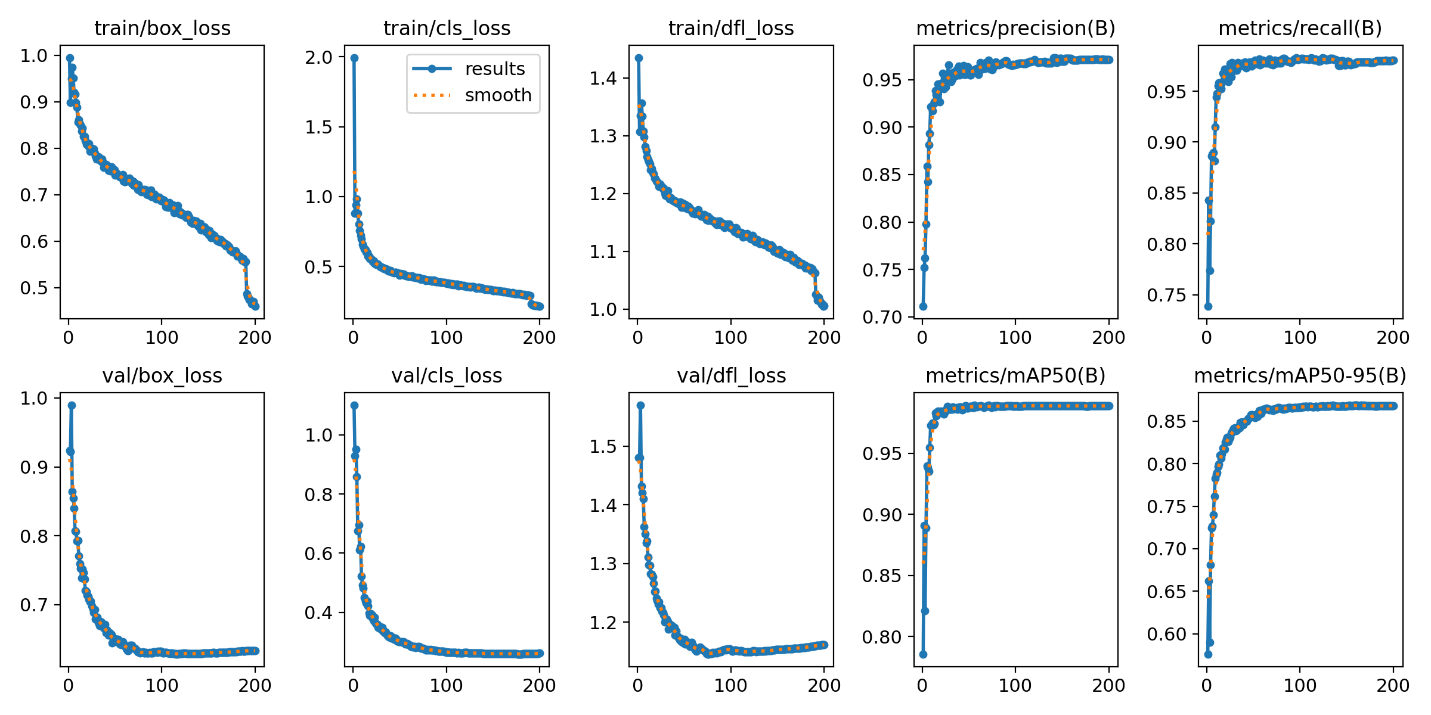


Figure 4.1: Model Training Performance

In YOLOv8, parameters are adjusted based on the GPU and VRAM capacity, with the Ultralytics library automatically detecting the GPU and optimizing settings accordingly, except for the epoch and image size parameters (Priyadi & Suharjito, 2023). For this project, the model was trained with an image size of 800 for 200 epochs, while the batch size remained at its default value of 16. A batch size of 16 is a common choice for balancing training speed and memory usage, particularly on GPUs with limited VRAM.

Training YOLO models for more epochs is essential for complex datasets, as it allows the model to learn complicated patterns and features. Given that this dataset consists of 12,335 images spanning 16 distinct fruit classes, training for 200 epochs facilitates stable convergence and improved accuracy. Studies have shown that object detection model improve their mean Average Precision with extended training epochs, particularly when dealing with variations in object shape, size, and lighting conditions (Bochkovskiy et al., 2021). Another study from Dixit and Bhoite (2024) observed that YOLOv8’s accuracy in pedestrian detection increased significantly with the increasing number of epochs from 10 to 150.

A key concern in this study is ensuring that the model effectively captures the differences between fresh and rotten fruits. Training for too few epochs may result in underfitting and poor generalization. Empirical findings in YOLO research suggest that 200 epochs can lead to notable accuracy improvements, especially when detecting subtle differences in object appearance. However, while increasing epochs generally enhances performance, it also raises training time and computational costs. Thus, 200 epochs strikes a practical balance, allowing the model to learn complex patterns while minimizing the risk of overfitting and diminishing returns (Najib et al., 2024; Niu et al., 2024).

After training the YOLOv8 with the dataset, various curves were produced, specifically illustrating its training loss, validation loss, and performance. Figure 4.1 showed the model training performance.

The first loss functions that must be analyzed are the training and validation for Box Loss. Box Loss is a measure that describes how well the predicted bounding box aligns with the ground truth bounding box (actual box). It essentially measures the location errors between the predicted box with the actual box, a lower value indicating that the model is able to detect the locations of the objects with precision (Ameerdin et al., 2024). Observing the “train/box\_loss” curve, it may be noticed that the box loss gradually decreases when approaching the higher epochs. This implies that the model’s bounding box predictions are improving over time, which in turn improves the model’s accuracy (Ocharo et al., 2024). A similar pattern may be observed in the “val/box\_loss” curve, as it portrays a comparable gradual decrease over time. Furthermore, there are no sudden spikes in box loss, indicating that there are no significant appearances of overfitting (Zakiyabarsi et al., 2024). Observing both training and validation box loss curves, the result indicate that the box loss starts at 1.0 and slowly stabilizes to around 0.5 at higher epochs.

The next loss functions that should be analyzed are the training and validation curves for Classification Loss (cls). Classification loss measures the error in the classification of the object within the bounding box. A low error value implies that the model is able to classify the object accurately (Yu & Liu, 2023). Looking at the “train/cls\_loss”, it may be seen that the classification loss begins at 2.0 followed by a sharp decrease to approximately 0.5 around the 30th epoch mark. Following that, the loss stabilized at the higher epochs. This sharp decrease in classification loss implies that the model was able to learn at an accelerated rate, as it did not take a substantial amount of epochs for the model to distinguish between fresh and rotten fruits. When comparing the “train/cls\_loss” curve to the “val/cls\_loss” curve, there are no significant indications of overfitting, as they have a comparable pattern, nor does the validation curve possess any sharp rises in loss at higher epochs (Xuan & Chong, 2024).

Finally, the last loss functions that need to be analyzed are the training and validation curves for Distribution Focal Loss (DFL). DFL is an advanced loss function which helps to enhance bounding box predictions (Julianda & Puriyanto, 2024). Observing the “train/dfl\_loss” curve, the result indicate that it starts at about 1.6 followed by a slow decrease to 1.0. This implies that the model’s confidence in bounding box regression increases at the higher epochs, further enhancing its ability to locate objects with precision (Ariharan et al., 2024). Looking at the “val/dfl\_loss” curve, it may be seen that the curve starts at around 1.6 and gradually flattens to around 1.2 at the higher epochs. However, it is noticeable that there are slight increases in validation loss after the 100th epoch mark, implying mild indications of overfitting.

Moving on to the model’s performance, the precision curve, recall curve, and the mean average precision (mAP) curves must be examined. By observing the “metric/precision(B)” curve, the result indicate that the model’s precision has a sharp increase to approximately 95% around the 30th epoch mark. Furthermore, this precision continues to stabilize at higher epochs. A similar pattern may be observed in the “metric/recall(B)” curve, as the curve also has a sharp increase to 95% around the 30th epoch mark. Following this sharp increase, the recall also stabilizes at higher epochs. Both precision and recall curves implies that this model is able to make confident predictions with both low false positives and negatives. As a result, this model has low errors in terms of falsely labelling an object (Dastagir et al., 2024).

Focusing attention on the mean average precision (mAP) curves, specifically the “metrics/mAP50(B)”, it may be noticed that the model produces a high mAP of approximately 95% when the intersection over union (IoU) is at 50%, which is a relatively loose overlap criteria. Based on its produced curve, this high percentage is produced around the 30th epoch mark, followed by a continuous stable performance across the higher epochs. Furthermore, when analyzing the “metrics/mAP50-95(B)” curve, a similar pattern may be observed. Under stricter criteria, the model is still able to produce a relatively high mAP of approximately 85%. With the model producing both strong mAPs under both IoU conditions, it implies that the model is adequate in detecting and does it with precision.

## **4.2 Model Validation Results**

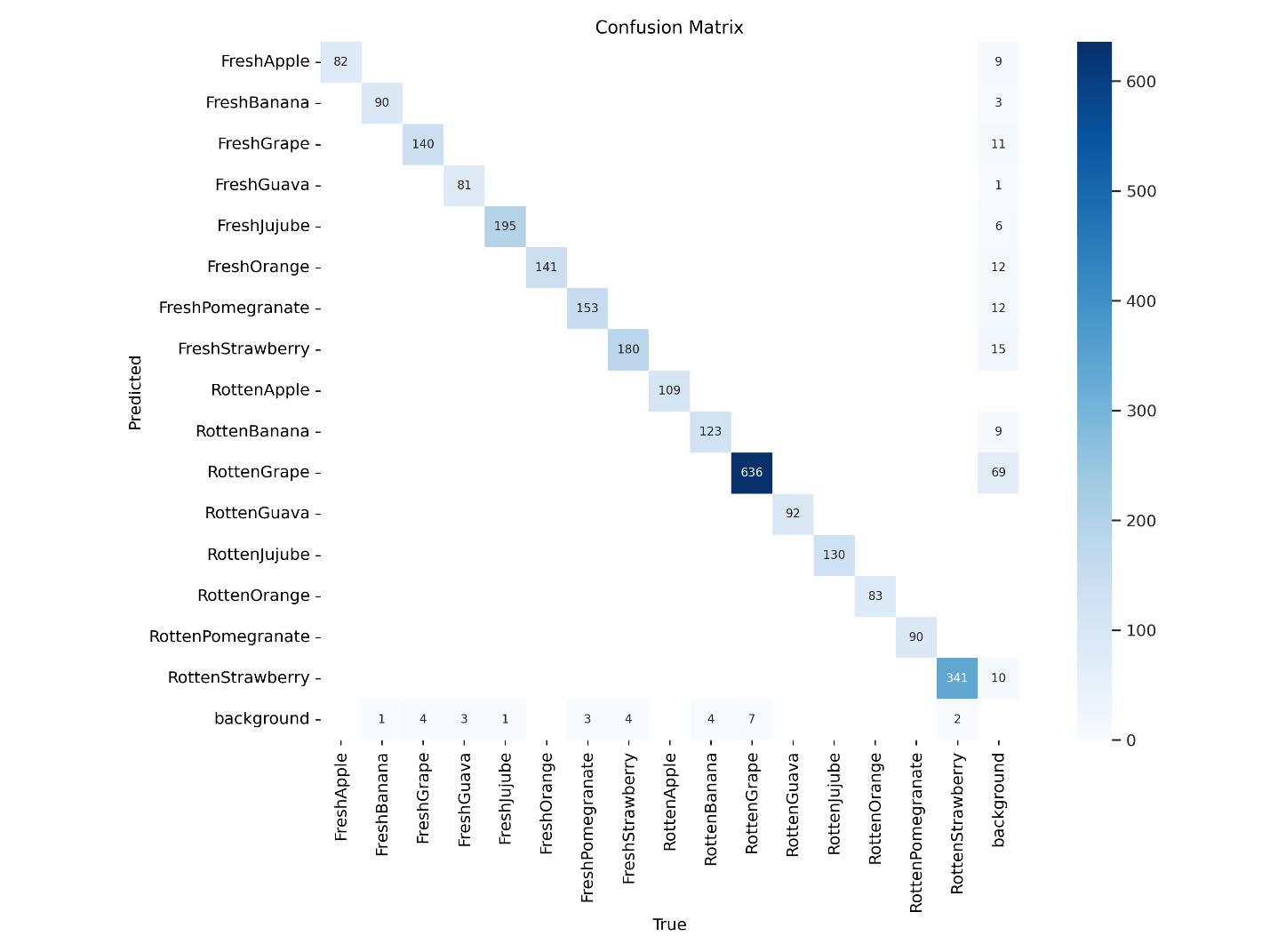


Figure 4.2: Model Validation Confusion Matrix

The confusion matrix plays an important role in evaluating a classification model’s performance, which provides a detailed assessment of its accuracy and potential misclassification (Beauxis-Aussalet & Hardman, 2014). Observing Figure 4.2, there are some notable observations that can be observed. One of the key observations is the model’s strong performance in classifying a group of categories accurately. The model showcases high accuracy for classes such as Rotten Grape, Rotten Strawberry and Fresh Jujube which have the value of correct predictions of 636, 341 and 195 respectively. The high values of these fruits along the diagonal indicate that the model can correctly identify these categories with minimal classification.

There are also other fruit categories which the model successfully classifies with a considerable level of accuracy. Categories like Fresh Strawberry and Fresh Orange have the value of correct prediction of 180 and 141 respectively. This shows that the model performs reasonably well in distinguishing both classes. The distribution of correct prediction showcases the model ability to learn the distinguishing features of these fruit categories effectively.

However, misclassifications are observed in two main areas which are background misclassification and similar fruit category misclassifications. The model occasionally misclassifies fruits as background elements, particularly for Rotten Grape (69 instances), Fresh Strawberry (15 instances), and Fresh Orange (12 instances). This suggests potential challenges in differentiating fruits from non-fruit elements within the dataset, possibly due to variations in lighting conditions, occlusions, or image artifacts (Sunil et al., 2022). On the other hand, some categories show overlapping features, leading to misclassification. For example, Fresh Apple (82 correct predictions) still has instances misclassified into other fruit categories. This suggests that the model struggles to distinguish fruits with similar colors, textures, or shapes, which is a common issue in fine-grained classification tasks.

Table 4.1: Performance Metrics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Class** | **Precision** | **Recall** | **F1-Score** | **mAP@0.5** | **mAP@0.5:0.95** |
| **All** | 0.973 | 0.977 | 0.974996 | 0.989 | 0.869 |
| **FreshApple** | 0.955 | 1 | 0.976982 | 0.994 | 0.963 |
| **FreshBanana** | 0.955 | 0.978 | 0.966363 | 0.966 | 0.892 |
| **FreshGrape** | 0.956 | 0.944 | 0.949962 | 0.98 | 0.814 |
| **FreshGuava** | 0.98 | 0.964 | 0.971934 | 0.994 | 0.942 |
| **FreshJujube** | 0.985 | 0.994 | 0.98948 | 0.994 | 0.868 |
| **FreshOrange** | 0.963 | 0.993 | 0.97777 | 0.995 | 0.96 |
| **FreshPomegranate** | 0.951 | 0.968 | 0.959425 | 0.99 | 0.931 |
| **FreshStrawberry** | 0.954 | 0.962 | 0.957983 | 0.99 | 0.807 |
| **RottenApple** | 0.997 | 1 | 0.998498 | 0.995 | 0.829 |
| **RottenBanana** | 0.975 | 0.902 | 0.93708 | 0.975 | 0.636 |
| **RottenGrape** | 0.945 | 0.942 | 0.943498 | 0.976 | 0.638 |
| **RottenGuava** | 0.998 | 1 | 0.998999 | 0.995 | 0.815 |
| **RottenJujube** | 0.997 | 1 | 0.998498 | 0.995 | 0.981 |
| **RottenOrange** | 0.995 | 0.995 | 0.995 | 0.995 | 0.995 |
| **RottenPomegranate** | 0.996 | 1 | 0.997996 | 0.995 | 0.994 |
| **RottenStrawberry** | 0.977 | 0.982 | 0.979494 | 0.991 | 0.834 |

Table 4.1 shows the results of the model used for fruit classification which distinguishes between fresh and rotten varieties. The model’s performance is evaluated across several key metrics which are Precision Recall, F1-Score, mean Average Precision (mAP) at an Intersection over Union (IoU) threshold of 0.5 (mAP@0.5) and mAP across IoU thresholds from 0.5 to 0.95 (mAP@0.5:0.95). These metrics are used to calculate different classes of fruits and the results highlighted the model’s ability to classify the categories correctly.

Precision is used to measure the number of predictive positive instances which are correct. Overall, the table shows that the model performs exceptionally well in this metric for most fruit categories. For example, the model achieved a precision of 0.955 for Fresh Apple which translates into 95.5% of the instances predicted as fresh apple were indeed correct. This level of consistent precision can be seen across other fruit categories such as Fresh Banana and Freh Guava with the value of 0.955 and 0.98 respectively. This finding also correlates with Chen et al. (2025), where they used YOLOv8-MDN-Tiny model to achieve a precision of 94.8% for passion fruit disease detections, highlighting its effectiveness in accurately identifying the fruit conditions. This highlights the model ability to accurately classify fresh fruit which indicates a high level of reliability in distinguishing these classes.

Precision values for rotten fruits are still relatively high overall however, categories like Rotten Banana and Rotten Grape have a precision of 0.902 and 0.945 respectively. While the results show high value, there is slightly higher rate of false positive for these rotten fruits compared to others. This result aligns with the research from Gu et al. (2024), on mango fruit and fruiting stem detection, where YOLOv8 model’s performance varied according to object visibility and environmental interference.

For recall, which reflects how many actual positive instances were correctly identified, the model also demonstrates strong performance across the fresh fruit categories. The most notable result is for Fresh Apple where the model achieved a perfect recall of 1, indicate that all actual fresh apple were identified correctly by the model. This trend of high recall is consistent for other fresh fruits, including Fresh Jujube with 0.994 and Fresh Pomegranate with 0.968. The overall results showcase the model ability to identify the fresh fruit categories when they are present. Similar results were obtained in Solimani et al. (2024), where using YOLOv8 model had improved the detection recall for small phenotypical traits in tomato plants.

For rotten fruits, the recall values are also relatively high with all the categories achieved values more than 0.9. There are 4 fruits that achieve perfect recall of 1 which are Rotten Apple, Rotten Guava, Rotten Jujube and Rotten Pomegranate which indicate that all these fruits were correctly identified by the model. This high value of recall performance is also shown in Chen et al. (2025), where the YOLOv8 model achieved improved performance in detecting disease in passion fruit with minimal false negative.

To further reinforce the model’s effectiveness, the F1-Score is used to validate the precision and recall results. According to Viveros Escamilla et al. (2024), F1-Score combined precision and recall into single metric which will be used to gauge the overall accuracy. For Fresh Apple, the F1-Score is 0.976982 which indicates a well-balanced performance in terms of both precision and recall. Similarly, for rotten fruits, the F1-Score is also relatively high, with all the fruit categories displaying similar results with the F1-Score above 0.94. This showcases that the model can maintain a good trade-off between false positives and false negatives.

The score in mAP for fresh fruits are also strong which highlights the model’s capabilities to not only classify but also to localize fresh fruits with higher accuracy. Fruits like Fresh Apple has an mAP@0.5 of 0.963 which showcases that the model is successful in detecting and placing bounding boxes around fresh apples with a high degree of precision. Likewise, Fresh Guava achieves achieve a high mAP@0.5 scores of 0.994 highlighting its superior performance in both detection and localization. Even for the mAP@0.5:0.95, the values for these fresh fruits are above 0.8 which further reflect the model’s ability to handle stricter IoU threshold which indicates high precision and minimal overlap errors. A similar trend is seen in Jrondi et al. (2024), where YOLOv8 model had outperformed DETR model in high-precision citrus fruit detection.

For rotten fruits, categories like Rotten Orange and Rotten Pomegranate achieve high mAP@0.5:0.95 with 0.995 and 0.994 respectively. This shows the model performs well in identifying and classifying these categories correctly. However, there are some categories like Rotten Banana and Rotten Grape that have low mAP@0.5:0.95 values with 0.636 and 0.638 respectively. This low value may suggest that the model opposed some challenges in distinguishing these categories possibly due to visual similarities with background or other fruit types. This finding is also similar to Gu et al. (2024), where occlusions and colour similarities between mango fruits and their environment had impacted the YOLOv8’s detection accuracy.

In conclusion, the YOLOv8 model demonstrates overall outstanding performance for detecting and classifying fruits, with high precision, recall and F1-Score. and mAP scores across all categories. The model excels in both identifying and localizing fruits which makes it suitable for detecting fresh and rotten fruits effectively.

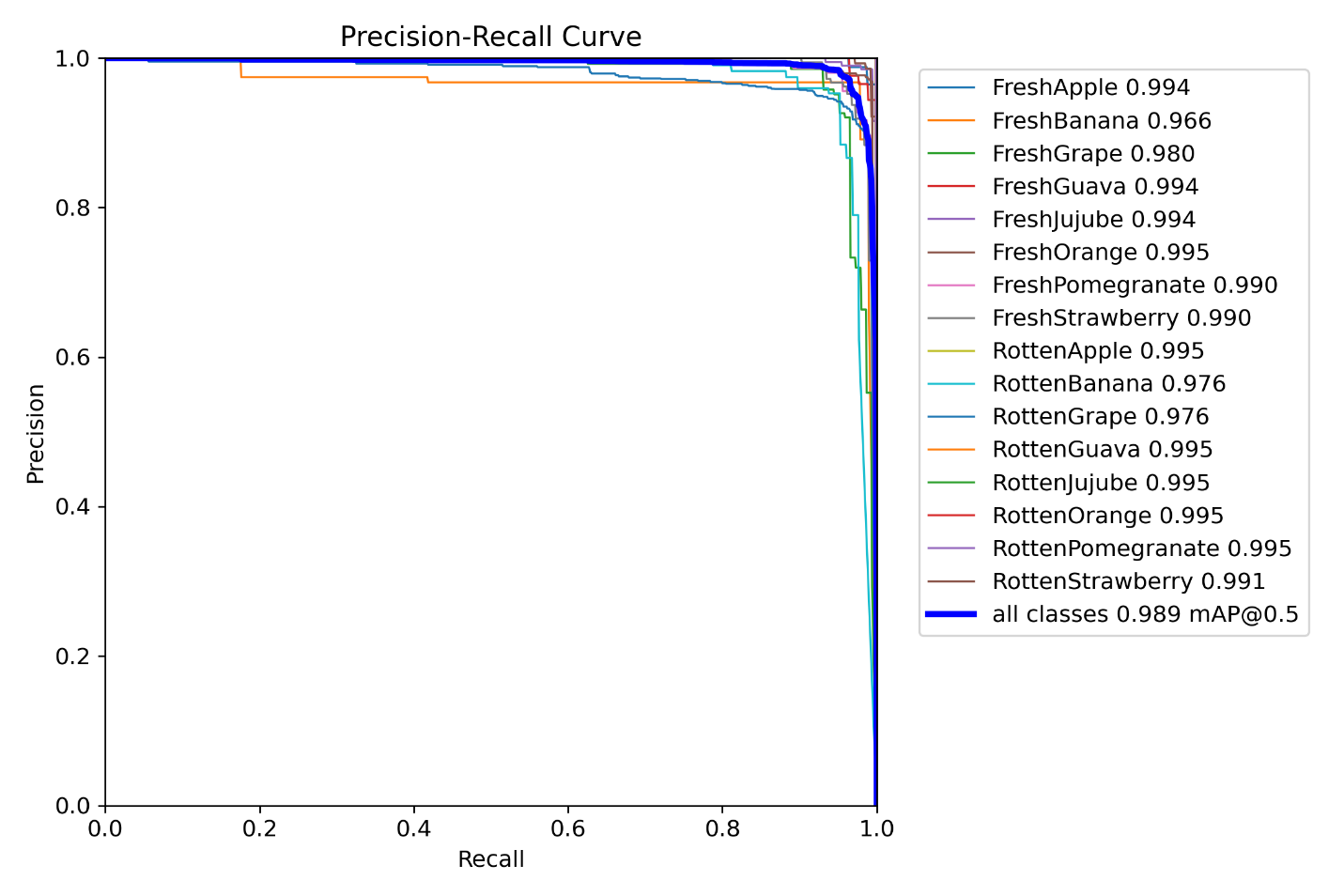


Figure 4.3: Precision-Recall Curve

The Precision-Recall (PR) curve can be used to evaluate the performance of classification models, particularly in object detection and imbalanced datasets Flach & Kull (2015). The curve shown in the graph represents the trade-off between precision which is the proportion of correct positive predictions out of all positive predictions and recall which is the proportion of actual positive instances correctly identified by the model. In this model, the PR curve highlights the performance of a fruit classification model which distinguishes between fresh and rotten fruits.

The most notable observation in this PR curve is that almost all fruit categories, including fresh and rotten varieties, exhibit high precision and recall values. This shows that the model is capable of effectively distinguishing between different fruit categories with minimal misclassification. Most of the fruit categories have a precision value of more than 0.99 which indicates that the model makes very few false positive errors. Likewise, the recall values are similarly high which shows the model ability to correctly identify nearly all instances of fresh and rotten fruits. Overall, the model demonstrates highly reliable performance in its classification task.

While the overall performance of the model is exceptionally well across all categories, there are minor variations that can be observed in precision and recall for some fruit categories. Fruits like Fresh Apple, Fresh Guava, Fresh Jujube, Fresh Orange, Rotten Apple, Rotten Guava and Rotten Jujube showcase a near-perfect classification performance with precision and recall values consistently above 0.99. This demonstrates that the model ability to distinguish these fruit categories with ease.

However, there are some categories like Rotten Banana and Rotten Grape which show slightly lower precision values of around 0.97. The drop in precision value may be explained due to the visual similarities between fresh and rotten versions which lead to occasional misclassification. The mAP@0.5 value of 0.989 confirms that the model achieves near-perfect classification across all fruit categories. The high value of mAP@0.5 suggests that the model ability to correctly identify the fruit categories and localizing object within an image.

The tightly clustered line of different fruit categories in the PR curve further reinforces the model ability to maintain consistent performance across all categories. It also can be observed that no single fruit type stands out as significantly underperforming, demonstrating that the model is well-balanced in handling different fruit classifications.

In conclusion, the PR curve provides a comprehensive overview of the model’s classification performance. It demonstrates the model’s effectiveness, consistency and reliability in classifying the fruit accurately with minimum errors. This is further supported by findings from Jrondi et al. (2024) and Gu et al. (2024) where YOLOv8 showed superior object classification in complex agricultural environments.

## **4.3 Inference on Test Data**

Following the training of the YOLO model on the fruit classification dataset, inference was conducted on the test set consisting of 1,237 images to assess the model’s capability in distinguishing between fresh and rotten fruits. The evaluation includes both qualitative and quantitative analyses.

To visually assess the model’s performance, three randomly selected test images with YOLO’s predictions were analyzed. The evaluation focused on prediction class accuracy, bounding box placement and confidence score. These qualitative observations help determine the model’s effectiveness in localizing and classifying fruit conditions under varying lighting and occlusion scenarios. In one of the test images, which is Figure 4.4, the model successfully detected two fresh apples with high confidence scores of 0.97 and 0.98. Similarly, in Figure 4.5, a single rotten orange was correctly identified with a confidence score of 0.96. Another test image, Figure 4.6, showed the detection of two rotten bananas with a confidence score of 0.81. These qualitative observations indicate that the model is capable of accurately localizing and classifying fresh and rotten fruits with high confidence, even in complex visual environments.

A close-up of apples

AI-generated content may be incorrect.

Figure 4.4: Sample Test Image I

A close up of a food

AI-generated content may be incorrect.

Figure 4.5: Sample Test Image II

A close-up of a banana

AI-generated content may be incorrect.

Figure 4.6: Sample Test Image III

The model’s accuracy was further evaluated using standard evaluation metrics, including precision, recall, mean Average Precision (mAP), and a confusion matrix. The results are summarized in Table 4.2.

Table 4.2: Performance Metrics on Test Dataset

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Mean Precision (mP)** | **Mean Recall (mR)** | **F1-Score** | **mAP@50** | **mAP@50-95** |
| 0.9711 | 0.9793 | 0.9752 | 0.9863 | 0.8737 |

Comparing the results in Table 4.2 with Table 4.1, the model’s performance on the test dataset closely aligns with its training and validation results, demonstrating strong generalization capabilities. These slight variations in mean precision (0.973 vs. 0.971), mean recall (0.977 vs. 0.979) and consistent value in F1-score indicate that the model maintains a consistent balance between precision and recall across different datasets. The high mAP@50 score (98.6% for test vs. 98.9% for training and validation) confirms that the model accurately detects fresh and rotten fruits. Furthermore, the mAP@50-95 score (87.4% vs. 86.9%) suggests that the model performs well across varying IoU thresholds, ensuring robustness in real-world applications. These findings suggest that the model exhibits a low false positive and false negative rate, further confirming its effectiveness in detecting fresh and rotten fruits with high accuracy.

To gain deeper insight into the model’s classification performance, a confusion matrix was generated in Figure 4.7. The matrix provides an overview of correct classifications and misclassifications across different fruit categories. Each row represents the actual class, while each column represents the predicted class, with diagonal values indicating correct classifications and off-diagonal values representing misclassifications. The color intensity in the matrix reflects the frequency of occurrences, with darker shades corresponding to higher counts.

The analysis of the confusion matrix reveals that the model performs well across most fruit categories, as indicated by the high number of correctly classified instances along the diagonal. For example, label 10, which represents rotten banana, was correctly classified 145 times, demonstrating the model’s strong ability to recognize this category. However, some misclassifications were observed, particularly among visually similar fruit classes. Label 10 was occasionally misclassified as 0, 1, 5, and 11, suggesting difficulties in differentiating between these categories due to overlapping visual features. Similarly, label 15 was frequently misclassified as 0, 6, 7, and 10, likely due to similarities in color, texture, or shape. Additionally, certain categories exhibited higher off-diagonal values, with label 10 often being misclassified as 0, 6, 7, and 11 multiple times.

These misclassification trends indicate that visual similarities between fresh and rotten variations of certain fruits pose challenges to accurate classification. The presence of overlapping color, texture, and shape characteristics may have contributed to these errors, highlighting the need for further refinement of the model. Possible improvements could include adjusting hyperparameters to enhance feature extraction or incorporating additional preprocessing techniques to improve class separability. Despite these challenges, the overall performance of the model remains strong, demonstrating its effectiveness in distinguishing between fresh and rotten fruits with a high degree of accuracy.

A table of numbers and a chart of a graph

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Figure 4.7: Confusion Matrix on Test Images

## **4.4 SHAP Analysis**

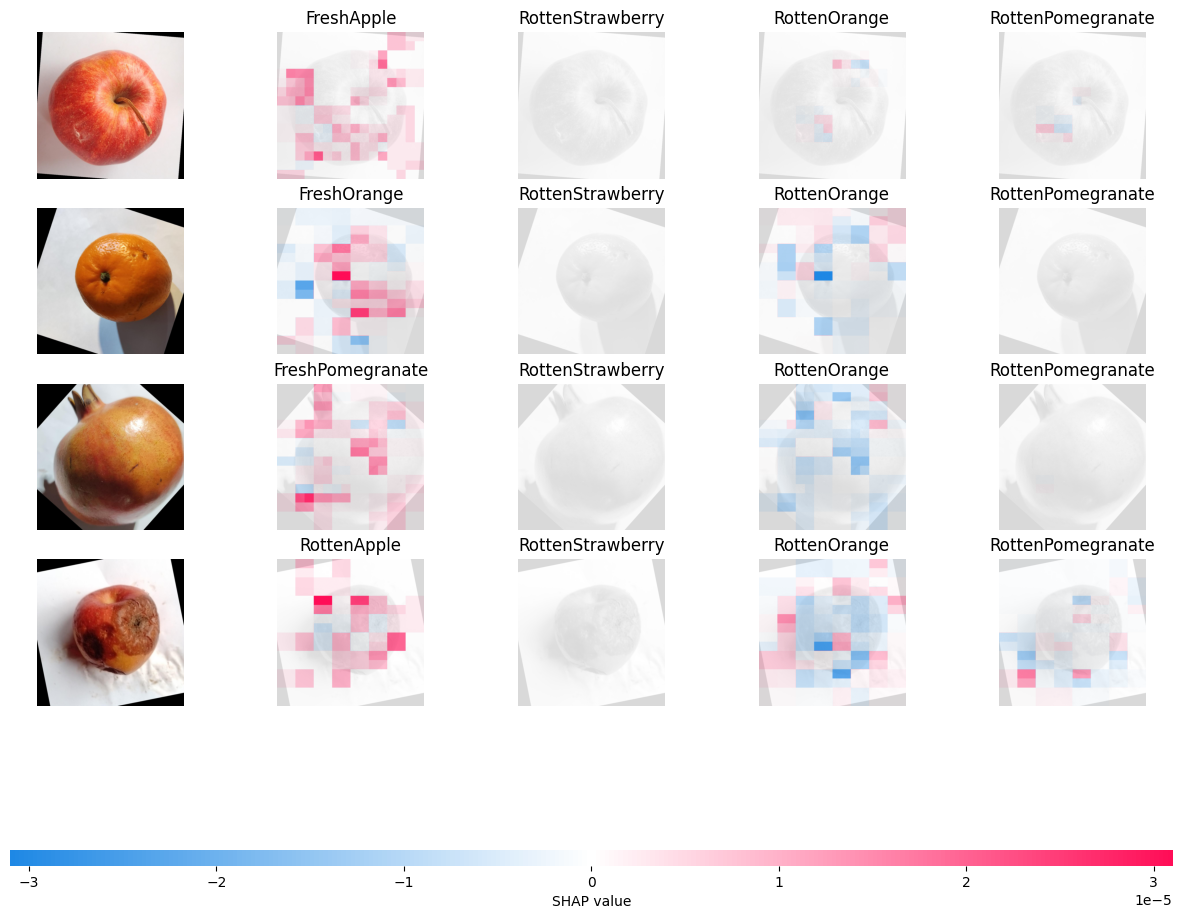


Figure 4.8: SHAP Analysis

After the best YOLOv8 model has gone through the training process with this dataset, the employment of XAI may begin through SHAP analysis. By performing SHAP analysis, the interpretability and transparency of the YOLOv8 model may be investigated, providing in-depth insights on how the model makes its decisions when classifying fruits. As seen in Figure 4.8 above, the first column is the fruit the model is trying to classify. The next four columns overlay a heatmap over the original image, indicating what areas of the image determine its decision making, with the second column being the label the model classified the image as. The heatmap will indicate areas of the image that determine the model’s decision; red areas contribute positively towards that class, while blue areas contribute negatively (Panati et al., 2022). The remaining three columns show how and why the model did not make a misclassification.

Looking into the first row, the original image is a fresh apple and the YOLOv8 model correctly classified it as “FreshApple”. As seen in the “FreshApple” heatmap, there are a substantial number of red and pink areas covering areas that indicate it is an apple along with areas that indicate it is fresh. In this case, it may be observed that the majority of the red areas are covering areas of the apple that are red in color and do not have any marks such as scratches or bruising. These characteristics are common in fresh apples, which is why these areas correlate positively to the model classifying this fruit as a fresh apple. On the other hand, there are a few areas of the heatmap that are light blue, indicating that these areas correlate negatively to the model classifying this fruit as a fresh apple. Based on the heatmap, it can be seen that the blue areas cover a small scratch seen on the apple’s skin, which could indicate that the apple is not fresh. Nonetheless, these blue areas only show a weak negative correlation and there is a lack of these areas for them to significantly affect the model’s decision. Looking into the other labels “RottenStrawberry”, “RottenOrange”, and “RottenPomegranate”, the heatmaps are all either relatively neutral, there are minimal red areas or there are a large number of blue areas. As a result of the “FreshApple” label possessing a substantial number of red areas and minimal blue areas, the model classified the image as “FreshApple”.

Focusing on the second row, the original image is a fresh orange and the YOLOv8 model correctly classified it as “FreshOrange”. As observed in the “FreshOrange” heatmap, there are a substantial number of strong red and pink areas covering the areas of the fruit that indicate it is an orange along with areas of the orange that indicate it is fresh. For example, a fresh orange would typically be orange in color, have a smooth texture, and have minimal signs of defects. On the contrary, there are a minimal number of blue areas on the heatmap. However, these areas were not significant enough to change the model’s decision. Observing the other labels, “RottenStrawberry” and “RottenPomegranate” both display a neutral heatmap, while “RottenOrange” displays a heatmap with a substantial number of strong blue areas covering the orange. Hence, the model classified the image as “FreshOrange”.

Moving onto the third row, the original image is a fresh pomegranate and the YOLOv8 model correctly classified it as “FreshPomegranate”. By observing the “FreshPomegranate” heatmap, it may be noticed that there are substantial number of strong red and pink areas covering the areas of the fruit that indicate it is a pomegranate along with areas that may be indicative of its freshness. The areas may be red in color, have smooth skin, and have minimal signs of defects. Furthermore, there are also a few light blue areas in the heatmap, however they are not significant enough to change the decision of the model. Observing the remaining heatmaps, a similar pattern to the previous rows is demonstrated, with the “RottenStrawberry” and “RottenPomegranate” heatmaps displaying an overall neutral correlation, while the “RottenOrange” heatmap displaying an overall negative correlation. As a result, the model classified the image as “FreshPomegranate”.

Finally, focusing on the fourth row, the original image is a rotten apple and the YOLOv8 model correctly classified is as “RottenApple”. Looking at the heatmap for “RottenApple” there are a substantial number of strong red and pink areas covering areas of the fruit that indicate it is a rotten apple. These areas may portray a rotten apple based on its red hues and the presence of defects such as bruising or wilting of the skin. This is evident as there are a number of red areas covering the bruised skin toward the right side of the apple. Hence, this area of the fruit has a strong positive influence on the model’s decision. Observing the remaining heat maps, the “RottenStrawberry” heat map portrays a relatively neutral correlation. Meanwhile, the “RottenPomegranate” heat map has a few light blue and pink areas, and the “RottenOrange” heat map has a substantial number of blue areas along with some pink areas. Overall, these heatmaps demonstrate a negative correlation. As a result, the model classified the image as “RottenApple”.

With the use of SHAP analysis, a better understanding of how the YOLOv8 model effectively distinguishes between fresh and rotten fruits is gained. By observing and analyzing the heatmaps produced through SHAP, certain characteristics of each fruit can be identified, which can be useful in understanding how the model makes its decisions.

## **4.5 PowerBI Implementation**

The Power BI dashboard demonstrated in Figure 4.9 was developed to facilitate fruit classification using an AI-based image recognition model. By integrating the YOLOv8 prediction model with SHAP analysis, the dashboard allows for both classification and interpretability, ensuring transparency in the decision-making process. The primary objective of this implementation is to assist key stakeholders, including farmers, suppliers, and restaurant owners, in assessing fruit quality efficiently. Through this system, businesses can minimize waste, optimize inventory management, and ensure that only high-quality fruits are used in food preparation.

A screenshot of a computer

AI-generated content may be incorrect.

Figure 4.9: PowerBI Dashboard

The dashboard provides an interactive interface where users can upload fruit images and receive classification results indicating whether the fruit is fresh or rotten. The classification result is displayed prominently, along with a confidence level gauge that shows how certain the model is in its prediction. A higher confidence score signifies greater reliability in classification, helping users trust the AI-generated insights. Additionally, a visual representation of the YOLOv8 prediction is included, where the original fruit image is displayed with a bounding box and a probability score, highlighting how the model identifies and classifies the fruit.

To further enhance interpretability, the SHAP analysis feature is integrated into the dashboard. This feature visualizes the most influential areas of the image that contributed to the classification decision. By understanding which aspects of the fruit’s appearance affected the model’s prediction, users can gain deeper insights into the reasoning behind each classification. This level of transparency is crucial in building trust among stakeholders who may be skeptical about relying on AI-driven classification for critical decision-making.

The AI model used in the dashboard demonstrated high accuracy and reliability, with confidence levels reaching 0.95 for certain fruit types. The ability to provide fruit quality monitoring makes this implementation particularly beneficial for businesses handling perishable goods. The dashboard supports more efficient inventory management, enhances quality control, and facilitates quick decision-making for suppliers and restaurant owners.

The Power BI dashboard has the potential to significantly reduce food waste by allowing businesses to quickly identify and separate rotten fruits before they enter the supply chain. This capability ensures that only fresh fruits are used in food preparation, which improves customer satisfaction and minimizes unnecessary losses. Furthermore, by incorporating an interactive and interpretable AI model, the dashboard empowers businesses to make data-driven decisions, enhancing their overall operational efficiency.

Future enhancements to this implementation may include expanding the dataset to include a wider variety of fruits, refining the model’s interpretability to provide more detailed insights, and integrating real-time data streams from supply chain operations for more effective monitoring. As technology continues to evolve, the Power BI dashboard can be further optimized to offer a comprehensive solution for fruit classification, ultimately contributing to better food quality management and sustainability in the industry.

The successful implementation of this Power BI dashboard demonstrates the effectiveness of AI-driven fruit classification in reducing food waste and optimizing quality control processes. By integrating YOLOv8 predictions with SHAP analysis, the system not only enhances classification accuracy but also provides valuable insights into the AI model’s decision-making process. Through data visualization and interpretability, this solution enables stakeholders to make informed decisions, improving efficiency, reducing waste, and maintaining high-quality standards across their operations.

# **CONCLUSION**

## **5.0 Introduction**

This section summarizes the research findings by highlighting the achievement of objectives, contributions from both theoretical and practical perspective as well as potential areas for future research to expand AI applications in food waste reduction.

## **5.1 Achievement of Objectives**

This research aimed to develop an explainable AI-based fruit classification model to ensure the decisions made by the model are transparent. The study successfully achieved its three research objectives:

**RO1: To train a YOLO-based deep learning model for classifying fresh and rotten fruits**

In this study, the YOLOv8 model was trained and evaluated using a diverse dataset that comprised both fresh and rotten fruits to make sure the model could generalize well across different fruit conditions. The classification performance was gauged using evaluation metrics such as precision, recall, F1-score as well as mean Average Precision and it achieved high accuracy in detecting fruits. The combination of a well-annotated dataset with iterative training and validation ensured reliable and consistent classification results, confirming the effectiveness of the model in practical applications. The model’s strong performance in real-world scenarios shows that it can be used in automated quality control systems in the food industry. This helps to reduce food waste and improve inventory management on a larger scale.

**RO2: To enhance model interpretability using SHapley Additive exPlanations (SHAP)** Although the YOLOv8 deep learning model had high classification performance, its “black box” nature often limits user trust and hesitates adoption among stakeholders. To address this issue, Shapley Additive Explanations (SHAP) which is an explainable AI (XAI) was implemented in this study to analyze the interpretability of the YOLOv8 model. With SHAP, key features that influenced the classification of fresh and rotten fruits were identified, providing important insights into the model’s decision-making process. By analyzing SHAP values, the study indicated the most significant visual attributes such as color, texture and surface blemishes that contributed to the classification outcome. These insights enhance transparency and assist stakeholders like farmers, food inspectors, and retailers in the food industry to make better decisions that ultimately reduce food waste.

**RO3: To develop an interactive Power BI dashboard that provides visualization of classification outputs**

In this study, an interactive Power BI dashboard was developed to translate the research findings into a practical and user-friendly tool. The dashboard acts as a visualization platform where users can analyze the model’s classification results and check the fruit’s freshness. Key features of the dashboard include:

* **Fruit Classification Result:** The dashboard shows the classification outcome, whether the fruit is identified as fresh or rotten.
* **Confidence Score:** A gauge visualization indicating the confidence score that reveals the model’s level of certainty in its classification outcome.
* **Classified Image with Bounding Box:** The fruit is detected with a bounding box, showing the YOLOv8 model’s ability to identify and classify it correctly.
* **SHAP Interpretability Output:** The display of SHAP value heatmap highlights key features that influenced the classification outcome. A color gradient (blue to red) represents the SHAP score, indicating the regions of the image that contributed most to the decision.

This dashboard ensures that stakeholders can make informed decisions to optimize purchasing decisions, reduce food waste and improve quality control processes. The ability of the dashboard to provide instant classification makes this AI model a scalable solution for a wider adoption in the food industry. It improves efficiency, helps people understand the results of the classification which leads to transparency and is accessible to everyone, including those without technical knowledge.

## **5.2 Contributions**

### **5.2.1 Theoretical**

**Advancement in Academic Knowledge**

This research significantly advances fields such as machine learning, artificial intelligence, image recognition and business analytics by integrating explainable AI techniques. Specifically, it introduces the use of SHapley Additive exPlanations (SHAP) to enhance model interpretability, enabling stakeholders to understand how AI models make decisions. By bridging the gap between high-accuracy models and the necessity for interpretability, the study contributes a crucial theoretical framework for future research. Additionally, the integration of Power BI to display AI model outputs assists stakeholders in monitoring fruit freshness, further advancing the academic understanding of practical AI implementations.

**Filling Gaps in Existing Literature**

The research addresses gaps in the literature by showcasing the application of SHAP for explaining model predictions, which has not been extensively explored in the context of fruit classification. By demonstrating the importance of transparency and interpretability, this study encourages further exploration of SHAP in other contexts where understanding AI decisions is crucial. In addition, the integration of Power BI bridges the gap between AI predictions and decision-making by providing visualization of model outputs, encouraging adoption among stakeholders.

### **5.2.2 Practical**

**Real-world Applications**

By implementing YOLOv8, the system can achieve accurate classification and sorting of fruits, reducing the manual effort and time required in the quality control process. This contributes to operational efficiency and minimizes food waste, directly addressing sustainability goals. The choice of YOLOv8 ensures that the solution remains fast and scalable, making it suitable for various industrial applications, from agriculture to retail.

The interpretability and transparency provided by SHAP empower decision-makers to understand the rationale behind the model’s prediction by highlighting the most important features. This increased understanding builds trust in AI tools, making them more reliable for enhancing classification systems for fruit quality. The model’s explanations are accessible to non-experts, which benefits various stakeholders, including restaurants, packaging companies, and everyday consumers purchasing fruits.

**Impact on Decision-making**

Using SHAP values to explain model predictions, combined with data visualization through a Power BI dashboard, supports more informed decision-making. Stakeholders can readily identify which features influence the model’s conclusions, enabling them to make better strategic choices in inventory management, waste reduction and quality control. This practical application of AI in decision-making aligns with the goal of improving operational efficiency across the food supply chain.

**Economic and Environmental Benefits**

By identifying the key features that lead to the classification of fresh and rotten fruits, this research paves the way for future studies focused on enhancing the model’s accuracy. More precise classification systems can significantly reduce operational costs for businesses by minimizing waste and improving efficiency. Ultimately, this contributes to substantial reductions in food waste, offering significant environmental and economic benefits. By aligning with the United Nations’ Sustainable Development Goals (SDGs), this research underscores the potential for AI to drive positive societal changes.

**Increase the Utilization of Spoiled Fruits**

One of the main ways AI-based fruit classification tools contribute to waste reduction is by increasing the utilization of spoiled fruits. Even when fruits are no longer fit to be sold or marketed in its fresh state, it can still serve other practical uses. There are many food products available in the market which are made from fruits that are no longer at their freshest or are slightly overripe. For example, food products such as jams, juices, fermented beverages like fruit wine and vinegar are produced in a way that maximizes the use of overripe fruits while at the same time, ensuring quality and taste. Similarly, fruit pomaces which are by-products from juice, jam and fermented beverage production are then repurposed as animal feed for poultry and livestock through the integration of enzymatic digestion and fermentation techniques (Kithama et al., 2021). When fruits that are unfit for direct consumption but remain viable for other uses are efficiently detected using AI tools, businesses can repurpose them for secondary processing instead of discarding them entirely, which in turn helps reduce food waste.

**Optimize Inventory Management**

AI classification tools optimize inventory management which plays a significant role in preventing waste before fruits spoil. Traditional inventory systems often use fixed expiration dates or manual inspections which can be inefficient and cause fresh produce to be overlooked and left to spoil. AI tools can integrate First-In-First-Out (FIFO) strategies which is a widely used method that ensures products stored for the longest time are utilized or marketed first based on their date of entry into storage (Mendes et al., 2020). In the context of fruit classification, FIFO strategies make sure that fruits that are nearing spoilage or over ripeness are prioritized for sale or repurposing. Furthermore, dynamic pricing models can be implemented, whereby retailers adjust prices in response to freshness and inventory levels which maximize revenue and minimize waste concurrently. A study by Fan et al. (2019) highlighted that as freshness of a fresh produce declines, demand decreases which calls for price adjustments to stimulate sales and prevent spoilage.

**Improve Supply Chain and Storage Practices**

The AI-driven fruit classification model provides valuable insights that can assist businesses in improving supply chain efficiency and storage practices which in turn ultimately reduce fruit spoilage. By analyzing the results of fruit classification, businesses can take advantage of the information to identify key factors that contribute to spoilage and take proactive actions to enhance storage and transportation conditions. For example, if the AI model frequently detects that fruits spoil due to surface damage, businesses can take immediate action by improving their packaging with sturdier containers and handling the fruits more carefully during transport to avoid bruising. In addition, insights from the AI model can help adjust storage conditions such as temperature and humidity to suit different types of fruits which will aid in keeping the fruits fresh for a longer period of time. By incorporating these insights into supply chain management and storage practices, businesses can enhance the quality of their products, reduce waste and improve overall operational efficiency that contributes to a more cost-effective food distribution system.

**Minimize Human Judgement Errors**

Manual inspection of fruit freshness is often inefficient because it is time consuming for humans to check each fruit individually. It is also highly prone to human judgement errors which lead to inconsistencies in quality assessment and the unnecessary discard of fruits. Factors that contribute to misclassification by humans include individual bias, fatigue and lack of standardization due to absence of clear preset rules from higher authorities, resulting in non-uniform decision-making. With the implementation of an AI-driven model, fruit classification becomes more objective, standardized and accurate, which significantly lowers the chances of misclassification. This automation offers several benefits. Firstly, it enhances efficiency in sorting and quality control. Secondly, it minimizes unnecessary waste by correctly identifying fruits that are still suitable for consumption. By reducing reliance on human inspection, this method streamlines operations and helps reduce waste.

## **5.3 Future Works**

This research has developed an explainable AI model to classify fruits. Nevertheless, there is still room for improvement that future studies can focus on. The key areas for enhancement are as follows: -

1. **Enhancing Model Performance with Larger and More Varied Fruit Datasets**

From this study, it can be noted that it only utilizes eight types of fruits (each categorized as fresh and rotten) which are apples, bananas, oranges, grapes, guavas, jujubes, pomegranates and strawberries. However, many other types of fruit are available in the market and should be included in future studies to improve model’s robustness. Additionally, future research should incorporate data augmentation techniques and domain adaptation to enhance model performance. In this context, data augmentation techniques, such as rotation, flipping, and scaling can help increase the diversity of the training dataset. Similarly, domain adaptation refers to the ability of an AI-driven model to perform well across different conditions such as variations in lighting, backgrounds and fruit varieties. Consequently, the model can generalize more effectively to real-world variations in fruit appearance.

1. **Diversifying to Wider Range of Perishable Food Products**

The model that is designed in this study focuses solely on fruit classification. However, the methodology could be extended to include other perishable food products such as vegetables, dairy products, meats, or baked goods. This integration of an AI-powered classification tool will make it versatile, flexible and applicable across a broader range of industries within the food sector. As a result, food waste can be minimized over a wide range of perishable food products, not just fruits.

1. **Real-Time Deployment with Edge Computing**

Edge computing is a type of computing approach that processes and stores data closer to its source such as IoT devices or local servers, thereby reducing dependance on centralized cloud systems which in turn deliver faster response times. In this context of fruit classification, deploying the AI model on edge devices like mobile applications, IoT devices and embedded cameras enables real-time processing without relying on cloud-based computation. This method can be a game change for farmers, food inspectors and business owners in the food industry as it can deliver instant classification results, allowing them to make better and more informed decisions.

# **REFERENCES**

Abayomi-Alli, O. O., Damaševičius, R., Misra, S., & Abayomi-Alli, A. (2024). FruitQ: a new dataset of multiple fruit images for freshness evaluation. Multimedia Tools and Applications, 83(4). <https://doi.org/10.1007/s11042-023-16058-6>

Abdullah, A., Manoj, A., & Selvakumar, S. (2021). Assessment and Evaluation of cancer CT images using deep learning Techniques. 2021 2nd International Conference on Secure Cyber Computing and Communications (ICSCCC), 399-403. https://doi.org/10.1109/ICSCCC51823.2021.9478176.

Adadi, A., & Berrada, M. (2018). Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI). IEEE Access, 6. <https://doi.org/10.1109/ACCESS.2018.2870052>

Ahmed, S., Mohamed, S., Aljanabi, M., Algburi, S., Majeed, D., Kurdi, N., Al-Sarem, M., & Tawfeq, J. (2024). A Novel Approach to Malware Detection using Machine Learning and Image Processing. Proceedings of the Cognitive Models and Artificial Intelligence Conference. https://doi.org/10.1145/3660853.3660931.

Aishwarya, N., & Kumar, V. (2023). Banana Ripeness Classification with Deep CNN on NVIDIA Jetson Xavier AGX. Proceedings of the 7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC 2023), 663–668. https://doi.org/10.1109/i-smac58438.2023.10290326

Aldughayfiq, B., Ashfaq, F., Jhanjhi, N. Z., & Humayun, M. (2023). Explainable AI for Retinoblastoma Diagnosis: Interpreting Deep Learning Models with LIME and SHAP. Diagnostics, 13(11). https://doi.org/10.3390/diagnostics13111932

Alharahsheh, H. H., & Pius, A. (2020). A Review of key paradigms: positivism VS interpretivism. Global Academic Journal of Humanities and Social Sciences, 2(3), 39–43. <https://doi.org/10.36348/gajhss.2020.v02i03.001>

Ali, M. L., & Zhang, Z. (2024). The YOLO framework: A comprehensive review of evolution, applications, and benchmarks in object detection. Computers, 13(12), 336.

Altaheri, H., Alsulaiman, M., & Muhammad, G. (2019). Date Fruit Classification for Robotic Harvesting in a Natural Environment Using Deep Learning. IEEE Access, 7. <https://doi.org/10.1109/ACCESS.2019.2936536>

Ameerdin, M. I., Jamaluddin, M. H., Shukor, A. Z., Kamaruzaman, L. a. H., & Mohamad, S. (2024). Towards Efficient Solar Panel Inspection: A YOLO-based Method for Hotspot Detection. In 2024 IEEE 14th Symposium on Computer Applications & Industrial Electronics (ISCAIE), 367–372. <https://doi.org/10.1109/iscaie61308.2024.10576312>

Amin, U., Shahzad, M. I., Shahzad, A., Shahzad, M., Khan, U., & Mahmood, Z. (2023). Automatic Fruits Freshness Classification Using CNN and Transfer Learning. Applied Sciences (Switzerland), 13(14). <https://doi.org/10.3390/app13148087>

Antunes, S. N., Okano, M. T., Nääs, I. de A., Lopes, W. A. C., Aguiar, F. P. L., Vendrametto, O., Fernandes, J. C. L., & Fernandes, M. E. (2024). Model Development for Identifying Aromatic Herbs Using Object Detection Algorithm. AgriEngineering, 6(3), 1924–1936. <https://doi.org/10.3390/agriengineering6030112>

Ariharan, M., Juliet, S., & Anitha, J. (2024). YOLO NAS-Powered Intelligent Vehicle Tracking and Monitoring System for enhanced parking management in urban environments. 2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS), 2415–2420. https://doi.org/10.1109/icaccs60874.2024.10716939

Babar, Z. (2024, November 25). You-Only-Look-Once: Object Detection with YOLO - Zia Babar - Medium. Medium. https://medium.com/%40zbabar/you-only-look-once-object-detection-with-yolo-de9fd5455306

Balasubramaniam, A., & Pasricha, S. (2022). Object Detection in Autonomous Vehicles: Status and Open Challenges. ArXiv, abs/2201.07706.

Beauxis-Aussalet, E., & Hardman, L. (2014, November). Simplifying the visualization of confusion matrix. In 26th Benelux conference on artificial intelligence (BNAIC).

Becker, L. T., & Gould, E. M. (2019). Microsoft Power BI: Extending Excel to Manipulate, Analyze, and Visualize Diverse Data. Serials Review, 45(3), 184–188. <https://doi.org/10.1080/00987913.2019.1644891>

Bhagya, A., & Perumal, S. (2024). Diverse Image Processing Techniques for Machine Learning Methods. 2024 Third International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS), 1-6. https://doi.org/10.1109/INCOS59338.2024.10527733.

Bhargava, D., & Gupta, L. K. (2022). Explainable AI in Neural Networks Using Shapley Values. In Intelligent Systems Reference Library (Vol. 222). <https://doi.org/10.1007/978-981-19-1476-8_5>

Bhattacharya, M., & Datta, D. (2023). Diabetes Prediction using Logistic Regression and Rule Extraction from Decision Tree and Random Forest Classifiers. 2023 4th International Conference for Emerging Technology (INCET), 1-7. https://doi.org/10.1109/INCET57972.2023.10170270.

Bilous, N., Malko, V., Frohme, M., & Nechyporenko, A. (2024). Comparison of CNN-Based Architectures for Detection of Different Object Classes. AI, 5(4), 2300-2320.

Bochkovskiy, A., Wang, C., & Liao, H. M. (2021). Scaled-YOLOV4: Scaling Cross Stage Partial network. 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). https://doi.org/10.1109/cvpr46437.2021.01283

Borowiec, M. L., Dikow, R. B., Frandsen, P. B., McKeeken, A., Valentini, G., & White, A. E. (2022). Deep learning as a tool for ecology and evolution. In Methods in Ecology and Evolution (Vol. 13, Issue 8, pp. 1640–1660). British Ecological Society. https://doi.org/10.1111/2041-210X.13901

Casas, E., Ramos, L., Bendek, E., & Rivas-Echeverria, F. (2024). YOLOv5 vs. YOLOv8: Performance Benchmarking in Wildfire and Smoke Detection Scenarios. Journal of Image and Graphics, 12(2), 127–136. <https://doi.org/10.18178/joig.12.2.127-136>

Chakraborty, S., Shamrat, F. M. J. M., Billah, M. M., Jubair, M. Al, Alauddin, M., & Ranjan, R. (2021). Implementation of Deep Learning Methods to Identify Rotten Fruits. Proceedings of the 5th International Conference on Trends in Electronics and Informatics, ICOEI 2021. <https://doi.org/10.1109/ICOEI51242.2021.9453004>

Chen, D., Lin, F., Lu, C., Zhuang, J. W., Su, H., Zhang, D., & He, J. (2025). YOLOv8-MDN-Tiny: A lightweight model for multi-scale disease detection of postharvest golden passion fruit. Postharvest Biology and Technology, 219. <https://doi.org/10.1016/j.postharvbio.2024.113281>

Chen, K., Lu, H., Wang, R., & Zheng, W. S. (2022, July). Improving Class Balancing at Both Feature Extractor and Classifier Head. In 2022 IEEE International Conference on Multimedia and Expo (ICME) (pp. 1-6). IEEE.

Chen, M. C., Cheng, Y. T., & Liu, C. Y. (2022). Implementation of a Fruit Quality Classification Application Using an Artificial Intelligence Algorithm. Sensors and Materials, 34(1). <https://doi.org/10.18494/SAM3553>

Chen, R., Dewi, C., Huang, S., & Caraka, R. (2020). Selecting critical features for data classification based on machine learning methods. Journal of Big Data, 7, 1-26. <https://doi.org/10.1186/s40537-020-00327-4>.

Chen, Y. (2024). The Investigation of Performance Comparison for VGG, YOLO, and DINO in Image Classification. Highlights in Science, Engineering and Technology. https://doi.org/10.54097/9bgem219.

City, Y., Angeles, L., & Francisco, S. (2012). Acknowledgments About NrDC. <http://uliwestphal.com/mutates.html>.

Darmawan, T. (2020). Credit Classification Using CRISP-DM Method On Bank ABC Customers. International Journal of Emerging Trends in Engineering Research, 8(6). <https://doi.org/10.30534/ijeter/2020/28862020>

Dastagir, R. B., Jami, J. T., Chanda, S., Hafiz, F., Rahman, M., Dey, K., ... & Chowdhury, M. M. (2024). AI-Driven Smartphone Solution for Digitizing Rapid Diagnostic Test Kits and Enhancing Accessibility for the Visually Impaired. arXiv preprint arXiv:2411.18007.

De Beuckelaer, A., & Wagner, S. M. (2007). Qualitative and quantitative international research: The issue of overlooking alternative explanations. Journal of Purchasing and Supply Management, 13(3), 213–215. <https://doi.org/10.1016/j.pursup.2007.09.011>

Desai, Z., Anklesaria, K., & Balasubramaniam, H. (2021). BUSINESS INTELLIGENCE VISUALIZATION USING DEEP LEARNING BASED SENTIMENT ANALYSIS ON AMAZON REVIEW DATA. 2021 12th International Conference on Computing Communication and Networking Technologies, ICCCNT 2021. <https://doi.org/10.1109/ICCCNT51525.2021.9579786>

Devineni, S. (2024). AI-Enhanced Data Visualization: Transforming Complex Data into Actionable Insights. Journal of Technology and Systems. <https://doi.org/10.47941/jts.1911>.

Dewangan, D. K., & Gupta, G. P. (2024). Explainable AI and YOLOV8-based framework for indoor fire and smoke detection. In 2024 IEEE International Conference on Information Technology, Electronics and Intelligent Communication Systems (ICITEICS), 1–6. https://doi.org/10.1109/iciteics61368.2024.10624874

Dewi, C., Kamlasi, O., Chhabra, G., Dai, G., Kaushik, K., & Khan, I. (2023). Automated Fruit Classification Based on Deep Learning Utilizing Yolov8. 2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), 10, 801-807. https://doi.org/10.1109/UPCON59197.2023.10434542.

Dewi, C., Thiruvady, D., & Zaidi, N. (2024). Fruit Classification System with Deep Learning and Neural Architecture Search. <http://arxiv.org/abs/2406.01869>

Dixit, I. A., & Bhoite, S. (2024). Analysis of performance of YOLOV8 Algorithm for Pedestrian Detection. 2022 7th International Conference on Communication and Electronics Systems (ICCES), 1918–1924. https://doi.org/10.1109/icces63552.2024.10859981

Dong, L., Xing, L., Liu, T., Du, H., Mao, F., Han, N., Li, X., Zhou, G., Zhu, D., Zheng, J., & Zhang, M. (2020). Very High Resolution Remote Sensing Imagery Classification Using a Fusion of Random Forest and Deep Learning Technique—Subtropical Area for Example. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 113-128. https://doi.org/10.1109/JSTARS.2019.2953234.

Dong, S., Wang, P., & Abbas, K. (2021). A survey on deep learning and its applications. In Computer Science Review (Vol. 40). Elsevier Ireland Ltd. https://doi.org/10.1016/j.cosrev.2021.100379

Doreswamy, Hooshmand, M.K., & Gad, I. (2020). Feature selection approach using ensemble learning for network anomaly detection. CAAI Trans. Intell. Technol., 5, 283-293.

Egi, Y., Hajyzadeh, M., & Eyceyurt, E. (2022). Drone-Computer Communication Based Tomato Generative Organ Counting Model Using YOLO V5 and Deep-Sort. Agriculture (Switzerland), 12(9), 1290. https://doi.org/10.3390/AGRICULTURE12091290/S1

Ezzeddini, L., Ktari, J., Frikha, T., Alsharabi, N., Alayba, A., Alzahrani, A. J., Jadi, A., Alkholidi, A., & Hamam, H. (2024). Analysis of the performance of Faster R-CNN and YOLOv8 in detecting fishing vessels and fishes in real time. PeerJ Computer Science, 10, e2033. https://doi.org/10.7717/peerj-cs.2033

Fan, J., Ma, C., & Zhong, Y. (2019). A Selective Overview of Deep Learning. <http://arxiv.org/abs/1904.05526>

Flach, P. A., & Kull, M. (2015). Precision-Recall-Gain Curves: PR Analysis Done Right (Vol. 1). MIT. <http://www.bristol.ac.uk/red/research-policy/pure/user-guides/brp-terms/>

Flores-Vidal, P., Castro, J., & Gómez, D. (2022). Postprocessing of Edge Detection Algorithms with Machine Learning Techniques. Mathematical Problems in Engineering. https://doi.org/10.1155/2022/9729343.

Gai, R., Chen, N., & Yuan, H. (2021). A detection algorithm for cherry fruits based on the improved YOLO-v4 model. Neural Computing and Applications, 35(19), 13895–13906. <https://doi.org/10.1007/s00521-021-06029-z>

Gamani, A. R. A., Arhin, I., & Asamoah, A. K. (2024). Performance Evaluation of YOLOv8 Model Configurations, for Instance Segmentation of Strawberry Fruit Development Stages in an Open Field Environment. arXiv preprint arXiv:2408.05661.

Gao, J., Dai, S., Huang, J., Xiao, X., Liu, L., Wang, L., Sun, X., Guo, Y., & Li, M. (2022). Kiwifruit Detection Method in Orchard via an Improved Light-Weight YOLOv4. Agronomy 2022, Vol. 12, Page 2081, 12(9), 2081. https://doi.org/10.3390/AGRONOMY12092081

Goldenberg, S., Nir, G., & Salcudean, S. (2019). A new era: artificial intelligence and machine learning in prostate cancer. Nature Reviews Urology, 16, 391-403. <https://doi.org/10.1038/s41585-019-0193-3>.

Goncalves, C. T., Goncalves, M. J. A., & Campante, M. I. (2023). Developing Integrated Performance Dashboards Visualisations Using Power BI as a Platform. Information (Switzerland), 14(11). <https://doi.org/10.3390/info14110614>

Gowda, D., Pathak, D., Prasad, K., Srinivas, V., M, M., & Reddy, S. (2024). Scalable Machine Learning Frameworks for Large-Scale Multimodal Image and Speech Signal Processing. 2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), 1693-1699. https://doi.org/10.1109/I-SMAC61858.2024.10714812.

Gu, Y., Hong, R., & Cao, Y. (2024). Application of the YOLOv8 Model to a Fruit Picking Robot. 2024 IEEE 2nd International Conference on Control, Electronics and Computer Technology (ICCECT). https://doi.org/10.1109/iccect60629.2024.10546041

Gu, Z., He, D., Huang, J., Chen, J., Wu, X., Huang, B., Dong, T., Yang, Q., & Li, H. (2024). Simultaneous detection of fruits and fruiting stems in mango using improved YOLOv8 model deployed by edge device. Computers and Electronics in Agriculture, 227. <https://doi.org/10.1016/j.compag.2024.109512>

Hawaldar, V., Jain, R., Mengde, M., & Agrawal, S. (2024). Revolutionizing plant disease detection in agriculture: a comparative study of yolov5 and yolov8 deep learning models.

Hephzibah, R., Anandharaj, H., Kowsalya, G., Jayanthi, R., & Chandy, D. (2022). Review on Deep Learning Methodologies in Medical Image Restoration and Segmentation.. Current medical imaging. <https://doi.org/10.2174/1573405618666220407112825>.

Hilliard, K., Hamilton, M., Jiang, S., & Davis, L. (2023). Usability Evaluation of Food Bank Data Visualizations using Eye-Tracking Technology. Human-Centered Design and User Experience. <https://doi.org/10.54941/ahfe1004260>.

Huynh, T., Le, T., That, L., Tran, L., & Dao, S. (2022). A Two-Stage Feature Selection Approach for Fruit Recognition Using Camera Images With Various Machine Learning Classifiers. IEEE Access, 10, 132260-132270. https://doi.org/10.1109/ACCESS.2022.3227712.

Ishangulyyev, R., Kim, S., & Lee, S. H. (2019). Understanding food loss and waste-why are we losing and wasting food? Foods, 8(8). <https://doi.org/10.3390/foods8080297>

Jacob-John, J., D’Souza, C., Marjoribanks, T., & Singaraju, S. (2023). Sustainable Development Goals: a review of SDG 12.3 in food supply chain literature. Benchmarking: An International Journal, 30(9), 3465–3481. https://doi.org/10.1108/BIJ-12-2021-0736

Jain, A., & Varshney, S. (2024). Deep Analysis of Machine Learning Techniques for the Effective Retrieval of Images Based on Content. 2024 2nd International Conference on Disruptive Technologies (ICDT), 163-167. https://doi.org/10.1109/ICDT61202.2024.10488968.

Jain, V., Nagpal, S., Aggarwal, A., & Gupta, T. (2023). Image Classification of Covid Chest X-Rays using a Game Theoretical Approach. 2023 14th International Conference on Computing Communication and Networking Technologies, ICCCNT 2023. <https://doi.org/10.1109/ICCCNT56998.2023.10306909>

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. Electronic Markets, 31(3), 685–695. <https://doi.org/10.1007/s12525-021-00475-2>

Jaya, S., & Latha, M. (2021). An Analysis of Pattern Recognition and Machine Learning Approaches on Medical Images., 35-54. <https://doi.org/10.4018/978-1-7998-3335> 2.ch003.

Jena, B., Saxena, S., Nayak, G. K., Saba, L., Sharma, N., & Suri, J. S. (2021). Artificial intelligence-based hybrid deep learning models for image classification: The first narrative review. In Computers in Biology and Medicine (Vol. 137). Elsevier Ltd. https://doi.org/10.1016/j.compbiomed.2021.104803

Jia, S., Jiang, S., Lin, Z., Li, N., Xu, M., & Yu, S. (2021). A survey: Deep learning for hyperspectral image classification with few labeled samples. Neurocomputing, 448, 179–204. <https://doi.org/10.1016/j.neucom.2021.03.035>

Jia, W., Xu, Y., Lu, Y., Yin, X., Pan, N., Jiang, R., & Ge, X. (2023). An accurate green fruits detection method based on optimized YOLOX-m. Frontiers in Plant Science, 14. https://doi.org/10.3389/fpls.2023.1187734.

Jiang, S., Odubela, K., & Davis, L. (2022). Evidence-based decision making using visual analytics for a local food bank. The Human Side of Service Engineering. <https://doi.org/10.54941/ahfe1002587>.

Jrondi, Z., Moussaid, A., & Hadi, M. Y. (2024). Exploring End-to-End object detection with transformers versus YOLOv8 for enhanced citrus fruit detection within trees. Systems and Soft Computing, 6. <https://doi.org/10.1016/j.sasc.2024.200103>

Julianda, R. R., & Puriyanto, R. D. (2024). Tracking Ball Using YOLOv8 Method on Wheeled Soccer Robot with Omnidirectional Camera. Buletin Ilmiah Sarjana Teknik Elektro, 6(2), 203–213. <https://doi.org/10.12928/biste.v6i2.10816>

Kazi, A., & Panda, S. P. (2022). Determining the freshness of fruits in the food industry by image classification using transfer learning. Multimedia Tools and Applications, 81(6). <https://doi.org/10.1007/s11042-022-12150-5>

Kazi, A., & Panda, S. P. (2022). Determining the freshness of fruits in the food industry by image classification using transfer learning. Multimedia Tools and Applications, 81(6), 7611-7624.

Keylabs. (2024, January 15). YOLOv8 vs Faster R-CNN: A Comparative Analysis | Keylabs. Keylabs: Latest News and Updates. https://keylabs.ai/blog/yolov8-vs-faster-r-cnn-a-comparative-analysis/

Khalili, B., & Smyth, A. W. (2024). SOD-YOLOv8—Enhancing YOLOv8 for Small Object Detection in Aerial Imagery and Traffic Scenes. MDPI Sensors.

Kithama, M., Hassan, Y., Guo, K., Kiarie, E., & Diarra, M. (2021). The Enzymatic Digestion of Pomaces From Some Fruits for Value-Added Feed Applications in Animal Production. , 5. <https://doi.org/10.3389/fsufs.2021.611259>.

Kulkarni, A., Chouknis, A., Choudhari, B., & Suryavanshi, S. (2024). Nutrient Value Estimator via Fruit Detection using YOLOv8. International Journal For Multidisciplinary Research. https://doi.org/10.36948/ijfmr.2024.v06i04.26322.

Li, Z., Kamnitsas, K., & Glocker, B. (2020). Analyzing overfitting under class imbalance in neural networks for image segmentation. IEEE transactions on medical imaging, 40(3), 1065-1077.

Liu, T., Nie, X., Wu, J., Zhang, D., Liu, W., Cheng, Y., Zheng, Y., Qiu, J., & Qi, L. (2022). Pineapple (Ananas comosus) fruit detection and localization in natural environment based on binocular stereo vision and improved YOLOv3 model. Precision Agriculture, 24(1), 139–160. https://doi.org/10.1007/s11119-022-09935-x

Liu, Z., Abeyrathna, R. R. D., Sampurno, R. M., Nakaguchi, V. M., & Ahamed, T. (2024). Faster-YOLO-AP: A lightweight apple detection algorithm based on improved YOLOv8 with a new efficient PDWConv in orchard. Computers and Electronics in Agriculture, 223, 109118.

Lundberg, S. M., & Lee, S.-I. (2017). Consistent feature attribution for tree ensembles. <http://arxiv.org/abs/1706.06060>

Masood, R., Khan, S., & Khan, M. (2016). Plants Disease Segmentation using Image Processing. International Journal of Modern Education and Computer Science, 8, 24-32. https://doi.org/10.5815/IJMECS.2016.01.04.

Mendes, A., Cruz, J., Saraiva, T., Lima, T. M., & Gaspar, P. D. (2020, November). Logistics strategy (FIFO, FEFO or LSFO) decision support system for perishable food products. In 2020 International Conference on Decision Aid Sciences and Application (DASA) (pp. 173-178). IEEE.

Meshram, V. A., Patil, K., & Ramteke, S. D. (2021). MNet: A framework to reduce fruit image misclassification. Ingenierie Des Systemes d’Information, 26(2). <https://doi.org/10.18280/isi.260203>

Miikkulainen, R., Liang, J., Meyerson, E., Rawal, A., Fink, D., Francon, O., Raju, B., Shahrzad, H., Navruzyan, A., Duffy, N., & Hodjat, B. (2019). Evolving deep neural networks. In Artificial Intelligence in the Age of Neural Networks and Brain Computing (pp. 293 312). Elsevier. https://doi.org/10.1016/B978-0-12-815480-9.00015-3

Mukhiddinov, M., Muminov, A., & Cho, J. (2022). Improved Classification Approach for Fruits and Vegetables Freshness Based on Deep Learning. Sensors, 22(21). <https://doi.org/10.3390/s22218192>

Naidu, G., Zuva, T., & Sibanda, E. M. (2023). A Review of Evaluation Metrics in Machine Learning Algorithms. Lecture Notes in Networks and Systems, 724 LNNS, 15–25. <https://doi.org/10.1007/978-3-031-35314-7_2>

Najib, T., Muntasir, F., & Wasi, W. a. W. (2024). Benchmark Study on YOLOv8 Variants in Localized Multiclass Fault Detection in PCBs. In 2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT), 562–567. <https://doi.org/10.1109/iceeict62016.2024.10534448>

Narwane, S. V., & Sawarkar, S. D. (2021). Effects of class imbalance using machine learning algorithms: case study approach. International Journal of Applied Evolutionary Computation (IJAEC), 12(1), 1-17.

Nergiz, M. (2023). YOLO-V7 based detection and classification of pomegranate fruits in different growing stages. ResearchGate, Tech. Rep. 3.

Niu, W., Lei, X., Li, H., Wu, H., Hu, F., Wen, X., Zheng, D., & Song, H. (2024). YOLOv8-ECFS: A lightweight model for weed species detection in soybean fields. Crop Protection, 184, 106847. https://doi.org/10.1016/j.cropro.2024.106847

Ocharo, D., Nganga, H. C., & Kiambi, S. (2024). Automatic PPE monitoring system for construction workers using YOLO algorithm based on deep reinforcement learning. International Journal of Computer Applications, 186(48), 10–15. https://doi.org/10.5120/ijca2024924094

Oleiwi, Z., Alshemmary, E., & Al-augby, S. (2023). Identify Best Learning Method for Heart Diseases Prediction Under impact of Different Datasets Characteristics. Journal of Kufa for Mathematics and Computer. https://doi.org/10.31642/jokmc/2018/100104.

Owoeye, O., & Ojo-Omoniyi, O. (2022). Deep Learning and Computer Vision: Machine Learning Analysis and Image Processing of Puromycin Treated Microscopy. International Journal of Current Microbiology and Applied Sciences. https://doi.org/10.20546/ijcmas.2022.1106.014.

Pahuja, L., & Kamal, A. (2023). EnLEFD-DM: Ensemble Learning based Ethereum Fraud Detection using CRISP-DM framework. Expert Systems, 40(9). <https://doi.org/10.1111/exsy.13379>

Panati, C., Wagner, S., & Bruggenwirth, S. (2022). Feature Relevance Evaluation using Grad-CAM, LIME and SHAP for Deep Learning SAR Data Classification. In 2022 23rd International Radar Symposium (IRS). https://doi.org/10.23919/irs54158.2022.9904989

Peker, S., & Kart, Ö. (2023). Transactional data-based customer segmentation applying CRISP-DM methodology: A systematic review. Journal of Data, Information and Management, 5(1–2). <https://doi.org/10.1007/s42488-023-00085-x>

Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Computers and Electronics in Agriculture, 161. https://doi.org/10.1016/j.compag.2018.04.002

Ponce-Bobadilla, A., Schmitt, V., Maier, C., Mensing, S., & Stodtmann, S. (2024). Practical guide to SHAP analysis: Explaining supervised machine learning model predictions in drug development.. Clinical and translational science, 17 11, e70056 . <https://doi.org/10.1111/cts.70056>.

Prabu, S., & Gnanasekar, J. (2021). A Study on Image Segmentation Method for Image Processing. Recent Trends in Intensive Computing. https://doi.org/10.3233/apc210223.

Priyadi, M. R. A., & Suharjito, N. (2023). Comparison of YOLOv8 and EfficientDet4 Algorithms in Detecting the Ripeness of Oil Palm Fruit Bunch. In 2023 10th International Conference on ICT for Smart Society (ICISS), 1–7. https://doi.org/10.1109/iciss59129.2023.10291928

Qi, Z., & Wang, J. (2024). PMDNet: An Improved Object Detection Model for Wheat Field Weed. Agronomy, 15(1), 55.

Qiao, Q. (2024). Image Processing Technology Based on Machine Learning. IEEE Consumer Electronics Magazine, 13, 90-99. https://doi.org/10.1109/MCE.2022.3150659.

Qiu, Z., Huang, Z., Mo, D., Tian, X., & Tian, X. (2024). GSE-YOLO: A Lightweight and High-Precision Model for Identifying the Ripeness of Pitaya (Dragon Fruit) Based on the YOLOv8n Improvement. Horticulturae, 10(8), 852. https://doi.org/10.3390/horticulturae10080852

Rahmadi, L., Hadiyanto, Sanjaya, R., & Prambayun, A. (2023). Crop Prediction Using Machine Learning with CRISP-DM Approach. Lecture Notes in Networks and Systems, 787 LNNS. https://doi.org/10.1007/978-981-99-6550-2\_31

Raj, R., Nagaraj, S. S., Ritesh, S., Thushar, T. A., & Aparanji, V. M. (2021). Fruit Classification Comparison Based on CNN and YOLO. IOP Conference Series: Materials Science and Engineering, 1187(1). <https://doi.org/10.1088/1757-899x/1187/1/012031>

Rajakumar, P., Geetha, S., & Ananthan, T. (2023). Fundamentals of Image Processing. . https://doi.org/10.47715/jpc.b.978-93-91303-80-8.

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 779–788. https://doi.org/10.1109/cvpr.2016.91

Ribeiro, M., Singh, S., ACM, C. G.-P. of the 22nd, & 2016, undefined. (2016). “ Why should i trust you?” Explaining the predictions of any classifier. Dl.Acm.Org, 13-17-August-2016, 1135–1144. <https://doi.org/10.1145/2939672.2939778>

Rojas-Aranda, J. L., Nunez-Varela, J. I., Cuevas-Tello, J. C., & Rangel-Ramirez, G. (2020). Fruit classification for retail stores using deep learning. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 12088 LNCS. <https://doi.org/10.1007/978-3-030-49076-8_1>

Salih, A., Raisi-Estabragh, Z., Galazzo, I. B., Radeva, P., Petersen, S. E., Menegaz, G., & Lekadir, K. (2023). A Perspective on Explainable Artificial Intelligence Methods: SHAP and LIME. <https://doi.org/10.1002/aisy.202400304>

Saqib, S. M., Aftab, A., Mazhar, T., Iqbal, M., Shahazad, T., Almogren, A., & Hamam, H. (2024). Integrating YOLO and WordNet for automated image object summarization. Signal Image and Video Processing. https://doi.org/10.1007/s11760-024-03560-z

Saranya, N., Srinivasan, K., Pravin Kumar, S. K., Rukkumani, V., & Ramya, R. (2020). Fruit classification using traditional machine learning and deep learning approach. Advances in Intelligent Systems and Computing, 1108 AISC. <https://doi.org/10.1007/978-3-030-37218-7_10>

Schröer, C., Kruse, F., & Gómez, J. M. (2021). A systematic literature review on applying CRISP-DM process model. Procedia Computer Science, 181. <https://doi.org/10.1016/j.procs.2021.01.199>

Sharma, A., Singh, V., & Singh, P. (2022). Deep CNN Based Hybrid Model for Image Retrieval. International Journal of Innovative Technology and Exploring Engineering. https://doi.org/10.35940/ijitee.g9203.0811922.

Sharma, J., Granmo, O., & Olsen, M. (2018). Deep CNN-ELM Hybrid Models for Fire Detection in Images. , 245-259. https://doi.org/10.1007/978-3-030-01424-7\_25.

Shrawne, S., Sawant, J., Chaubal, O., Suryawanshi, K., Sirwani, D., & Sambhe, V. (2024). Multiclass Fruit Detection Using Improved YOLOv3 Algorithm. International Journal of Advanced Computer Science and Applications. https://doi.org/10.14569/ijacsa.2024.01509100.

Shrikumar, A., Greenside, P., & Kundaje, A. (2017). Learning important features through propagating activation differences. 34th International Conference on Machine Learning, ICML 2017, 7.

Singh, J., Rani, S., & Srilakshmi, G. (2024). Towards Explainable AI: Interpretable Models for Complex Decision-making. 2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS), 1, 1-5. https://doi.org/10.1109/ICKECS61492.2024.10616500.

Sinha, S., Ohashi, H., & Nakamura, K. (2020). Class-wise difficulty-balanced loss for solving class-imbalance. In Proceedings of the Asian conference on computer vision.

Sofana Reka, S., Bagelikar, A., Venugopal, P., Ravi, V., Devarajan, H., & Prakash, V. (2024). Deep Learning-Based Classification of Rotten Fruits and Identification of Shelf Life. Cdn.Techscience.CnSS Reka, A Bagelikar, P Venugopal, V Ravi, H DevarajanComputers, Materials & Continua, 2024•cdn.Techscience.Cn. <https://doi.org/10.32604/cmc.2023.043369>

Sohan, M., Ram, T. S., & Reddy, C. V. R. (2024). A review on YOLOV8 and its advancements. Algorithms for Intelligent Systems, 529–545. https://doi.org/10.1007/978-981-99-7962-2\_39

Solimani, F., Cardellicchio, A., Dimauro, G., Petrozza, A., Summerer, S., Cellini, F., & Renò, V. (2024). Optimizing tomato plant phenotyping detection: Boosting YOLOv8 architecture to tackle data complexity. Computers and Electronics in Agriculture, 218. <https://doi.org/10.1016/j.compag.2024.108728>

Su, Y., Qiu, Z., Huang, X., & Lu, D. (2024, May). Enhanced YOLOv8 algorithm for large-scale multi-object detection and its application in defect detection in power systems. In Eighth International Conference on Energy System, Electricity, and Power (ESEP 2023) (Vol. 13159, pp. 2094-2099). SPIE.

Sultana, N., Jahan, M., & Uddin, M. S. (2022). An extensive dataset for successful recognition of fresh and rotten fruits. Data in Brief, 44, 108552. https://doi.org/10.1016/J.DIB.2022.108552

Sultana, N., Jahan, M., & Uddin, M. S. (2023). Freshness Identification of Fruits Through the Development of a Dataset. <https://doi.org/10.1007/978-981-99-3754-7_4>

Sun, Y., Yen, G. G., & Yi, Z. (2018). Evolving Unsupervised Deep Neural Networks for Learning Meaningful Representations. IEEE Transactions on Evolutionary Computation, 23(1), 89–103. <https://doi.org/10.1109/TEVC.2018.2808689>

Sun, Y., Yen, G. G., & Yi, Z. (2018). Evolving Unsupervised Deep Neural Networks for Learning Meaningful Representations. IEEE Transactions on Evolutionary Computation, 23(1), 89–103. https://doi.org/10.1109/TEVC.2018.2808689

Sunil, G. C., Koparan, C., Ahmed, M. R., Zhang, Y., Howatt, K., & Sun, X. (2022). A study on deep learning algorithm performance on weed and crop species identification under different image background. Artificial Intelligence in Agriculture, 6, 242-256. https://doi.org/10.1016/j.aiia.2022.11.001

Tan, J., Yang, J., Wu, S., Chen, G., & Zhao, J. (2021). A critical look at the current train/test split in machine learning. <http://arxiv.org/abs/2106.04525>

Tan, M., Pang, R., & Le, Q. V. (2020). Efficientdet: Scalable and efficient object detection. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 10781-10790).

Tang, Y., Zhou, H., Wang, H., & Zhang, Y. (2023). Fruit detection and positioning technology for a Camellia oleifera C. Abel orchard based on improved YOLOv4-tiny model and binocular stereo vision. Expert Systems with Applications, 211, 118573. https://doi.org/10.1016/J.ESWA.2022.118573

Tasnim, F., & Habiba, S. (2021). A Comparative Study on Heart Disease Prediction Using Data Mining Techniques and Feature Selection. 2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), 338-341. <https://doi.org/10.1109/ICREST51555.2021.9331158>.

Taylor, L., Gupta, V., & Jung, K. (2024). Leveraging Visualization and Machine Learning Techniques in Education: A Case Study of K-12 State Assessment Data. Multimodal Technologies and Interaction, 8(4). https://doi.org/10.3390/mti8040028

Temenos, A., Temenos, N., Kaselimi, M., Doulamis, A., & Doulamis, N. (2023). Interpretable Deep Learning Framework for Land Use and Land Cover Classification in Remote Sensing Using SHAP. IEEE Geoscience and Remote Sensing Letters, 20. <https://doi.org/10.1109/LGRS.2023.3251652>

Thomas, W. S. (2024). Using the AI in Power BI to do root cause analyses.

Thoyyibah, T., Abdurachman, E., Heryadi, Y., & Zahra, A. (2022). CRISP-DM Method for Mood Classification in Indonesian Music 70 and 80 era. International Journal of Applied Engineering and Technology (London), 4(1).

Tropea, M., & Fedele, G. (2019). Classifiers Comparison for Convolutional Neural Networks (CNNs) in Image Classification. 2019 IEEE/ACM 23rd International Symposium on Distributed Simulation and Real Time Applications (DS-RT), 1-4. https://doi.org/10.1109/DS-RT47707.2019.8958662.

Turaev, S., Almisreb, A. A., & Saleh, M. A. (2020). Application of Transfer Learning for Fruits and Vegetable Quality Assessment. Proceedings of the 2020 14th International Conference on Innovations in Information Technology, IIT 2020. <https://doi.org/10.1109/IIT50501.2020.9299048>

Udawant, P., Patidar, A., Singh, A., & Yadav, A. (2019). Comparative Study of Artificial Intelligence Techniques for Image Classification. International Journal of Scientific Research in Computer Science, Engineering and Information Technology. https://doi.org/10.32628/CSEIT1952187.

Vijayakumar, A., & Vairavasundaram, S. (2024). YOLO-based Object Detection Models: A Review and its Applications. Multimedia Tools and Applications, 83(35), 83535–83574. https://doi.org/10.1007/s11042-024-18872-y

Vimbi, V., Shaffi, N., & Mahmud, M. (2024). Interpreting artificial intelligence models: a systematic review on the application of LIME and SHAP in Alzheimer’s disease detection. In Brain Informatics (Vol. 11, Issue 1). Springer Science and Business Media Deutschland GmbH. <https://doi.org/10.1186/s40708-024-00222-1>

Viveros Escamilla, L. D., Gómez-Espinosa, A., Escobedo Cabello, J. A., & Cantoral-Ceballos, J. A. (2024). Maturity Recognition and Fruit Counting for Sweet Peppers in Greenhouses Using Deep Learning Neural Networks. Agriculture (Switzerland), 14(3). <https://doi.org/10.3390/agriculture14030331>

von Eschenbach, W. J. (2021). Transparency and the Black Box Problem: Why We Do Not Trust AI. Philosophy and Technology, 34(4). <https://doi.org/10.1007/s13347-021-00477-0>

Walia, S., Kumar, K., Agarwal, S., & Kim, H. (2022). Using XAI for Deep Learning-Based Image Manipulation Detection with Shapley Additive Explanation. Symmetry, 14(8). <https://doi.org/10.3390/sym14081611>

Wang, C., Wang, H., Han, Q., Zhang, Z., Kong, D., & Zou, X. (2024). Strawberry Detection and Ripeness Classification Using YOLOv8+ Model and Image Processing Method. Agriculture, 14(5), 751. https://doi.org/10.3390/agriculture14050751

Wang, H., Liu, C., Cai, Y., Chen, L., & Li, Y. (2024). YOLOv8-QSD: An improved small object detection algorithm for autonomous vehicles based on YOLOv8. IEEE Transactions on Instrumentation and Measurement.

Wang, P., Fan, E., & Wang, P. (2020). Comparative analysis of image classification algorithms based on traditional machine learning and deep learning. Pattern Recognition Letters, 141, 61–67. <https://doi.org/10.1016/j.patrec.2020.07.042>

Wang, Y., Yu, C., Lin, X., Mgbejime, G. T., Nneji, G. U., & Monday, H. N. (2024). Leveraging Ensemble Deep Learning Model for Fruit Image Recognition with Explainable AI. 2024 5th International Conference on Big Data & Artificial Intelligence & Software Engineering (ICBASE), 195–199. https://doi.org/10.1109/icbase63199.2024.10762632

Wang, Z., Jin, L., Wang, S., & Xu, H. (2022). Apple stem/calyx real-time recognition using YOLO-v5 algorithm for fruit automatic loading system. Postharvest Biology and Technology, 185, 111808. https://doi.org/10.1016/J.POSTHARVBIO.2021.111808

Wu, Z., Wang, X., Jia, M., Liu, M., Sun, C., Wu, C., & Wang, J. (2024). Dense object detection methods in RAW UAV imagery based on YOLOv8. Scientific Reports, 14(1). https://doi.org/10.1038/s41598-024-69106-y

Xiao, B., Nguyen, M. & Yan, W.Q. Fruit ripeness identification using YOLOv8 model. Multimed Tools Appl 83, 28039–28056 (2024). https://doi.org/10.1007/s11042-023-16570-9

Xu, Y., & Goodacre, R. (2018). On Splitting Training and Validation Set: A Comparative Study of Cross-Validation, Bootstrap and Systematic Sampling for Estimating the Generalization Performance of Supervised Learning. Journal of Analysis and Testing, 2(3). <https://doi.org/10.1007/s41664-018-0068-2>

Xuan, A. W. Q., & Chong, C. W. (2024). Exploration of Terrace or Linked Houses Detection from Satellite Images Using Deep Learning. In 2024 International Conference on Green Energy, Computing and Sustainable Technology (GECOST). https://doi.org/10.1109/gecost60902.2024.10474880

Yan, E., Luo, L., & Ceze, L. (2021, November). Characterizing and Taming Resolution in Convolutional Neural Networks. In 2021 IEEE International Symposium on Workload Characterization (IISWC) (pp. 189-200). IEEE.

Yang, C., Guan, X., Xu, Q., Xing, W., Chen, X., Chen, J., & Jia, P. (2024). How can SHAP (SHapley Additive exPlanations) interpretations improve deep learning based urban cellular automata model? Computers, Environment and Urban Systems, 111, 102133. <https://doi.org/10.1016/J.COMPENVURBSYS.2024.102133>

Yaseen, M. (2024). What is YOLOv8: An In-Depth Exploration of the Internal Features of the Next-Generation Object Detector. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2408.15857

Young, T., Hazarika, D., Poria, S., & Cambria, E. (2018). Recent trends in deep learning based natural language processing [Review Article]. In IEEE Computational Intelligence Magazine (Vol. 13, Issue 3, pp. 55–75). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/MCI.2018.2840738

Younisse, R., Ahmad, A., & Abu Al-Haija, Q. (2022). Explaining Intrusion Detection-Based Convolutional Neural Networks Using Shapley Additive Explanations (SHAP). Big Data and Cognitive Computing, 6(4). <https://doi.org/10.3390/bdcc6040126>

Yu, L., & Liu, S. (2023). A Single-Stage deep learning-based approach for Real-Time license plate recognition in smart parking system. International Journal of Advanced Computer Science and Applications, 14(9). https://doi.org/10.14569/ijacsa.2023.01409119

Yuan, J., Chen, C., Yang, W., Liu, M., Xia, J., & Liu, S. (2021). A survey of visual analytics techniques for machine learning. Computational Visual Media, 7(1), 3–36. https://doi.org/10.1007/S41095-020-0191-7/METRICS

Yue, M., Zhang, L., Zhang, Y., & Zhang, H. (2024). An improved YOLOV8 detector for multi-scale target detection in remote sensing images. IEEE Access, 12, 114123–114136. https://doi.org/10.1109/access.2024.3444606

Zakiyabarsi, F., Aras, R. A., H, Y. D. N., Nur, M. M., Alfarizi, D. A., & Amri, M. U. (2024). Towards The Future of Crab Farming: The Application Of AI with Yolox And Yolov9 To Detect Crab Larvae. Inspiration Jurnal Teknologi Informasi Dan Komunikasi, 14(2), 118–129. https://doi.org/10.35585/inspir.v14i2.93

Zhang, J., Xie, J., Zhang, F., Gao, J., Yang, C., Song, C., Rao, W., & Zhang, Y. (2023). Greenhouse tomato detection and pose classification algorithm based on improved YOLOv5. Computers and Electronics in Agriculture, 216, 108519. https://doi.org/10.1016/j.compag.2023.108519

Zhang, W., Wang, J., Liu, Y., Chen, K., Li, H., Duan, Y., Wu, W., Shi, Y., & Guo, W. (2022). Deep-learning-based in-field citrus fruit detection and tracking. Horticulture Research, 9. https://doi.org/10.1093/HR/UHAC003

Zhang, Y., Jiang, J., & Fu, S. (2024). Research on Apple Fruit Detection Algorithm Based on Improved YOLOV8. In 2024 2nd International Conference on Algorithm, Image Processing and Machine Vision (AIPMV), 71–74. https://doi.org/10.1109/aipmv62663.2024.10692117

Zhang, Z., Umar, S., Hammadi, A. Y. A., Yoon, S., Damiani, E., Ardagna, C. A., Bena, N., & Yeun, C. Y. (2023). Explainable Data Poison Attacks on Human Emotion Evaluation Systems Based on EEG Signals. IEEE Access, 11. <https://doi.org/10.1109/ACCESS.2023.3245813>

Zhao, B., Chen, C., Ju, Q., & Xia, S. (2021). Energy aligning for biased models. arXiv preprint arXiv:2106.03343.

Zhou, J., Hu, W., Zou, A., Zhai, S., Liu, T., Yang, W., & Jiang, P. (2022). Lightweight Detection Algorithm of Kiwifruit Based on Improved YOLOX-S. Agriculture 2022, Vol. 12, Page 993, 12(7), 993. <https://doi.org/10.3390/AGRICULTURE12070993>