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Detecting Avocado Freshness In Real-Time: A Yolo-Based Deep Learning Approach

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Abstract

The increasing consumption of avocados in Indonesia highlights the need for an effective method to ensure fruit freshness. The main problem lies in the absence of an objective and standardized system for assessing avocado freshness, which may lead to consumer dissatisfaction and food waste. This study aims to address the challenge of identifying avocado freshness to ensure suitability for consumption. Conducted from May 23 to June 5, 2024, the research used butter avocado samples sourced from supermarkets. The method employed is the You Only Look Once version 8 (YOLOv8) deep learning algorithm, known for its real-time object detection capabilities. YOLOv8 offers enhanced performance compared to earlier versions through anchor-free detection, improved speed, and accuracy, making it suitable for fast and reliable freshness detection tasks. Avocados were classified based on estimated spoilage time under room and refrigerator temperatures, ranging from "up to 5 days at room temperature and 14 days in refrigeration" to "not fit for consumption." The model was validated using 120 images categorized into six freshness levels. Evaluation results demonstrated high performance, with 98% accuracy, an F1-Score of 0.978, mAP50 of 0.994, and mAP50-95 of 0.972 after 50 training epochs, confirming the model's robustness. Real-time tests yielded confidence levels of 96% and 94%, further validating its effectiveness in detecting avocado freshness. To facilitate daily use, a mobile application named Avo Freshify was developed. The app accurately identifies the freshness of avocados and provides valuable information for consumers and sellers. This research contributes to the advancement of artificial intelligence and object detection in food quality control and agricultural technology.

Keywords : *Avo Freshify, Butter Avocado, Detection, Freshness, YOLOv8.*

1. INTRODUCTION

Indonesia, a tropical country, is rich in fruit diversity, which constitutes a significant part of its natural wealth [1]. Fruits are essential sources of nutrients and vitamins; however, without proper handling, they are highly susceptible to physical, chemical, and microbiological deterioration [2]. Fresh fruit is particularly valued for its high vitamin, fiber, and mineral content, making it highly recommended for consumption to support overall health [3]. In Indonesia, avocados have been gaining popularity, with consumption data first recorded in 2022 after a lack of data from 2018 to 2021 [4]. The average weekly per capita consumption increased from 0.013 in 2022 to 0.017 in 2023, while annual per capita consumption rose from 0.671 to 0.864 [5], indicating a significant rise in avocado popularity.

The main problem lies in the absence of an objective and standardized system for assessing avocado freshness, which may lead to consumer dissatisfaction, food waste, and economic losses for sellers. With the growing consumption of fruits, including avocados, a key challenge is ensuring that the fruit remains in an edible state. When freshness is lost, not only does the nutritional value decline, but there is also a risk of potential health issues [6]. Fresh fruit has specific characteristics that differentiate it from fruit that is no longer fresh. Understanding how to accurately assess fruit freshness is crucial for preserving its nutritional and vitamin content [7]. However, the sorting process remains

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largely manual, often leading to inconsistencies and inaccuracies due to subjective assessments of freshness. These inconsistencies can negatively impact both sellers and buyers [8].

Previous studies on fruit freshness detection using deep learning mainly focused on other fruit types, such as apples, bananas, and citrus, and often relied on traditional machine learning methods or earlier versions of object detection models. This research presents a novelty by applying the latest YOLOv8 model specifically to avocado butter, with real-time detection capabilities and classification into six freahness levels based on spoilage time. To address this issue, deep learning technology offers a modern and efficient solution, particularly through the implementation of the YOLO (You Only Look Once) algorithm, which enables automated and accurate fruit freshness detection.

YOLOv8 is an advanced model that builds upon the achievements of previous YOLO versions, incorporating new features and improvements to enhance efficiency and adaptability [9]. In the context of fruit freshness detection, YOLOv8 not only identifies different stages of ripeness but also predicts the expected shelf life of avocados under various storage conditions, such as room temperature or refrigeration. This model is implemented through a mobile application that utilizes a phone camera to detect avocado freshness in real time, providing users with an efficient and accessible solution. This technology allows consumers to determine fruit ripeness and shelf life simply by pointing a camera at the fruit, thereby streamlining the selection process. On a larger scale, this technology can be utilized for inventory management in stores and supermarkets, ensuring that consumers receive high-quality, fresh fruit while enabling sellers to set prices that reflect product quality. The application facilitates rapid and efficient fruit freshness assessment using a mobile phone camera. With a user-friendly interface, it provides real-time information on fruit ripeness and shelf life, helping consumers make informed purchasing decisions and allowing sellers to optimize pricing strategies.

2. METHOD

This research applies the YOLOv8 model to detect avocado freshness, following a structured research flow as illustrated in Figure 1. The process begins with the identification of a problem related to avocado freshness, followed by a literature review to explore relevant detection methods. Avocado image data were collected under varying conditions of freshness and storage environments, then labeled using Roboflow. Then labeled data were split into training (80%), validation (10%), and testing (10%) sets. Pre-processing and data augmentation were conducted to enhance the diversity and quality of the training data. The processed dataset was exported in YOLO format used to train the YOLOv8 model. During the training process, the validation set was evaluated using the testing set. Performance metrics such as precision, recall, F1-score, and mean Average Precision (mAP) were used to assess the effectiveness of the detection. In cases where objects were not detected accurately, the process was iteratively refined by rechecking labels, tuning hyperparameters, or enhancing data quality. Once the model achived satisfactory results, it was intergrated into an Android application to enable mobile-based detection of avocado freshness.

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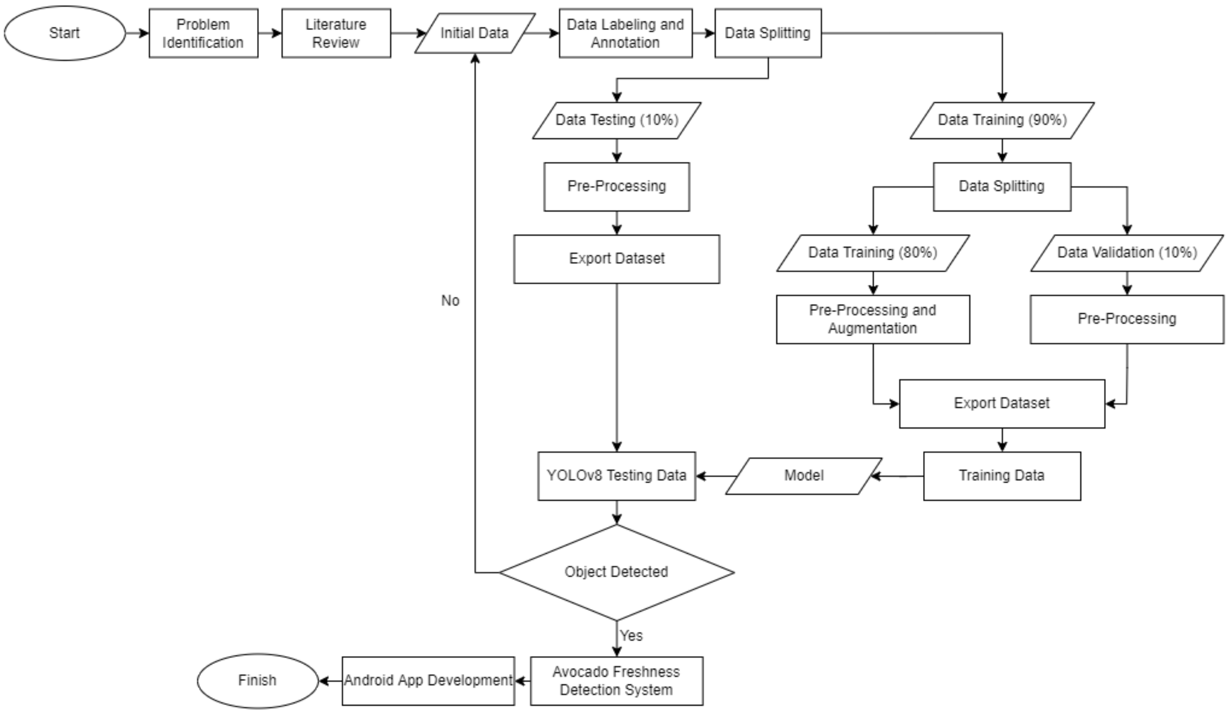

Figure 1. Research Flowchart

2.1. Object Detection

Object detection is a subfield of computer vision that aims to recognize and locate semantically meaningful objects within images or videos [10]. This method is crucial in analyzing imagery obtained from remote sensing, where images often contain various objects of different sizes, offering rich and diverse data for object detection purposes [11]. The process of object detection in digital image processing involves identifying the presence of specific objects in an image by utilizing various techniques to analyze object characteristics and compare them with predefined templates [12].

Object detection determines the presence of an object in an image, including identifying its area and location. This process can be understood as object recognition in two categories: one for the object itself and another for areas that do not contain the object. Furthermore, object detection can be classified into two types: soft detection and hard detection. Soft detection focuses solely on the presence of the object, whereas hard detection not only identifies the object's presence but also determines its precise location within the image [13].

2.2. Deep Learning

Since the 1950s, a small branch of Artificial Intelligence (AI) known as Machine Learning (ML) began to emerge, bringing significant transformations across various sectors. Neural Networks (NN), a subset of ML, eventually evolved into a more complex concept referred to as Deep Learning (DL) [14]. Deep learning is a learning approach that utilizes artificial neural networks with multiple layers. These neural networks are designed to mimic the functioning of the human brain, where each neuron is interconnected, forming a complex network system [15].

Various methods in Deep Learning (DL) can be categorized into three main groups: supervised, semi-supervised, and unsupervised learning. Additionally, other techniques such as Reinforcement Learning (RL) or Deep Reinforcement Learning (DRL) are often classified under semi-supervised or unsupervised learning categories [16].

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2.3. You Only Look Once (YOLO)

You Only Look Once (YOLO) is a real-time object detection algorithm based on a convolutional neural network (CNN) architecture. First introduced in 2015 by Joseph Redmon and Ali Farhadi, YOLO was inspired by GoogleNet, a model originally designed for image classification tasks [17]. The YOLO algorithm detects objects by processing an input image and dividing it into an S×S grid. Each grid cell generates bounding boxes, and the system estimates class probabilities based on the model's confidence in recognizing objects within the image [18].

Each cell in the grid produces B bounding box predictions, each accompanied by a confidence score. This confidence score represents both the probability that an object is present within the bounding box and the accuracy of the predicted box location. If a grid cell does not contain an object, the confidence score is set to zero. However, if an object is present, the confidence score corresponds to the Intersection over Union (IoU) value between the predicted and actual bounding boxes [19].

Each bounding box consists of five key prediction parameters: the box center coordinates (x, y), width (w), height (h), and confidence score. The center position is expressed relative to the grid cell in which it is located, while the width and height are measured relative to the overall image dimensions. An example illustration is shown in Figure 2.

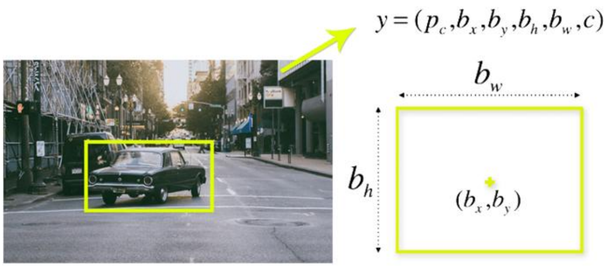

Figure 2. Bounding Box Attributes in YOLO Algorithm

The confidence score indicates how accurately the predicted bounding box aligns with the actual object, as measured by the Intersection over Union (IoU) value. Additionally, each grid cell estimates a conditional class probability C, which represents the likelihood of a specific object class being present in that cell. This probability is conditioned on the assumption that an object exists within the grid cell. Regardless of the number of bounding boxes B, only one set of class probabilities is predicted per grid cell.

During the testing phase, the conditional class probabilities are combined with the confidence scores of each bounding box. This combination results in a final confidence score for each object class within the box. These scores not only indicate the probability of a particular class appearing in the bounding box but also reflect the accuracy of the predicted box in capturing the actual detected object. A simplified illustration of the YOLO algorithm is presented in Figure 3.

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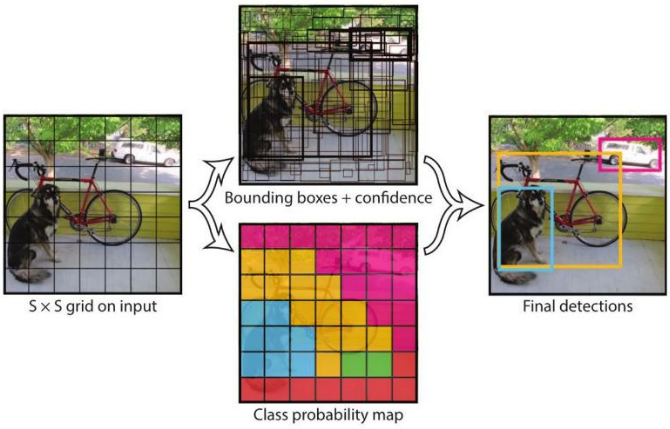

Figure 3. YOLO Algorithm

In the YOLO algorithm, the convolutional network processes the input image and generates bounding boxes, along with confidence scores and class probabilities for each grid cell. Following this process, YOLO produces an output consisting of bounding boxes for all successfully detected objects.

To generate these bounding boxes, YOLO utilizes a convolutional network structured as S*S*B*(5+C), where S represents the number of grid cells, B denotes the number of bounding boxes predicted per cell, and C corresponds to the number of object classes to be recognized. The number 5 accounts for the bounding box parameters, which include the center coordinates (x,y), width (w), height (h), and confidence score. The values of x and y range from 0 to 1, while w and h can exceed 1, as the bounding box dimensions may be larger than the grid cell size [20].

2.4. YOLOv8

In January 2023, YOLOv8 was officially released as the latest iteration in the YOLO family. It introduces five variants, YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), and YOLOv8x (extra-large), designed to support various computer vision tasks, including object detection, segmentation, pose estimation, tracking, and classification. YOLOv8 can be executed via the Command Line Interface (CLI) or installed as a Python package using pip, allowing seamless integration for labelling, training, and deployment.

This latest version incorporates several key enhancements, such as the ability to add images online during training, making YOLOv8 more efficient than its predecessors. One of its most notable improvements is a higher mean Average Precision (mAP), which significantly enhances its overall performance [21].

The architecture of YOLOv8 consists of two main components: the backbone and the head, as illustrated in Figure 4. The backbone is responsible for feature extraction and generating a feature pyramid, while the head is tasked with identifying objects and displaying bounding boxes along with object scores [22].

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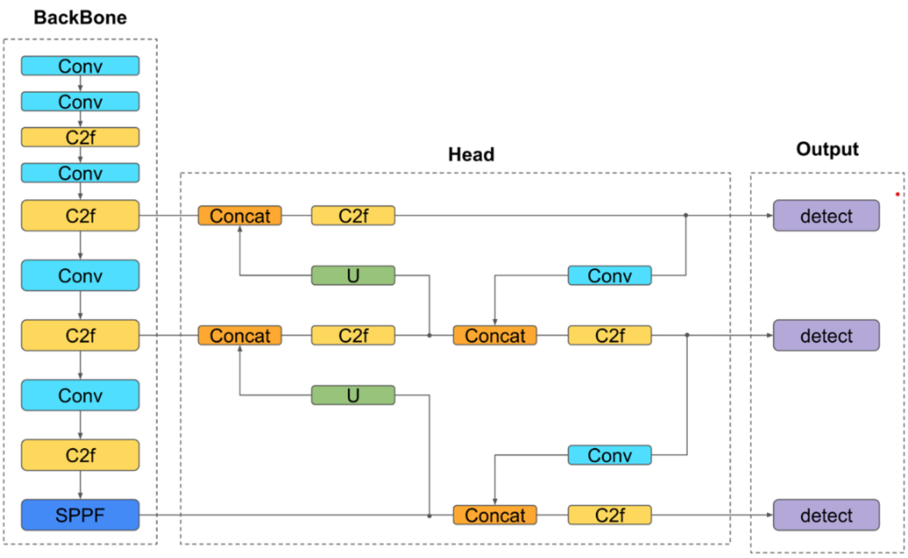

Figure 4. YOLO Architecture

The backbone of YOLOv8 is built on the CSPDarknet53 architecture, which consists of 53 convolutional layers and employs the Cross-Stage Partial (CSP) connection technique to enhance the flow of information. The C2f module integrates key features with contextual information, while the Spatial Pyramid Pooling-Fast (SPPF) module processes features at multiple scales, thereby improving object detection accuracy.

The YOLOv8 head is designed for flexibility in processing features extracted by the backbone, enabling highly efficient predictions of object location and classification. This process is further enhanced by U-layers, which capture finer details, along with convolutional and linear layers that refine the final predictions [23].

2.5. Confusion Matrix

One common approach to evaluating the performance of a classification model is through precision and recall analysis. In this context, several key terms are frequently used, such as "positive tuple," which refers to data belonging to the target class, and "negative tuple," which refers to data outside the target class. Additionally, fundamental concepts including True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), often represented in a confusion matrix, serve as essential tools for assessing classification model performance [24], as illustrated in Figure 5.

By utilizing this approach, various evaluation metrics such as accuracy, precision, recall, and F1-score can be derived, all of which are critical for measuring the effectiveness of a classification model [25].

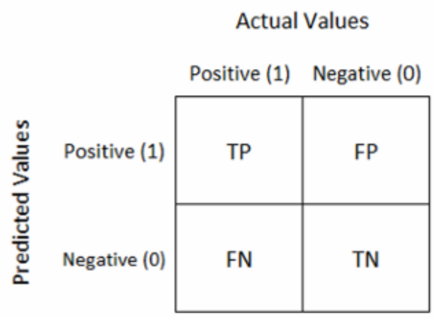

Figure 5. Confusion Matrix

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Accuracy is a ratio that measures the proportion of correct predictions, both for positive and negative categories, compared to the total amount of data available. This figure gives an idea of how precise the classification model applied is [26].

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision is a ratio that measures the proportion of correct positive predictions when compared to all results generated as positive. It reflects the extent to which the data of interest matches the predicted results released by the classification model.

$$precision = \frac{TP}{TP + FP} \quad (2)$$

Recall is a ratio that measures the proportion of accurate positive predictions compared to the total data that should have been identified as positive. It reflects the classification model's ability to retrieve relevant information.

$$recall = \frac{TP}{TP + FN} \quad (3)$$

F1-Score is a metric that is a combination of precision and recall values, the result of which is known as a performance measure [19].

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

2.6. Mean Average Precision (mAP)

One metric that is often used in evaluating object detection is Mean Average Precision (mAP). This metric is a popular standard for assessing the precision of an object detection model. The mAP value is calculated from the average precision (AP) result. After the Average Precision (AP) value is obtained, the next step to obtain Mean Average Precision (mAP) is to calculate the average of the AP values for each category in the data based on a certain threshold value [27].

$$mAP = \frac{1}{n} \sum_{k=1}^{n} APk \quad (5)$$

3. RESULT

3.1. Dataset Collection, Labelling, and Annotation

The dataset consists of images of butter avocados, which are used to evaluate their ripeness levels and shelf life. The images were captured under two different storage conditions: room temperature and refrigeration. In total, the dataset includes 1,200 images of butter avocados in various stages of ripeness, ranging from fully ripe to no longer suitable for consumption, as summarized in Table 1.

Table 1. Dataset Composition

No	Class	Number of Images
1	Approaching 5 Days of Decay at Room Temperature and 14 Days in the Refrigerator	200
2	Approaching 4 Days of Decay at Room Temperature and 11 Days in the Refrigerator	200
3	Approaching 3 Days of Decay at Room Temperature and 9 Days in the Refrigerator	200

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No	Class	Number of Images
4	Approaching 2 Days of Decay at Room Temperature and 6 Days in the Refrigerator	200
5	Approaching 1 Day of Decay at Room Temperature and 3 Days in the Refrigerator	200
6	Not Suitable for Consumption	200

The annotation or labelling process involves identifying objects within images by creating bounding boxes around them and assigning the appropriate category or class labels. This step is intended to specify the exact regions within the images that will serve as data for training an object detection model. Prior to initiating the labelling process, the collected image dataset is uploaded to the Roboflow platform, which facilitates efficient data annotation and labelling.

Once the dataset has been uploaded to Roboflow, the next step is to manually draw bounding boxes around each object within the images. This process requires precisely delineating the object areas to ensure accurate identification, followed by assigning the correct label or category to each object. The annotation and labelling process of the dataset is illustrated in Figure 6.

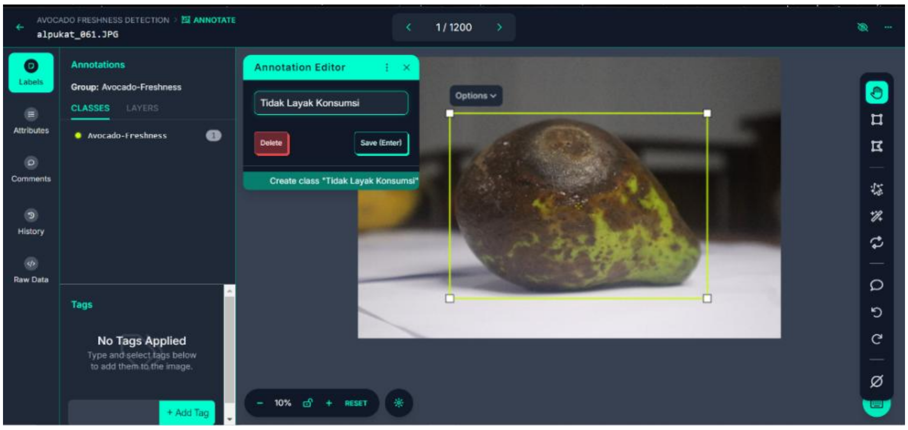

Figure 6. Dataset Annotation and Labelling Process

3.2. Data Splitting

At this stage, the dataset is divided into three groups: training data, validation data, and testing data. The division is made by allocating 80% of the data for training, while 10% is assigned to validation and 10% to testing, as shown in Table 2. The purpose of this division is to ensure that the model has sufficient data to learn from, is validated with a separate dataset during training to avoid overfitting, and is tested with new data to measure its performance objectively. With this strategy, the model's performance can be optimized because it is trained with adequate data, properly validated, and tested with data that was not involved in the training process.

Table 2. Distribution of Images for Training, Validation, and Testing

No	Class	Number of Training Images	Number of Validation Images	Number of Testing Images
1	Approaching 5 Days of Decay at Room Temperature and 14 Days in the Refrigerator	166	14	20
2	Approaching 4 Days of Decay at Room Temperature and 11 Days in the Refrigerator	157	23	20

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No	Class	Number of Training Images	Number of Validation Images	Number of Testing Images
3	Approaching 3 Days of Decay at Room Temperature and 9 Days in the Refrigerator	156	25	19
4	Approaching 2 Days of Decay at Room Temperature and 6 Days in the Refrigerator	162	12	26
5	Approaching 1 Day of Decay at Room Temperature and 3 Days in the Refrigerator	162	20	18
6	Not Suitable for Consumption	157	26	17

3.3. Pre-Processing and Augmentation

In the object detection model training process, pre-processing and augmentation steps are crucial to ensure that the image data used is of high quality and sufficiently diverse. The pre-processing stage is carried out to prepare the images before they are used in the training process. In this study, two main steps are applied: Auto-Orient and Resize. The Auto-Orient step automatically adjusts the image orientation based on metadata stored by the camera device, ensuring that images are displayed correctly and preventing orientation-related display errors. Meanwhile, the Resize step involves changing the image dimensions to 640 × 640 pixels without preserving the original aspect ratio, resulting in uniform image dimensions across the dataset. This process ensures a more efficient training phase, as the model receives input images with consistent sizes.

To enhance data variability during training, image augmentation is applied to enable the model to learn to recognize objects from various angles, orientations, and other transformations. Several augmentation techniques are employed by the researchers, including flipping, which reverses the image either horizontally (left to right) or vertically (top to bottom), allowing the model to recognize objects in different positions. The 90° rotation, which rotates images by 90 degrees either clockwise or counterclockwise, introduces variations in the viewing angles of objects. Cropping is applied with a minimum zoom of 0% and a maximum of 20%, altering the size of objects in the image to improve the model's robustness in detecting objects of varying scales. In addition, shearing is used to shift the image by up to ±10 degrees horizontally or vertically, creating distortions that help the model recognize objects appearing in slightly altered forms. Each augmented image produces three different variations, thereby enriching the dataset and strengthening the model's ability to handle changes in object orientation, position, and distortion when applied to real-world data.

3.4. Training Data

The model was trained for 50 epochs with an automatic batch size of 16 and a confidence threshold of 0.25, enabling the model to filter predictions so that only plausible results are recognized. These settings are expected to enhance the model's ability to effectively distinguish the freshness of avocados. Upon completion of the training process, the YOLOv8 model is exported in .pt file format, making it ready for field implementation. The training results after 50 epochs are presented in Figure 7 and Figure 8.

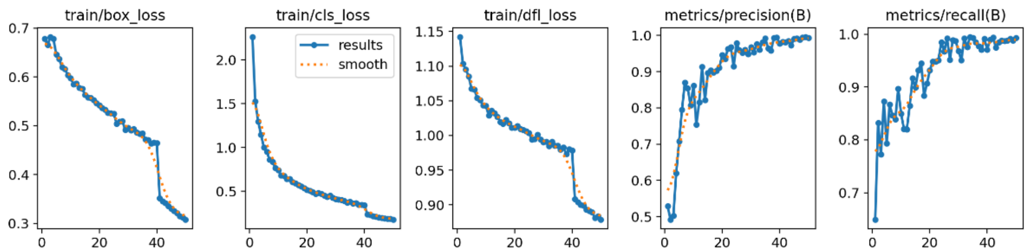

Figure 7. Training Graphics

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From the graph in Figure 7, it can be observed that as the number of iterations increases, the loss value decreases, while precision and recall improve. However, the loss rate on the training data should not be considered the primary indicator of the model's performance, as the model has already learned the patterns within the dataset.

A more objective measure of accuracy can be obtained by evaluating the model's performance on the validation dataset, as illustrated in the graph in Figure 8.

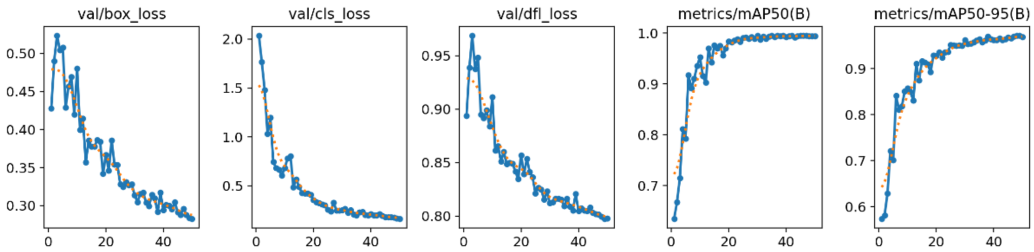

Figure 8. Validation Graphics

The graph in Figure 8 shows a significant decrease in the loss value on the validation dataset, indicating that the model's performance improves as training iterations increase. This suggests that the loss value becomes more stable and controlled, leading to satisfactory results. Additionally, the mean Average Precision (mAP) at an Intersection over Union (IoU) threshold of 0.5, as well as across multiple IoU values (0.5 to 0.95), continues to improve. This indicates the model's increasing ability to detect objects with high accuracy across various IoU thresholds.

The final validation results are presented in Table 3.

Table 3. Overall Validation Process Results

Class	Images	Precision	Recall	mAP50	mAP50-95
All	120	120	0.994	0.992	0.994
Approaching 5 Days of Decay at Room Temperature and 14 Days in the Refrigerator	14	14	0.993	1	0.995
Approaching 4 Days of Decay at Room Temperature and 11 Days in the Refrigerator	23	23	0.995	1	0.995
Approaching 3 Days of Decay at Room Temperature and 9 Days in the Refrigerator	25	25	0.995	1	0.995
Approaching 2 Days of Decay at Room Temperature and 6 Days in the Refrigerator	12	12	0.993	1	0.995
Approaching 1 Day of Decay at Room Temperature and 3 Days in the Refrigerator	20	20	0.99	0.964	0.991
Not Suitable for Consumption	26	26	1	0.986	0.995

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The validation results demonstrate excellent performance in detecting fruit freshness, with a precision of 0.994 and a recall of 0.992. Additionally, the mAP metric for object detection using the YOLOv8 model yields highly satisfactory results.

The mAP calculation is based on the Intersection over Union (IoU) metric, where at mAP 0.5, a model prediction is considered accurate if there is at least 50% overlap between the predicted bounding box and the target box, resulting in a high score of 99.4%. Meanwhile, the average mAP score across multiple IoU thresholds from 0.5 to 0.95 reached 97.2%. These results indicate that the model performs exceptionally well and provides reliable detection accuracy

3.5. Model Evaluation

The confusion matrix is a crucial evaluation tool in object detection, as it provides a comprehensive overview of the model's performance in identifying objects across different classes, both correctly and incorrectly. It consists of four key components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

By analyzing these metrics, the model's ability to accurately detect objects can be assessed while also identifying misclassifications. This evaluation helps minimize errors and optimize the model's performance on new data. The results of the model evaluation are presented in Table 4.

Table 4. Model Evaluation

Metric	Value
Precision	97.7%
Recall	97.9%
Accuracy	98.4%
F1-Score	97.8%

The trained model achieved a high accuracy of 98.4%, demonstrating excellent performance in classifying the data. With an F1-score of 0.9779 (approximately 97.8%), the model consistently detected the target category accurately while minimizing detection errors.

High precision ensures that positive predictions are accurate, while strong recall indicates the model’s ability to detect most positive instances. With an optimal balance between precision and recall, the model proves to be highly reliable for detecting avocado freshness and is well-prepared for practical implementation

3.6. Curve Performance

The F1 Confidence Curve is a graph that illustrates the relationship between the F1 Score, a metric that measures the balance between precision and recall, and the confidence threshold in a classification model. This graph provides insights into how well the model maintains the balance between precision and recall at various confidence levels, thereby facilitating the identification of an appropriate optimal threshold. As a result, the model can adjust the trade-off between precision and recall according to the specific requirements of the application or its contextual use. The results of the F1 Confidence Curve are presented in Figure 9.

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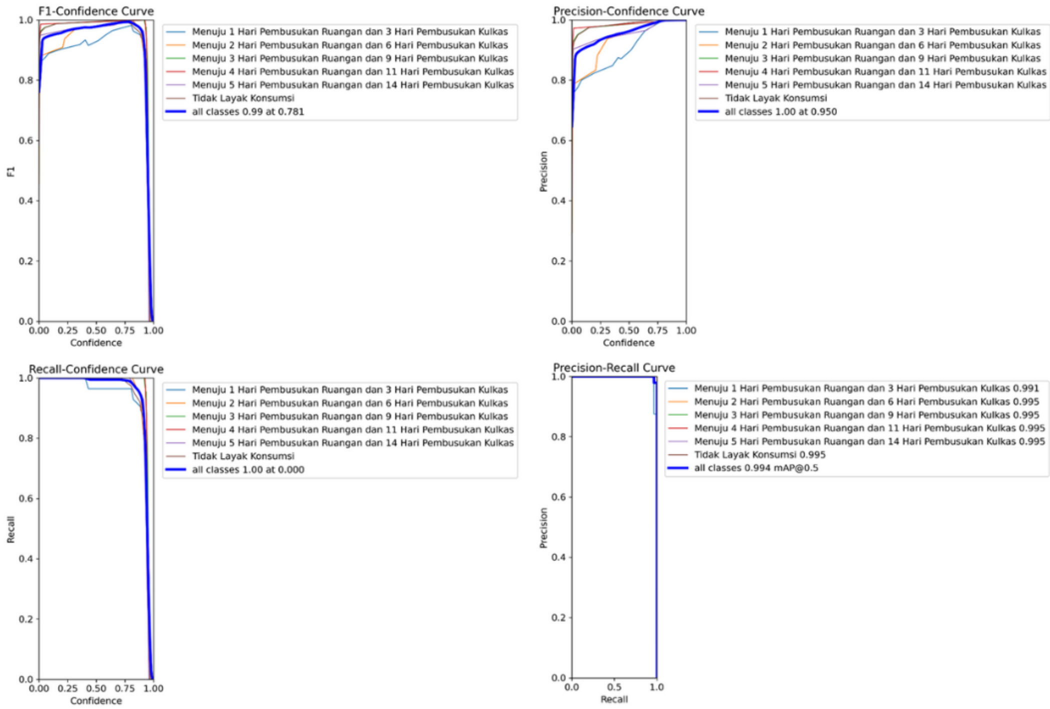

Figure 9. Curve Performance

Training the YOLOv8 model over 50 epochs resulted in outstanding performance, achieving a peak F1-score of 0.99 at a confidence threshold of 0.781, a maximum precision of 1.00 at 0.950, and a maximum recall of 1.00 at 0.000. The Precision-Recall graph demonstrates high precision and consistency across the recall range, with a mean average precision (mAP) of 0.994 at a 0.5 threshold, indicating an accurate, consistent, and well-balanced model for detecting all positive classes.

3.7. New Data Prediction

New data prediction is performed to evaluate the model's ability to classify objects in previously unseen data. This stage is crucial for assessing how accurately the model can recognize patterns in real-world scenarios.

In image prediction, as shown in Figure 10, the YOLOv8 model is used to detect avocado objects in new images. The model generates bounding boxes around detected objects and assigns classification labels indicating the condition of the object. Each detection is accompanied by a confidence score, representing the model's certainty in its prediction.

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Figure 10. Image Prediction

Each avocado is identified with a blue bounding box that includes a maturity label, such as spoilage within 1 day at room temperature or 3 days in the refrigerator. The confidence scores of 0.95 and 0.94 indicate highly accurate and reliable model predictions.

To facilitate the detection of avocado ripeness, the YOLOv8 model is further applied for real-time detection, as shown in Figure 11.

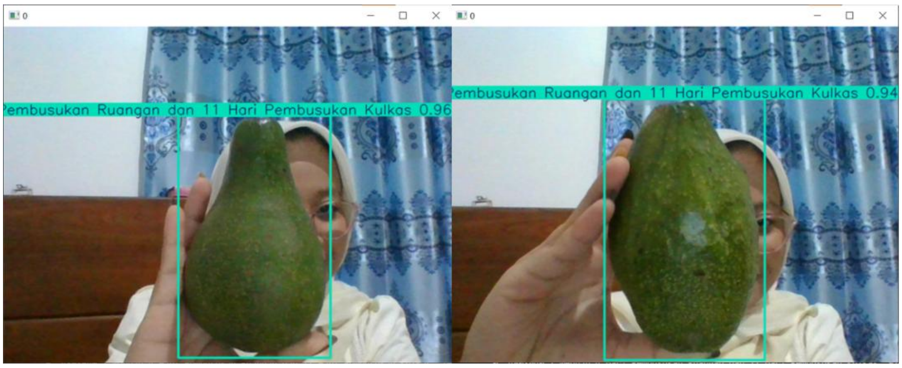

Figure 11. Real-Time Prediction

In real-time detection, the model identifies an avocado and displays it within a green bounding box, along with a prediction label stating: “Towards 4 Days Room Decay and 11 Days Fridge Decay”. The confidence levels of 0.96 and 0.94 indicate the model’s strong certainty in its prediction. This label suggests that the avocado is expected to start spoiling within 4 days at room temperature and 11 days when stored in the refrigerator.

3.8. Avo Freshify

Avo Freshify, as illustrated by its logo in Figure 12, is an innovative mobile application designed to efficiently detect the ripeness level of avocados using a smartphone camera. The app analyzes the fruit's condition and estimates its spoilage time under both room temperature and refrigerated storage, enabling users to make informed decisions regarding storage, consumption, and pricing. This solution not only enhances efficiency and user experience in the culinary industry but also helps reduce food waste caused by spoilage. The results of avocado ripeness detection using Avo Freshify are shown in Figure 13.

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Figure 12. App Logo

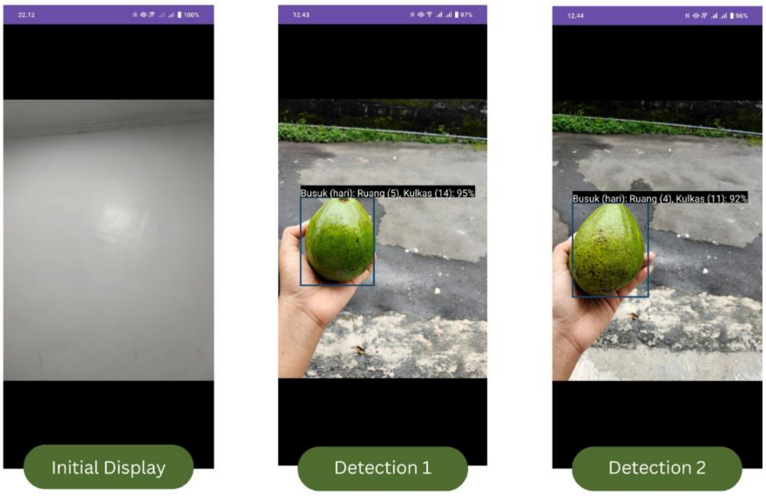

Figure 13. Avo Freshify App

The Avo Freshify app is designed for immediate usability, opening directly to the camera view upon launch. This allows users to instantly scan avocados without navigating through additional menus, ensuring a fast and seamless experience. Users simply point their phone at an avocado to assess its ripeness level.

The app's intuitive interface enhances accessibility for users of all ages, including the elderly, by eliminating the need to search for extra buttons or menus. Once the avocado is detected, the app displays predicted spoilage time at the top of the detection box, providing estimates for both room and refrigerated storage conditions. This feature assists sellers and buyers in making informed decisions regarding storage, consumption, and pricing.

4. DISCUSSIONS

Previous research has demonstrated the effectiveness of the YOLOv8 algorithm across various agricultural applications. For example, YOLOv8 has been successfully employed in a web-based system to predict the optimal harvest time of pakcoy, achieving remarkable performance with a precision of 97.123%, recall of 97.452%, and mAP50 of 98.001% [28]. Similarly, in pest detection tasks involving Potato Beetles in potato crops, YOLOv8-m outperformed other variants with a recall of 76.1%, precision of 95.2%, mAP of 82.5%, and mAP-95 of 39.7% [29]. Another study applied YOLOv8 to evaluate fruit freshness and recorded an average accuracy of 88%, with final precision and recall values of 74% and 75%, respectively, after 100 training epochs [30]. These findings collectively underline the strong potential of YOLOv8 in agricultural image classification tasks.

In the context of this study, YOLOv8 also delivered robust performance in classifying avocados based on freshness levels under different environmental conditions. The model benefited significantly

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from data augmentation techniques such as horizontal flipping, rotation, and brightness adjustment, which enhanced its learning capability by exposing it to a wider range of visual patterns. The detection results exhibited consistent levels of precision and recall across all classes, indicating the model's reliability in distinguishing between fresh and deteriorated avocados.

Moreover, the model maintained stable classification accuracy regardless of whether the fruit images were taken under room temperature or refrigeration, suggesting that YOLOv8 adapts well to real-world variability in image acquisition. Compared to similar applications reported in prior studies [28]-[30], the current model achieved comparable or slightly improved performance metrics. The integration of this model into a mobile-based platform further extends its practical utility, enabling real-time assessment that supports better post-harvest decision-making and inventory control. This reflects a meaningful contribution to the development of intelligent agriculture systems, particularly in the domain of informatics-based food quality monitoring.

5. CONCLUSION

The increasing consumption of avocados in Indonesia reflects a growing awareness of nutritional benefits; however, maintaining fruit freshness remains a significant challenge. Deep learning technologies, particularly YOLOv8, offer a solution by enabling automatic and accurate detection of fruit freshness. Deep learning technologies, particularly YOLOv8, offer a promising solution by enabling automatic and accurate detection of fruit freshness through real-time object recognition.

The validated model demonstrated exceptional performance, achieving 97.7% precision, 97.9% recall, 98.4% accuracy, and a 97.8% F1-score. Additionally, the mean Average Precision (mAP) at IoU 0.5 (mAP50) reached 99.4%, while mAP across IoU thresholds from 0.5 to 0.95 (mAP50-95) attained 97.2%. The findings demonstrate that using YOLOv8 offers a notable enhancement over traditional approaches, which typically depend on manual evaluation and are susceptible to inconsistent and subjective outcomes. In the realm of computer science and informatics, this study reflects the momentum of modern advancements in deep learning and computer vision. By deploying YOLOv8's sophisticated object detection features in agricultural settings, the research introduces an innovative leap forward in automating fruit quality assessment with high precision and efficiency.

Furthermore, this model presents future opportunities for integration with smart technologies such as IoT devices and advanced sensor systems. Such synergy would enable seamless, real-time monitoring of fruit freshness across the supply chain, thereby not only increasing predictive reliability but also fostering the development of intelligent, data-driven agricultural ecosystems in line with the principles of Industry 4.0.

The YOLOv8-based application not only assists consumers in selecting ripe avocados but also enables sellers to manage inventory more efficiently, enhance service quality, and increase customer satisfaction in the fruit trade industry.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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