JURNAL INFORMATIKA
PROXIES

Vol.10, No.1, July, 2026

Freshness Detection of Food Ingredients Using Yolov5

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https://doi.org/10.18280/proxies.v10i1.15419

Received: 2026-04-28
Revised: 2026-07-20
Accepted: 2026-07-20
Available online: 2026-07-23

Keywords:food_freshness,YOLO, YOLOv5, freshness_detection

ABSTRACT

Maintaining the quality and freshness of food ingredients is vital, especially during storage. The freshness of food ingredients directly affects the health of those who consume them. Therefore, detecting the freshness of food ingredients is important to help prevent health risk. Unfortunately, traditional or manual methods for food freshness detection still lack speed and accuracy because they rely on someone's subjective judgment and often lead to human error. Using YOLO for food freshness detection helps make the detection process faster and reduces the risk of human error. The model used in this project is YOLOv5, which is known as fast and lightweight versions of YOLO but still delivering a good performance in recognizing the food ingredient freshness levels. The dataset consists of food ingredient images such as plant-based products (fruits and vegetables) and non-plant-based products.

1. INTRODUCTION

In recent years, maintaining the freshness and quality of food during storage has become crucial, as suboptimal storage conditions can lead to quality degradation and impact consumer health. Manual freshness detection methods are still frequently used, but they have limitations in consistency, efficiency, and accuracy, and are susceptible to human error. Therefore, an automated solution capable of detecting food freshness more quickly and reliably is needed.

To address these issues, this study utilized the YOLOv5 model to detect and assess the freshness of food ingredients. Through a training process supported by appropriate data labeling, YOLO is able to recognize visual patterns of objects and automatically determine their freshness level. This approach is used to improve the efficiency of the detection process and reduce human error, potentially improving food quality and safety standards.

2. LITERATURE STUDY

Deep Learning has been applied in multiple sectors especially for classification and detection of visual images. The application of deep learning technology is considered to bring more benefits, especially for speed and efficiency, compared to manual detection methods. Among various deep learning methods, YOLO is known for its accuracy and speed in object detection. Anas et al. [1] has shown the application of YOLOv5 and Faster R-CNN are able to automates the fish freshness detection with high accuracy and speed that making them more eficient and less time-consuming. This is consistent fit the finding of Pan et al. [2], who applied YOLOv4-Tiny to enhance the portable fluorescence device for rapid and effective fish freshness detection.

YOLO algorithms is an object detection method that growing rapidly since the initial release. Until now, YOLO continually improved its performance regarding the accuracy, efficiency, and speed of the model. YOLO is ideal for food freshness detection because it supports to perform detection and classification at the same time. Also, YOLO ability to detect multiple object and its high accuracy are suitable for food freshness detection. Wang et al. [3] shows that the implementation of YOLO can demonstrates the high accuracy and speed in classification of freshness. Wei et al. [4] also presents that YOLO integration has the potential increase the detection speed and accuracy in food freshness classification.

The application of YOLO in both freshness and maturity detection for plant-based products has demostrated strong potential results. Gillani Fahad et al. [5] and Mukhiddinov et al. [6] has shown that implementing deep learning to analyze visual data, reporting improved perfomance in recognizing the freshness of fruits and vegetables. Similarly, Zaho et al. [7] and Trinh and Nguyen [8] have demonstrated the efectiveness of YOLO in detecting fruits maturity especially tomato and pineapple. Their findings show that the implementation of YOLO can achieving high accuracy and speed, while also enhance the recognition of fruits maturity.

Not limited to plant-based products detection, YOLO also applicable to non-plant-based products and has proven promising results. Anas et al. [1] developed a fish freshness level detection combining YOLOv5 and faster R-CNN. The model delivered dependable result in distinguishing fresh and non-fresh fish. Equally, Samaniego et al. [9] applied YOLOv8 to classify Bangus (milkfish) into multiple freshness levels, achieving strong accuracy and precision.

In this project, the preprocessing stage is crucial for preparing the data before the training process. Using LBP to recognize the texture patterns of food images can help boost the model's effectiveness. Wahyuningrum and Cahyono [10] introduced a hybrid method combining Advanced Local Binary Pattern (ALBP) and Chain Code algorithms to recognize alphabet images based on texture features and shape. Even though their study did not specifically use YOLO, the texture-based features and shape share similarities with YOLO's detection methods.

Unlike earlier studies that mostly focused on limited categories for freshness detection, such as only specific fruits or fish. This project develops a multi-class freshness detection using various plant-based and non-plant-based food ingredients. This project also aiming for better accuracy and speed in real time situations.

3. RESEARCH METHODOLOGY

Dataset Collection

For this study the dataset contains 3 categories: fruits, vegetables, and non-plant-based food ingredients. Each category is divided into 3 freshness levels: fresh, less fresh, and spoiled. In this study, 597 images representing different levels of freshness in food ingredients. The dataset was compiled using Pexels API, the scraping process was performed in Python and Request as the library. Apart from Pexels, the dataset was also collected from Kaggle as another source. Each category is divided into 3 freshness levels: fresh, less fresh, and spoiled. The total dataset consist of 597 images of food ingredients with various levels of freshness.

Data Labeling

The labeling process was performed using a web-based tool for annotating object detection called Roboflow. Labeling was done manually by annotating images with bounding boxes to determine freshness levels. This annotation process was carried out by four different annotators to reduce bias during the labeling process.

Image Resizing

To ensure consistency, the input to the model was resized to 416x416 pixels. Image resizing aims to equalize the image size so that all data input into the model has the same size. With the same size, the model can learn data patterns more optimally without being affected by variations in image size.

Augmentation

To enhance the size and diversity of the training dataset, augmentation was used to add various kinds of transformations to the dataset. With the increased size and diversity of the dataset, it is expected to help the model improve its ability to recognize food freshness under various conditions. The augmentation techniques used included horizontal and vertical flips, rotations within a range of -15° to +15°, brightness adjustments of ±15%, blur additions of up to 2.5 pixels, and noise reduction of up to 0.1%. This process increased the dataset to 1,791 images.

Table 1. Examples of Data Augmentation

Augmentation	**Image Example**	
	Before	**After**

Flip: Horizontal, Vertical		 Horizontal Flip  Vertical Flip
Rotation: Between -15° and +15°		
Brightness: Between -15% and +15%		

Blur: Up to 2.5px		
Noise: Up to 0.1% of pixels		

Dataset Splitting and Feature Extraction

After augmentation, the dataset was divided into training and validation sets using an 80:20 ratio from the 1,791 augmented images, while 20 images were reserved as test data that had not been used during the training or validation process. Feature extraction was then performed using Rotation Local Binary Pattern (RLBP) to capture the texture characteristics of the images. RLBP was chosen because it represents texture patterns more robustly to rotational changes, resulting in more stable features. These extracted features were then used as additional features in the model training process to improve the detection ability to distinguish object freshness levels.

YOLO Training

In this phase, YOLOv5 was used as the model in this study. YOLOv5 is known to balance speed and accuracy in object detection. The training process was conducted using a dataset that had undergone preprocessing, augmentation, and feature addition using the RLBP method. This study employed two training scenarios: the original model and the enhanced model. The original model was trained using default parameters without adjustment, while the enhanced model underwent hyperparameter tuning to improve model performance. Hyperparameter adjustments included changes to the learning rate, HSV parameters, scale, mosaic, and cls and mixup parameters.

Data Testing

In the testing phase, 20 new test images were used that were not involved in the training or validation processes to measure the model's generalization ability to new data. Before the detection process, the test data underwent preprocessing, which involved background removal to focus the model on the main object. Next, the model performed an inference process to detect the freshness of the object. The detection results were then analyzed to evaluate prediction accuracy and identify potential detection errors.

Model Evaluation

Model evaluation was conducted to measure detection performance using validation data and test results. At this stage, model performance is assessed using precision, recall, average precision (AP), and mean average precision (mAP) metrics. Furthermore, detection results are analyzed by calculating the number of true positives (TP), false positives (FP), and false negatives (FN) to determine the success rate and error rate of model predictions. Based on these values, the precision, recall, and F1-score metrics are then recalculated to determine the balance between the model's ability to correctly detect objects and avoid false detections.

IMPLEMENTATION AND RESULT

Implementation

The dataset was obtained from Roboflow and downloaded in YOLOv5 format. The dataset was then processed by dividing it into training and validation data with an 80:20 ratio. Next, oversampling was performed to balance the class distribution, particularly for classes with fewer data sets, namely the semi-fresh class. This was done by randomly duplicating the data and storing it as new data without overwriting the original data. Furthermore, feature extraction was performed using the Rotation Local

Binary Pattern (RLBP) method to capture the texture characteristics of the images. This process included converting the images to grayscale and extracting texture patterns using RLBP. All images were then resized to 416x416 pixels, and the extracted features were used as additional input in the YOLOv5 model training process.

Results

The results show that model performance is influenced by dataset distribution and hyperparameter tuning. In the original model, using a balanced dataset yielded better performance than using an unbalanced dataset, with the mAP50 value increasing from 0.79 to 0.93. A similar trend was observed in the refined model, where the balanced dataset yielded higher results (mAP50 of 0.91) compared to the unbalanced dataset (0.85). Overall, the original model with the balanced dataset performed better than the others. Further analysis of the detection results showed that the model was capable of detecting objects in multi-object conditions, but errors such as false positives and false negatives were still found. Evaluation scores calculated based on TP, FP, and FN showed that the model with the balanced dataset had the highest precision, but recall was still relatively low, indicating that there were still undetected objects. This suggests that although the model is quite good at classification, improvements are still needed to increase detection sensitivity in more complex conditions.

Table 2. Comparison of mAP50 Values

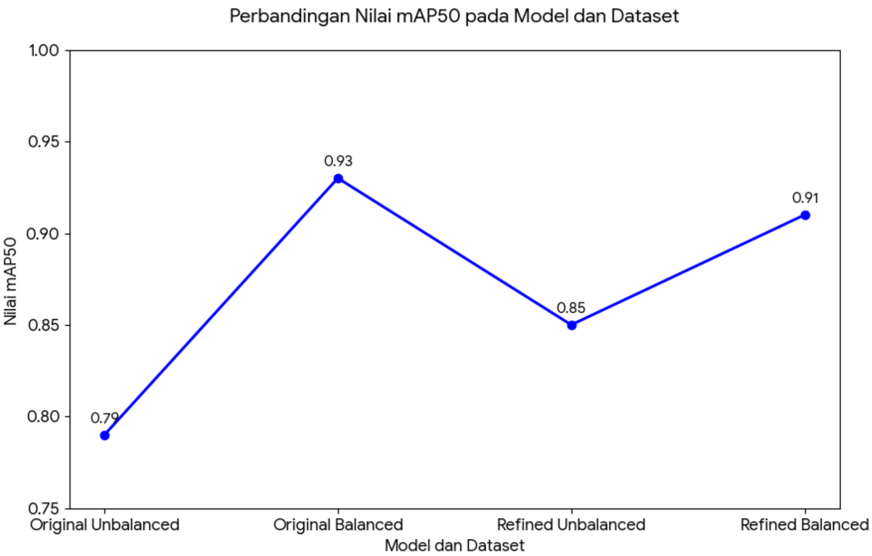

Table 3. Comparison of TP, FP, and FN for Each Model and Dataset

Model - Dataset	**True Positive (TP)**	**False Positive (FP)**	**False Negative (FN)**
Original Model - Unbalanced Dataset	28	12	21
Original Model - Balanced Dataset	29	7	20
Refined Model - Unbalanced Dataset	22	9	27
Refined Model - Balanced Dataset	22	8	27

Table 4. Comparison of YOLO Model Performance Based on Precision, Recall, and F1-Score

Model - Dataset	**Precision (P)**	**Recall (R)**	**F1-Score**
Original Model - Unbalanced Dataset	0.70	0.57	0.63

Original Model - Balanced Dataset	0.81	0.59	0.68
Refined Model - Unbalanced Dataset	0.71	0.45	0.55
Refined Model - Balanced Dataset	0.73	0.45	0.56

Discussion

This study shows that the YOLOv5 model is capable of detecting food freshness with good precision, recall, and mAP values. However, good dataset distribution significantly impacts model performance compared to hyperparameter tuning. Balanced datasets yield more stable performance than imbalanced datasets because an even class distribution helps the model optimally learn each class and reduces bias toward the majority class.

The model refined through hyperparameter tuning showed improvement on imbalanced datasets, but the improvement was not significant compared to the original model on balanced datasets. This indicates that data quality and distribution play a more dominant role than parameter optimization in improving model performance. Furthermore, in multi-object testing, the model was able to detect some objects well, but errors such as false positives and false negatives were still found, especially in complex conditions. Overall, the performance of the YOLOv5 model is influenced not only by the training technique but also by dataset quality, labeling consistency, and variations in environmental conditions such as lighting and visual differences between objects.

4. CONCLUSIONS

Based on the research results, the YOLOv5 model proved capable of detecting food freshness effectively, even in multi-object situations, although there were still detection errors such as false positives and false negatives. The results also showed that hyperparameter tuning did not always provide significant performance improvements. Therefore, model performance depended not only on parameter optimization but was also significantly influenced by dataset quality, labeling consistency, and variations in environmental conditions.

Furthermore, dataset distribution played a role in determining model performance. A balanced dataset produced more stable performance than an unbalanced dataset because it reduced bias toward the dominant class and improved the model's ability to recognize all classes. Therefore, improving model performance needs to be done holistically, paying attention to data balance and dataset quality, rather than focusing solely on the training process or parameter tuning.

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