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# YOLOv8-Based Quality Detection of Bali MSMEs Staple Food

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**ABSTRACT**

Ensuring the quality of staple foods such as rice, cooking oil, milk, and meat is crucial for consumer safety and health. In Indonesian Micro, Small and Medium Enterprises (MSMEs), quality assessment often depends on subjective and time-consuming visual inspection. This study develops an automatic quality detection system using YOLOv8, applied to food MSMEs in Bali, to detect 14 quality categories across the four commodities based on image data. The methodology includes dataset collection from MSMEs, image annotation, preprocessing, training YOLOv8s and YOLOv8m models, and evaluating performance using mAP50, accuracy, precision, recall, and F1-score. Results show that YOLOv8m achieved a mAP50 of 96.5%, indicating high detection accuracy. The system, implemented as a web-based application, has strong potential to improve efficiency, ensure consistent product quality, and support Sustainable Development Goals (SDGs) 2, 3, 8, and 9.

**Keywords**: Staple food quality; YOLOv8; Deep learning; Image detection; MSMEs.

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## 1. INTRODUCTION

Food safety and quality are fundamental aspects in maintaining consumer health as well as supporting national food security [1]. Staple foods such as rice, cooking oil, milk, and meat dominate Indonesian consumption [2], yet quality assessment at the MSME level still relies on subjective and time consuming visual inspection [3].

The adoption of Artificial Intelligence (AI), particularly deep learning, offers a more objective and efficient solution [4]. YOLOv8, a state of the art object detection framework, provides high accuracy and fast processing in image-based detection tasks [5]. The implementation of this technology aligns with efforts to support the Sustainable Development Goals (SDGs) [6], especially SDG 2 (Zero Hunger), which aims to ensure safe and quality food to strengthen food security [7], as well as SDG 3 (Good Health and Well-being), which focuses on improving public health through better food consumption [8]. Additionally, this research supports SDG 8 (Decent Work and Economic Growth) by assisting food MSMEs in improving efficiency and competitiveness [9], and SDG 9 (Industry, Innovation, and Infrastructure) by promoting innovation in food quality assurance through AI-based technology [10].

Previous studies have shown that traditional machine learning algorithms, such as Random Forest and Support Vector Machines, can support food quality evaluation, but their reliance on handcrafted features limits robustness under diverse real-world conditions [11][12]. The development of deep learning, particularly convolutional neural networks, has enabled end-to-end feature extraction and significantly improved accuracy in food quality assessment. This progress is reflected in the adoption of YOLO-based models, where earlier versions such as YOLOv3 and YOLOv5 demonstrated strong performance in tasks including Asian food recognition and mold detection on food surfaces [13][14]. However, these models still face challenges in multi-class detection due to anchor-based mechanisms, difficulty distinguishing visually similar classes, and reduced robustness under variable lighting and texture conditions commonly found in MSMEs. Compared to earlier YOLO versions, YOLOv8 eliminates anchor-based prediction, uses a decoupled detection head for faster convergence, and employs Distribution Focal Loss (DFL) to improve localization accuracy, particularly for small and visually similar food items. These architectural improvements make YOLOv8 more suitable for multi-class staple food detection at the MSME level. [15][16]. YOLOv8 has been successfully applied in quality assessment tasks such as biscuit inspection and large-scale food image classification, demonstrating improved performance over previous YOLO versions [5][17].

Despite these advancements, empirical studies applying YOLOv8 to multi-commodity staple food quality, particularly involving rice (*beras*), cooking oil (*minyak goreng*), milk (*susu*), and meat (*daging*) remain limited. Detecting multiple food categories simultaneously is more complex than single-product detection, as models must recognize variations in texture, color, and lighting [18]. For MSMEs that handle diverse products, robust multi-class detection is therefore both technically challenging and practically essential [19]. This study focuses on MSMEs in Bali, where food production underpins both local consumption and the tourism economy. As a major tourist destination, Bali demands high food quality standards to protect consumers and sustain its global reputation [20]. However, many small-scale MSMEs still struggle with consistent quality due to limited technological access. Implementing AI-based detection helps address these issues, improving food quality management and promoting sustainable MSME growth in the region.

Despite the potential of deep learning, MSME adoption remains low due to limited data, AI literacy, and access to image based technology [21]. Thus, this research develops an automated YOLOv8-based detection system for staple food quality, focusing on MSMEs in Bali [22]. The novelty of this research lies in being one of the first to apply YOLOv8 for the detection and analysis of multiple staple food items at MSMEs, including various categories of *Beras (Beras_Bagus_Utuh, Beras_Patah, Beras_Kekuningan, Beras_Rusak_Mengapur*) [23], *Minyak Goreng (MG Murni, MG Terpakai, MG Jelantah)* [24], *Susu (Susu Murni, Susu Campuran, Susu Tidak Segar)* [25], *and Daging (Daging_Ayam_Segar, Daging_Ayam_Busuk, Daging_Sapi_Segar, Daging_Sapi_Busuk)* [26][27].

This research follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, which includes dataset collection, image preprocessing, YOLOv8 model training and evaluation, and system deployment through a web platform to support MSMEs in ensuring food quality, enhancing efficiency, and reducing manual dependency. Image datasets of staple foods (rice, cooking oil, milk, and meat) were collected from MSMEs in Badung Regency, Bali, and preprocessed through annotation in YOLOv8 format using Roboflow and augmentation techniques to improve model robustness [28] [29].

YOLOv8 was selected for its high accuracy and real-time detection capability [30]. Two model variants, YOLOv8s and YOLOv8m, were compared to determine the best balance between detection accuracy and processing speed. Model performance was evaluated using mAP50, Precision, Recall, and F1-score metrics [31]. The CRISP-DM framework guided all stages: Business Understanding identified MSME needs; Data Understanding and Preparation ensured dataset quality; Modeling involved training YOLOv8s and YOLOv8m; Evaluation analyzed results; and Deployment implemented the best model into a web-based detection system that enables MSMEs to upload product images and automatically receive quality assessments [32].

This integration of AI-based detection into a structured CRISP-DM workflow promotes innovation and sustainability in MSME food quality management. Beyond system development, this research also provides AI training for MSMEs to strengthen product quality assurance, improve competitiveness, and contribute to achieving the Sustainable Development Goals related to food security and industrial innovation.

## 2. RESEARCH METHOD

This study utilizes the YOLOv8 (You Only Look Once) framework to assess food quality through image based analysis. YOLO is a real-time object detection system based on a Convolutional Neural Network (CNN) that process the entire image at once to identify objects and their locations efficiently [33].

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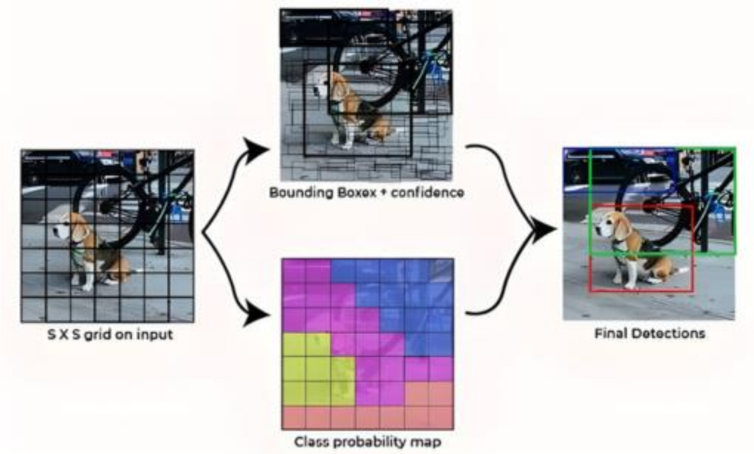



Figure 1. YOLO system model

The YOLO algorithm begins by dividing the input image into an S×S grid, where each cell predicts bounding boxes with corresponding confidence scores derived from the product of object presence probability and Intersection over Union (IoU) values. Non-Maximum Suppression (NMS) is applied to remove redundant detections, ensuring precise results [34] [35].

The model's performance is evaluated using standard metrics, including precision, recall, and mean Average Precision (mAP), which are calculated as in (1), (2), and (3).

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$mAP = \sum_{i=1}^{N} \frac{AP(i)}{N} \ x \ 100\% \tag{3}$$

To assess the balance between precision and recall, an additional metric known as F1-Score is used. F1-Score is a measure that calculates the harmonic average of precision and recall. The F1-Score value can be obtained by using the formula as in (4).

$$F1 - Score = \frac{2 \ x \ Precision \ x \ Recall}{Precision + Recall} \tag{4}$$

YOLOv8 [36] introduces key improvements over its predecessors. It delivers faster and more accurate object detection, features a more compact and efficient model design, and incorporates enhanced feature extraction techniques that boost detection precision. Additionally, its multi-scale capability enables effective recognition of objects of various sizes within a single image, while its ability to detect multiple objects simultaneously and maintain high accuracy even in large, high-resolution images makes YOLOv8 a highly reliable and versatile object detection model.

This study adopts the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology, a widely used framework for data-driven projects. CRISP-DM provides a structured approach through six iterative phases: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment [37]. These stages are outlined below:

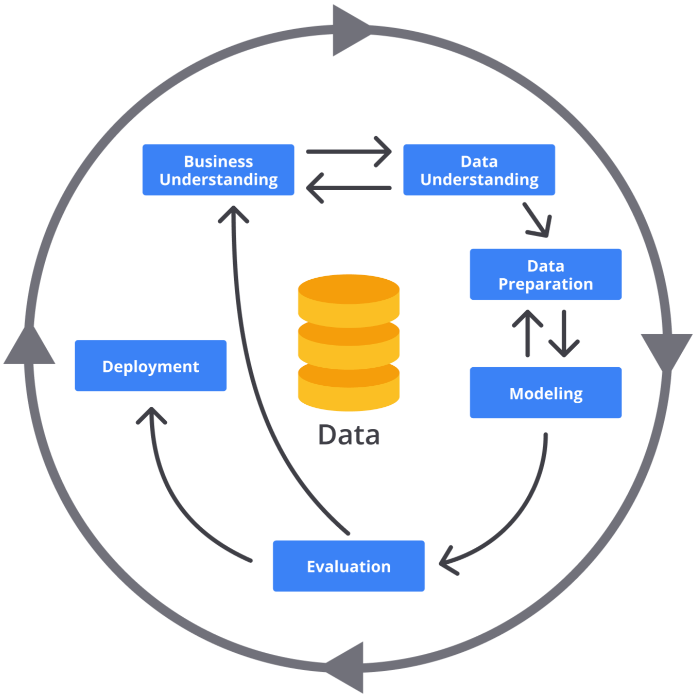



Figure 2. CRISP-DM Method

Table 1. Research Workflow Based on the CRISP-DM Approach

| Aspect | Details |
|---|---|
| Phase 1: Business Understanding | The Business Understanding phase identified the core challenges faced by MSMEs in Bali, including limited access to standardized quality assessment and reliance on subjective manual inspection. |
| Phase 2: Data Understanding | In the Data Understanding phase, food images of rice, cooking oil, milk, and meat were collected and analyzed to examine class variability and dataset suitability. |
| Phase 3: Data Preparation | The Data Preparation phase involved annotation using Roboflow and the application of controlled augmentations to improve generalization, followed by dataset partitioning into training, validation, and testing subsets. |
| Phase 4: Modeling | In the Modeling phase, two YOLOv8 variants (YOLOv8s and YOLOv8m) were trained using standardized hyperparameters to evaluate accuracy–speed trade-offs. |
| Phase 5: Evaluation | The Evaluation phase assessed model performance through mAP50, precision, recall, and F1-score to determine the most suitable model for practical deployment. |
| Phase 6: Deployment | In the Deployment phase, the best-performing model was integrated into a web-based application that enables MSMEs to upload images and obtain automated quality assessments. |

## 3. RESULTS AND DISCUSSION

This study was developed using the CRISP-DM framework, which provides a structured six-phase process to guide the design and implementation of the YOLOv8-based staple food quality detection system. The framework ensures that each stage, from problem identification to system deployment, is aligned with the operational needs of MSMEs in Bali. A summary of the stages and their key outputs is presented in the research workflow diagram. Here is a detailed description and progress of the completion for each stage in several sub-sections [32].

### 3.1. Phase 1: Business Understanding

The initial phase identified the core challenges faced by food MSMEs in Bali in assessing the quality of staple foods such as rice, oil, milk, and meat. Interviews with MSME food partners (UD. Sony Jaya) revealed limitations in expert availability, inconsistent quality standards, and the absence of adequate laboratory facilities, resulting in subjective manual evaluations. These conditions highlight the need for an automated system capable of providing fast, objective, and standardized food quality assessment [38].

As discussed earlier in the introduction section, several studies have demonstrated the effectiveness of computer vision and deep learning for food quality detection. However, most studies focused on a single food type and relied on traditional machine learning or earlier YOLO versions. Comprehensive analyses using YOLOv8 for detecting the quality of multiple staple foods such as rice, cooking oil, milk, and meat under different MSME-level conditions remain limited. Moreover, comparisons between YOLOv8 variants, particularly YOLOv8s and YOLOv8m, have not yet been explored. Therefore, this study aims to address these gaps by rigorously evaluating model performance and adopting the CRISP-DM framework to guide implementation from MSME needs analysis to web-based model deployment.

Based on the results of the identification of field needs and the support of the latest literature, this study then sets the main goal of developing an automatic detection system based on YOLOv8 in the assessment of the quality of staple foods. This system is expected to be able to provide practical solutions for MSMEs, while being in line with food quality assurance standards set by the government [39], so that business sustainability and consumer trust in local food products can be improved.

### 3.2. Phase 2: Data Understanding

This stage focuses on collecting and analyzing the food image dataset used in the study. Data acquisition was carried out in collaboration with an MSME food partner in Badung Regency (UD. Sony Jaya), which provided samples of rice, cooking oil, milk, and meat. Image collection followed these specifications:

a. The food image was taken using a smartphone camera with a 9 MP main camera, the original image resolution produced was 3024x3024 pixels [40].
b. The shooting distance was adjusted to the object size, not exceeding one meter [41].
c. The image was taken on a location with sufficient lighting [41].

A total of 483 images were collected, and all images were then classified based on categories, namely rice / *beras* (*Beras_Bagus_Utuh, Beras_Patah, Beras_Kekuningan, Beras_Rusak_Mengapur*) [23], cooking oil / *minyak goreng* (*MG_Murni, MG_Terpakai, MG_Jelantah*) [24], milk / *susu* (*Susu_Murni, Susu_Campuran, Susu_Tidak_Segar*) [25], and meat / *daging* (*Daging_Ayam_Segar, Daging_Ayam_Busuk, Daging_Sapi_Segar, Daging_Sapi_Busuk*) [26][27] refers to the applicable food quality standards in Indonesia [23]. Although the dataset size was limited, it reflects real MSME conditions where image collection is constrained by production scale and resources. Figure 3 below is a representation of all classes used in food quality detection research.

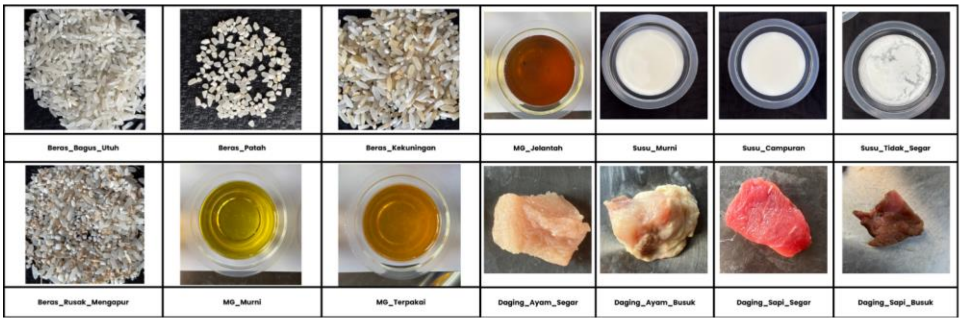
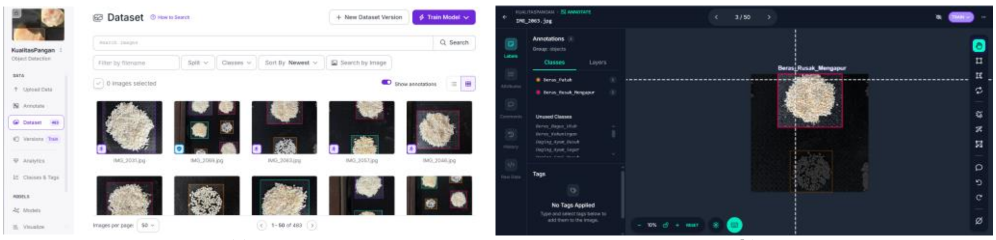



Figure 3. Food Quality Dataset

### 3.3. Phase 3: Data Preparation

All images were annotated using Roboflow to ensure accurate object localization, as annotation quality strongly affects YOLO-based performance [42]. Figure 4(a) show all the images in the dataset and 4(b) shows the image annotation process carried out using Roboflow.



(a) (b)

Figure 4. (a) All images in the dataset and (b) Annotation Process with Roboflow

All images were resized to 512×512 pixels to reduce computational load and ensure efficient processing during model training. To improve generalization across diverse real-world MSME conditions, several augmentation techniques were applied, including: (1) horizontal and vertical flips to handle varied object orientations; (2) rotations between –15° and +15° to simulate different shooting angles; (3) brightness adjustments of –20% to +20% to reflect inconsistent lighting; (4) mild blurring up to 1 pixel to account for camera shake or lower-quality devices; and (5) noise injection up to 1% of pixels to increase robustness against visual artifacts. These augmentations were selected based on the characteristics of food images that have a diversity of shooting conditions, both in terms of orientation, lighting, and camera capture quality [43]. Figure 5(a), 5(b), and 5(c) below is a detailed process and the results of augmentation carried out in the research.


(a) (b) (c)

Figure 5. (a) Image Augmentation, (b) Original Image, and (c) Image After Augmentation Examples with Roboflow

During data preparation, randomized data augmentation was applied with an output setting of three images per original sample, due to the limitations of the Roboflow package used. Each original image generated three random augmentations from the predefined combination methods, ensuring sufficient data diversity despite the limited number of augmented images. This randomization effectively improves model generalization by exposing the model to different image variations in each epoch, thereby reducing the risk of overfitting [43]

The initial dataset consisted of 483 images divided by the Pareto principle: 60% training data (290 images), 20% validation data (97 images), and 20% testing data (96 images). Of these, only training data was increased, so that the total training data increased to 870 images [39]. This approach aims to enrich the diversity of data used for model learning, allowing the YOLOv8 model to recognize food object patterns under various conditions more effectively.

Validation and testing datasets were intentionally left unaugmented to maintain their representativeness of real-world conditions. This aligns with standard machine learning practices, where validation data is used for model tuning and testing data for evaluating generalization performance. Augmenting these datasets could bias evaluation results by altering the original data distribution [44]. Hence, this strategy ensures that the training process benefits from increased data diversity, while model evaluation remains objective and reflective of actual field conditions.

### 3.4. Phase 4: Modelling

This stage focuses on developing YOLOv8 models for food quality detection using two variants, YOLOv8s (small) and YOLOv8m (medium), trained on the prepared dataset. Here are the steps in the modeling process.

1) Library Installation and Dataset Preparation
   The process begins with installing essential libraries: ultralytics (for YOLOv8), roboflow (for dataset retrieval), and pandas and matplotlib (for analysis and visualization). Datasets are downloaded from Roboflow via API key and formatted to YOLOv8 standards, containing annotated images of staple foods. Model training was conducted in Visual Studio Code 1.104.0 using Python 3.10.9.
2) YOLOv8 Model Initialization
   Both YOLOv8s and YOLOv8m were initialized with pre-trained weights from the *ultralytics* library. Model structure and computational complexity were reviewed using the *model.info(verbose=True)* function [45].

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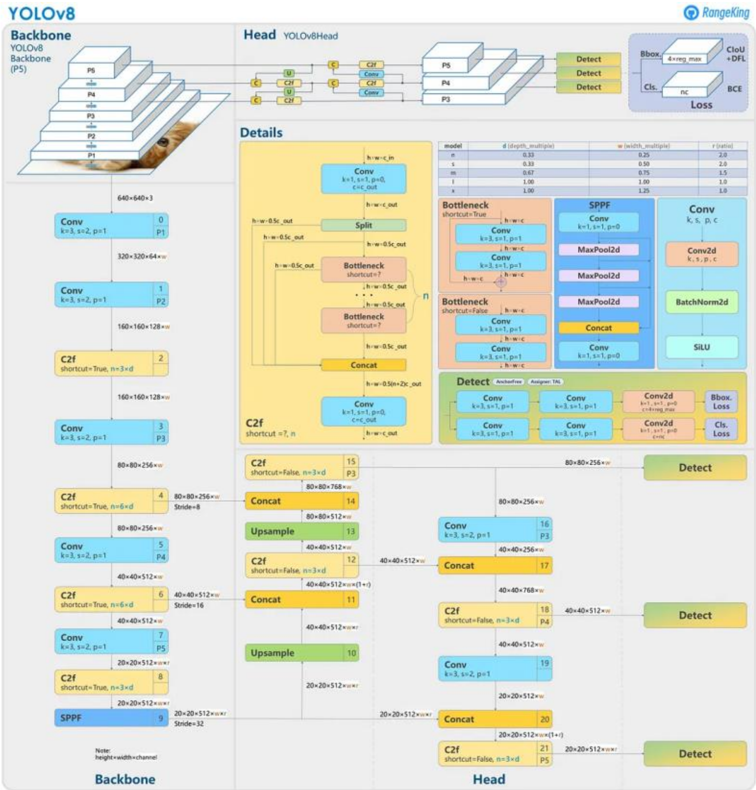

Figure 6. YOLOv8 Architecture [46]

The YOLOv8 architecture consists of Backbone (sequential Conv layers, C2f blocks for efficient gradient flow, and SPPF for multi-scale context extraction), Neck (FPN/PAN structure for multi-resolution feature fusion), and Head (decoupled, anchor-free detection head using Distribution Focal Loss (DFL) and CIoU for optimization). YOLOv8s (~11M parameters, 28 GFLOPs) offers faster inference and is suitable for limited hardware, while YOLOv8m (~26M parameters, 79 GFLOPs) provides higher accuracy with greater computational demands. Both models were trained for 50 epochs using 512×512 image resolution, batch size 16, learning rate 0.01, and SGD optimizer. The best-performing model weights were saved for evaluation [47].

### 3.5. Phase 5: Evaluation

The next stage is evaluation, which focuses on measuring the performance of the training outcome model. Two variants of the model, namely YOLOv8s and YOLOv8m, have been compared based on performance in training, validation, testing (predict), and evaluation of key metrics such as mAP50, precision, recall, and F1-score. The following is a description of the results of the model performance evaluation that has been carried out.

#### 3.5.1. Training Process

The training process for both models, YOLOv8s (small) and YOLOv8m (medium), was carefully monitored through the trends of loss functions and validation metrics. This monitoring was essential to ensure that the models converged properly without signs of overfitting.

Table 2. Comparison of YOLOv8s and YOLOv8m Training Performance and Accuracy Metrics

| Aspect | YOLOv8s (Small Model) | YOLOv8m (Medium Model) |
|---|---|---|
| Total Parameters | 11.1 million | 25.9 million |
| Total Training Time | 2.96 hours | 6.35 hours |
| Average Training Time per Epoch | 3.55 minutes (213 seconds) | 7.62 minutes (457 seconds) |
| Training Duration | 50 epochs (~55 batches/epoch) | 50 epochs (~55 batches/epoch) |
| Classification Loss (Epoch 1 → 50) | 2.559 → 0.274 | 2.631 → 0.330 |
| mAP50 | 0.971 | 0.979 |
| Key Strengths | Faster training, efficient on limited hardware | Higher precision and better generalization in evaluation |
| Remarks | Ideal for lightweight deployment | More accurate for production or industrial-scale use |

### 3.5.2. Validation Process

The validation process functions as an early warning system that monitors the development of the model periodically. Each epoch, the model is tested on a validation dataset separate from the training data to observe whether the model is truly learning or stagnant, overfitting detection, and convergence stability. The following is an explanation of the validation results in Figure 7 and Figure 8, as well as Table 3.

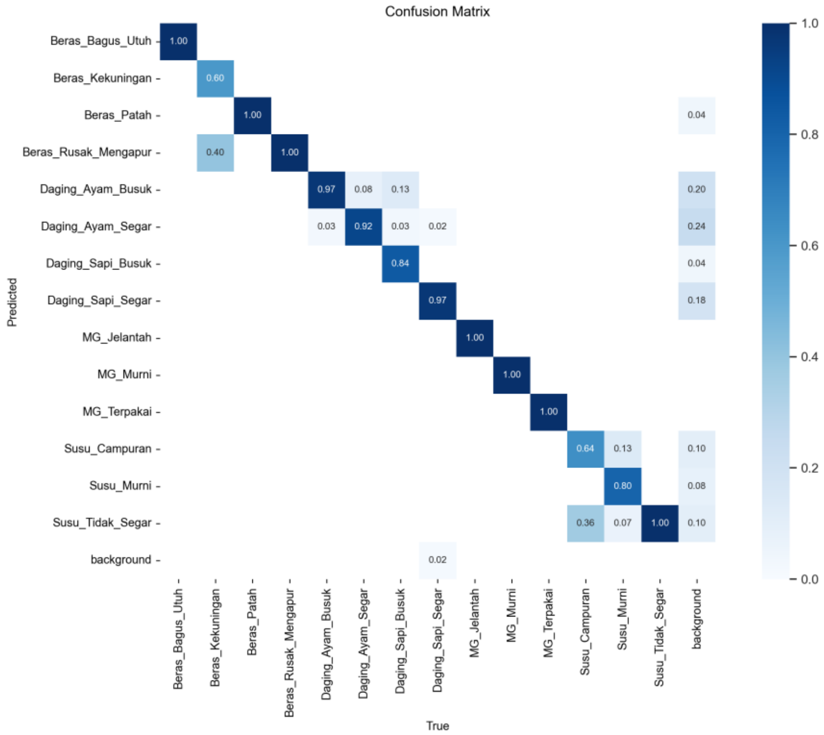


Figure 7. Confusion Matrix Data Validation with YOLOv8s

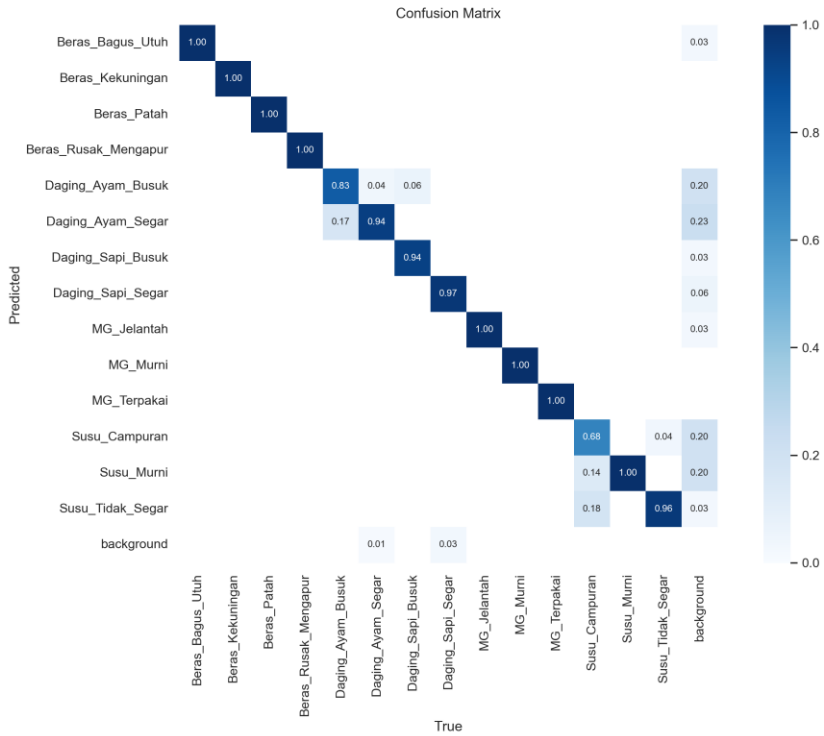


Figure 8. *Confusion Matrix* Data *Validation* with YOLOv8m

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Table 3. Confusion Matrix Data Validation Results

| Model | mAP50 | Precision | Recall | Parameter |
|---|---|---|---|---|
| YOLOv8s | 0.971 | 0.923 | 0.909 | 11.1 M |
| YOLOv8m | 0.979 | 0.948 | 0.945 | 25.9 M |

The performance evaluation indicates that the YOLOv8m model consistently outperformed the YOLOv8s variant across all evaluation metrics. In terms of precision, YOLOv8m achieved a value of 94.8%, which is higher than the 92.3% obtained by YOLOv8s, indicating a lower rate of false positive detections. Similarly, the recall of YOLOv8m reached 94.5%, surpassing YOLOv8s at 90.9%, demonstrating a stronger capability in identifying relevant objects and reducing false negatives. Both models exhibited excellent detection accuracy, with mAP50 values exceeding 97%. However, YOLOv8m achieved a slightly higher mAP50 of 97.9% compared to 97.1% for YOLOv8s, confirming its superior overall performance in the context of food quality detection.

### 3.5.3. Testing Process

The testing process is the final evaluation stage that determines the success of the model in handling completely new and never-before-seen data. The following is a comprehensive analysis based on the results of testing on 96 images. The following is an explanation of the results of testing (predict) in Figure 9 and Figure 10, as well as Table 4, Table 5, and Table 6.

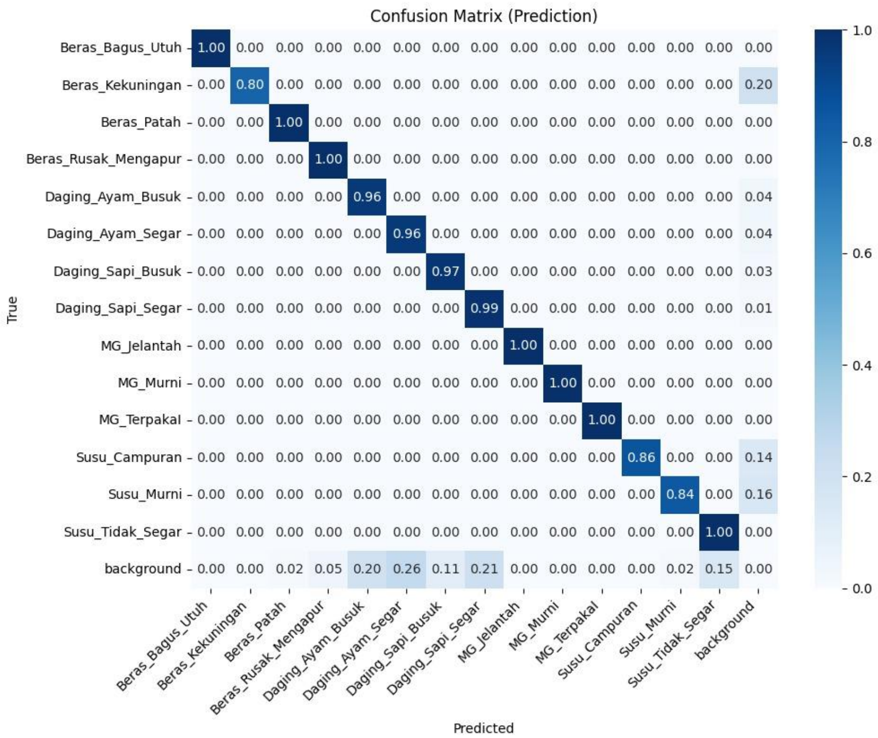


Figure 9. Confusion Matrix Data Testing with YOLOv8s

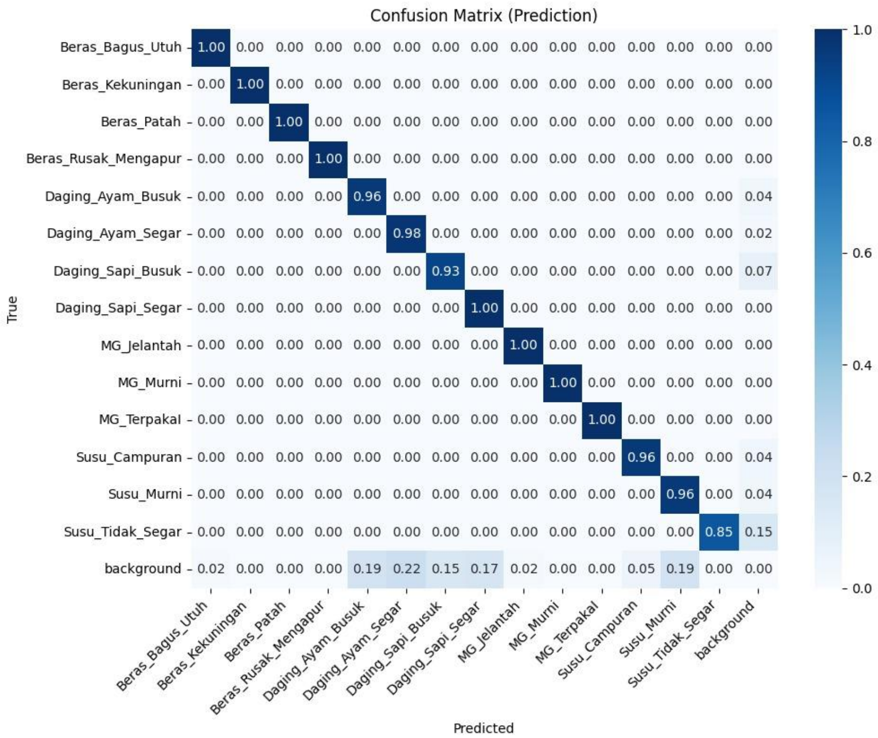


Figure 10. Confusion Matrix Data Testing with YOLOv8m

Table 4. Confusion Matrix Data Testing Results

| Model | mAP50 | Precision | Recall | F-1 Score |
|---|---|---|---|---|
| YOLOv8s | 0.9524 | 0.934 | 0.897 | 0.915 |
| YOLOv8m | **0.9651** | **0.951** | **0.932** | **0.941** |
| Difference | **+0.013** | **+0.017** | **+0.035** | **+0.026** |

An in-depth evaluation of each performance metric further confirms the consistent advantages of the YOLOv8m model over YOLOv8s. The YOLOv8m variant achieved an accuracy of 96.51%, outperforming YOLOv8s by a margin of 1.27%, which indicates a more reliable detection capability. In addition, both models demonstrated strong generalized stability, maintaining performance levels above 95% that were consistent with the validation results, thereby reflecting excellent robustness. The observed performance margin of 1.27% further suggests that YOLOv8m possesses a meaningful advantage in handling variations in previously unseen data, reinforcing its suitability for real-world food quality detection tasks.

Table 5. Detection Analysis by Food Category

| Aspect | Details |
|---|---|
|   Figure 11. Rice category prediction results (Example: IMG_2076.jpg) | a. Multi-detection of 4 rice classes in one frame.<br>b. High classification precision: B*eras_Bagus_Utuh*, *Beras_Patah*, *Beras_Kekuningan*, and *Beras_Rusak_Mengapur*<br>c. Challenge resolved: small object size & similar visual characteristics handled well |

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Figure 12. Meat category prediction results (Example: IMG_2259.jpg, IMG_5177.jpg)

a. High Complexity: Detect up to 15+ objects in *dense* frames
b. Meat Type Differentiation: Differentiate *Daging_Ayam_Segar, Daging_Ayam_Busuk, Daging_Sapi_Segar, Daging_Sapi_Busuk* simultaneously.
c. Condition Variance: Handle variations in texture, color, and shape in non-uniform rotten conditions

Figure 13. Milk category prediction results (Example: IMG_2303.jpg)

a. Mass detection: 12+ milk objects identified
b. Fine-grained classification: *Susu_Murni, Susu_Campuran,* and *Susu_Tidak_Segar*
c. Complex environment: robust in varied lighting & backgrounds

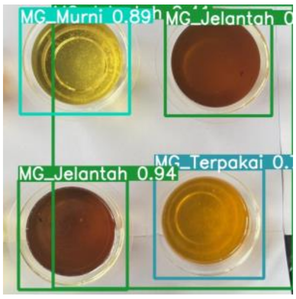

Figure 14. Oil category prediction results (Example: IMG_2103.jpg)

a. Transparent objects: successful detection despite transparency
b. Accurate classification: *MG_Murni, MG_Terpakai,* and *MG_Jelantah.*

Table 6. Quantitative Analysis Based on Detection Logs

| Aspect | Details |
|---|---|
| YOLOv8s – Quantitative | 1. ~450+ bounding boxes (96 images)<br>2. Avg. 4.7 detections/image<br>3. Max 15+ objects/frame (IMG_2285)<br>4. Inference speed: 65.4 ms/image (15.3 FPS) |
| YOLOv8m – Quantitative | 1. ~480+ bounding boxes (96 images)<br>2. Avg. 5.0 detections/image<br>3. Max 16+ objects/frame (IMG_5158)<br>4. Inference speed: 147.1 ms/image (6.8 FPS) |
| Error & Limitations | 1. False Positives (Overlap): duplicate detections when objects overlap (high IoU).<br>2. False Negatives (Small Objects): objects <20px missed, especially in poor lighting. Error analysis showed that both models often failed to detect objects smaller than 20 pixels, especially in poor lighting. This issue stems from the 512×512 input size, which limits detail for tiny objects, and YOLOv8's FPN/PAN design that favors medium-to-large features. Improving small object detection may require higher resolution or attention-based enhancements. |
| Testing Conclusion | Although YOLOv8s achieved higher processing speed (15.3 FPS) than YOLOv8m (6.8 FPS), the MSME partner (UD. Sony Jaya) prioritized detection precision over speed, considering the 1.27% accuracy gain of YOLOv8m (mAP50 96.51%) more valuable for minimizing misclassification in product quality control. During pilot testing, users reported that YOLOv8m's slower inference speed remained acceptable for desktop-based operations, as detection accuracy directly impacted decision-making reliability and reduced the need for manual rechecking. Thus, while YOLOv8s offers advantages for lightweight and mobile deployments, YOLOv8m was deemed more appropriate for scenarios where precision and consistency hold greater operational importance, reaffirming that model selection should align with user priorities and real-world application needs. |

The performance of the YOLOv8-based model developed in this study demonstrates competitive results compared to similar research in food quality detection. The YOLOv8m model achieved 96.51% mAP50, 95.1% precision, 93.2% recall, and a 94.1% F1-score across 14 classes representing rice, cooking oil, milk, and meat quality attributes. Although these values are slightly lower than those reported in YOLOv5-based mold detection [14], the comparison must consider the substantial difference in task complexity, as prior works generally focused on single-product datasets with homogeneous visual features. In contrast, this study addresses multi-commodity, multi-class detection involving diverse textures, colors, and lighting variations typical of MSME environments. The results align with improvements reported in recent YOLOv8 applications, and its anchor-free architecture with a decoupled head further enhances adaptability to heterogeneous object shapes, offering advantages over YOLOv3 and YOLOv5. Similar studies using YOLOv8 for biscuit quality inspection [5] and soybean defect detection [15] also demonstrate strong performance, and the results obtained here fall within this performance range while extending the model's applicability to a more challenging multi-commodity context. Despite the strong overall performance, some misclassifications occurred in visually similar categories, particularly between *Beras_Bagus_Utuh* and *Beras_Patah*, and between *MG_Terpakai* and *MG_Jelantah*. These errors primarily contributed to false negatives and reflect the high intra-class similarity within staple food categories. Future work may incorporate lighting normalization or texture-sensitive feature enhancement to mitigate such issues. In addition, the dataset used in this study was collected under relatively uniform lighting and background conditions, which does not fully represent the variability typically encountered in MSME environments. This limitation affected the model's robustness, particularly for classes with subtle color differences under low-light or uneven illumination. Future work should include expanding data collection across diverse lighting conditions, image qualities, and capture devices to improve generalization in real-world scenarios. Overall, the comparative analysis indicates that the YOLOv8m model is highly competitive and operationally robust, validating its feasibility for real-world MSME food quality assessment and demonstrating strong generalization across multiple staple food categories.

### 3.6. Phase 6: Deployment

The final stage of this research was the deployment of the food quality detection model into a web-based system accessible to end users titled "*Deteksi Kualitas Pangan* – YOLOv8". The system architecture is structured as follows:

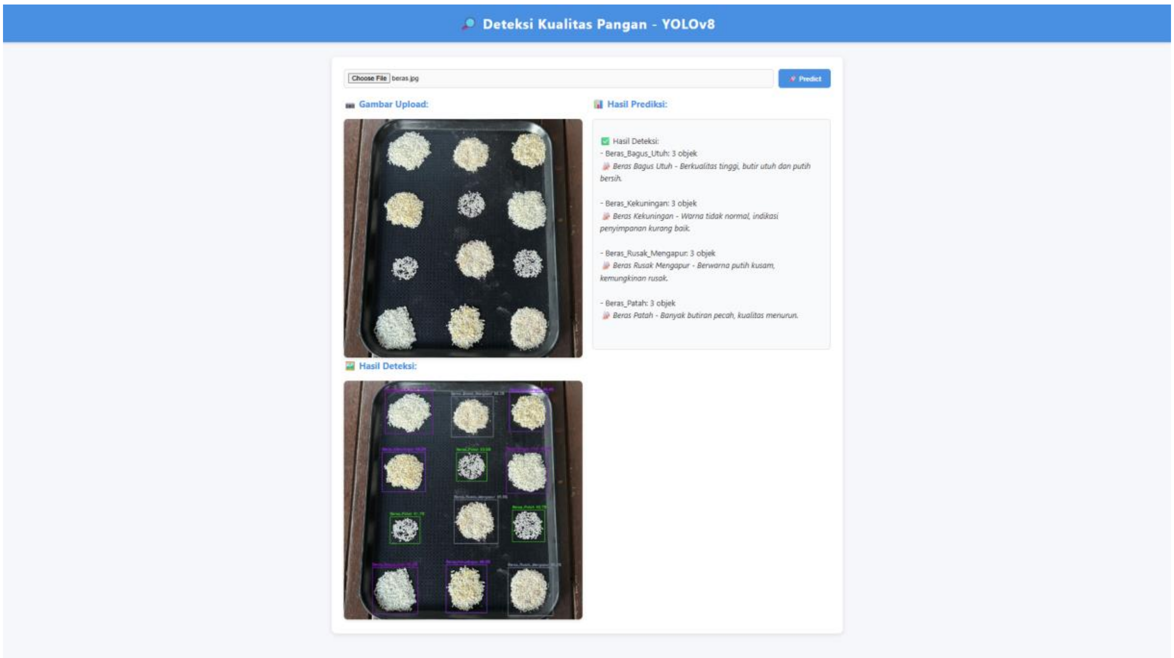


Figure 15. Food *Quality Detection* Website Design

The web-based application developed in this study is designed to support automated food quality detection using the YOLOv8 deep learning model. The top section of the interface presents the title "Deteksi Kualitas Pangan – YOLOv8," indicating the core function of the system. Users can upload food images, such as rice samples, through the image upload panel, and the selected image is immediately displayed to ensure correct file selection. Once the image is uploaded, the detection process is initiated by activating the prediction function, which triggers the YOLOv8-based analysis.

After the prediction is completed, the system displays the detection results in a dedicated results panel. This section presents the detected food quality categories, the number of objects identified for each class, and a brief explanation of the physical condition associated with each category to support interpretation of the results. In addition, the processed image output is shown in the detection visualization area, where bounding

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boxes are drawn around each detected object. Each bounding box is accompanied by a color-coded class label and a confidence score, representing the model's certainty level. The overall system integrates the YOLOv8m model within a Flask-based backend and a Bootstrap-based frontend, ensuring seamless processing and a responsive user interface suitable for practical use by food MSMEs.

## 4. CONCLUSION

This study developed a deep learning–based system for detecting the quality of staple foods rice, meat, cooking oil, and milk using YOLOv8. The YOLOv8m model achieved the best performance, with an mAP50 of 0.9651 (96.51%), demonstrating strong detection capability across multiple categories and realistic conditions. The web-based deployment confirmed the model's practical potential for real-time food quality assessment among MSMEs.

Despite its promising results, this study is limited by the relatively small dataset, which may affect generalization. Future work will expand the dataset through collaboration with more MSMEs and apply model optimization techniques such as quantization and pruning to improve inference speed while maintaining accuracy.

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## CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

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