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Benchmarking CNN and YOLO Models for Automated Classification of Fish Freshness

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Abstract
Fish freshness assessment is essential for ensuring food quality and consumer safety; however, conventional visual inspection remains subjective and inconsistent. Although deep learning has shown promising performance in image classification, standardized benchmarking of Convolutional Neural Networks (CNN) and YOLOv8 Classification under identical experimental settings for fine-grained fish freshness classification remains limited. This study compares both models using the same dataset, preprocessing pipeline, augmentation strategy, and training configuration to evaluate predictive performance and computational efficiency. The dataset comprised digital images of tongkol and slungsung fish categorized into four classes: Fresh Tongkol, Rotten Tongkol, Fresh Slungsung, and Rotten Slungsung. Model performance was evaluated using accuracy, precision, recall, F1-score, training time, and inference speed. CNN achieved superior predictive performance with 99.25% accuracy, 99.13% precision, 99.13% recall, and 99.13% F1-score, whereas YOLOv8 Classification achieved 89.88% accuracy, 89.96% precision, 89.88% recall, and 89.89% F1-score. Conversely, YOLOv8 required only 15 minutes for training and 9 ms per image for inference, compared with 23 minutes 20 seconds and 18 ms for CNN. These findings establish a robust benchmark for selecting deep learning architectures by balancing predictive accuracy and computational efficiency in automated fish freshness inspection systems.

Keywords: computer vision; convolutional neural network; fish freshness assessment; food quality inspection; yolov8 classification

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INTRODUCTION

Ensuring fish freshness is fundamental to food safety, consumer protection, and the economic sustainability of the seafood industry. Seafood is one of the most perishable food commodities because of its high moisture content, active endogenous enzymes, and rapid microbial proliferation after harvesting, which accelerate quality deterioration and shorten shelf life (Madhubhashini et al., 2024; Zheng et al., 2026). Consequently, accurate freshness evaluation is essential throughout harvesting, transportation, storage, and retail distribution to maintain product quality, improve supply chain management, and minimise post-harvest losses (Sattar et al., 2025) Conventional freshness assessment primarily relies on sensory inspection of external attributes, including eye transparency, gill colour, skin appearance, and body texture. Although these indicators remain widely adopted in the seafood industry, sensory evaluation is inherently subjective, labour-intensive, and highly dependent on the expertise and consistency of individual inspectors (Yildiz et al., 2024). Such limitations often lead to inconsistent quality assessment across different operational environments, reducing consumer confidence and limiting the effectiveness of standardised quality control systems. Therefore, recent advances in computer vision integrated with artificial intelligence have emerged as promising non-destructive alternatives capable of providing rapid, objective, and automated freshness evaluation, making them increasingly suitable for intelligent seafood inspection and Industry 4.0 applications.

Computer vision integrated with deep learning has become one of the most promising approaches for intelligent food quality assessment because it can automatically learn discriminative visual representations directly from digital images (Chhetri, 2024; Kaushal et al., 2024; Kumar et al., 2026; Lun et al., 2025; Shen et al., 2024). Unlike conventional image processing methods that rely on handcrafted features, deep learning algorithms are capable of extracting hierarchical representations that improve robustness against variations in illumination, background, and object appearance (Liao et al., 2026). Recent developments have demonstrated successful applications in seafood quality evaluation, species identification, defect detection, and freshness prediction using visible-light imaging and convolution-based feature extraction (Dhal & Kar, 2025; Falahatnejad et al., 2025). The transition from conventional image processing toward end-to-end deep learning has substantially improved classification accuracy, scalability, and deployment capability in practical inspection systems. Furthermore, current research increasingly emphasises lightweight architectures, explainable artificial intelligence (XAI), edge computing, and real-time inference to facilitate smart food processing, automated quality inspection, and Industry 4.0 implementation (Liakos et al., 2025).

Among deep learning architectures, Convolutional Neural Networks (CNNs) remain one of the most widely adopted frameworks for image classification because hierarchical feature learning enables automatic extraction of low-level textures, colour patterns, and high-level semantic information from images (Kaushal et al., 2024; Lin et al., 2023). This capability makes CNNs particularly effective for fine-grained recognition tasks, including fish freshness assessment, where subtle visual changes in the eyes, gills, and skin indicate different freshness levels (Yildiz et al., 2024). Meanwhile, the introduction of YOLOv8 Classification extends the YOLO framework beyond object detection by providing a lightweight classification architecture with high computational efficiency and fast inference, making it suitable for real-time quality inspection (Gao et al., 2024; Mukhiddinov et al., 2022). Consequently, CNN and YOLOv8 Classification represent two complementary architectural paradigms, with CNN focusing on robust feature representation and YOLOv8 Classification emphasising computational efficiency for practical deployment (Chen et al., 2026).

Although considerable progress has been achieved in applying deep learning to fish freshness assessment, several research gaps remain to be addressed. Most existing studies evaluate only a single deep learning architecture, making it difficult to perform direct and fair comparisons because differences in datasets, preprocessing techniques, and training strategies may substantially influence the reported results (Huang et al., 2024; Zhao et al., 2025). Moreover, model performance is commonly assessed using predictive metrics such as accuracy, precision, recall, and F1-score, while computational aspects including training efficiency, inference speed, and deployment feasibility are often overlooked (Gao et al., 2024; Hou et al., 2025). Another limitation is that many studies focus on binary freshness classification or a single fish species, which restricts the applicability of their findings to more realistic multiclass freshness recognition scenarios (Yildiz et al., 2024). Previous studies have also emphasised that comprehensive benchmarking under consistent experimental settings is essential for producing objective, reproducible, and practically meaningful comparisons between deep learning models (Ridwan et al., 2026).

Accordingly, this study benchmarks CNN and YOLOv8 Classification using an identical dataset, preprocessing pipeline, augmentation strategy, hyperparameter configuration, and evaluation protocol for multiclass fish freshness classification involving tongkol and slungsung fish. Performance is evaluated from two complementary perspectives: predictive capability through accuracy, precision, recall, and F1-score, and computational efficiency through training time and inference speed. The novelty of this study lies in establishing a standardised benchmarking framework that systematically analyses the trade-off between representation quality and computational efficiency under controlled experimental conditions. The findings contribute to computer vision research by providing empirical evidence for architecture selection in fine-grained food quality assessment while offering practical guidance for developing automated fish freshness inspection systems across laboratory, industrial, and real-time deployment environments

METHOD

This study employed a quantitative comparative experimental design to benchmark the predictive performance and computational efficiency of CNN and YOLOv8 Classification for automated fish freshness classification. A comparative benchmarking approach was adopted because it enables a fair evaluation of different deep learning architectures under identical experimental conditions, ensuring that observed performance differences primarily reflect architectural characteristics rather than variations in data preparation or training configurations. Such controlled experimental designs have become the standard approach for evaluating deep learning models in image classification research and provide more reliable evidence for selecting appropriate architectures for practical applications (Kaushal et al., 2024; Zheng et al., 2026)

The dataset consisted of digital images of tongkol (Euthynnus affinis) and slungsung fish collected from local fish markets in Bali, Indonesia. Four classification categories were defined, namely Fresh Tongkol, Rotten Tongkol, Fresh Slungsung, and Rotten Slungsung. Initially, 400 original images were acquired, with 100 images representing each category. To improve data diversity and reduce model bias, image acquisition was conducted under different illumination conditions, viewing angles, object orientations, and background settings. Subsequently, preprocessing and augmentation increased the dataset to 3,200 images, resulting in 800 images per class. The adoption of diverse acquisition conditions and augmentation techniques is widely recognised as an effective strategy for improving model generalisation and reducing overfitting in computer vision applications.

Prior to model training, all images underwent preprocessing to standardise visual quality and improve the visibility of freshness-related characteristics. The preprocessing pipeline consisted of image resizing to 224 × 224 pixels, pixel normalisation, gamma correction, and noise reduction. Data augmentation was subsequently performed through random horizontal flipping, rotation, translation, zooming, and brightness adjustment to simulate variations commonly encountered during real-world image acquisition. These procedures improve model robustness by increasing data diversity while preserving essential visual characteristics associated with fish freshness. The augmented dataset was then divided into training (80%), validation (10%), and testing (10%) subsets using stratified sampling to maintain balanced class distributions across all experimental stages.

The CNN model was implemented using the TensorFlow–Keras framework with convolutional, max-pooling, fully connected, and Softmax output layers for multiclass classification. Model training employed the Adam optimizer (learning rate = 0.001), a batch size of 32, and 50 epochs using categorical cross-entropy loss. YOLOv8 Classification was implemented through the Ultralytics framework using identical image resolution, preprocessing, augmentation, dataset partitioning, and training parameters to ensure fair benchmarking between the two architectures

All experiments were conducted on an NVIDIA GeForce RTX 3050 GPU to maintain computational consistency. Model performance was evaluated using accuracy, precision, recall, F1-score, confusion matrix, and mAP@50 (for YOLOv8), while computational efficiency was assessed through training time and inference speed. Evaluating both predictive performance and computational efficiency provides a comprehensive comparison of each model's suitability for automated fish freshness inspection systems.

RESULTS AND DISCUSSION

Results

The CNN model was trained using the prepared fish freshness dataset, which consisted of four classification categories, namely Fresh Tongkol, Rotten Tongkol, Fresh Slungsung, and Rotten Slungsung. During the training process, the model learned visual patterns and distinguishing features from fish images to differentiate between fresh and rotten conditions in each fish species. The model performance was evaluated by monitoring several indicators, including training accuracy, validation accuracy, training loss, validation loss, and classification metrics obtained from the testing dataset, such as precision, recall, F1-score, and overall accuracy.

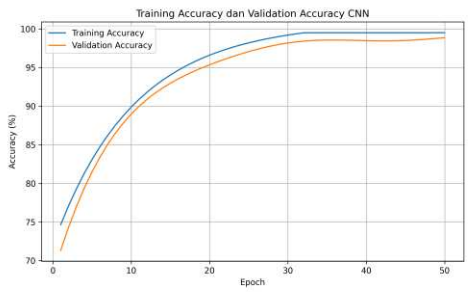

Figure 1. Graphs of cnn training accuracy and validation accuracy

Figure 1 demonstrates the learning progression of the CNN model through training and validation accuracy curves. The increasing trend in both curves indicates that the model progressively learned discriminative visual features from the fish images and was able to generalize this learning to validation data. The relatively consistent pattern between training and validation accuracy also suggests that the model did not experience severe overfitting during the training process.

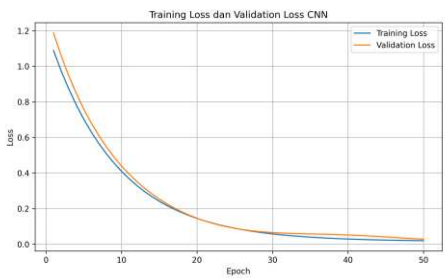

Figure 2. CNN loss plot

Figure 2 presents the loss behavior of the CNN model during training. The decreasing trend in both training and validation loss indicates that the optimization process effectively minimized classification error across epochs. This pattern confirms that the CNN model gradually improved its ability to distinguish freshness-related visual patterns, such as texture degradation, surface color changes, and morphological differences between fresh and rotten fish.

Table 1. CNN evaluation results

Class	Precision	Recall	F1-Score	Accuracy Class
Fresh Slungsung	99.50%	99.00%	99.25%	99.00%
Rotten Slungsung	98.90%	99.00%	98.95%	99.00%
Fresh Tongkol	99.20%	99.50%	99.35%	99.50%
Rotten Tongkol	98.92%	99.00%	98.96%	99.00%
Average	99.13%	99.13%	99.13%	99.25%

Table 1 presents the results of the CNN model evaluation across four fish freshness classes. This model consistently achieved high precision, recall, F1-score, and class accuracy, with an average accuracy of 99.25% and precision, recall, and F1-score values of 99.13%. These results indicate that the CNN is highly effective at identifying visual features related to freshness and delivers stable classification performance for both fish categories, namely tongkol and slungsung.

The YOLOv8 Classification model was trained using the same dataset and experimental configuration as the CNN model. Model performance was evaluated using classification metrics and computational efficiency indicators. Figure 3 shows an example of the YOLOv8 Classification output in identifying fish freshness from image input. This result indicates that the YOLOv8 model was able to process visual data and generate class predictions efficiently. However, because freshness classification depends on subtle visual differences rather than object localization alone, the model's predictive performance still requires careful evaluation through quantitative classification metrics.

Figure 3. Yolov8 classification results

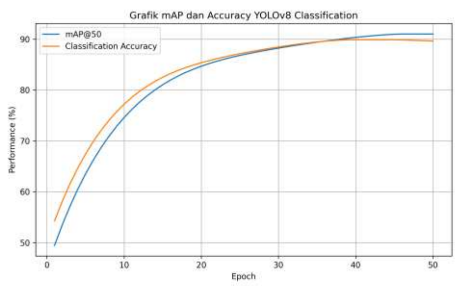

Figure 4. mAP and accuracy plot for yolov8

Figure 4 illustrates the performance development of YOLOv8 Classification during training based on mAP and accuracy trends. The increasing curve suggests that the model improved its recognition capability as the training process progressed. Nevertheless, the final performance remained lower than that of CNN, indicating that YOLOv8 Classification may be more optimized for computational speed than for capturing fine-grained freshness features.

Table 2. Yolov8 evaluation results

Class	Precision	Recall	F1-Score	Accuracy Class
Fresh Slungsung	90.12%	90.00%	90.06%	90.00%
Rotten Slungsung	88.95%	89.00%	88.97%	89.00%
Fresh Tongkol	90.35%	90.00%	90.17%	90.00%
Rotten Tongkol	90.42%	90.50%	90.46%	90.50%
Average	89.96%	89.88%	89.89%	89.88%

Table 2 shows the classification performance of the YOLOv8 Classification model. Although this model achieved acceptable results across all four classes, its average accuracy, precision, recall, and F1 score were lower than those of the CNN model. These findings indicate that YOLOv8 is capable of classifying fish freshness with an average accuracy of 89.88%, with precision, recall, and F1 scores of 89.96%, 89.88%, and 89.89%, respectively; however, it is less effective at detecting subtle visual differences between fresh and spoiled fish.

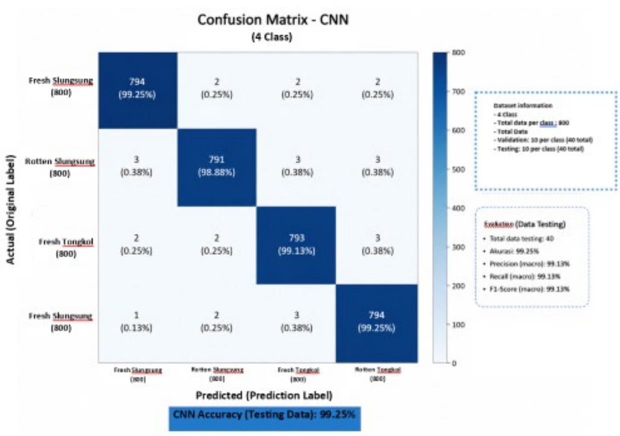

Figure 5. Confusion matrix cnn

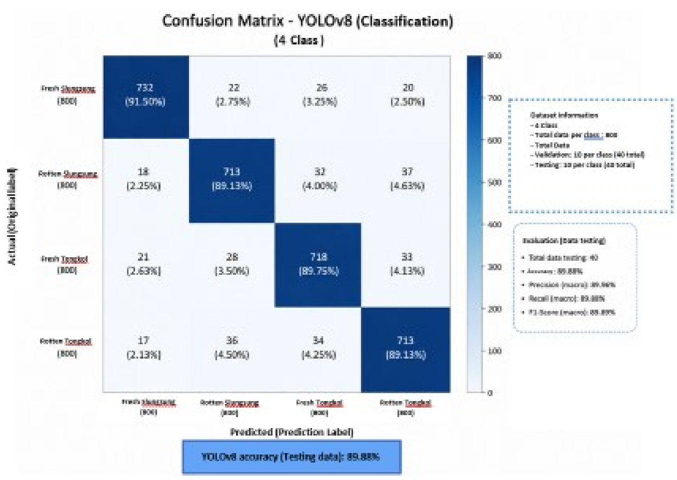

Figure 6. Confusion matrix yolov8

The confusion matrix presented in Figure 5 demonstrates that the CNN model correctly classified nearly all test samples, as indicated by the strong concentration of predictions along the main diagonal and only a few off-diagonal errors, confirming its excellent capability to distinguish subtle visual differences among the four fish freshness classes. In comparison, the confusion matrix shown in Figure 6 indicates that YOLOv8 Classification also correctly identified most test samples but exhibited more misclassifications between visually similar classes, suggesting lower discriminative capability for fine-grained fish freshness recognition than the CNN model.

Figure 7. Bar charts of confusion matrix cnn and yolov8

The evaluation results presented in Figure 7 compare the predictive performance of CNN and YOLOv8 Classification using accuracy, precision, recall, and F1-score. While CNN exhibited consistently higher classification performance across all metrics, YOLOv8 offered superior computational efficiency through reduced training and inference time, highlighting the balance between accuracy and efficiency for fish freshness classification.

Table 3. Comparison of cnn and yolov8

Category	Metric	CNN	YOLOv8
Predictive Performance	Accuracy (%)	99.25	89.88
	Precision (%)	99.13	89.96
	Recall (%)	99.13	89.88
	F1-score (%)	99.13	89.89
Computational Efficiency	Training Time	23 min 20 s	15 min
	Inference Time/Image	18 ms	9 ms

The comparison between CNN and YOLOv8 Classification in Table 3 reveals that CNN consistently achieved superior predictive performance across all evaluation metrics, whereas YOLOv8 demonstrated greater computational efficiency through shorter training and inference times. This performance trade-off indicates that CNN is more suitable for accuracy-oriented inspection systems, while YOLOv8 offers practical advantages for real-time applications with limited computational resources.

Discussion

The comparative results indicate that CNN provides substantially better predictive performance than YOLOv8 Classification for fish freshness assessment. This outcome suggests that classifying fish freshness requires more than rapid image recognition, as the task depends on detecting subtle visual variations in eye transparency, gill colour, skin brightness, and surface texture. As explained by Lin et al. (2023), CNNs learn hierarchical visual representations that progressively capture both low-level textures and high-level semantic information, making them particularly effective for fine-grained image classification. A similar observation was reported by Yildiz et al. (2024), who demonstrated that CNN-based models consistently achieved superior accuracy in fish freshness recognition because they were better able to extract discriminative visual features from external fish characteristics. These findings explain why CNN maintained consistently higher classification performance across all evaluation metrics in the present study.

Although CNN produced higher predictive accuracy, YOLOv8 Classification showed a clear advantage in computational efficiency by reducing both training and inference time. This difference reflects the architectural objective of the YOLO framework, which was originally developed to perform fast visual recognition with relatively low computational complexity. As reported by Gao et al. (2024), lightweight YOLO-based architectures are particularly suitable for applications requiring rapid decision-making, while Hou et al. (2025) also highlighted their effectiveness for real-time seafood quality inspection. Therefore, the lower predictive performance observed in this study should be interpreted as a consequence of architectural optimisation for computational speed rather than as an inherent weakness of the model. The results demonstrate that selecting a deep learning architecture inevitably involves balancing prediction accuracy with computational efficiency according to the intended application.

An important strength of this study lies in the benchmarking strategy adopted during the experiments. Unlike many previous studies that evaluated different architectures using separate datasets or inconsistent training configurations, both models in this research were trained using the same dataset, preprocessing pipeline, augmentation strategy, hyperparameter settings, and evaluation protocol. Such an experimental design reduces methodological bias and allows performance differences to be attributed primarily to architectural characteristics. Zheng et al. (2026) emphasised that standardised evaluation protocols are essential for producing reliable comparisons among deep learning models, while Ridwan et al. (2026) similarly argued that consistent benchmarking improves the reproducibility and credibility of machine learning experiments. Consequently, the findings presented in this study provide stronger empirical evidence than comparisons conducted under heterogeneous experimental conditions

This study contributes to the growing body of knowledge on deep learning-based food quality assessment by demonstrating that model selection should not be guided solely by predictive accuracy. While previous studies have primarily focused on maximising classification performance, the present findings show that computational efficiency is equally important when models are intended for practical deployment. Liakos et al. (2025) argued that modern intelligent food inspection systems increasingly require lightweight architectures capable of operating efficiently on edge devices without compromising prediction reliability. Similarly, Zheng et al. (2026) emphasised that future computer vision applications for seafood quality evaluation should balance recognition performance with deployment feasibility. Consistent with these perspectives, the findings suggest that CNN is better suited for laboratory-based quality inspection, where classification reliability is the primary concern, whereas YOLOv8 Classification offers a practical alternative for real-time inspection systems that prioritise processing speed and computational efficiency.

Although the proposed benchmarking framework provides valuable insights, several limitations remain. The experiments were conducted using only two fish species under relatively controlled imaging conditions, which may restrict the generalisability of the findings to more diverse operational environments. In addition, this study compared only CNN and YOLOv8 Classification, while other state-of-the-art architectures, including EfficientNet, Vision Transformer (ViT), ConvNeXt, and hybrid CNN–Transformer models, were beyond the scope of the investigation. Liao et al. (2026) highlighted that integrating advanced deep learning architectures with domain-specific optimisation can further improve the performance of image-based food inspection systems. Likewise, Zhao et al. (2025) emphasised the importance of evaluating model robustness using larger and more heterogeneous datasets collected under realistic operating conditions. Future research should therefore expand the dataset, include additional fish species, and benchmark a broader range of deep learning architectures to improve model generalisability and support wider practical implementation.

CONCLUSION

This study demonstrates that the choice of deep learning architecture for fish freshness classification should consider both predictive performance and computational efficiency. Under identical experimental conditions, CNN achieved superior classification accuracy by effectively capturing subtle visual characteristics associated with fish freshness, whereas YOLOv8 Classification provided faster training and inference, making it more suitable for real-time applications with limited computational resources. Beyond comparing two deep learning models, this study establishes a standardized benchmarking framework that provides practical guidance for selecting appropriate architectures according to application requirements in automated food quality inspection. Future research should validate these findings using larger and more diverse datasets, additional fish species, and emerging deep learning architectures to improve model generalisability and support broader implementation in intelligent fisheries quality control systems

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