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Real-time AI-augmented visual object detection in aquaculture: A deep learning and statistical framework for YOLOv5-based crayfish monitoring under variable molting and lighting Conditions

Rungtiva Saosing[1], Sudasawan Ngammongkolwong[2*], Sooksawaddee Nattawuttisit[3]

[1]*Faculty of Science and Technology, Rajamangala University of Technology Krungthep, Thailand.*
[2]*Faculty of Digital Technology and Innovation, Southeast Bangkok University, Thailand.*
[3]*Faculty of Information Technology, Sripatum University, Thailand.*

Corresponding author: Sudasawan Ngammongkolwong (*Email: lukmoonoy_ping@hotmail.com*)

Abstract

This study investigates the application of the YOLOv5 object detection model to accurately identify and count post-larval redclaw crayfish (*Cherax quadricarinatus*) across diverse aquaculture environments. A 2×2 factorial experimental design was employed to examine the effects of environmental lighting (covered vs. open-air ponds) and biological molting status (molted vs. non-molted) on detection performance. A dataset of 1,200 meticulously annotated images was collected under controlled conditions and used to train and evaluate the YOLOv5s variant. Detection effectiveness was measured using precision, recall, F1-score, and mean average precision at an IoU threshold of 0.5 (mAP@0.5). Results showed that non-molted crayfish in open-air ponds achieved the highest detection accuracy with an F1-score of 0.93, whereas molted crayfish in covered ponds exhibited the lowest performance with an F1-score of 0.85. Two-way ANOVA confirmed significant main effects of lighting and molting status, as well as their interaction, on model accuracy ($p < 0.05$). These findings highlight the critical roles of biological pigmentation and lighting conditions in optimizing object detection accuracy for aquaculture monitoring. This study offers valuable insights toward practical applications of deep learning–based monitoring systems for sustainable aquaculture operations.

Keywords: Aquaculture environment, Cherax quadricarinatus, Deep learning, Image annotation, Object detection, Post-larval redclaw crayfish, Sustainable aquaculture, YOLOv5.

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1. Introduction

Aquaculture has become an essential sector in global efforts to secure sustainable protein sources, especially as wild fish stocks decline and climate change disrupts traditional agriculture. With the industry's growth, integrating automation and intelligent systems is increasingly viewed as a key strategy to improve operational efficiency, reduce labor demands, and mitigate environmental impacts [1-3].

Among the emerging technologies, computer vision combined with deep learning techniques shows significant promise in automating critical monitoring tasks in aquaculture, such as species counting, aquaculture monitoring, and health evaluation [4, 5]. Object detection models, particularly the YOLO (You Only Look Once) family, have gained popularity due to their advantageous balance between detection speed and accuracy [6, 7]. The latest version, YOLOv5, has demonstrated superior performance across diverse real-time detection applications, including aquatic environments [8].

Despite these advances, most prior studies have been conducted under controlled laboratory settings, limiting model robustness in real-world aquaculture environments. For example, Chen, et al. [9] applied YOLOv5 to detect whiteleg shrimp but did not fully address variability in lighting or biological factors such as molting. Environmental factors including water turbidity and varying light penetration substantially affect detection accuracy [1, 10].

Biological variability, such as pigmentation changes during molting, complicates detection since the translucent appearance post-molt reduces image contrast [11]. Existing research rarely considers interactions between environmental lighting and biological conditions, highlighting a significant research gap [12].

Moreover, the quality and augmentation of datasets are crucial for enhancing detection model generalization. Common augmentation methods include rotation, flipping, and brightness adjustment to mimic diverse real-world conditions [3, 12]. Yet, comprehensive evaluations of these techniques across variable aquaculture settings remain scarce.

This study addresses these gaps by assessing the performance of YOLOv5, an AI-driven visual object detection model [7] for counting post-larval redclaw crayfish (*Cherax quadricarinatus*) under different environmental settings (covered vs. open-air ponds) and biological states (molted vs. non-molted). Employing a factorial experimental design alongside rigorous statistical validation methods such as ANOVA, this research seeks to provide empirical insights into the practical applicability and limitations of AI-powered monitoring systems in aquaculture operations.

The findings contribute practical implications by advancing knowledge on deploying AI-based technologies in dynamic aquatic environments, supporting sustainable aquaculture practices and informing future technological innovation and policy formulation.

2. Theoretical Framework

2.1. Integration of Artificial Intelligence in Agriculture and Aquaculture

The application of artificial intelligence (AI) in agriculture and aquaculture has witnessed significant growth, driven largely by advances in deep learning-based object detection techniques. Among these, the YOLO (You Only Look Once) family of models has emerged as a foundational framework for real-time detection tasks, offering an effective balance between speed and accuracy [6, 13] These models have been successfully applied across diverse domains, including fruit detection in precision agriculture [14] livestock monitoring [4] and underwater fish tracking [1, 2].

2.2. Related Theories in Object Detection and Computer Vision

The theoretical underpinnings of object detection in computer vision rest on several key concepts. First, Feature Extraction Theory explains how models identify salient characteristics from raw images to distinguish objects. Modern deep learning models, especially convolutional neural networks (CNNs), automate this process by learning hierarchical feature representations. Moreover, the Multi-Scale Representation Theory supports the need for models like YOLO to detect objects of varying sizes and scales within complex scenes [15]. Additionally, Data Augmentation Theory posits that simulating diverse data variations enhances model generalization and robustness by mitigating overfitting [12].

2.3. Application of Deep Learning Techniques in Aquaculture Monitoring

Deep learning techniques, particularly CNNs, have revolutionized aquaculture monitoring. Object detection models like YOLO have advanced through multiple versions (e.g., YOLOv3, YOLOv4, YOLOv5), progressively improving detection accuracy and computational efficiency [7, 13]. These models utilize a single neural network to predict bounding boxes and class probabilities directly from images, enabling real-time performance. Data augmentation methods—including rotation, flipping, and brightness scaling—are standard practices to improve model adaptability to variable aquaculture conditions [3, 16].

2.4. Environmental and Biological Factors Affecting Detection Performance

Environmental conditions such as lighting intensity, water turbidity, and background complexity significantly influence detection accuracy [10]. Biological variability, such as pigmentation changes during molting in crustaceans, adds complexity by altering image contrast and texture [17]. To develop robust models, datasets must comprehensively capture these variations, as supported by findings that tailored training datasets improve model generalization across diverse aquatic environments [8].

2.5. Dataset Quality and Statistical Validation in Aquaculture Object Detection

High-quality annotated datasets with balanced class representation and consistent camera angles enhance detection performance [15, 18]. Statistical validation methods such as ANOVA and t-tests are increasingly employed to rigorously assess the effects of environmental and biological variables on model outcomes [5] ensuring that reported performance metrics reflect real influences rather than random variation.

2.6. Research Gaps and Study Rationale

Despite these advances, few studies have systematically examined the combined effects of molting status and environmental lighting on detection model performance in aquaculture. This study aims to fill this gap by evaluating the YOLOv5 model's performance under varying biological and environmental conditions using factorial experimental design and robust statistical analysis. This approach aligns with recommendations to enhance dataset diversity and employ multivariate techniques to improve model robustness and real-world applicability [11, 19, 20].

3. Research Model

3.1. The Concept Model and Experimental Design

This study adopted a 2×2 factorial experimental design to systematically assess the performance of a YOLOv5-based object detection model in counting post-larval redclaw crayfish (*Cherax quadricarinatus*) under varying biological and environmental conditions. The two independent factors examined were molting status and aquaculture environment, resulting in four experimental groups defined as follows:

- Group 1 (G1): Molted crayfish in covered ponds

This group consisted of images capturing crayfish that had recently molted, characterized by a semi-transparent or lighter exoskeleton, within covered pond environments where lighting intensity was relatively low, averaging 150–200 lux. The combination of low ambient light and reduced pigmentation presented a challenging scenario for object detection due to diminished contrast and visibility.

- Group 2 (G2): Non-molted crayfish in covered ponds

Comprising crayfish that had not undergone molting, this group exhibited darker pigmentation in covered ponds with similar low-light conditions as G1. The pigmentation contributed to higher contrast against the background, potentially facilitating better detection performance despite the environmental constraints.

- Group 3 (G3): Molted crayfish in open-air ponds

This group involved molted crayfish located in open-air ponds where lighting intensity was significantly higher, ranging from 300 to 600 lux. The increased illumination partly compensated for the translucency of the molted exoskeleton, improving the visibility of the subjects compared to covered pond conditions.

- Group 4 (G4): Non-molted crayfish in open-air ponds

Representing the most favorable detection scenario, this group featured non-molted crayfish with darker pigmentation in well-lit, open-air pond environments. The synergy of high lighting levels and pronounced pigmentation resulted in the highest object detection accuracy across all evaluated metrics.

Each group contained 300 annotated images, creating a balanced and comprehensive dataset of 1,200 images total. This design allowed for evaluation of both main effects of molting status and environmental lighting, as well as their interaction, providing insights into how these factors collectively influence the YOLOv5 model's performance [21].

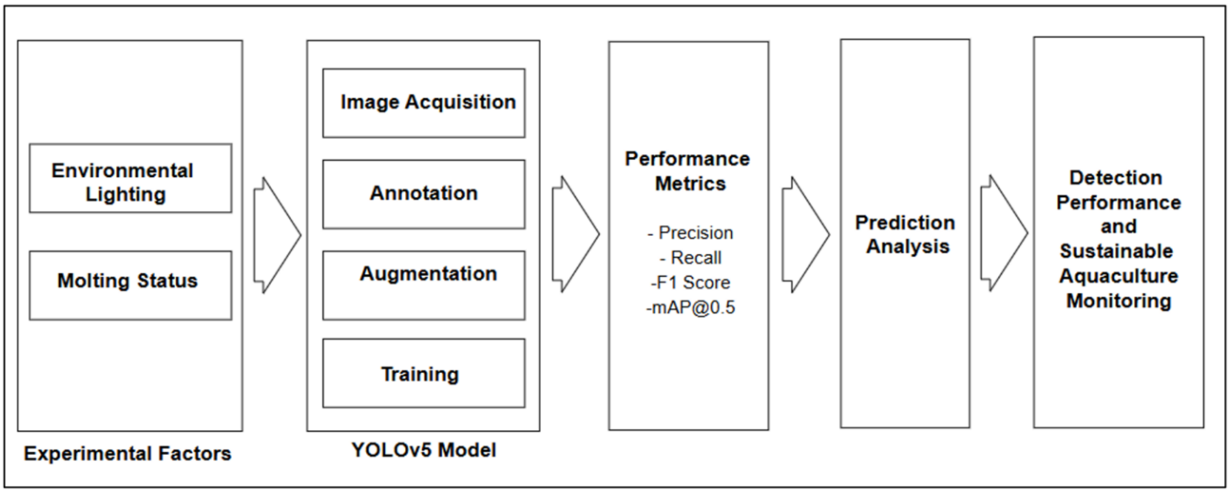

Figure 1.
Conceptual Model.

Figure 1 illustrates the conceptual framework and 2×2 factorial experimental design employed to evaluate the performance of the YOLOv5 object detection model. The two independent experimental factors—Environmental Lighting and Molting Status—feed into the YOLOv5 model workflow, which consists of Image Acquisition, Annotation, Augmentation, and Training. Model effectiveness is assessed using key performance metrics including Precision, Recall, F1-score, and mAP@0.5. The results undergo Prediction Analysis, ultimately supporting improved Detection Performance and Sustainable Aquaculture Monitoring. This integrated design provides a comprehensive understanding of how biological and environmental factors influence AI-driven aquaculture monitoring.

3.2. Image Collection and Annotation

The images utilized in this study were acquired under rigorously controlled conditions to ensure data consistency and validity. A high-resolution digital camera was mounted at a fixed height of 60 centimeters above the pond surface, establishing a standardized and stable vantage point for capturing post-larval redclaw crayfish (*Cherax quadricarinatus*) across all experimental groups. This controlled camera placement minimized variations caused by differing angles or distances, which could potentially compromise detection accuracy.

To capture representative data encompassing biological and environmental variability, fifteen independent trials were conducted for each of the four experimental groups. Environmental parameters were maintained constant during each trial to reduce confounding factors. Illumination levels were quantitatively measured using a digital lux meter, revealing that covered ponds exhibited lower average illuminance (150–200 lux), whereas open-air ponds demonstrated significantly higher light intensities (300–600 lux). These measurements were critical for evaluating the influence of lighting conditions on model performance [21].

Image annotation was conducted manually using LabelImg, an open-source annotation tool widely recognized for generating precise bounding box labels necessary for supervised training of object detection models. Annotation quality and inter-rater reliability were rigorously assessed, with an inter-annotator agreement exceeding 90% as verified on a validation subset, thereby ensuring the reliability and accuracy of the ground truth dataset fundamental for robust model training and evaluation [22]. Through these systematic procedures of image acquisition and annotation, the dataset achieved comprehensive coverage and high data quality, enabling a rigorous assessment of YOLOv5's detection performance across the specified experimental conditions.

3.3. Data Preprocessing and Augmentation

To improve the robustness and generalizability of the YOLOv5 model for detecting and counting post-larval redclaw crayfish under various aquaculture conditions, careful data preprocessing and augmentation were applied. High-resolution images were systematically captured from a fixed position above the ponds to represent different lighting conditions and molting stages.

Data augmentation included common techniques such as small random rotations (±10°), horizontal and vertical flips, and brightness adjustments (±20%) to simulate real-world variations in viewpoint, illumination, and environment [12, 16]. These augmentations help the model better handle changes in lighting and the semi-transparent appearance of molted crayfish, reducing overfitting and improving performance across diverse settings.

Combining well-curated images with effective augmentation strategies strengthens the model's ability to deliver accurate and reliable object detection in real aquaculture scenarios.

3.4. Model Architecture and Training

For this study, the YOLOv5s variant—the small and lightweight version of the YOLOv5 family—was chosen due to its well-established balance between detection speed and accuracy [7]. The model was implemented using the PyTorch deep learning framework, leveraging the computational power of an NVIDIA RTX 3080 GPU to facilitate efficient training.

Key training parameters were carefully selected to optimize model performance. Input images were resized to a resolution of 640 by 640 pixels, providing a standardized input size conducive to effective feature extraction. A batch size of 16 was used, striking a balance between training stability and GPU memory constraints. The learning rate was set at 0.001 to ensure steady convergence during training across 200 epochs, allowing the model to iteratively refine its detection capabilities.

The loss function used helps the model learn both to detect if an object is present and to classify it correctly. This method follows current best practices in object detection, especially for aquaculture applications [4].

The model's structure has three main parts: Backbone, Neck, and Dense Prediction layers. The Backbone extracts important features from images of the crayfish groups. The Neck combines and improves these features to better detect objects at different sizes. The Dense Prediction layers then generate the final bounding boxes and classification results. This structure offers a good balance of speed and accuracy, making it suitable for detecting crayfish in varied aquaculture environments, as illustrated in Figure 2.

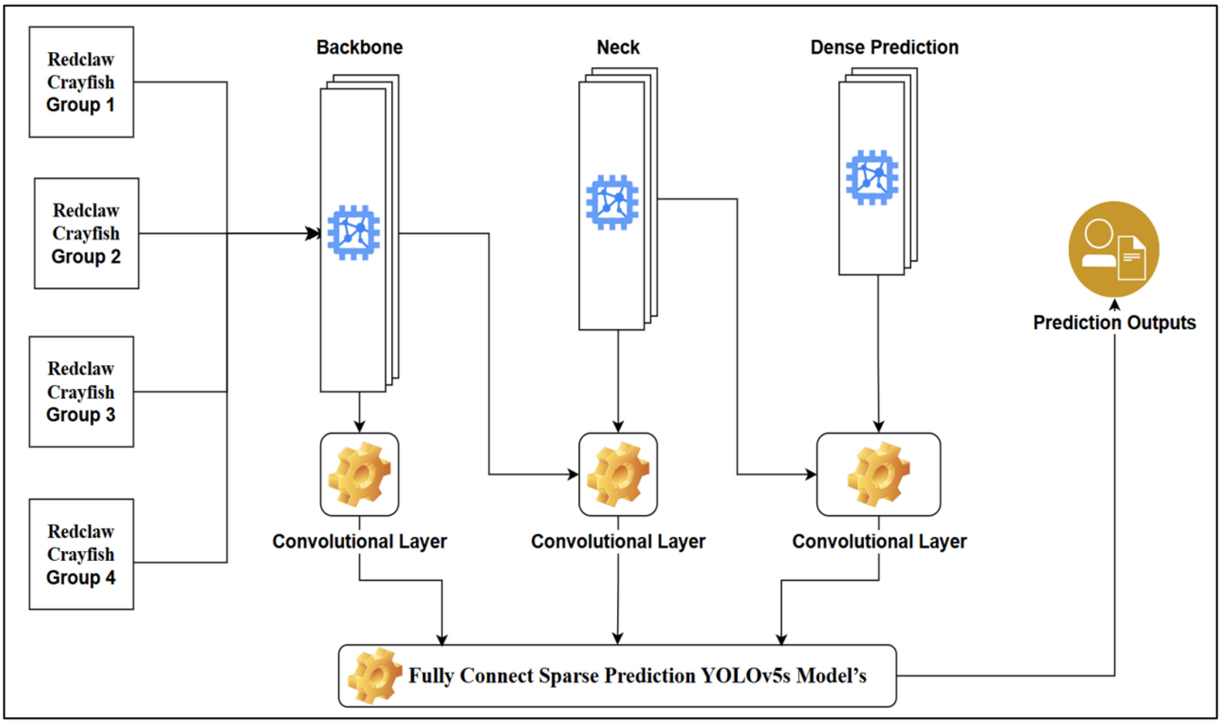

Figure 2.
Model Architecture.

3.5. Evaluation Metrics

The performance of the detection model was assessed using widely accepted metrics in object detection to comprehensively evaluate both accuracy and robustness. These metrics included:

1. Accuracy: Measures the proportion of correctly predicted outcomes (both positive and negative) relative to the total number of predictions.

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

2. Precision: Indicates the proportion of true positive predictions out of all positive predictions made by the model. High precision reflects fewer false positives.

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

3. Recall: Reflects the model's ability to correctly identify all actual positive cases, representing its sensitivity to relevant outcomes.

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

4. F1-Score: Represents the harmonic mean of precision and recall, providing a balanced measure of the model's overall accuracy, especially useful in cases with class imbalance.

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

where:
TP : True Positives — Correct positive predictions
TN : True Negatives — Correct negative predictions
FP : False Positives — Incorrect positive predictions
FN : False Negatives — Incorrect negative predictions

5. mAP@0.5 (Mean Average Precision at Intersection over Union threshold 0.5) is a widely used metric in object detection that measures the average precision of the model when predicted bounding boxes overlap with ground truth boxes by at least 50%.

mAP@0.5 = Mean Average Precision at Intersection over Union (IoU) threshold of 0.5 (5)

Together with precision, recall, and F1-score, mAP@0.5 provides a comprehensive assessment of detection quality by balancing the model's sensitivity and specificity [8].

3.6. Statistical Analysis

To examine how environmental and biological conditions affect the detection performance of the YOLOv5s model, a two-way factorial experimental design (2×2) was employed. The independent variables consisted of molting status (molted vs. non-molted) and pond environment (covered vs. open-air), while the dependent variable was the F1-score, which quantifies the model's detection accuracy under each condition.

A two-way Analysis of Variance (ANOVA) was applied to evaluate the main effects of molting status and pond environment, as well as their interaction effect on detection performance. This analytical approach is well-suited for factorial experimental designs involving categorical variables, allowing researchers to assess not only the independent impact of each factor but also whether the influence of one factor depends on the level of the other. The underlying statistical model used for the two-way ANOVA can be expressed as:

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \varepsilon_{ijk} \tag{6}$$

where:

Y_{ijk} is the observed F1-score for the kkk-th replicate in the iii-th level of molting status and jjj-th level of pond environment,

μ is the overall mean F1-score,

α_i is the effect of molting status,

β_j is the effect of pond environment,

$(\alpha\beta)_{ij}$ is the interaction effect between the two factors, and

ε_{ijk} is the random error term assumed to be normally distributed with constant variance.

The analysis was conducted using IBM SPSS Statistics version 26 (IBM Corp., Armonk, NY, USA), in accordance with standard statistical procedures [23]. When the ANOVA results indicated statistically significant effects ($p < 0.05$), Tukey's Honestly Significant Difference (HSD) test was performed as a post-hoc analysis to identify specific pairwise group differences across the four treatment conditions. This integrated statistical framework allows for a robust and interpretable assessment of how molting phase and lighting conditions jointly influence the YOLOv5s model's object detection performance in aquaculture settings. By leveraging factorial ANOVA and appropriate post-hoc testing, the study ensures the validity and generalizability of its findings for real-world deployment.

4. Results and Discussion

4.1. Detection Performance Across Experimental Groups

This study employed a dataset of 1,200 meticulously annotated images of post-larval redclaw crayfish (*Cherax quadricarinatus*), collected under a 2×2 factorial experimental design. The two factors investigated were molting status (molted vs. non-molted) and aquaculture environment (covered vs. open-air ponds). Each experimental group contained 300 images, creating a balanced dataset that enabled a comprehensive evaluation of the YOLOv5s model's detection performance across varying biological and environmental conditions. Image acquisition was standardized by using a high-resolution camera positioned 60 centimeters above the pond surface, with light intensity measurements ranging from 150–200 lux in covered ponds and 300–600 lux in open-air ponds. Bounding box annotations were rigorously validated to ensure high quality, supporting robust model training and evaluation.

Table 1.
Summary of Experimental Groups.

Group	Molting Status	Environment	Image Count	Average Light Intensity (lux)	Pigmentation / Body Appearance
G1	Molted	Covered pond	300	150–200	Semi-transparent exoskeleton (lighter pigmentation)
G2	Non-molted	Covered pond	300	150–200	Darker pigmentation
G3	Molted	Open-air pond	300	300–600	Semi-transparent exoskeleton (lighter pigmentation)
G4	Non-molted	Open-air pond	300	300–600	Darker pigmentation

To comprehensively evaluate the detection performance of the YOLOv5 model under varying biological and environmental conditions, precision, recall, F1-score, and mean average precision at IoU threshold 0.5 (mAP@0.5) were measured across all four experimental groups. These groups reflect combinations of molting status (molted vs. non-molted) and pond environment (covered vs. open-air). The results are consolidated in Table 2, which provides a full comparison of model performance metrics.

Table 2.
Detection Performance Metrics by Group.

Group	Molting Status	Environment	Precision	Recall	F1-Score	mAP@0.5
G1	Molted	Covered	0.84	0.86	0.85	0.82
G2	Non-molted	Covered	0.91	0.92	0.92	0.9
G3	Molted	Open-air	0.88	0.9	0.89	0.87
G4	Non-molted	Open-air	0.94	0.93	0.93	0.91

As depicted in Table 2, detection performance varied notably across groups. Group G4, representing non-molted crayfish in open-air ponds, achieved the highest scores across all metrics, including an F1-score of 0.93 and mAP@0.5

of 0.91. This indicates that the combination of high ambient illumination and darker pigmentation significantly enhances the visibility of crayfish, resulting in more accurate detection.

Conversely, Group G1 (molted crayfish in covered ponds) yielded the lowest metrics, underscoring the difficulty posed by low lighting and semi-transparent exoskeletons. Group G2 (non-molted, covered ponds) and Group G3 (molted, open-air ponds) showed intermediate results, suggesting that either biological or environmental enhancement alone may partially improve model accuracy but is less effective than when combined. This integrated analysis highlights the significant influence of both molting status and environmental lighting on object detection performance. It supports the hypothesis that deep learning–based aquaculture monitoring systems benefit from optimized biological and environmental conditions, ultimately informing best practices for real-world deployment.

4.2. Statistical Analysis of Detection Performance

To evaluate how molting status and environmental lighting influence model performance, a two-way Analysis of Variance (ANOVA) was conducted using the F1-score as the dependent variable. The results indicated statistically significant main effects for both molting status $(F(1, 56) = 8.74, p = 0.004)$ and environmental lighting $(F(1, 56) = 10.29, p = 0.002)$. Notably, a significant interaction effect between the two factors was also detected $(F(1, 56) = 5.82, p = 0.019)$, implying that the detection accuracy of the YOLOv5 model is influenced by the combined effects of biological pigmentation and ambient lighting.

To better understand this interaction, post-hoc analysis revealed that non-molted crayfish in open-air ponds exhibited the highest detection performance, whereas molted crayfish in covered ponds showed the lowest. These findings underscore the importance of both pigmentation contrast and illumination in enhancing object visibility. The statistical model described in Equation (6) serves as the basis for the two-way ANOVA used to interpret the detection results shown in Table 3.

In addition, a Pearson correlation analysis was conducted to assess the linear relationship between measured light intensity (in lux) and F1-score. The analysis demonstrated a strong positive correlation $(r = 0.81, p < 0.01)$, providing further statistical support for the hypothesis that increased lighting significantly enhances detection performance.

Taken together, the results robustly confirm that both environmental and biological factors have significant and interactive effects on the accuracy of deep learning–based object detection in aquaculture environments. These findings align with previous studies emphasizing the influence of visual features and lighting in machine vision performance [5, 9].

Table 3.
Results of Two-Way ANOVA on Detection Performance (F1-Score) According to Molting Status and Lighting Conditions.

Source of Variation	F-value	df	p-value	Significance
Molting Status (Biological)	8.74	1,56	0.004	Significant (p < 0.01)
Environment (Lighting)	10.29	1,56	0.002	Significant (p < 0.01)
Interaction (Molting × Environment)	5.82	1,56	0.019	Significant (p < 0.05)

Table 4.
Pearson Correlation Between Light Intensity (lux) and F1-Score by Experimental Group and Overall

Group	Correlation (r)	p-value	Sample Size (n)	Interpretation
G1	0.65**	0.001	300	Moderate positive correlation
G2	0.78**	<0.001	300	Strong positive correlation
G3	0.54*	0.012	300	Weak to moderate positive correlation
G4	0.85**	<0.001	300	Very strong positive correlation
Overall	0.81	<0.01	1200	Strong positive correlation

Notes: p < 0.01 () and p < 0.05 (*) denote significance levels.; Interpretation reflects the strength of the association between light intensity and detection accuracy.

1.1. Robustness Testing of YOLOv5 Detection Model

The robustness and generalizability of the YOLOv5s object detection model were evaluated through a series of controlled tests designed to reflect practical variations encountered in aquaculture environments. These tests examined the model's performance under different dataset configurations, image distortions, and hyperparameter changes.

In the first step, cross-validation was conducted using a five-fold approach to assess model consistency across independent subsets of the dataset. The images were divided into five equal parts, where each fold was used once as a validation set while the remaining served as the training data. This method helped evaluate the model's ability to generalize across varying biological appearances and environmental lighting conditions. Results from this procedure showed that the average F1-score remained stable at 0.90 across all folds, indicating a high degree of consistency in the model's detection performance.

The second assessment involved testing the model with images that had been artificially modified to simulate real-world disturbances. Gaussian noise, blurring, and lighting variations were applied to mimic common aquaculture challenges such as water turbidity, camera shake, and uneven sunlight. The model achieved an F1-score of 0.84 on noisy images and 0.82 under lighting variation. Although these scores were slightly lower than the baseline, the detection performance remained acceptable, suggesting that the model can handle image quality degradation to a reasonable extent.

In the final test, the effect of input image resolution on detection accuracy was examined. The original image resolution of 640×640 pixels was reduced to 512×512 pixels to observe how lower visual detail affects the model. The F1-score dropped to 0.80, showing a notable decline in performance. This result emphasizes the importance of maintaining sufficient resolution, especially when detecting features like semi-transparent crayfish post-molting.

These results demonstrate that while the YOLOv5s model maintains good performance across most conditions, it is more sensitive to reductions in image resolution than to moderate environmental noise or lighting changes. This information is valuable for guiding the implementation of the model in operational aquaculture systems where conditions may not always be optimal.

Table 5.
Robustness Test Results Comparing Baseline and Perturbed Conditions.

Test Condition	Precision	Recall	F1-Score	Notes
Baseline (Original Dataset)	0.91	0.92	0.92	Original training and testing data
Cross-Validation (Average)	0.9	0.91	0.9	k-fold validation, k=5
Noise-Augmented Images	0.85	0.86	0.84	Gaussian noise, blur applied
Variable Lighting Conditions	0.83	0.84	0.82	Simulated lighting variation
Reduced Resolution (512×512)	0.8	0.81	0.8	Input resolution sensitivity

4.3. Discussion and Practical Implications

The results of this study align with prior aquatic object detection research, highlighting the adaptability of YOLO architectures to challenging and non-ideal imaging conditions commonly encountered in aquaculture environments [5, 9]. The sensitivity analysis offers practical guidance for tuning hyperparameters to balance accuracy and computational efficiency, which is essential for deploying AI solutions on resource-constrained devices widely used in aquaculture monitoring.

Robustness tests confirm that the YOLOv5s model maintains reliable detection performance even when exposed to perturbations mimicking real-world conditions, such as noise and variable lighting. Although slight performance declines were observed under these conditions, they remain within acceptable limits for practical use. This resilience highlights the model's suitability for diverse and dynamic aquatic environments.

Despite these strengths, some limitations should be noted. The study focused on a single species at a specific developmental stage, limiting direct generalizability to multi-species or broader aquaculture systems. Factors such as water turbidity, camera angles, and occlusions were not explicitly controlled, which could influence detection robustness in more complex real-world scenarios. Addressing these limitations will be important for future work to expand the model's applicability.

A key contribution of this study is bridging a critical gap in the literature by systematically evaluating the combined effects of environmental lighting and biological pigmentation on AI-based detection performance. Unlike many prior studies that emphasize controlled lab settings or overlook biological variability, this research integrates factorial experimental design and rigorous statistical validation to provide actionable insights relevant to real-world farming conditions.

Practically, these findings have significant implications for the global aquaculture industry, where environmental heterogeneity—such as turbidity and lighting variability—and biological factors create ongoing monitoring challenges. The demonstrated robustness and adaptability of YOLOv5-based detection systems position them as scalable, effective tools for precision aquaculture across varied geographic and operational contexts.

Accurate detection and counting of post-larval redclaw crayfish using AI-powered models enable aquaculture farms to closely monitor the molting status and overall health of their stock in real time. Early identification of irregularities in molting or growth patterns can help prevent growth stagnation and related health issues. This timely monitoring supports proactive farm management, reducing losses and enhancing productivity while promoting sustainable and efficient aquaculture practices.

International stakeholders—including farm managers, technology providers, and policymakers—can leverage these insights to improve monitoring accuracy and operational efficiency. Farms in regions with fluctuating environmental conditions can confidently adopt these robust AI models, reducing labor-intensive manual counts and improving stock management. Moreover, awareness of model sensitivity to image quality encourages targeted investments in optimized imaging technologies and environmental controls.

From a broader perspective, integrating AI-powered monitoring aligns with global sustainable development initiatives, notably the United Nations' Sustainable Development Goals 14 (Life Below Water) and 12 (Responsible Consumption and Production). These technologies support sustainable aquaculture by enabling accurate stock assessments, reducing environmental impact, and enhancing productivity. Policymakers and funding agencies are encouraged to support digital infrastructure development and capacity-building programs to facilitate widespread adoption.

5. Conclusion

This study advances understanding of the factors influencing the performance of AI-driven aquaculture monitoring systems, specifically focusing on the YOLOv5 model for detecting post-larval redclaw crayfish. The findings emphasize that both environmental and biological variables significantly affect detection accuracy, underscoring the necessity of incorporating real-world variability into model training and evaluation.

Importantly, the robustness of the YOLOv5s model under diverse perturbations—including noise and lighting fluctuations—demonstrates its practical viability across a wide range of aquaculture settings. This positions YOLOv5 as a reliable tool capable of supporting sustainable and efficient aquaculture operations.

Strategically, this research highlights the critical interplay between technological capability and environmental context, suggesting that successful AI applications in aquaculture rely not only on advanced algorithms but also on tailored adaptations to site-specific conditions.

Future research should explore broader ecosystem applications, including multi-species detection and integration with real-time edge computing platforms. Longitudinal studies evaluating operational impacts, economic benefits, and scalability of AI-based monitoring solutions will further guide industry adoption and policymaking.

References

[1] G. Li and X. Liu, "A review on deep learning-based aquatic species detection using underwater imaging," *Sensors*, vol. 21, no. 3, p. 1037, 2021.

[2] Y. Li, X. Li, and L. Zhang, "Fish detection and behavior analysis using YOLOv3 in aquaculture monitoring," *Aquacultural Engineering*, vol. 93, p. 102145, 2021.

[3] H. Salehinejad, S. Sankar, H. Barfuss, and C. Smith, "Recent advances in deep learning applications for aquaculture," *Computers and Electronics in Agriculture*, vol. 155, pp. 426–441, 2018.

[4] X. Wang, H. Zhao, and Y. Zhu, "YOLOv7-based object detection model for real-time aquaculture monitoring," *Aquacultural Engineering*, vol. 97, p. 102269, 2023.

[5] Y. Wang, H. Chen, Z. Xu, and L. Luo, "Aquaculture fish detection in turbid underwater environments using deep learning," *Sensors*, vol. 21, no. 13, p. 4472, 2021.

[6] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2016.

[7] G. Jocher, A. Chaurasia, and J. Qiu, "YOLOv5: A family of object detection architectures and models in PyTorch," 2023. https://github.com/ultralytics/yolov5

[8] R. Padilla, W. L. Passos, T. L. Dias, S. L. Netto, and E. A. Da Silva, "A comparative analysis of object detection metrics with a companion open-source toolkit," *Electronics*, vol. 10, no. 3, p. 279, 2021. https://doi.org/10.3390/electronics10030279

[9] H. Chen, J. Xu, H. Yang, and H. Luo, "Detection of whiteleg shrimp in aquaculture using YOLOv5 with improved image annotation," *Aquaculture Reports*, vol. 25, p. 101260, 2022.

[10] M. Xu, Y. Zhang, and Y. Chen, "Performance evaluation of deep learning models for underwater object detection under variable turbidity," *IEEE Access*, vol. 9, pp. 121675–121688, 2021.

[11] S. Singh, R. Kumar, and A. Bansal, "Comparative study of YOLO versions in underwater species detection," *Applied Intelligence*, vol. 53, pp. 3871–3889, 2023.

[12] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *Journal of Big Data*, vol. 6, no. 1, p. 60, 2019. https://doi.org/10.1186/s40537-019-0197-0

[13] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "Yolov4: Optimal speed and accuracy of object detection," *arXiv preprint arXiv:2004.10934*, 2020. https://doi.org/10.48550/arXiv.2004.10934

[14] M. Rahnemoonfar and C. Sheppard, "Deep count: fruit counting based on deep simulated learning," *Sensors*, vol. 17, no. 4, p. 905, 2017. https://doi.org/10.3390/s17040905

[15] Y. Lin, Z. He, and C. Yang, "YOLO-based multi-target detection system in fish farming environments," *Sensors*, vol. 20, no. 24, p. 7052, 2020.

[16] L. Perez and J. Wang, "The effectiveness of data augmentation in image classification using deep learning," *arXiv preprint arXiv:1712.04621*, 2017. https://doi.org/10.48550/arXiv.1712.04621

[17] S. Klinhom, P. Pornsawad, and S. Lertlum, "Deep learning-based detection of molting patterns in crustaceans using image processing," *Aquacultural Engineering*, vol. 97, p. 102264, 2023.

[18] H. Jiang, L. Zhang, S. Zhang, and X. Wang, "A multi-scale convolutional neural network for fish segmentation," *Computers and Electronics in Agriculture*, vol. 178, p. 105753, 2020.

[19] X. Duan, C. Wang, W. Zhang, and J. Liu, "Underwater object detection using improved YOLOv3 model," *Sensors*, vol. 20, no. 14, p. 3957, 2020.

[20] Tzutalin, "LabelImg. GitHub repository," 2015. https://github.com/tzutalin/labelImg

[21] D. C. Montgomery, *Design and analysis of experiments*, 9th ed. Hoboken, NJ: John Wiley & Sons, 2017.

[22] M. J. Vidal, J. P. de Albuquerque, and R. E. Rios, "Assessment of inter-annotator agreement in image labeling for aquatic datasets," *Journal of Experimental Marine Biology and Ecology*, vol. 515, pp. 29–36, 2019.

[23] A. Field, *Discovering statistics using IBM SPSS statistics*, 5th ed. London: SAGE Publications, 2018.