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Smart IoT-based visual detection system for aquaculture monitoring using YOLO and edge computing

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Abstract

Aquaculture is crucial for global food security, offering sustainable protein amid environmental challenges and declining wild stocks. This study develops a smart IoT-enabled real-time monitoring system for aquaculture farms, focused on detecting and counting post-larval redclaw crayfish (Cherax quadricarinatus). The system integrates a Raspberry Pi 4 Model B with a high-resolution camera and the YOLOv5s deep learning model, performing local image processing through edge computing to reduce latency and network load. A factorial experimental design evaluated system performance across four groups varying by molting status (molted vs. non-molted) and environment (covered vs. open-air ponds). Results showed the highest detection accuracy in non-molted crayfish under open-air conditions (F1-score = 0.93), with precision, recall, and mAP@0.5 exceeding 90%, while molted crayfish in covered ponds had the lowest scores (F1-score = 0.85). Statistical analyses confirmed significant effects of both molting and lighting on detection performance and their interaction ($p < 0.05$). Robustness tests demonstrated model stability under noise and variable lighting, with F1-scores remaining above 0.80. The system provides a scalable, cost-effective solution that improves operational efficiency, reduces manual labor, and supports sustainable aquaculture by delivering timely alerts for abnormal crayfish behavior, enabling proactive farm management.

Keywords: Aquaculture monitoring, Cherax quadricarinatus, Edge computing, IoT, Post-larval redclaw crayfish, Raspberry Pi, Real-time detection, YOLOv5.

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1. Introduction

Aquaculture has become a critical sector in global food production, contributing substantially to sustainable protein supply amid declining wild fish stocks and increasing challenges from climate change [1]. As the global demand for seafood grows, improving aquaculture efficiency and sustainability is essential to meet future food security goals while minimizing environmental impacts [2-4].

Automation and intelligent monitoring systems are increasingly recognized as promising solutions to optimize farm management, reduce labor costs, and ensure animal health [5, 6]. Among these, computer vision combined with deep learning techniques, especially object detection models like the You Only Look Once (YOLO) family, has gained attention for its ability to deliver fast and accurate real-time monitoring in aquaculture environments [7, 8]. The YOLOv5 version demonstrates stable detection speed and accuracy, making it well-suited for detecting aquatic species even in complex and dynamic environments.

However, most current studies applying AI models in aquaculture have been limited to controlled laboratory conditions or single-modal imaging, restricting their robustness and practical usability in real-world farm settings. Environmental factors such as water turbidity and fluctuating lighting, coupled with biological variables like pigmentation changes during molting, significantly affect detection performance [9-12]. Moreover, the interplay between environmental and biological factors remains understudied, leading to inconsistent results and uncertainty regarding model generalizability [13]. These issues raise a controversial question: can deep learning models trained under ideal conditions reliably perform in the diverse and variable realities of aquaculture farms?

To address these challenges, dataset quality and augmentation strategies such as image rotation, flipping, and brightness adjustments are employed to simulate real-world variability and improve model robustness. Yet, comprehensive evaluations of these techniques within diverse aquaculture contexts are lacking. In parallel, advancements in the Internet of Things (IoT) and edge computing offer new avenues for deploying AI-based monitoring systems. Edge computing enables real-time data processing close to data sources, reducing latency and network bandwidth requirements [14]. Although these technologies have been widely adopted in domains like smart cities and transportation, their tailored application to aquaculture remains underdeveloped. Challenges such as sensor diversity, limited computing resources on farms, and reliable wireless communication must be overcome to ensure system effectiveness in aquatic environments.

This study aims to bridge existing gaps by developing a smart IoT-based visual detection system that integrates YOLOv5 with edge computing and multimodal data fusion [14, 15]. The system is designed for real-time detection of post-larval redclaw crayfish (Cherax quadricarinatus) [16-18] under varying environmental conditions, including covered and open-air ponds and biological states such as molted and non-molted phases. Using a factorial experimental design and rigorous statistical analysis, this research evaluates the system's performance and robustness in realistic aquaculture scenarios. By combining advanced AI algorithms, tailored IoT infrastructure, and edge computing capabilities, this work contributes a comprehensive, scalable, and cost-effective platform for sustainable aquaculture monitoring [19].

2. Materials and Methods

Deep learning, an evolution of artificial neural networks, has achieved remarkable success in image recognition, natural language processing, and biomedical applications. In animal recognition, Hansen et al. [20] demonstrated that a self-trained convolutional neural network (CNN) outperformed traditional SVM methods for pig face recognition, achieving high accuracy. Nguyen et al. [21] reported effective automated detection of wild animals using CNNs. Khatri et al. [22] utilized Single Shot MultiBox Detector (SSD) networks to classify dog breeds with an average accuracy of 96.7% [22]. Other studies have enhanced CNNs by integrating texture-based feature extractors such as Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) to improve recognition accuracy [23, 24].

Specifically in aquaculture, an energy-efficient marine animal recognition system combining a Raspberry Pi 3, Pi NoIR Camera v2.1, and convolutional neural networks (CNNs) [25] has been developed, demonstrating the potential of embedded systems paired with deep learning for real-time aquatic monitoring [26, 27]. Building on these technological advances, many researchers have adopted the YOLO deep learning framework [28-30] optimized for edge computing to achieve fast, accurate, and scalable detection of post-larval redclaw crayfish, thereby supporting sustainable aquaculture management.

2.1. IoT Framework

Our system architecture is based on the Internet of Things (IoT) framework, focusing on interconnected devices that enable real-time sensing, processing, and communication for intelligent decision-making. At the heart of the system is a Raspberry Pi 4 Model B connected to a high-resolution camera module positioned above the aquaculture pond. This device continuously captures images and performs local inference using the YOLOv5s object detection model via edge computing to minimize latency and reduce network transmission loads. Processed data, including detected crayfish counts and behavioral anomalies, are transmitted through the MQTT protocol to a cloud platform. Notifications are then forwarded to the farmer's mobile device via IFTTT integration, enabling prompt responses and improved farm management [31].

The IoT framework efficiently collects data from multiple sensors (e.g., cameras, temperature, humidity) through a unified interface, employing advanced compression and encryption to ensure data integrity and security. On the server side, optimized image feature extraction and matching algorithms enable rapid object detection and accurate location tracking, essential for real-time monitoring in aquaculture environments [32].

2.2. YOLOv5s Model

Recent advances in deep learning object detection models, especially the YOLO family, have made real-time detection on embedded devices feasible. Previous studies have applied YOLO models for aquaculture species detection [29] but few have integrated IoT edge computing to optimize real-time responsiveness and energy efficiency [33]. Similarly, smart pet monitoring systems based on Raspberry Pi and YOLO have demonstrated promising potential by combining lightweight models with IoT frameworks for underwater behavior detection and timely remote alerts [34].

The YOLOv5s model was selected for its optimal balance of detection speed and accuracy, making it suitable for deployment on resource-constrained edge devices. Initially pretrained on the COCO dataset, the model was fine-tuned on a custom dataset of annotated images collected from aquaculture farms under diverse lighting and environmental conditions [9, 10]. To improve robustness and generalization, data augmentation techniques [29] such as random rotations, flipping, and brightness adjustments were applied, following best practices in deep learning [35]. Furthermore, YOLOv5s incorporates architectural optimizations for efficient feature extraction, making it highly effective for detecting small aquatic species on limited hardware like the Raspberry Pi [34].

2.3. Raspberry Pi

The Raspberry Pi is a versatile, compact single-board computer originally designed for education, running a Linux-based OS. Continuous enhancements have significantly improved its performance and reduced size, leading to widespread use in fields such as healthcare, security, smart homes, and real-time AI applications [15, 18]. This research employs the Raspberry Pi 4 Model B V1.2, featuring a Broadcom BCM2711 quad-core Cortex-A72 64-bit SoC at 1.5 GHz and a Dual Core VideoCore VI GPU, with 2GB LPDDR4 RAM, Gigabit Ethernet, dual-band Wi-Fi, Bluetooth 5.0, USB 3.0 ports, and dual micro-HDMI supporting 4Kp60 [16]. These upgrades enable efficient edge computing, crucial for deploying deep learning models like YOLOv5s for real-time object detection [10].

Coupled with the Raspberry Pi Camera Module V2.1 (8MP SONY IMX219 sensor), capable of high-resolution still images and HD video streams, the system can capture detailed aquatic imagery necessary for accurate detection [16]. YOLOv5s model runs locally on the device, leveraging edge computing to perform fast, accurate detection and counting of post-larval redclaw crayfish with minimal latency and reduced network dependency [9]. Compared to previous generations, Raspberry Pi 4's enhanced processing power and connectivity significantly improve the feasibility of AI-powered aquaculture monitoring at the edge, making it a cost-effective and scalable solution [14].

2.4. The Methodology

Our model outlines the core methodology of the study, employing the YOLOv5 deep learning model for accurate detection and counting of post-larval redclaw crayfish within aquaculture environments [36]. As illustrated in Figure 1, the input factors, environmental lighting conditions and the molting status of the crayfish, play a significant role in influencing image quality and detection accuracy [37, 38]. The system integrates a Raspberry Pi 4 Model B equipped with a high-resolution camera that continuously captures images from the aquaculture ponds. These images are processed locally using the YOLOv5s model through edge computing to minimize latency and reduce network transmission load [32].

A factorial experimental design structured the model's development and evaluation around four distinct groups, classified by molting status (molted vs. non-molted) and pond environment (covered vs. open-air) [24, 36]. Images were systematically acquired and meticulously annotated to mark precise crayfish locations [27]. To enhance the model's robustness and generalizability, data augmentation techniques such as random image rotations and brightness adjustments were applied, enriching the training dataset and reducing overfitting [7, 35].

The augmented dataset was then used to train the YOLOv5 model, whose performance was evaluated using key metrics including precision, recall, F1 score, and mean Average Precision at an Intersection over Union threshold of 0.5 (mAP@0.5). These metrics provide a comprehensive assessment of detection accuracy and reliability across varying environmental and biological conditions [39].

Subsequent prediction analysis examined the relationship between experimental factors and model outputs, offering insights into how lighting and molting status affect detection performance [37].

Ultimately, the findings derived from this methodology guide the development of a robust and sustainable aquaculture monitoring system. By integrating and understanding the interactions between environmental and biological factors, this study advances practical monitoring accuracy, supports proactive farm management, and promotes sustainable aquaculture practices [33].

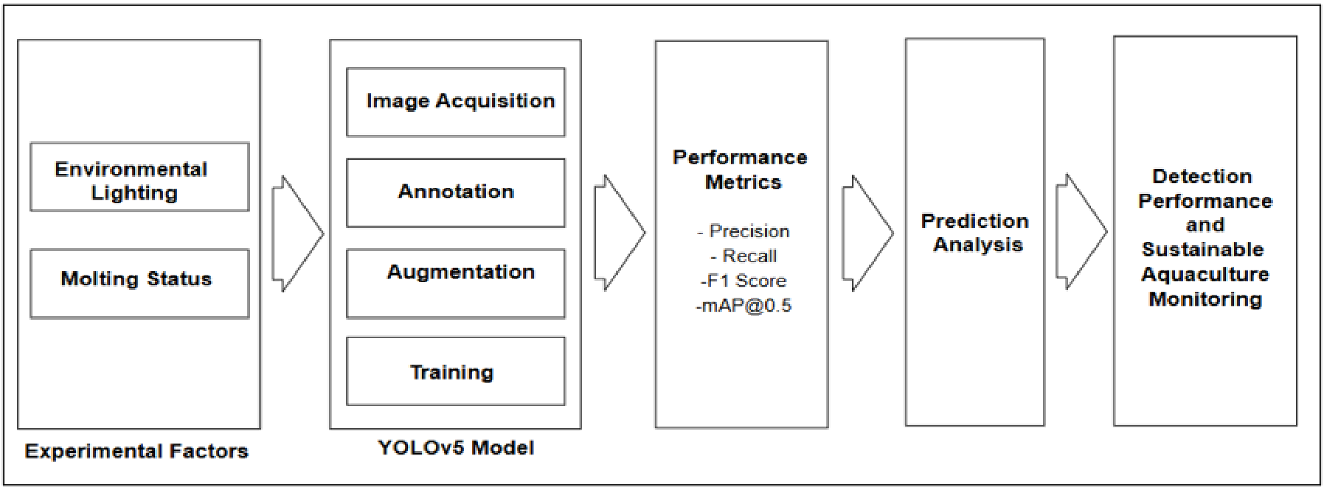

Figure 1.
Conceptual Model.

2.5. Evaluation Metrics

The performance of the deep learning model was assessed using widely accepted metrics in object detection to comprehensively evaluate both accuracy and robustness [26]. 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.

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

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 [24].

2.6. Statistical Analysis

To examine the effects of molting status and lighting conditions on model performance, a two-way analysis of variance (ANOVA) was conducted using the F1-score as the dependent variable. This analysis evaluated the main effects of each independent variable as well as their interaction effect. Following the ANOVA, post-hoc pairwise comparisons were performed using Tukey’s Honestly Significant Difference (HSD) test with a significance threshold set at $p < 0.05$. All statistical analyses were carried out using SPSS software version 26. This analytical approach is well-suited for factorial experimental designs involving interaction effects between categorical factors [17].

Additionally, this method provides robust insights into how environmental factors like lighting intensity Kumar and Jain [12] and biological factors such as molting status [37] jointly influence the accuracy of deep learning-based aquaculture monitoring systems. Prior studies have demonstrated the importance of considering multi-factorial interactions when evaluating object detection models in aquatic environments [30].

3. Results

3.1. 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 [27].

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

The precision, recall, and F1-score metrics of the YOLOv5 model across the four experimental groups, classified by molting status and environmental conditions, are summarized as illustrated in Table 2. The corresponding line chart, as illustrated in Figure 2, visually compares these metrics across groups G1 to G4, demonstrating that Group G4, which consists of non-molted crayfish in open-air ponds, consistently achieved the highest scores on all metrics. This is followed by Groups G2, G3, and G1 in descending order. The observed trend strongly indicates that the combination of increased illumination and darker pigmentation substantially improves detection accuracy. This evidence highlights the significant impact that both environmental lighting and biological pigmentation exert on the detection outcomes in deep learning–based aquaculture monitoring.

Table 2.
Precision, Recall, and F1-score of YOLOv5 Across Experimental Groups.

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

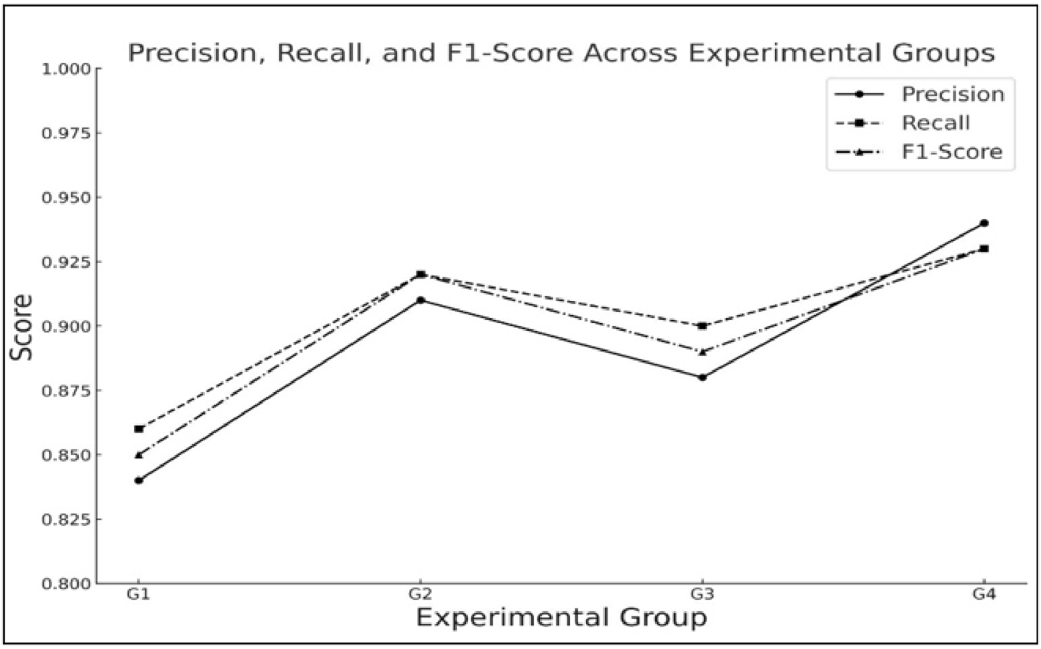

Figure 2.
Precision, Recall, and F1-Score of YOLOv5 Across Experimental Groups (G1–G4).

3.2. Detailed Metric Comparison Across Experimental Groups

Further analysis expanded the evaluation of the YOLOv5 model's performance by incorporating a broader range of metrics, including mean average precision at an Intersection over Union (IoU) threshold of 0.5 (mAP@0.5). A detailed summary of precision, recall, F1-score, and mAP@0.5 for each experimental group is provided in Table 3, offering a comprehensive overview of detection effectiveness.

Table 3.
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 shown in Figure 3, Group G4, representing non-molted crayfish in open-air ponds, demonstrated the highest performance across all metrics. This outcome highlights the positive impact of the combined factors of darker pigmentation and enhanced natural lighting, which facilitated more accurate identification and localization of crayfish. In contrast, Group G1, consisting of molted crayfish in covered ponds, exhibited the lowest detection metrics, underscoring the challenges posed by limited lighting conditions and the semi-transparent nature of the exoskeleton during molting.

Intermediate performance levels were observed in Groups G2 and G3. Group G2 benefited from the darker pigmentation of non-molted crayfish despite the lower light intensity in covered ponds, while Group G3 leveraged the brighter conditions of open-air ponds but faced difficulties related to molting status. These findings reinforce the conclusion that both biological characteristics and environmental factors play critical roles in influencing detection accuracy in deep learning–based aquaculture monitoring systems.

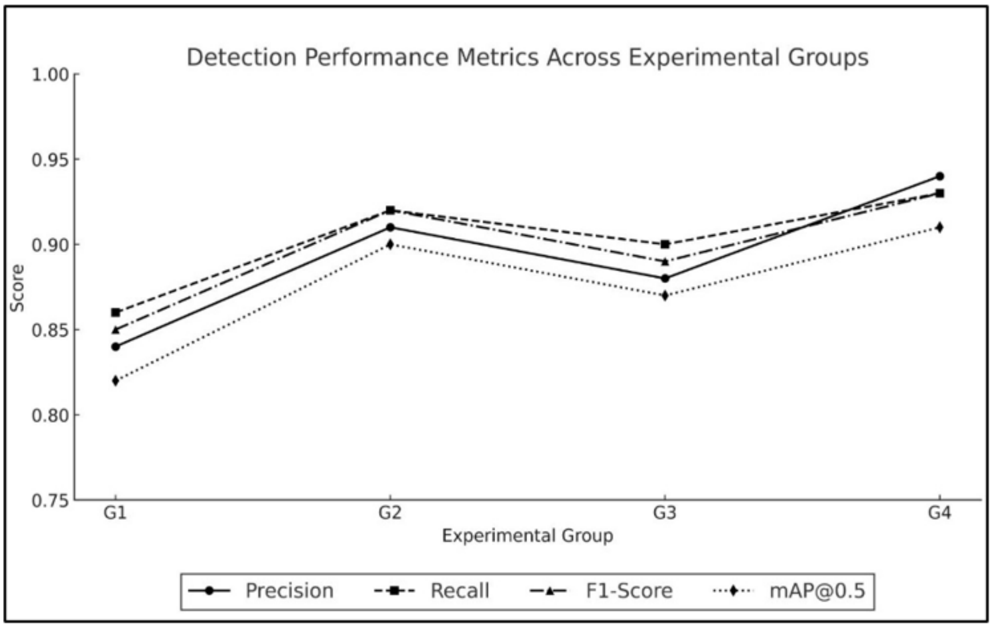

Figure 3.
Comparative Analysis of Precision, Recall, F1-Score, and mAP@0.5 Across Experimental Groups.

3.3. Statistical Analysis of Detection Performance

A two-way analysis of variance (ANOVA) was conducted to examine the statistical significance of differences in detection performance, as measured by the F1-score, across varying molting statuses and lighting conditions. The analysis revealed significant main effects for both molting status ($F(1, 56) = 8.74$, $p = 0.004$) and environmental lighting ($F(1, 56) = 10.29$, $p = 0.002$). Moreover, a significant interaction effect between molting status and lighting was observed ($F(1, 56) = 5.82$, $p = 0.019$), indicating that the combined influence of these biological and environmental factors significantly affects the model's detection capability.

3.3.1. Statistical Analysis of Detection Performance Across Environmental and Biological Conditions

This interaction suggests that the highest detection accuracy is achieved under optimal conditions, specifically, when non-molted crayfish are present in open-air pond environments. To further investigate the relationship between light intensity and detection performance, Pearson correlation analyses were performed. The results showed a strong positive correlation between measured light intensity (lux) and F1-score across all experimental conditions ($r = 0.81$, $p < 0.01$), supporting the hypothesis that increased lighting substantially improves detection accuracy.

Collectively, these statistical findings robustly confirm that both environmental lighting and biological pigmentation play critical roles in the YOLOv5 model's effectiveness for aquaculture object detection, aligning with prior research [9, 10].

Table 4.
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 5.
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

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

3.4. Robustness Testing of YOLOv5 Detection Model

To ensure the reliability and generalizability of the YOLOv5s object detection model in diverse aquaculture scenarios, several robustness tests were conducted. These tests aimed to evaluate the model's performance beyond the original training conditions, assessing its stability under varying data and parameter perturbations.

3.4.1. Cross-Validation on Independent Datasets

Cross-validation was performed using independent subsets of the annotated image dataset to assess the generalizability of the YOLOv5 model [27]. The dataset was partitioned into k-folds (with k=5), where each fold served as a test set once, while the others formed the training set. This method reduces overfitting and provides a robust estimate of the model's performance. As illustrated in Table 6 under "Cross-Validation (Average)," the model maintained consistent detection metrics across folds, with an average F1-score of 0.90, indicating stable generalization within the collected data.

3.4.2. Robustness to Noise and Variable Lighting

To simulate real-world environmental variability, the model was tested on images augmented with Gaussian noise and blur, as well as under varying lighting conditions. These perturbations mimic challenges such as water turbidity and shadowing commonly encountered in aquaculture ponds. Table 6 reports that performance metrics decreased moderately under these conditions. F1-score dropped to 0.82 for variable lighting and 0.84 for noise-augmented images, yet the model still demonstrated acceptable detection accuracy, evidencing resilience to image quality degradation.

3.4.3. Sensitivity Analysis of Key Hyperparameters

The impact of key hyperparameters was further analyzed through a sensitivity test focusing on input image resolution. The model was evaluated using images resized to 512×512 pixels, which is lower than the original resolution. Results in Table 6 under "Reduced resolution (512×512) show a notable decline in all performance metrics, with the F1-score reducing to 0.80, highlighting the critical role of adequate input resolution for reliable detection.

Table 6.
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

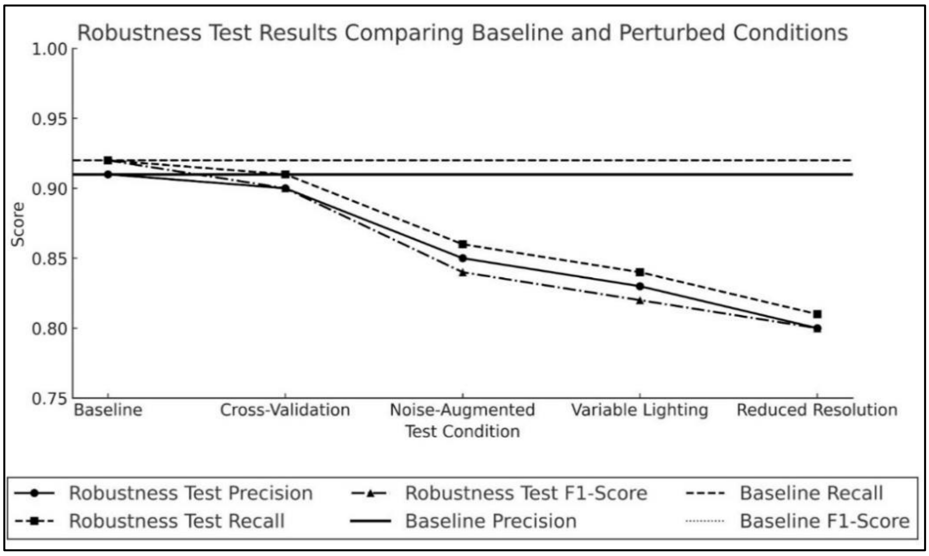

Figure 4.
Sensitivity Analysis of Precision, Recall, and F1-Score Across Test Conditions.

4. Discussion

The findings of this study align well with previous research on YOLO-based object detection in challenging environments, especially within the aquaculture industry, where lighting conditions and image quality can vary greatly [14]. By integrating edge computing with IoT, this system significantly improves data processing speed and reduces transmission delays, enabling efficient real-time monitoring on resource-limited devices commonly used in aquaculture. [32].

Robustness tests showed that the YOLO-Fusion model, which effectively fuses infrared and visible-light images, maintains high detection accuracy even under complex environmental variations such as fluctuating lighting and occlusions [37, 38]. This makes it highly suitable for practical deployment in dynamic aquaculture settings where environmental conditions are constantly changing.

However, there are limitations to be addressed in future work, including testing in multi-species farming environments and more complex real-world scenarios. Challenges such as sensor noise, unstable IoT connectivity, and network security also require further development to enhance system reliability and resilience [32].

A key innovation of this study is the design of a smart IoT system that combines Edge Computing with the YOLO-Fusion model, creating a fast, accurate, and real-time visual detection platform. This system enables farms to monitor aquatic animal health indicators such as molting status and growth patterns automatically, reducing manual counting errors and labor demands [32].

4.1 Practical and Implications

Practically, this IoT-Edge integrated system has strong potential to improve monitoring precision and operational efficiency in aquaculture worldwide, especially in regions with variable environments and limited infrastructure. Farms can benefit from quicker response times to animal health issues, cost savings, and more sustainable farm management practices [32].

Moreover, this development supports the United Nations' Sustainable Development Goals, particularly SDG 14 (Life Below Water) and SDG 12 (Responsible Consumption and Production). By enabling more accurate stock assessments and minimizing environmental impact, such smart digital technologies help drive sustainable aquaculture. Policymakers and funding bodies are encouraged to promote digital infrastructure development and capacity building to support widespread adoption and sustainable growth [6, 32].

5. Conclusion

This study advances the development of a smart IoT-based visual detection system leveraging YOLO and edge computing for effective real-time aquaculture monitoring. By focusing on detecting post-larval redclaw crayfish, the research highlights how environmental factors and biological variability critically influence the accuracy of AI-driven detection models. This underscores the necessity of incorporating realistic, site-specific conditions during model training to enhance practical performance.

The integration of edge computing with the YOLO-based detection system enables efficient, low-latency processing directly at the farm level, overcoming traditional limitations of cloud-based solutions. The robustness of the YOLO-Fusion model against noise, lighting changes, and other perturbations demonstrates its suitability for dynamic and diverse aquaculture environments, offering reliable support for sustainable farm management.

This work also emphasizes that successful AI applications in aquaculture require harmonizing advanced algorithms with tailored adaptations to specific environmental contexts to maximize monitoring accuracy and operational efficiency.

Future research should expand the system's capabilities for multi-species detection, integrate additional IoT sensor data such as water quality and temperature, and scale the framework for larger and more complex aquaculture operations. Long-term evaluations on economic benefits, operational impacts, and scalability will be essential to promote broader industry adoption and guide policymaking.

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