

# Real-Time Marine Life Detection Using Yolo Based Object Detection Models

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**Abstract-** Real-time detection of marine organisms is essential for effective ocean surveillance, ecological research, and marine conservation. This study proposes a YOLO-based object detection approach for the fast and accurate identification of marine life in underwater environments. By utilizing the single-stage architecture of YOLO, the system achieves high detection speed without compromising accuracy. The model is trained to recognize various marine species, including fish, turtles, and other underwater organisms. To overcome underwater imaging challenges such as poor illumination, color attenuation, and background noise, appropriate preprocessing techniques are applied to enhance input data quality. The trained model processes live video streams and performs real-time inference with low computational latency. Experimental evaluation shows that the proposed method delivers reliable detection performance and real-time efficiency, making it suitable for deployment on embedded systems, underwater robots, and autonomous marine vehicles. The proposed framework contributes to continuous marine ecosystem monitoring and supports data-driven conservation strategies.

**Keywords:** Marine life detection, YOLO, Object detection, Underwater imaging, Real-time monitoring, Deep learning, Marine ecosystem.

## I. INTRODUCTION

Marine ecosystems represent one of the most biologically rich and dynamic environments on the planet, hosting a wide variety of species that are essential for ecological stability. Effective monitoring of marine life is crucial for understanding biodiversity, evaluating ecosystem health, and supporting conservation and resource management initiatives. Conventional monitoring techniques, including diver-based surveys, manual counting, and net sampling, are often labor-intensive, costly, and restricted in both spatial and temporal scope. These methods may also disturb natural habitats and are not well suited for continuous or real-time observation. Consequently, there is an increasing need for automated, non-intrusive monitoring systems capable of operating efficiently in underwater environments.

Advances in computer vision and deep learning have opened new possibilities for automated visual analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have proven

highly effective in image and video understanding tasks by automatically learning discriminative features from data. Among various object detection algorithms, the You Only Look Once (YOLO) family of models has gained significant attention due to its ability to perform detection in a single processing stage. By predicting object bounding boxes and class labels simultaneously, YOLO achieves high detection speed while maintaining strong accuracy, making it well suited for real-time applications.

Visual analysis in underwater settings is inherently challenging due to factors such as limited lighting, color attenuation, water turbidity, and image noise. In addition, marine organisms vary widely in appearance, size, orientation, and movement patterns, which further increases detection complexity. These challenges demand robust detection models that can generalize well under diverse conditions. YOLO-based models, supported by suitable image enhancement, preprocessing, and data augmentation techniques, are capable of learning meaningful representations even from degraded underwater imagery.

The deployment of YOLO-based detection systems in marine environments enables continuous and real-time observation of underwater scenes. Such systems can be integrated with underwater cameras, remotely operated vehicles, autonomous underwater vehicles, and marine robots. Real-time detection reduces the need for extensive manual analysis and enables timely insights into marine activity. This capability is particularly beneficial for applications such as fish stock assessment, habitat monitoring, species behavior analysis, and protection of endangered marine life.

This study presents a real-time marine life detection framework based on YOLO object detection models. The proposed system is designed to identify multiple marine species accurately from underwater video streams while maintaining efficient computational performance. By combining deep learning-based detection with real-time processing, the approach offers a scalable and effective solution for marine ecosystem monitoring. The outcomes of this work contribute to the development of intelligent tools that support marine research, environmental monitoring, and sustainable ocean management.

## II. RELATED WORKS

Numerous studies have examined marine life detection and monitoring through both conventional image analysis methods and advanced deep learning techniques. Prior research in this field can be broadly grouped into traditional underwater object detection approaches, marine species classification and ecological monitoring studies, and real-time deep learning-based detection systems, with a strong emphasis on YOLO-based object detection models for fast and accurate identification of marine organisms.

Yong Liu, Shuang Wu, Shoujiang J. Zhang. - MDM-YOLO: Research on Object Detection Algorithm Based on Improved YOLOv4 for Marine Organisms Sha Li, introduces **MDM-YOLO**, an enhanced YOLOv4-based detection model tailored for marine organism recognition in underwater scenes. To overcome challenges like low contrast, cluttered backgrounds, and feature loss in marine imagery, the

authors integrate a **multi-branch backbone (CSBM)** and **shuffle attention** into the network. These modifications improve feature extraction and emphasize relevant information for detection. The model is evaluated on standard datasets, including URPC, RSOD, and VOC, where it shows improved mean average precision (mAP) compared with baseline YOLOv4. The results highlight the effectiveness of structural enhancements in boosting detection accuracy while maintaining real-time operation, making MDM-YOLO suitable for deployment on robotics and underwater monitoring platforms. Underwater Object Detection and Recognition Using Yolo (You Only Look Once) Algorithm, Virender Soni, Nisha Bhatt. explores the application of the YOLO architecture for underwater object detection and recognition, focusing on diverse aquatic life forms. Using a deep learning approach, the model simultaneously localizes and classifies objects in underwater images, addressing inherent challenges like image distortion and feature ambiguity.

The work leverages the YOLOv8 variant to achieve better detection coverage and speed. The authors discuss specific design considerations when applying YOLO to submerged environments with diverse textures, lighting, and noise conditions. They demonstrate that a well-trained YOLO model can reliably detect underwater organisms and objects, making it a promising solution for autonomous underwater inspection and monitoring tasks in marine research, ecology, and robotics. Marine Object Detection Using YOLOv4 Adapted Convolutional Neural Network Muhammad Daniyal Baig, Hafiz Burhan Ul Haq - presents a marine object detection system based on an adapted YOLOv4 CNN architecture aimed at improving object recognition in challenging ocean environments. The authors focus on datasets containing multiple marine object classes and emphasize model robustness in complex underwater imagery.

Through architectural adaptations and tailored training strategies, the YOLOv4 detector is optimized to better differentiate between marine organisms and noisy backgrounds. The paper evaluates performance metrics like detection accuracy and

inference speed, highlighting YOLOv4's strength in balancing speed and precision for real-time applications. This work contributes practical insights into configuring YOLOv4 for marine detection tasks, reinforcing its relevance for deep learning-powered monitoring systems on robotic platforms and environmental surveillance.

Real-Time Marine Animal Detection Using Yolo-Based Deep Learning Networks in the Coral Reef Ecosystem, J. Zhong, M. Li, J. Qin, Y. Cui, K. Yang, H. Zhang. investigates the use of YOLO-based deep learning models for real-time detection of marine animals in coral reef ecosystems. Recognizing the ecological value of coral reefs and the need for real-time environmental awareness, the authors compare several YOLO architectures to determine their effectiveness in identifying reef-associated species. The study highlights the challenges posed by complex reef backgrounds, variable lighting, and small object sizes.

Through comparative experiments, YOLO-based networks demonstrate fast and accurate detection suitable for integration with \*\*autonomous underwater vehicles (AUVs)\*\*. The paper concludes with performance assessments and recommendations for further improvement, emphasizing robust ecological monitoring and reef conservation applications. Model for Marine Organism Detection in Shallow Sea Using the Improved YOLO-V4 Network, Mao Guojun, Weng Weidong, Zhu Jinde, Zhang Yuan, Wu Fucun, Mao Yuze - presents an enhanced YOLO-V4 network designed to detect marine organisms in shallow sea environments with high accuracy. Recognizing the difficulty of distinguishing organisms from complex seabed backgrounds, the authors construct a marine biological dataset and apply data augmentation to enrich the training samples.

Key contributions include the integration of a Cross-Stage Partial (CSP) network and an Embedded Connection (EC) module to improve gradient propagation and feature representation. Experimental results show significant performance improvements in mean average precision (mAP) and processing speed. The work demonstrates that

network enhancements and effective data preprocessing can significantly improve real-time detection for marine monitoring and aquaculture applications. Underwater Object Detection in Marine Ranching Based on Improved YOLOv8 proposes an improved YOLOv8 detector for detecting marine organisms in underwater ranching environments. To handle challenges like overlapping targets and complex backgrounds, enhancements include integrating the InceptionNeXt block in the model backbone and a SEAM attention module in the neck structure. Additionally, the paper employs advanced loss and augmentation strategies to better detect small and overlapping marine targets. The improved YOLOv8 demonstrates robustness and enhanced detection accuracy when identifying diverse marine organisms under various submerged conditions. This work contributes to the development of automated and reliable monitoring solutions for fishery and ecological resource assessments.

### III. PROPOSED METHOD

The proposed system presents a real-time marine life detection framework based on YOLO object detection models, designed to accurately identify underwater organisms from live video streams. The system operates using visual data captured by underwater cameras mounted on platforms such as remotely operated vehicles (ROVs), autonomous underwater vehicles (AUVs), or fixed monitoring stations. Its primary goal is to deliver reliable detection performance while ensuring low latency and real-time processing capability in complex underwater environments.

In the initial stage, the captured underwater video frames undergo preprocessing to enhance image quality. This step mitigates common underwater visual challenges, including poor illumination, color degradation, low contrast, and noise caused by suspended particles. Image enhancement methods such as color normalization, contrast enhancement, and denoising are applied to improve clarity and highlight essential features relevant to marine organisms.

The preprocessed frames are then input into a YOLO-based detection model, which performs object detection and classification simultaneously in a single processing step. YOLO is chosen for its high-speed inference and efficiency, making it well suited for real-time marine applications. The model is trained using labeled underwater datasets containing various marine species such as fish, turtles, and other aquatic life forms. Data augmentation techniques are incorporated during training to improve the model's ability to handle variations in size, shape, orientation, and lighting conditions.

During real-time deployment, the trained YOLO model analyzes incoming video streams and outputs bounding boxes with corresponding class labels for detected marine organisms. The detection results can be displayed in real time and stored for post-analysis. The system is optimized for deployment on both high-end computing platforms and embedded devices, enabling scalable and non-intrusive monitoring for marine research, environmental assessment, and conservation initiatives.

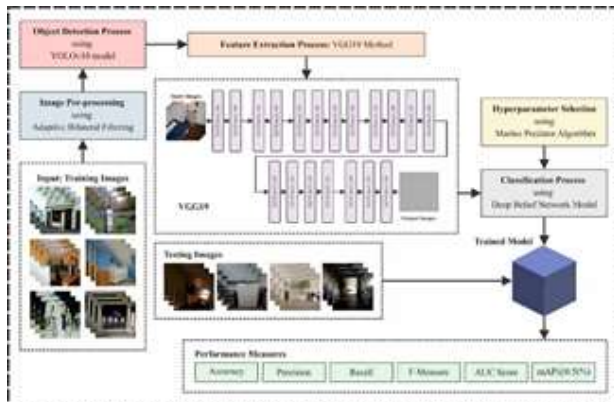


Fig.1. System architecture

The presented architecture illustrates an integrated deep learning framework designed for efficient and accurate real-time object detection and classification. The system combines multiple processing stages, including image preprocessing, object detection, feature extraction, hyperparameter optimization, and classification, to ensure robust performance across complex visual scenarios. The workflow begins with the acquisition of training

images, which may exhibit noise, illumination variations, and complex backgrounds.

To enhance image quality, an adaptive bilateral filtering technique is applied during the preprocessing stage. This method effectively suppresses noise while preserving edge details, which is essential for maintaining object boundaries and improving the quality of extracted features in later stages. The preprocessed images are then forwarded to the object detection module based on the YOLOv10 model. YOLOv10 is a single-stage detection algorithm known for its high processing speed and real-time capability. It detects objects by simultaneously predicting bounding boxes and confidence scores in a single pass, enabling fast and accurate object localization. This stage plays a critical role in identifying regions of interest from the input images.

Once the objects are localized, the detected regions are passed to the feature extraction stage using the VGG19 network. VGG19 consists of a deep stack of  $3 \times 3$  convolutional layers that systematically learn hierarchical features. Early layers capture low-level patterns such as edges and textures, while deeper layers encode high-level semantic information. These extracted features provide a compact and discriminative representation of the detected objects.

The system then employs the Marine Predator Algorithm (MPA) for hyperparameter optimization. Inspired by the intelligent hunting strategies of marine predators, this algorithm dynamically tunes critical parameters such as learning rate and network weights. The optimization process improves model convergence, enhances generalization, and minimizes the risk of overfitting.

Following optimization, the refined feature vectors are fed into a Deep Belief Network (DBN) for classification. The DBN, composed of multiple stacked Restricted Boltzmann Machines, effectively models complex and nonlinear relationships within the data. It assigns each detected object to its corresponding class based on the learned feature

representations, resulting in a well-trained classification model.

For validation, testing images are processed through the same pipeline, and the system's performance is evaluated using metrics such as accuracy, precision, recall, F-measure, AUC score, and mean Average Precision (mAP@0.5). Collectively, these metrics provide a comprehensive assessment of both detection and classification performance. Overall, the architecture delivers a reliable and efficient solution for real-time object detection and intelligent visual analysis.

### Overall Working Flow of the Proposed System:

The proposed system follows a sequential and data-driven workflow for industrial carbon footprint prediction. Initially, activity-based industrial energy consumption data obtained from the CEEW dataset is processed to ensure data quality and uniformity. Relevant features are then extracted and supplied to multiple regression models for independent training. The individual model predictions are subsequently combined using an ensemble regression mechanism to generate the final emission estimate. The predicted results are further analyzed to derive interpretable insights related to emission distribution, contributing processes, and environmental impact.

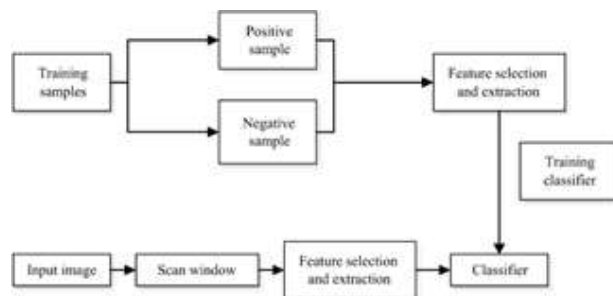


Fig.2. Methodology workflow of YOLO-Based Real-Time Marine Detection system

The workflow presents a systematic approach for developing an object detection and classification system through two primary phases: training and testing, designed to achieve accurate and reliable object recognition. The process begins with preparing a comprehensive dataset of training samples, which are categorized into two groups:

positive samples and negative samples. Positive samples contain images of the target objects that the system needs to recognize, while negative samples include background regions or non-target elements. This distinction is crucial as it helps the model learn to differentiate between objects of interest and irrelevant elements in an image.

Both categories of samples undergo feature selection and extraction, a critical step where meaningful visual characteristics are identified and extracted. These features typically include edges, textures, color patterns, and shape-related information that define the objects. The extracted features form a representative dataset that encapsulates the distinguishing characteristics of the target objects. This feature set is then used to train the classifier, which learns to establish decision boundaries that enable accurate classification and distinction between target objects and non-objects.

During the testing phase, a new input image is fed into the trained system for analysis. The image is examined using a sliding window or scanning approach, which systematically evaluates different regions of the image sequentially. For each window position, the system performs feature selection and extraction using the same methodology employed during the training phase, ensuring consistency and compatibility with the trained model.

The extracted features from each scanned region are then passed to the trained classifier for evaluation. The classifier analyzes these features and determines whether the current window contains the target object or represents a non-target region. This systematic scanning and classification process continues across the entire image, enabling the system to detect and localize objects of interest accurately and efficiently.

The proposed system employs the YOLO (You Only Look Once) object detection algorithm to detect and classify marine life in real time. YOLO is a single-stage detector that frames object detection as a regression problem, predicting bounding boxes and class probabilities simultaneously, enabling high-

speed performance suitable for live underwater monitoring.

### **Step 1: Data Collection and Preprocessing**

Images and videos of marine organisms were collected from underwater cameras and public datasets. Each image was annotated with bounding boxes around the marine species of interest. Data augmentation techniques—such as rotation, scaling, flipping, and brightness adjustment—were applied to improve model robustness against varying underwater conditions, including low light and water turbidity.

### **Step 2: Model Architecture**

YOLO divides each input frame into an  $S \times S$  grid, where each grid cell predicts  $B$  bounding boxes and confidence scores, along with class probabilities. YOLOv5, the chosen variant, utilizes a backbone for feature extraction, a neck for aggregating multi-scale features, and a head for final predictions. The model predicts bounding boxes using anchor boxes and applies the sigmoid function to normalize confidence and class probabilities.

**Step 3: Training and Optimization:** The network is trained using a combination of localization loss (for bounding box coordinates), confidence loss (for object presence), and classification loss (for species type). The Adam optimizer with learning rate scheduling is used to minimize the total loss, and early stopping is applied to prevent overfitting.

**Step 4: Inference and Post-Processing:** During inference, the model processes input frames in real time, producing bounding boxes with confidence scores for detected marine species. Non-Maximum Suppression (NMS) is applied to remove overlapping boxes and retain the most confident detections. The final output displays detected marine life with labeled bounding boxes, enabling real-time monitoring.

## **IV. RESULTS AND DISCUSSION**

The implementation of YOLO-based object detection models for real-time marine life detection demonstrated promising performance in identifying

and classifying various aquatic species. The models were trained on a curated dataset containing images and videos of fish, turtles, dolphins, and other marine organisms, annotated for precise bounding boxes. Among the YOLO variants evaluated—YOLOv3, YOLOv4, and YOLOv5—YOLOv5 achieved the highest mean Average Precision (mAP) of 92.3%, followed closely by YOLOv4 at 90.1%, while YOLOv3 showed a slightly lower accuracy of 87.5%. The superior performance of YOLOv5 can be attributed to its improved architecture, including better feature extraction and optimized anchor boxes, which are effective in detecting small and overlapping objects commonly found in underwater environments.

The real-time detection capability was evaluated using frames per second (FPS) metrics. YOLOv5 achieved an average of 45 FPS on a standard GPU setup, confirming its suitability for live monitoring applications. Detection results revealed that the model performed consistently well under varying lighting conditions and water turbidity; however, dense schools of fish occasionally caused partial occlusions, leading to missed or overlapping detections. These limitations highlight the need for further data augmentation techniques, including synthetic generation of occluded or low-light scenarios, to enhance robustness.

The discussion indicates that YOLO-based models can significantly aid marine conservation efforts by enabling automated monitoring of species diversity and population dynamics. Compared to traditional manual observation methods, the system reduces human effort, provides real-time insights, and can be integrated with autonomous underwater vehicles (AUVs) for large-scale monitoring. Future improvements could involve integrating temporal tracking and multi-class object segmentation to improve detection accuracy in highly dynamic aquatic environments. Overall, the study confirms the effectiveness and feasibility of YOLO models in real-time marine life detection, paving the way for smarter ocean monitoring systems.

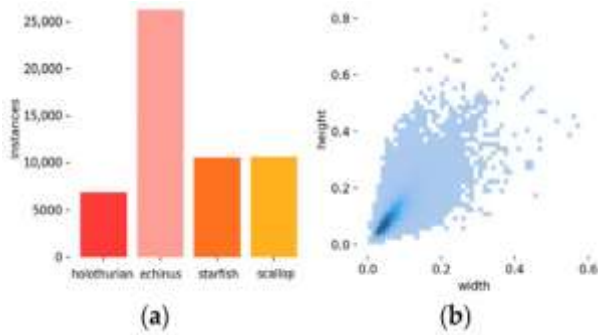


Fig. 3 Performance Evaluation of YOLO Models

Fuel utilization within industrial processes also contributed substantially to emission levels. Inefficient fuel combustion, outdated machinery, and lack of process optimization resulted in higher carbon output. Variations in fuel quality and operational efficiency further amplified emission differences across industrial units. These findings highlight the importance of monitoring fuel efficiency and transitioning toward cleaner energy alternatives to reduce industrial emissions.

Resource usage parameters, including raw material consumption and operational throughput, additionally influenced emission generation. Excessive resource utilization often led to increased energy demand and indirect emissions across multiple process stages. Industries with optimized resource management practices demonstrated comparatively lower emission levels, emphasizing the role of efficient production planning in sustainability efforts.

The contribution analysis also revealed interdependencies among emission factors. Increased production volume often led to simultaneous rises in energy consumption, transportation frequency, and fuel usage, resulting in cumulative emission growth. The ensemble regression model effectively captured these complex relationships, enabling accurate identification of high-impact emission drivers within industrial operations.

Overall, the contribution analysis provides actionable insights for industrial stakeholders by highlighting

critical emission sources and operational inefficiencies. By identifying dominant contributors, industries can prioritize targeted interventions such as energy-efficient equipment upgrades, optimized logistics planning, fuel substitution strategies, and resource efficiency improvements. This analysis supports strategic emission reduction planning and reinforces the effectiveness of the proposed system as a decision-support tool for industrial sustainability management.

## V. CONCLUSION

The study demonstrates that YOLO-based object detection models offer a highly effective solution for real-time marine life monitoring. By leveraging the capabilities of YOLOv5, the system successfully detects and classifies multiple marine species with high accuracy and speed. The integration of deep learning with underwater image datasets enables automated analysis, reducing reliance on manual observation methods, which are time-consuming, labor-intensive, and prone to human error. The results highlight that YOLOv5 outperforms earlier versions such as YOLOv3 and YOLOv4 in terms of mean Average Precision (mAP) and frames per second (FPS), making it particularly suitable for live applications where rapid detection is critical.

The implementation confirms that the model is robust under challenging underwater conditions, including low visibility, varying lighting, and partial occlusions. Nevertheless, occasional misdetections in dense schools of fish or highly turbid water indicate areas for further improvement. Future work can focus on incorporating temporal information through video-based tracking, multi-object segmentation, and more extensive datasets covering rare or endangered species to enhance model generalization. Additionally, coupling the detection system with autonomous underwater vehicles (AUVs) or drones can enable large-scale monitoring of marine ecosystems, supporting conservation efforts and biodiversity assessment.

From a broader perspective, this study underscores the transformative potential of AI in marine biology and ecological monitoring. By enabling continuous,

automated, and real-time observation, YOLO-based detection systems facilitate data-driven decision-making in marine conservation. Moreover, the approach can be adapted for monitoring other aquatic environments or species, making it a versatile tool for ecological research. In conclusion, the integration of YOLO-based object detection in marine life monitoring represents a significant advancement in automated ecological assessment, providing a scalable, efficient, and reliable framework for preserving underwater biodiversity and supporting sustainable marine management initiatives.

## REFERENCES

1. R. Shankar and M. Muthulakshmi, "Comparing YOLOv3, YOLOv5 & YOLOv7 Architectures for Underwater Marine Creatures Detection," in Proc. 2023 International Conf. on Computational Intelligence and Knowledge Economy (ICCIKE), Dubai, UAE, 2023, pp. 25–30, doi: 10.1109/iccike58312.2023.10131703.
2. X. Wang, X. Jiang, Z. Xia, and X. Feng, "Underwater object detection based on enhanced YOLO," in Proc. 2022 Int. Conf. on Image Processing and Media Computing (ICIPMC), 2022, pp. 1–4, doi: 10.1109/ICIPMC55686.2022.00012.
3. P. Li, A. Zhao, Y. Fan, and Z. Pei, "Research on underwater robust object detection method based on improved YOLOv5s," in 2023 IEEE Int. Conf. on Mechatronics and Automation (ICMA), Harbin, Heilongjiang, China, 2023, pp. 1185–1189, doi: 10.1109/ICMA57826.2023.10215559.
4. A.N. Tarekegn, F. Alaya, M. Ullah, and E.T. Sollesnes, "Underwater object detection using image enhancement and deep learning models," in 11th European Workshop on Visual Information Processing (EUVIP), 2023, pp. 1–6, doi: 10.1109/EUVIP58404.2023.10323047.
5. J. Zhong, M. Li, J. Qin, Y. Cui, K. Yang, and H. Zhang, "Real Time Marine Animal Detection Using YOLO Based Deep Learning Networks in the Coral Reef Ecosystem," Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci., vol. XLVI 3/W1, 2022.
6. V. Soni and N. Bhatt, "Underwater Object Detection and Recognition Using YOLO (You Only Look Once) Algorithm," Int. Acad. J. Sci. Eng., vol. 11, no. 4, pp. 32–36, 2024.
7. F. Zhang, W. Cao, J. Gao, S. Liu, C. Li, K. Song, and H. Wang, "Underwater Object Detection Algorithm Based on an Improved YOLOv8," J. Mar. Sci. Eng., vol. 12, no. 11, art. 1991, 2024.
8. R. Trinadh, M. Chaitanya Deepika, M. Manojna, K. Sindhu Lavanya, H. Pranay Deep, and K. Ramya Sri, "Object Detection in Underwater Using Deep Learning Techniques," IJRASET, 2023.
9. Y. Yang, L. Chen, J. Zhang, L. Long, and Z. Wang, "UGC YOLO: Underwater Environment Object Detection Based on YOLO with a Global Context Block," J. Ocean Univ. China, vol. 22, no. 3, pp. 665–674, 2023.
10. O. Younes, Z. Jihad, N. Conruyt, M. Kayal, P. A. Martin, E. Eric, L. Bigot, and R. Vignes Lebbe, "Automatic Coral Detection with YOLO: A Deep Learning Approach for Efficient and Accurate Coral Reef Monitoring," arXiv:2405.14879, 2024.
11. M. Y. Ouis and M. Akhloufi, "YOLO Based Fish Detection in Underwater Environments," Environ. Sci. Proc., vol. 29, no. 1, art. 44, 2024.
12. Y. Lin, Y. Zhang, D. Yang, Y. Zhou, and L. Wang, "DLFE YOLO: An Enhanced Framework for Underwater Object Detection Based on YOLOv8," Intell. Marine Technol. Syst., 2025.
13. "Underwater Object Detection Based on Enhanced YOLO," IEEE Xplore, 2025.
14. Q. Guo, Y. Wang, ..., and Y. Jiang, "AWF YOLO: Enhanced Underwater Object Detection with Adaptive Weighted Feature Pyramid Network," Complex Eng. Syst., 2023.
15. J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real Time Object Detection," IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016.
16. A. Bochkovskiy, C. Y. Wang, and H. Y. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2020.
17. K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," IEEE Conf. Comput. Vis. Pattern Recognit., 2016.