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Improved YOLOv8-based Marine Life Detection Algorithm

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Abstract: Aiming at the problems of insufficient feature extraction ability for small targets, complex image background, and low detection accuracy in marine life detection, this paper proposes a marine life detection algorithm SGW-YOLOv8 based on the improvement of YOLOv8. First, the Adaptive Fine-Grained Channel Attention (FCA) module is fused with the backbone layer of the YOLOv8 network to improve the feature extraction ability of the model. This paper uses the YOLOv8 network backbone layer to improve the feature extraction capability of the model. Second, the Efficient Multi-Scale Attention (C2f_EMA) module is replaced with the C2f module in the Neck layer of the network to improve the detection performance of the model for small underwater targets. Finally, the loss function is optimized to Weighted Intersection over Union (WIoU) to replace the original loss function, so that the model is better adapted to the target detection task in the complex ocean background. The improved algorithm has been experimented with on the Underwater Robot Picking Contest (URPC) dataset, and the results show that the improved algorithm achieves a detection accuracy of 84.5, which is 2.3% higher than that before the improvement, and at the same time, it can accurately detect the small-target marine organisms and adapts to the task of detecting marine organisms in various complex environments.

Keywords: Yolov8; Marine organisms; Target detection; Deep learning; Attention mechanisms

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1. Introduction

The ocean accounts for about 71% of the Earth's surface area and contains very rich biological, petroleum, and mineral resources, especially marine biological resources, which are an important source of food for human beings [1]. Deep learning-based target detection technology can be applied to the detection of marine organisms, which can not only provide a large amount of reliable data support for scientific management and real-time monitoring of marine biological resources but also greatly reduce the cost of manual sea operations [2,3]the swift and accurate detection of underwater targets is of considerable significance. Recently, methods based on Convolutional Neural Networks (CNN. However, the existing detection methods, due to the complexity of the marine environment, are still faced with several challenges such as insufficient capability of feature extraction for small targets, complex image background, and low detection accuracy.

2. YOLOv8 network structure

YOLOv8 is a target recognition network in the YOLO family, proposed in 2023 [4]. Compared with YOLOv5 and YOLOv7 in the previous YOLO series, YOLOv8 is an excellent network model with higher detection accuracy and faster detection speed. The structure of the YOLOv8 network is divided into three parts: Backbone, Neck, and Head.

The Backbone and Neck part is inspired by the design of YOLOv7 [5,6]. They replaced the YOLOv5 C3 structure with a C2f structure, which facilitates wider gradient flow. In addition, they adjusted the number of channels for various scale models, which greatly improved the overall performance of the model.

The Head section has undergone significant changes from YOLOv5. It adopts the current mainstream decoupled head, separates the classification and regression tasks, and improves the Anchor based to Anchor Free based. The Anchor Free method mainly utilizes multiple key points or centroid and boundary information to describe the object, which is more suitable for the detection of underwater targets [7].

3. Proposed method

3.1. Improve YOLOv8 target detection structure

In this paper, YOLOv8 is selected as the benchmark model, which has the advantages of a small number of parameters and fast detection speed. On this basis, this paper proposes an improved YOLOv8 underwater target detection algorithm. For the problem of insufficient feature extraction ability in marine life detection, the FCA module is fused with the backbone layer in the YOLOv8 network to improve the feature extraction ability of the model [8]. For the problem of low detection accuracy of small and sparse targets in multi-targets, the C2f_EMA module is used to replace the C2f module in the Neck layer of the network [9]. At the same time, by improving the loss function, the model is better adapted to the task of target detection in the complex ocean background, and the improved structure of the YOLOv8 network is shown in **Figure 1**.

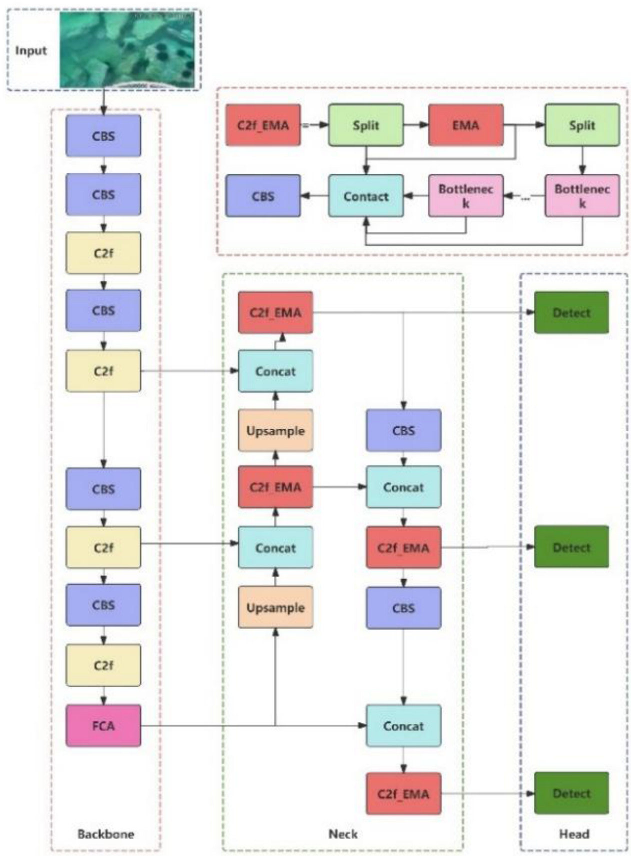

Figure 1. Improved YOLOv8 network architecture

4. Experiment and result analysis

4.1. Experimental setup

All experiments in this paper are operated on Ubuntu 20.04 LTS operating system with the integrated development environment PyCharm. The experiments were run on a server with a 15 vCPU Intel(R) Xeon(R) Platinum 8474C and a GPU model NVIDIA GeForce RTX 4090D (with 24 GB of video memory). All experiments are executed in the same experimental environment. The experimental hyperparameters are set as shown in **Table 1**.

Table 1. Experimental hyperparameter settings

Method	Configuration
Learning rate	0.01
Momentum	0.0005
Batch size	16
Optimizer	SGD
Image size	640 × 640
Epochs	200

4.2. Experimental dataset

In this paper, we use the URPC dataset, which is derived from the National Underwater Robotics Competition, and the images with different backgrounds, contrasts, brightnesses, blurring levels, and color differences at different depths are captured by the filming device on the underwater robot, which can simulate the detection of the underwater biological targets realistically. The dataset contains images of four types of underwater biological targets, namely holothurian, echinus, starfish, and scallops, with a total of 8,200 images, which are randomly divided into training set, validation set, and test machine according to the ratio of 8:1:1. images as the validation set and 820 as the test set.

4.3. Experimental results

4.3.1. Comparison experiments of different attention mechanisms

To verify the effectiveness of the FCA and C2f_EMA modules, this paper conducts comparison experiments on YOLOv8 using FCA and C2f_EMA and some mainstream attention mechanisms on the UPRC public dataset, with consistent settings for other training conditions. The experimental results are shown in **Table 2**. The experimental results show that after adding FCA, the model's Precision, Recall, mAP@0.5, and mAP@0.95 improved by 1.57%, 1.81%, 1.82%, and 1.04% compared with the original model. After adding C2f_EMA, the model's Precision, Recall, mAP@0.5, and mAP@0.95 improved the original model by 2.39%, 0.18%, 1.24%, and 1.46%.

Table 2. Comparison of different attention mechanisms

Detection network	Precision (%)	Recall (%)	mAP@0.5 (%)	mAP@0.95 (%)
YOLOv8	81.57	75.72	82.13	48.23
YOLOv8 + SMAF	81.56	75.97	82.16	48.25
YOLOv8 + FCA	83.14	77.53	83.95	49.27
YOLOv8 + C2f_EMA	83.96	75.90	83.37	49.69

4.3.2. Comparison experiments of different detection models

To verify the performance of the proposed model, the URPC dataset is used as the experimental data. Using the evaluation indexes mentioned in the previous section, the SGW-YOLOv8 model proposed in this paper is compared with the current mainstream target detection algorithms in the experiments, and all the experiments are conducted under the same experimental conditions.

Table 3. Comparison of different detection models

Model	Precision (%)	Recall (%)	mAP@0.5 (%)	mAP@0.95 (%)
Faster-RCNN [10]	75.2	64.6	74.3	41.5
SSD [11]	74.2	68.7	75.4	38.8
FCOS [11]	78.6	62.1	76.5	55.4
YOLOv5 [12]	83.1	76.0	82.4	46.5
YOLOv6 [13]	85.1	76.1	82.5	63.7
YOLOv7 [5]	81.6	75.2	82.4	47.2
YOLOv8	81.6	75.7	82.2	48.2
SGW-YOLOv8	84.0	77.7	84.5	48.6

The experimental results are shown in **Table 3**, in which it can be seen that the detection accuracy of this paper's algorithm reaches 84.5%, which is 10.2%, 9.1%, and 8.0% higher than that of Faster R-CNN, SSD, and FCOS, and it is 2.1%, 2.0%, 2.1%, 2.1%, and 2.3% higher than that of the single-stage algorithms of the same YOLO family, YOLOv5, YOLOv6, YOLOv7, and YOLOv8, respectively, and all of them achieve the highest detection accuracy at 2.1%, 2.0%, 2.1% and 2.3%, respectively, and the highest detection accuracy was achieved in each index.

4.3.3. Ablation experiments

In order to verify the impact of the loss of each module: FCA, C2f_EMA module, and WIoU on the final detection performance, ablation experiments are conducted on the URPC dataset. The results are shown in **Table 4**.

Table 4. Ablation experiments

YOLOv8	FCA	C2f_EMA	WIoU	AP (%)				mAP (%)
				echinus	holothurian	scallop	starfish	
√	-	-	-	91.2	73.6	87.2	76.6	82.2
√	√	-	-	91.6	77.8	88.1	78.3	83.9
√	√	√	-	91.5	77.8	87.7	78.7	84.2
√	√	√	√	91.9	78.5	89.3	78.6	84.5

From the table, we can see that after adding the FCA module to the backbone layer of YOLOv8, the mAP increases from 82.2% to 83.9%, which is because the FCA module can fully utilize the global and local channel information to enhance the feature extraction capability and improve the detection accuracy. Then, replacing the

C2f module in the Neck layer of the network with the C2f_EMA module, the detection accuracy of the marine organisms in the small target is improved, and the mAP increases from 83.9% to 84.2%. After improving the WIoU loss function, the mAP increases to 84.5%. Replacing the C2f_EMA module with the C2f module in the Neck layer further improves detection accuracy for small target marine organisms, raising the mAP from 83.9% to 84.2%. Overall, the improved model achieves an mAP of 84.5%, which is 2.3% higher than that of the pre-improved model. The detection effect and index curve are shown in **Figure 2** and **Figure 3**.

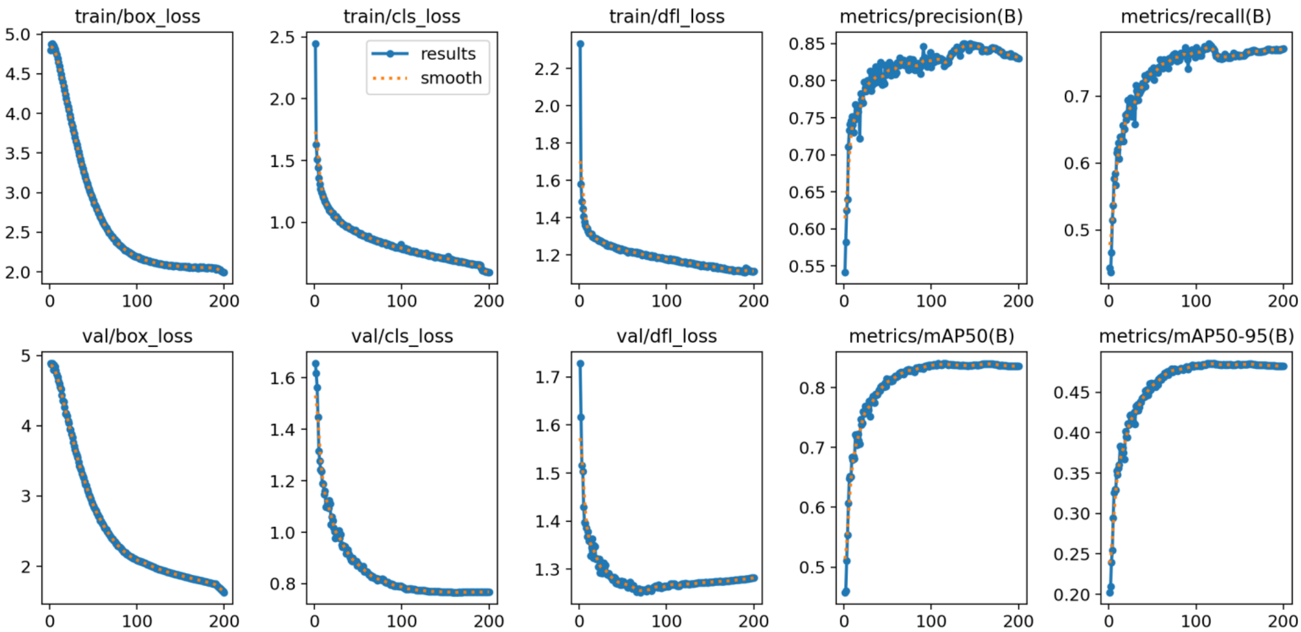

Figure 2. Detection effect diagram

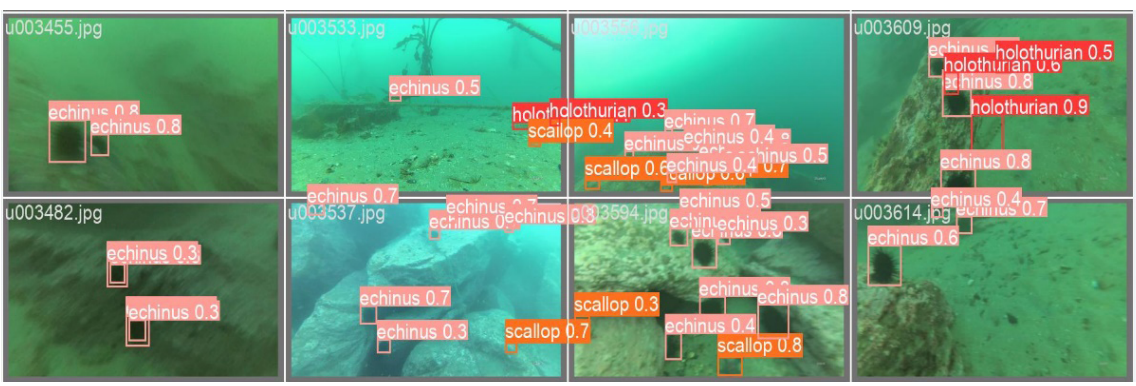

Figure 3. Indicator curves

5. Conclusion

The marine organism detection algorithm SGW-YOLOv8 based on the improved YOLOv8 proposed in this paper introduces the FCA module, the C2f_EMA module, and the WIoU v3 loss function based on the original

YOLOv8, which effectively improves the detection accuracy and robustness of the marine organisms with small targets. Through experimental validation, the improved model achieves a detection accuracy of 84.5% on the URPC dataset, which is a 2.3% improvement over the original YOLOv8. In the comparison experiments of different attention mechanisms, the introduction of FCA and C2f_EMA modules effectively enhances the feature extraction capability and small target detection performance. In addition, the optimization of the WIoU v3 loss function further improves the model's adaptability to complex underwater backgrounds and small targets. Marine life target detection has a wide range of application prospects, especially in the fields of marine ranch construction, ecological monitoring, and aquaculture. Future research can continue to explore algorithm optimization, real-time detection, and multi-task learning to further enhance the model's practicality and generalization ability.

Authors contribution

Conceptualization: Qiang Li
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Writing: Qiang Li, Ziying Weng
Supervision: Gui Ming Lin

Disclosure statement

The authors declare no conflict of interest.

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