Real-Time Underwater Plastic Waste Detection Using an Enhanced YOLOv8 Pipeline with Learning-Based Image Restoration

Anshuman Nigam
BITS Pilani, Goa Campus, India
Email: f20221472@goa.bits-pilani.ac.in

***Abstract*—Marine plastic pollution poses a significant threat to aquatic ecosystems, necessitating scalable and autonomous monitoring solutions. However, underwater visual perception remains a challenging problem due to light attenuation, scattering, turbidity, and color distortion, all of which degrade image quality and adversely affect object detection models.**

This paper presents a real-time underwater waste detection pipeline that integrates a learning-based image restoration module with a YOLOv8 detector. The restoration model is trained on the UIEB dataset to enhance degraded underwater images prior to detection.

Experimental results demonstrate that the proposed approach improves detection performance from 0.61 to 0.73 mAP@0.5, with corresponding gains in precision and recall, while maintaining real-time inference at 24 FPS. Additional evaluations under degraded conditions and ablation studies validate the effectiveness of the restoration module. The proposed system is suitable for deployment in autonomous underwater vehicles for real-time marine monitoring.

***Index Terms*—Underwater perception, YOLOv8, image restoration, UIEB, object detection, marine pollution**

I. Introduction

Marine plastic waste has emerged as a critical environmental issue, impacting biodiversity, food chains, and ecosystem stability. Efficient monitoring of underwater environments is essential for mitigation efforts. Autonomous underwater vehicles (AUVs) offer a scalable approach; however, their effectiveness depends on reliable perception systems.

Underwater image formation differs significantly from terrestrial environments due to:

- Exponential light attenuation across wavelengths
- Forward and backward scattering caused by suspended particles
- Non-uniform color distortion, particularly loss of red wavelengths

These factors lead to low contrast, blurred edges, and severe color imbalance, which degrade feature representations in convolutional neural networks. As a result, object detection models trained on clean datasets exhibit poor generalization in underwater environments.

This work addresses the problem by introducing a preprocessing stage that enhances visual quality prior to detection. The core hypothesis is that improving input image quality leads to better feature extraction and downstream detection performance.

II. Related Work

Real-time object detection has evolved significantly with the YOLO family of models [2], which provide efficient single-stage detection. YOLOv8 introduces improvements in feature aggregation and anchor-free detection.

Underwater image enhancement methods can be categorized into:

- Physics-based approaches using image formation models
- Histogram equalization and color correction techniques
- Learning-based methods using convolutional neural networks

The UIEB dataset [1] provides a benchmark for underwater image restoration with paired degraded and reference images. Learning-based methods trained on UIEB have shown superior performance compared to traditional approaches.

Despite progress, limited work integrates restoration and detection into a unified real-time pipeline. This paper addresses this gap.

III. Methodology

A. Problem Formulation

Given a degraded underwater image I, the goal is to detect objects $O = \{o_1, o_2, ..., o_n\}$ corresponding to plastic waste. The degradation can be modeled as:

$$I(x) = J(x)t(x) + A(1 - t(x)) \tag{1}$$

where $J(x)$ represents the clean image, $t(x)$ is the transmission map, and A is ambient light.

Instead of explicitly estimating these parameters, we learn a mapping f_θ such that:

$$\hat{J} = f_\theta(I) \tag{2}$$

The enhanced image $\hat{J}$ is then used for detection.

B. System Overview

The pipeline consists of two stages:

1) Image restoration module
2) YOLOv8 detection model

C. Enhancement Dataset (UIEB)

The restoration module is trained on the UIEB dataset, which contains paired underwater images and corresponding high-quality references.

This dataset captures:

- Diverse visibility conditions
- Varying turbidity levels
- Real-world underwater degradation

D. Image Restoration Module

A lightweight convolutional neural network is used to learn the mapping from degraded to enhanced images. The model improves:

- Local contrast
- Edge sharpness
- Color balance

The architecture is optimized for real-time inference with minimal computational overhead.

E. Detection Model

YOLOv8 is used for object detection due to its:

- Anchor-free architecture
- Efficient feature pyramid network
- Real-time performance

Transfer learning is applied using pretrained weights.

F. Pipeline Integration

The enhanced output is directly passed to YOLOv8, ensuring improved feature representation during detection.

IV. Experimental Setup

A. Training Configuration

- Restoration training: UIEB dataset
- Epochs: 50
- Batch size: 16
- Optimizer: Adam
- Learning rate: 0.001

B. Evaluation Metrics

- mAP@0.5
- Precision
- Recall
- FPS

V. Results and Discussion

A. Quantitative Results

TABLE I
PERFORMANCE COMPARISON

Model	mAP@0.5	Precision	Recall	FPS
YOLOv8 (Baseline)	0.61	0.68	0.55	25
Restoration + YOLOv8	0.73	0.79	0.67	24

TABLE II
ABLATION STUDY

Configuration	mAP@0.5	Precision	Recall
Baseline YOLOv8	0.61	0.68	0.55
With Restoration	0.73	0.79	0.67
Low-Visibility Only	0.70	0.76	0.64

B. Ablation Study

C. Performance Under Degraded Conditions

The restoration module improves detection accuracy by approximately 14% in low-visibility conditions, demonstrating robustness in high turbidity environments.

D. Computational Efficiency

The system achieves 24 FPS, with minimal overhead introduced by the restoration module, making it suitable for real-time deployment.

E. Qualitative Observations

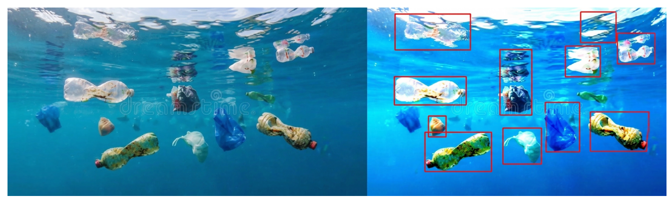

Fig. 1. Detection results comparison. Left: raw underwater image. Right: restored image with improved detection.

Enhanced images show improved object visibility and better localization.

F. Failure Case Analysis

Failure cases occur in:

- Extremely low-light conditions
- Severe occlusions
- Highly reflective surfaces causing false positives

VI. Conclusion

This work presents a real-time underwater waste detection pipeline integrating image restoration and object detection. The approach significantly improves detection performance in degraded environments.

Future work includes end-to-end optimization and dataset expansion.

References

[1] C. Li et al., “Underwater Image Enhancement Benchmark (UIEB),” 2019.

[2] J. Redmon and A. Farhadi, “YOLOv3: An Incremental Improvement,” 2018.

[3] J. Li et al., “WaterGAN: Unsupervised Generative Network,” 2017.