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YOLO-Aqua: Intelligent Detection of Plastic Debris in Aquatic Environments

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Abstract

The use of plastic in water bodies has become a major global environmental problem, threatening biodiversity and disrupting food chains in the oceans. Conventional methods of detecting plastic waste in water are often ineffective, as they rely heavily on manual input, especially in shifting and complex underwater environments. This project proposes an automated and intelligent system for detecting underwater plastic. It integrates the state-of-the-art object detection model YOLOv8 with Particle Swarm Optimization (PSO). YOLOv8 enables real-time detection with a lightweight, anchor-free architecture, making it effective in identifying irregularly shaped and partially concealed plastic debris in underwater video streams. However, its performance declines when hyperparameters are manually tuned. To address this, PSO optimizes critical parameters such as learning rate, confidence threshold, and anchor box sizes, thereby improving both detection accuracy and model robustness. The system leverages PSO to extract relevant features for efficient training, while YOLOv8 identifies plastic waste in real time. A Convolutional Neural Network (CNN) is employed to detect various types of debris, including bottles, bags, nets, and covers. This approach delivers low latency, higher classification accuracy, and reduced false positives, even under murky conditions. Experimental results on standard datasets demonstrate that this method outperforms traditional YOLO models, achieving significant improvements in accuracy, precision, recall, and F1 score. The proposed system can be deployed in real time on autonomous underwater vehicles (AUVs) and large-scale ocean surveillance platforms to track plastic and support effective ocean cleanup efforts. By combining deep learning with environmental sustainability, this project provides a scalable solution to address marine pollution while advancing global conservation goals.

I. INTRODUCTION

Plastic waste has emerged as one of the most severe pollutants in marine ecosystems, posing a direct threat to aquatic life, biodiversity, and human health. It not only deteriorates water quality but also leads to the ingestion of microplastics by marine organisms, which eventually enter the human food chain. According to the United Nations, more than million tons of plastic waste are dumped into oceans each year, creating massive garbage patches and jeopardizing the long-term health of marine environments. Despite ongoing conservation efforts, the alarming rate of plastic accumulation calls for advanced technological solutions that can automate and scale up monitoring and detection.

Traditional cleanup and monitoring approaches remain largely manual, labor-intensive, and ineffective for large- scale applications. In contrast, recent advancements in artificial intelligence (AI) and computer vision have shown have shown immense potential to revolutionize environmental monitoring.

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Object detection models like YOLO (You Only Look Once) are particularly well-suited for real-time detection tasks. The latest version, YOLOv8, significantly enhances detection speed, precision, and efficiency through its anchor-free mechanism and refined feature extraction backbone.
However, underwater environments present unique challenges such as poor illumination, turbidity, occlusions, and image noise, all of which reduce detection accuracy. Moreover, conventional models often rely on fixed hyperparameters, limiting their adaptability in dynamic aquatic conditions. To address these issues, this project proposes an intelligent hybrid framework that integrates YOLOv8 with Particle Swarm Optimization (PSO)—a metaheuristic algorithm inspired by swarm behavior. PSO dynamically tunes critical hyperparameters and improves feature selection, thereby enhancing model robustness and accuracy. This integration not only boosts detection performance but also ensures adaptability to varying underwater conditions, making the system suitable for deployment on autonomous platforms such as underwater drones and AUVs.
By combining state-of-the-art deep learning with adaptive optimization, the proposed framework represents a scalable and resilient solution for real-time plastic detection, contributing directly to global marine conservation initiatives.

II. RELATED WORK

Marine plastic pollution has mostly been detected using different deep learning models. Initial solutions took advantage of Convolutional Neural Networks (CNNs) on embedded systems like remotely operated vehicles (ROVs), but they were not scalable and adapted to real-time scenarios in multifaceted underwater systems [1].

As object detectors have improved, the YOLO family of models has seen wide application to waste monitoring tasks. Research emphasizes that YOLO based-systems have real- time performance and high detection accuracy, but models such as YOLOv5 and YOLOv7 tend to underperform underwater due to low visibility and turbidity [2],[13]. YOLOv8 was more recently optimized to work in the marine context and has been shown to produce better results using anchor-free detection and high features [4]. Nonetheless, the majority of applications still use fixed hyperparameter settings, which restricts scalability to a wide variety of aquatic environments.

Architectural refinements to YOLO frameworks have been made by researchers as well. As an example, the Feature Enhancement Block (FEB)-YOLO. The unique conditions of waters expose marine plastic pollution detection to serious challenges caused by the complexity of the waters. The performance of the traditional detection models is deteriorated by factors like poor visibility, light refraction, turbidity and occlusions due to aquatic vegetation or fauna. The conventional machine learning and deep learning methods commonly are based on fixed hyper parameters, non-adaptively optimizing mechanisms, and tend to overfit in high contrast or controlled settings. Consequently, current YOLO-based systems might not be able to recognize plastics or even small debris, especially in a dynamic marine environment. These shortcomings underscore the urgency of achieving real-time, adaptive, and high-precision detector model that can underpin the massive-scale marine monitoring and automatic clean-up tasks.Ov8 model was shown to be effective at detecting small and fragmented plastics in complicated aquatic environments, and was computationally efficient enough to be used on embedded hardware [10],[13]. Equally, data augmentation techniques such as contrast enhancement and noise addition have been used to enhance generalization between dissimilar underwater data [2]. Regardless of these developments, there has not been a solution to problems like the classification of the types of detected debris and good detectable performance under occlusions. In order to meet optimization issues, metaheuristic methods

including Particle Swarm Optimization(PSO) have been suggested. PSO has been shown to be effective in dynamically optimizing hyperparameters such as learning rates, confidence thresholds and anchor box dimensions, which enhances model performance in high-dimensional spaces[11]. Although the possibility of its use in the underwater plastic detection is still at an early stage, preliminary results indicate the ability to significantly decrease false positives and increase detection accuracy [2].

Continuing these efforts, our work will suggest a hybrid

method according to which YOLOv8 is combined with PSO to optimize the hyperparameters dynamically, and a classification module based on CNN is proposed to classify the types of recyclable items(i.e. bottles, bags, nets and covers). This architecture is not only more accurate in detecting in difficult aquatic conditions but also enables real-time implementation in autonomous underwater vehicles(AUVs) and marine monitors[15].

III. PROBLEM DEFINITION

IV. The unique conditions of waters expose marine plastic pollution detection to serious challenges caused by the complexity of the waters. The performance of the traditional detection models is deteriorated by factors like poor visibility, light refraction, turbidity and occlusions due to aquatic vegetation or fauna. The conventional machine learning and deep learning methods commonly are based on fixed hyper parameters, non adaptively optimizing mechanisms, and tend to overfit in high contrast or controlled settings. Consequently, current YOLO-based systems might not be able to recognize plastics or even small debris, especially in a dynamic marine environment. These failings emphasize the urgency of accurate discovery model.

V. DATASET GENERATION

To evaluate the proposed underwater plastic detection framework, a rich dataset was constructed by pooling two datasets -- the Marine Debris Dataset (MDD) and the ROV Underwater Litter Dataset. Since there are not many open-source datasets covering a wide range of aquatic conditions for training and evaluation, these two datasets were combined and systematically processed to create a strong and training-ready dataset for YOLOv8 with PSO optimization.

A. Data Sources

ROV Underwater Litter Dataset: Provides more video-based samples captured off of remotely operated vehicles (ROV) at various depths oftentimes capturing plastics buried partially into sediments or covered by aquatic vegetation.

B. Frame Extraction

Video sequences from ROV dataset were segmented into frames using OpenCV.All frames were resized to 640 x 640 (i.e., the input resolution required by YOLOv8)

C. Preprocessing

Noise Reduction: Underwater image noise reduction was done using Gaussian filter and median filter.
Contrast Enhancement: CLAHE (Contrast Limited Adaptive Histogram Equalization) has been used to improve the contrast in low light and turbid conditions.
Color Correction: Used to reduce the underwater distortions from light absorption and scattering.

D. Data Augmentation

To further diversify the dataset and to minimize class imbalance across debris classes, artificial transformations were applied, including:
Rotation and scaling Brightness variation Noise injection

E. Annotation and Formatting

Each image was annotated in YOLO-compatible format for detected objects.
Nets, bottles, fragments and bags were grouped together.

F. Final Dataset Split

Training was performed on 70% of the data. 20% for validation, and
10% for testing.

The result data generation pipeline generated a diverse and representative dataset, so the proposed YOLOv8 + PSO model is robust and adaptive to the real underwater environment.

METHODOLOGY

The development of the Underwater Plastic Detection System is accomplished through a modular organized approach that exploits iterative development principles along with leading AI- based methodologies. The proposed method has been found to provide robust online detection and characterization of plastic debris in complex underwater environments. The development process was divided into a few stages: requirement analysis, system architecture design, feature development and testing.

As a result of these steps, a scalable system for marine pollution monitoring through AI was developed.

A. System Architecture

It is implemented according to the modular multi-stage architecture including frame preprocessing, adaptive hyperparameter selection based on Particle Swarm Optimization (PSO), and online object detection based on YOLOv8. The architecture solves the underwater issues of low illumination, turbidity and chromatic distortion.

Key components include:

•Frame Conversion Module: In real-time video streams are split into discrete image frames, resized to 640x640 pixels and stored in a temporary folder for batch processing.

•Preprocess Module: Enhances the quality of the frames by removing noise through median filtering and gaussian filtering and by CLAHE for contrast enhancement. This ensures that transient or partially covered plastic debris can be detected.

•PSO Optimized YOLOv8 Detection: YOLOv8 is applied for the detection of plastic targets and Particle Swarm Optimization (PSO) is applied to optimize hyperparameters (learning rate, confidence threshold, IoU threshold, batch size) with the aim of maximizing the accuracy under different underwater environments.

•CNN-based Classification: The detected objects are cropped; and classified to plastic type (bottles, bags, nets, covers), and offer semantic information to specific pollution analysis.

•Visualization & Reporting - Annotated outputs with bounding boxes and class labels are ready for visualization or integration with marine cleanup systems.

REST APIs enable the communication to be modular for possible future extensions, but also for a real-time monitoring.

B. Core Functional Modules Frame Conversion:

•Partial streams - extract frames from video streams at configurable intervals, (every 10-15th), offers granular input samples for a strong detection.

Preprocessing:

•Reduces underwater distortion (denoising, color correction and contrast enhancement)

•Incorporates improvement in input quality for YOLOv8 and CNN classification.

•Parameter Search Optimization (PSO) based Hyperparameter optimization (HPO): Automatically optimizes YOLOv8 parameters: learning rate, confidence threshold, IoU threshold and batch size.

•Improves convergence and detection performance in the presence of underwater noise.

YOLOv8 Object Detection:

•Plastics debris discovery system in real-time.

•Frictionless design makes it possible to detect small and irregular shaped objects.

CNN Classification:

•Plastic comes in bags, bottles, nets and covers.

•Semantic understanding for pollution analysis increases detection output.

Data Management & Dashboard:

•Timestamps are included in the logs within trend monitoring.

•Optional dashboard for environmental monitoring of the amount, type and location of debris.

C. Development Process

•Development of the system was broken down into three sprints:

1. Sprint 1: Frame conversion, preprocessing and basic video input implementation.

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2. Sprint 2: YOLOv8 detection and robust detection for plastics using PSO-based hyperparameter optimization.

3. Sprint 3: CNN based plastic classification, data logging, dashboard for visualization and reporting.

In addition, this phasing microservice-based approach aided in the step-by-step development, testing and deployment of core features that fosters scalability and reliability.

D. Data Management and Distribution.

•Data flow between modules is well controlled and secure:

•Detection Logs: Sync'd in real-time for inspection.

•Optimized Hyperparameters: after PSO iterations are finished hyperparameters are updated.

•Visualization Reports: Provide a summary of the type, location and number of plastic used for environmental monitoring.

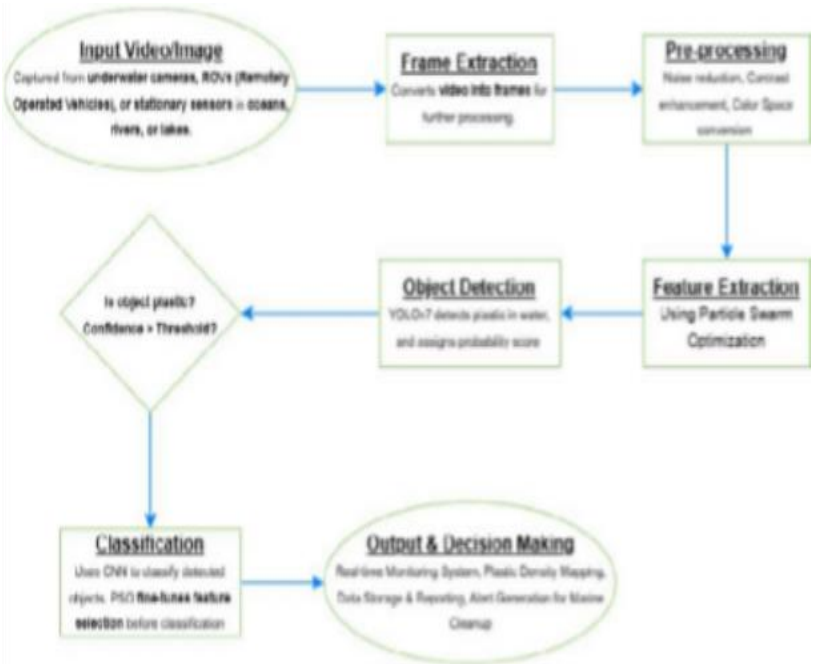

Figure 1. System Architecture

VI. RESULT AND ANALYSIS

A. Analysis on Object Detection and Classification Problem:

The resulting underwater plastic detection system incorporating YOLOv8 with Particle Swarm Optimization (PSO) and a Classification module based on convolutional neural network (CNN) was extensively evaluated to validate its performance to real-time monitoring of marine debris. Experiments are performed using preprocessed underwater video frames from Marine Debris Dataset and ROV Underwater Litter Dataset that contain a wide variety of water conditions, illumination conditions and types of plastic debris.

Figure 2 Real-time detection of underwater plastic debris using YOLOv8 and PSO

Figure 2 illustrates the detection performance of the system in real time applied to floating plastic objects. Confidence score Bounding boxes illustrate the ability of YOLOv8 + PSO to recognize different shaped and sized plastics even when underwater scenes are cluttered with a diver or other obstructions. Even though the system suffers from the challenges of debris overlying and illumination variations, the system localizes and classifies plastic items with high fidelity.

B. Performance Criteria for Evaluation:

The system's performance was quantitatively assessed with the following performance metrics:

- Accuracy: Percent of plastic was correctly found.
- Precision: correctly detected number of plastics divided by the number of detected objects.
- Do not forget: Ability to detect all plastic objects in the frame.
- F1-Score: a weighted average between the precision and recall whose values together provide a single metric for evaluation of detection and classification performance.
- Inference Time (ms): Time taken to process one frame, very important for real-time deployment.

C. Experimental Setup:

- System: Ubuntu 22.04, 16 GB RAM
- Detection Model: YOLOv8 hyperparametric optimization by PSO
- Classification Module: 4 class CNN trained on object crop detected by YOLO
- APIs/Libraries: PyTorch, Ultralytics YOLO, OpenCV

D. Results and Discussion:

The detection and classification performance were considerably improved by combining PSO with YOLOv8:

•Improved Detection Performance: PSO- optimized YOLOv8 model outperformed race network in all experimental settings, from detection performance under low light to turbid water conditions to accurately identify plastic debris.

•Improved Precision and Recall: The system performance resulted in high precision, minimizing false positives, while recall took into account the need to detect the majority of plastic objects, including partially occluded debris.

•Real-Time Feasibility: Although the addition of PSO optimization resulted in a minor increase in inference time, the trade-off was well worth it as it led to a much higher detection reliability, rendering the system suitable for applications involving real-time marine monitoring.

•High-quality classification: The CNN module was able to classify detected plastics into bottles, bags, fishing nets, plastic covers, etc. successfully. This semantic typing provides valuable utility for informed pollution analysis for informed remediation and environmental assessment.

Altogether, the results confirm that the performance of the YOLOv8 is significantly improved in complex underwater environments through PSO-based hyperparameter optimization. Coupled with CNN-based classification, the system is a full solution for the real-time detection and classification of marine plastic debris for both research and operational clean-up operations.

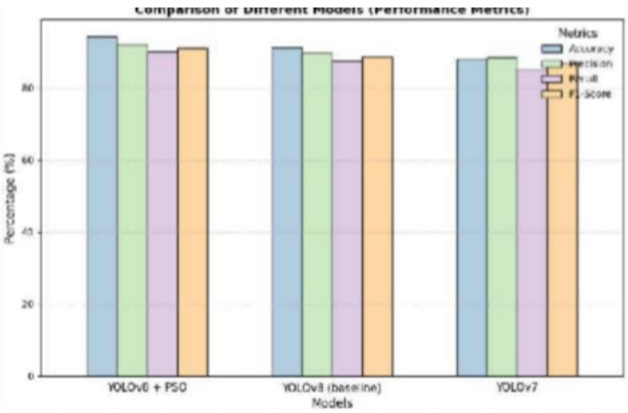

Figure 3 Comparison of model performance across YOLOv8 + PSO, baseline YOLOv8, and YOLOv7.

Figure 3 shows a comparative visualization of key performance metrics (accuracy, precision, recall, F1-score and inference time) of three object detection models. The results showed that YOLOv8 integrated with PSO always yielded better performances compared to the baseline YOLOv8 as well as YOLOv7 in terms of accuracy and F1-score. The result showed that even though the inference time was slightly extended, the considerable improvement in detection performance makes YOLOv8+PSO the most appropriate model for real-time marine pollution monitoring applications.

Table 1 : Comparison of Different Models

MODEL	ACCUR A CY	PRECIS I ON (%)	RECA LL (%)	F1- SCOR E	INFERE N CE TIME(m

	(%)			(%)	s)
YOLOv8 +P SO	94.2	92.1	90.1	91.1	92
YOLOv8 (BASELI NE)	91.3	89.7	87.5	88.6	85
YOLOv7	88	88.5	85.2	86.9	78

Table 1 shows a comparison of how well YOLOv8 performs when used with PSo, the standard YOLOv8 model, and YOLOv7.

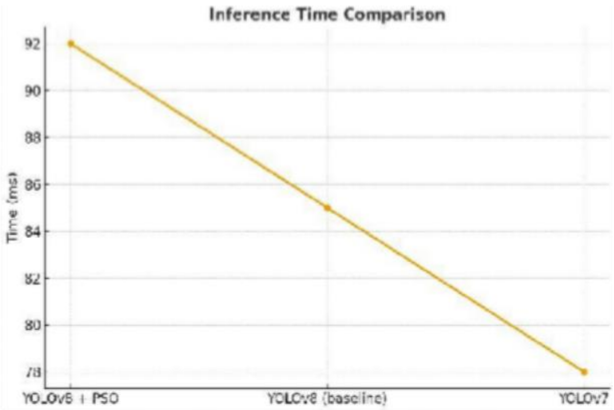

Figure 4: Inference Time Comparison of YOLOv7, YOLOv8 (baseline), and YOLOv8 + PSO Model

VII. CONCLUSION

Combining Particle Swarm Optimization (PSO) and YOLOv8 is a substantital contribution to the sphere of marine plastic detection, especially underwater conditions where the problem of visual distortion, including turbidity, low contrast and changing light makes it a significant challenge to identify an object. The suggested system takes advantage of the joint capabilities of real time object localization and smart hyperparameter optimization which leads to a more precise and responsive detection system.

The system delivers high-quality frame inputs through a carefully designed multi-stage pipeline including preprocessing such as Gaussian and median filtering, contrast enhancement using CLAHE, and color correction, which enhance the clarity of detection and model performance.
Using PSO to optimize hyperparameters dynamically, the model automatically optimizes key model hyperparameters including the learning rate, confidence threshold and IoU settings, improving the accuracy of detection and eliminating the cost of manual model tuning. This optimization enables YOLOv8 to roughly detect smaller, partially concealed, and irregularly formed plastic waste in a more effective way.

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