AquaGuard: AI-Powered Underwater Pollution Detection and Classification

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Abstract
Context: Marine pollution poses a significant threat to aquatic ecosystems, necessitating innovative approaches for monitoring and assessment. Automated systems leveraging machine learning can provide efficient solutions for identifying and classifying underwater debris.

Purpose: This study aims to develop a system that utilizes object detection and classification techniques to assess underwater pollution levels. By detecting various types of debris and calculating a pollution risk score based on predefined coefficients, the system categorizes images into low, medium, or high pollution risk levels.

Method: The research employs a publicly available underwater image dataset, enhanced using the Dark Prior Channel method for better object detection. YOLOv8 is utilized to detect objects, which are then assigned pollution coefficients. Each image's total pollution score is computed, and a risk classification model is applied. The system's performance is evaluated by comparing predicted scores with actual labels using accuracy, precision, and recall metrics.

Results: The proposed system achieved high accuracy in object detection and pollution risk classification. The results demonstrate its potential for real-time marine pollution monitoring and highlight the importance of leveraging machine learning in environmental conservation efforts.

***Keywords*: Underwater pollution, object detection, YOLOv8, pollution risk classification, marine debris, environmental monitoring.**

1. INTRODUCTION

Marine pollution poses a significant threat to aquatic ecosystems, endangering marine life and compromising the health of underwater environments. This issue is exacerbated by human activities, with over 80% of marine contaminants originating from land-based sources, such as agricultural runoff and plastic waste. These pollutants accumulate in coastal areas, disproportionately affecting ecosystems in lower-income regions and contributing to global environmental challenges, including climate change [1][2]. Effective monitoring of underwater pollution is critical for understanding its impact and guiding mitigation efforts. However, traditional methods of assessing pollution, such as manual inspections, are not only labor-intensive but also insufficient for addressing the vast and complex nature of marine environments. Advances in technologies like satellite monitoring and autonomous drones have been proposed to enhance efficiency and coverage [1][2].

The primary challenge is the lack of automated and scalable tools to evaluate underwater pollution levels. Current approaches fail to provide a quick and accurate assessment of pollution severity, particularly in distinguishing between normal, slightly polluted, and highly polluted conditions based on the types and quantities of pollutants. This limits the ability of researchers, policymakers, and environmental agencies to monitor and address pollution effectively.

This study proposes the development of an AI-based system utilizing machine learning and computer vision techniques to classify underwater images based on their pollution levels. The system will employ the YOLOv8 [3] model, a state-of-the-art object detection framework known for its superior accuracy and real-time performance in detecting and identifying various types of pollution (e.g., plastics, metals, and nets) (Jocher et al.). The model will be trained and evaluated using datasets like the *Underwater Plastic Pollution Detection* [4] dataset available on Kaggle. By categorizing images into three pollution severity levels—normal, slightly polluted, and highly polluted—the solution aims to provide a scalable, real-time, and user-friendly tool for marine pollution monitoring, empowering stakeholders to track pollution hotspots and implement mitigation strategies efficiently.

The remainder of this article is organized as follows. Section 2 provides an overview of related studies and highlights the need for this research with respect to related studies. Section 3 explains the methodology employed while carrying out this study. Section 4 provides the results in correspondence with the research questions. Section 5, we provide overall conclusions and plans for future work.

2. BACKGROUND AND RELATED WORK

Marine pollution caused by underwater debris is a critical environmental challenge, threatening marine ecosystems worldwide. Recent advancements in computer vision, particularly object detection models like YOLO and Faster R-CNN, have been utilized to identify and classify marine debris. Additionally, preprocessing techniques such as Dark Prior Channel enhance image quality, improving detection performance in underwater environments. In this section, we summarize related studies, focusing on their objectives, methodologies, and contributions to underwater pollution detection. In Table 1 we summarize these studies with year, title, objective …

Table 1: Summary of the related work

Year [ref], Venue	Title	Objective	Datasets	Findings w.r.t. ....
Li et al. [5], 2022, Journal	A modified YOLOv4 detection method for a vision-based underwater garbage cleaning robot	To enable underwater garbage removal robots to detect objects with high speed and accuracy using an advanced YOLOv4 sensing method. This is accomplished with a four-scale mesh (13×13, 26×26, 52×52 and 104×104) and model pruning methods to improve the accuracy of garbage detection.	Underwater Garbage Dataset	Detection accuracy: 95.1% mAP (Mean Average Precision). Detection speed: 66.67 fps (frames per second). Model size: Reduced to 9.499% of the original YOLOv4 model's weight.
Wang et al. [6], 2022, Journal	Underwater Trash Detection Algorithm	To develop a lightweight and accurate garbage	ICRA19-Trash Dataset	Detection accuracy: 97.5% mAP.

	Based on Improved YOLOv5s	detection algorithm for mobile underwater devices, taking into account their limited storage and processing capacity. For this purpose, the YOLOv5s network is replaced with MobileNetv3 and the CBAM attention mechanism is added.		Computational requirements: Operates with only one-ninth of YOLOv5s parameters. Processing speed: 2.5 times faster than YOLOv5s on a CPU.
Pavani et al. [7], 2023, Conference	Octacleaner: Underwater Trash Detection Through YOLO	To compare YOLOv5 and YOLOv8 models to improve the performance of the Octacleaner robot designed to detect and clean underwater debris.	No specific dataset name provided, but the paper mentions the use of labeled underwater images for training and evaluation.	YOLOv5: A faster and more efficient detection model suitable for real-time applications. YOLOv8: Provides superior accuracy (90% mAP) and speed. Challenges: Underwater conditions such as shape changes in trash due to water currents and decomposition, as well as low light, complicate detection. YOLOv8 has shown promise in overcoming these challenges.
Jain et al. [8], 2024,Conference	Advancing Underwater Trash Detection: Harnessing Mask R-CNN, YOLOv8, EfficientDet-D0, and YOLACT	To evaluate and compare the performance of advanced deep learning models (Mask R-CNN, YOLOv8, EfficientDet-D0, and YOLACT) for underwater trash detection. The study aims to enhance detection accuracy and efficiency for cleaner aquatic environments, leveraging the benchmark TrashCan 1.0 dataset.	TrashCan 1.0	YOLOv8 achieved the highest mAP of 71.4% compared to Mask R-CNN (62.7%), EfficientDet-D0 (56.0%), and YOLACT (54.2%). YOLOv8 demonstrated superior training time efficiency (2.79 hours), significantly outperforming Mask R-CNN (26.8 hours), EfficientDet-D0 (6.33 hours), and YOLACT (6.5 hours) YOLOv8 is identified as the most suitable

				for real-time trash detection in dynamic underwater settings, while Mask R-CNN excels in detecting smaller trash objects in complex environments.
Zhu et al. [9], 2024, Sensors Journal	YOLOv8-C2f-Faster-EMA: An Improved Underwater Trash Detection Model Based on YOLOv8	To enhance the detection of underwater debris, focusing on small targets by improving the YOLOv8 architecture. This is achieved through the integration of the C2f-Faster-EMA module, attention mechanisms, and multi-scale feature fusion to increase accuracy, speed, and robustness.	TRASH-ICRA19 Dataset	Achieved a 6.7% increase in precision, a 4.1% surge in recall, and a 5% enhancement in mAP compared to the standard YOLOv8n. Maintained real-time processing capabilities on ROV platforms with optimized computational resources. Reduced computational demands and model weight, making it suitable for deployment on memory-constrained underwater platforms.

Grouped Summaries of Studies

1. Advanced Underwater Object Detection Models (Mask R-CNN, YOLOv8, EfficientDet, and YOLACT)

- The study *"Advancing Underwater Trash Detection: Harnessing Mask R-CNN, YOLOv8, EfficientDet-D0, and YOLACT"* explored several deep learning models for underwater trash detection, using the TrashCan 1.0 dataset. Among them, YOLOv8 exhibited the highest mAP of 71.4% and the fastest training time, making it ideal for real-time detection on AUVs.

2. Modified YOLO Models for Enhanced Detection

- *"A Modified YOLOv4 Detection Method for a Vision-Based Underwater Garbage Cleaning Robot"* developed a four-scale version of YOLOv4 tailored for underwater garbage detection robots. This modification achieved 95.1% mAP and a detection speed of 66.67 FPS, significantly enhancing both accuracy and speed.
- *"YOLOv8-C2f-Faster-EMA: An Improved Underwater Trash Detection Model Based on YOLOv8"* proposed the YOLOv8-C2f-Faster-EMA model, focusing on small-object detection and efficiency. The study reported a 6.7% increase in precision, a 4.1% improvement in recall, and a 5% gain in mAP compared to the baseline YOLOv8 framework.

3. YOLOv5 and YOLOv8 Comparisons

- The study *"Octacleaner: Underwater Trash Detection Through YOLO"* examined YOLOv5 and YOLOv8 for underwater trash detection using the Octacleaner robot. YOLOv8 achieved superior precision (90%) and real-time capabilities, showcasing its potential for practical implementations.

4. Environmental Contributions and Robotics Integration

- Robotic garbage-cleaning platforms integrated with modified YOLO models were utilized for automated trash collection, significantly reducing manual intervention risks and increasing operational efficiency, as seen in *"A Modified YOLOv4 Detection Method for a Vision-Based Underwater Garbage Cleaning Robot"* and *"YOLOv8-C2f-Faster-EMA: An Improved Underwater Trash Detection Model Based on YOLOv8"*.

METHODOLOGY

1) Business Requirements:

   Goal: Building an AI system to classify underwater images based on pollution levels.
   Scope: Automating marine pollution monitoring by categorizing images as normal, slightly polluted, or highly polluted.
   Research Questions: How can machine learning and computer vision be used to detect and classify underwater pollution effectively?

2) Data Requirements:

   Dataset Sources:

   - Kaggle Underwater Plastic Pollution Dataset
   - Extracted images from YouTube video footage to supplement the dataset.

   Data Characteristics:

   Images with varying levels of pollution and different underwater conditions.

   Diversity in pollution types: plastics, metals, fishing nets, etc.

   Class Names - ['Mask', 'can', 'cellphone', 'electronics', 'gbottle', 'glove', 'metal', 'misc', 'net', 'pbag', 'pbottle', 'plastic', 'rod', 'sunglasses', 'tire']

3) Model Requirements

   In this stage, we determine the features and models that are feasible and optimal for the problem of underwater pollution classification:

   - ***Feature Requirements****:*
     - *Objects commonly found in polluted underwater environments, such as plastics, metals, fishing nets, and other debris.*

- *Visual characteristics like object size, shape, texture, and color that differentiate pollution types.*
- *Contextual features, such as water clarity and background noise, which may influence detection accuracy.*

- ***Model Requirements**:*
  - ***Object Detection Models**:*
    1. ***YOLOv8 (You Only Look Once)** – Chosen for its real-time detection capabilities, making it suitable for integration into mobile or robotic systems.*
- ***Classification Model Requirements**:*
  - *We will assign weights for each class in the dataset. After detecting objects with YOLOv8, we will multiply the count values and weights of the objects in corresponding images. The model will classify images according to that algorithm.*

4) Data Exploration and Understanding:

Data Collection: Collecting images from both public datasets and video footage.

Exploratory Data Analysis:

a. Analyzing the distribution of pollution types.
b. Visualizing the image data to understand variations in lighting, object size, and background noise.

Assigning Coefficients for Pollution Items:

Class Name	**Coefficient**	**Scientific Justification**
Mask	3	[10]
Can	2	[11]
Cellphone	4	[12]
Electronics	4	[13]
Gbottle	1	[14]
Glove	3	[15]
Metal	2	[16]
Misc	2	[17]
Net	5	[18]
Pbag	3	[19]

Pbottle	3	[20]
Plastic	3	[21]
Rod	1	[22]
Sunglasses	2	[23]
Tire	4	[24]

5) Data preprocessing:
Data quality assessment & management

- Checking for missing or corrupted images.
- Handling inconsistent labeling or annotations.
- Data cleaning
- Removing noisy data or irrelevant images.
- Resizing and normalizing image dimensions for consistency.

6) Development Iterations
Feature Engineering:

- Extracting and selecting informative features from detected objects to improve classification performance.
- Key activities include:
    - **Object Shape**: Geometric properties like area, perimeter, and aspect ratio.
    - **Texture Features**: Haralick features, edge detection, and surface roughness.
    - **Color Properties**: RGB and HSV color distributions to differentiate pollution types.
    - **Contextual Features**: Water clarity and background characteristics.

Algorithm Selection/Model Design:

Object Detection:

- Training YOLOv8 on labeled underwater images to detect various pollution objects.

Classification:

- Using detected objects as input features to classify images into pollution levels.
- Implementing a deep learning classification model for multi-class classification.

Outcome: Classification Results + Visualizations

Classification Results:

a. Assigning each image a pollution level label (Normal, Slightly Polluted, Highly Polluted).

Visualizations:

a. Displaying detected objects, their categories, and pollution severity in a user-friendly interface.

b. Provide statistical summaries and trend analysis for pollution monitoring.

7) Model Evaluation

To ensure reliability and robustness, the models will be evaluated using the following metrics:

- **Accuracy**:
  - Measure the overall correctness of the pollution level classification.
- **Precision**:
  - Assess how well the model identifies specific pollution types without false positives.
- **Recall**:
  - Evaluate the model's sensitivity to detecting all instances of pollution.
- **F1-Score**:
  - Provide a balanced evaluation between precision and recall for each pollution level.
- **Confusion Matrix**:
  - Visualize the classification performance across different categories to identify misclassifications.
- **Cross-Validation**:
  - Perform k-fold cross-validation to assess model generalization on unseen data.

Additional evaluations may include:

- **Real-time Performance**: Measure inference time and frame rate to ensure applicability in real-world scenarios.
- **Robustness to Environmental Variations**: Test the model's performance under different underwater conditions, such as varying light levels and water clarity.

Outcome: A reliable, accurate, and scalable system for automated underwater pollution monitoring and classification.

3. EXPERIMENTS

4.1 Experimental Setup

4.1.1 Datasets

The dataset used in this project was selected for its relevance to addressing underwater pollution detection and classification tasks. It consists of images depicting underwater scenes contaminated with various types of debris, such as plastics, metals, nets, and other waste materials. The dataset has been preprocessed using the Dark Prior Channel method to enhance image contrast, which significantly improves the visibility and detectability of underwater objects. The dataset is organized into three directories: the train directory contains 3,628 images with corresponding labels, the validation directory includes 1,001 images, and the test directory comprises 501 images, all annotated with bounding box coordinates and class labels. The dataset encompasses 15 object classes, each assigned a pollution coefficient based on its environmental impact. These coefficients are used to calculate a pollution score for each image by summing the weighted contributions of detected objects. This score is then classified into three risk levels: low, medium, and high. The combination of object detection and image classification tasks, coupled with the realistic challenges of underwater scenes, makes this dataset ideal for developing and evaluating models that aim to tackle marine pollution monitoring.

4.2 Experiment Results

The experimental results are based on the evaluation of our model's performance in both object detection and image classification tasks, leveraging the dataset described in Section 4.1.1. The evaluation pipeline includes detecting objects in underwater images using the YOLOv8 model, assigning pollution coefficients to each detected object, and calculating an overall pollution score for each image. This score is then used to classify the image into one of three risk categories: low, medium, or high. The YOLOv8 model achieved high precision and recall for most object classes, demonstrating its capability to accurately identify underwater debris. The weighted average accuracy across all 15 object classes was 92%, with particularly strong performance on frequently occurring objects such as plastic bottles, tires, and gloves. However, certain less common objects, such as sunglasses and rods, showed lower recall due to limited representation in the dataset. The risk classification system was evaluated by comparing the pollution scores derived from YOLOv8 predictions against the ground truth labels in the test set. The results, as shown in the classification report, indicate an overall accuracy of 84% in predicting the correct risk level. The model performed best in identifying low-risk images, with a precision of 95% and a recall of 87%. Medium-risk and high-risk categories were slightly more challenging, with precision values of 74% and 67%, respectively. This discrepancy is attributed to overlapping score ranges and object misclassifications during detection.

Summary of Key Metrics:

Object Detection Accuracy: 92%

Risk Classification Accuracy: 84%

Macro-Average F1-Score: 80%

Weighted Average F1-Score: 85%

4. CONCLUSION

This study successfully combines object detection and pollution scoring to classify underwater images into three risk levels: low, medium, and high. The YOLOv8 model accurately detected 15 classes of underwater debris, and a pollution coefficient-based scoring system determined the overall risk level for each image. The system achieved a high object detection accuracy of 92% and a classification accuracy of 84%, demonstrating its potential for marine pollution monitoring. However, the performance varied across risk levels, with low-risk images achieving higher precision and recall compared to medium and high-risk categories. This result highlights the system's strength in detecting frequently occurring objects and its limitations in handling less common debris or overlapping scores. Overall, the proposed system provides a practical and scalable solution for assessing underwater pollution levels, contributing to environmental monitoring and management.

One of the primary limitations of this work is the imbalance in the dataset, where certain object classes, such as sunglasses and rods, are underrepresented. This imbalance impacts the model's ability to generalize and leads to lower recall for rare objects. Additionally, the fixed thresholds used for pollution scoring may not fully capture the variability in real-world scenarios, causing overlaps between medium and high-risk classifications. The static pollution coefficients assigned to debris types also limit the system's flexibility, as they do not consider the density or spatial arrangement of objects, which could influence pollution levels. Furthermore, while the dataset has been enhanced with preprocessing techniques, it may not adequately represent the diverse underwater environments, lighting conditions, and debris types encountered in real-world applications. These limitations highlight areas for improvement in future iterations of the system.

Future efforts will focus on addressing the limitations of the current system to improve its performance and applicability. Data augmentation techniques and the collection of additional real-world images will be employed to balance the dataset and enhance the model's ability to detect rare objects. A dynamic scoring system could replace static pollution coefficients, using machine learning models to account for context, density, and environmental factors. Adaptive thresholding methods will be explored to better differentiate between medium and high-risk categories, reducing classification errors. Additionally, extending the system to analyze video footage rather than static images could enable real-time pollution monitoring and provide a more comprehensive assessment of marine environments. Finally, integrating multimodal approaches, such as combining object detection with water quality measurements or sonar imaging, could further enhance the system's accuracy and robustness. Deploying the system in real-world scenarios and validating its performance will provide valuable insights for further refinement and broader adoption.

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Conflict of interest

The authors declare that they have no conflict of interest.

Data Availability

The dataset used in this study is publicly available and can be accessed from [https://www.kaggle.com/datasets/arnavs19/underwater-plastic-pollution-detection/data]. It contains annotated underwater images depicting various debris types, which were used for both object detection and pollution risk classification. The dataset is structured into train, validation, and test directories, comprising 3,628, 1,001, and 501 images, respectively. Each image is accompanied by labels specifying bounding box coordinates and class labels for 15 debris categories, including masks, cans, electronics, and nets. The dataset has been preprocessed using the Dark Prior Channel method to enhance contrast for better object detection.

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APPENDIX