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Detection of Underwater Trash Objects using Deep Learning Algorithms and Yolo v8

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ABSTRACT

Trash deposits in aquatic environments cause severe damage to marine ecosystems and pose long-term environmental threats. This thesis focuses on evaluating deep learning algorithms, specifically YOLO and Faster R-CNN, for visually identifying trash objects underwater in challenging real-world conditions. Initially, a literature review is conducted to understand various algorithms suitable for underwater trash detection. Subsequently, experiments are performed to compare these algorithms in terms of accuracy and detection speed. Data labeling is done in a Linux environment, and training is executed on Google Colab to improve the detection accuracy. Results show that YOLO outperforms Faster R-CNN in real-time object detection underwater. The thesis concludes that the YOLO algorithm is the best choice for underwater trash object detection, enabling improved accuracy in real-time scenarios, which is critical for aquatic ecosystem conservation.

1. INTRODUCTION

The accumulation of trash in underwater environments is an escalating global environmental crisis that poses significant threats to marine biodiversity, aquatic health, and ecosystems worldwide (1, 3, 4). Marine debris, mainly consisting of plastics and other pollutants, permeates the ocean floor and coastal areas, deteriorating habitats and endangering marine species through ingestion, entanglement, and habitat destruction. Traditional detection and removal techniques rely heavily on manual inspection methods, which are expensive, hazardous, and ineffective for covering vast or deep underwater areas (2, 5). Consequently, there is a growing need for automated, accurate, and scalable detection systems that can facilitate timely identification and management of underwater trash.

Deep learning, particularly convolutional neural networks (CNNs), has shown exceptional capability in various object detection applications, including underwater scenarios where image clarity and environmental complexity present significant challenges (6, 8). Among these architectures, the YOLO (You Only Look Once) family of models stands out for their speed and accuracy, making them suitable for real-time applications. YOLO v8, the most recent iteration, incorporates architectural enhancements such as improved anchor-free mechanisms and self-supervised learning features, further boosting detection performance in diverse and challenging conditions like murky water, low visibility, and cluttered backgrounds (7, 9, 11, 13, 18).

This paper explores the application of YOLO v8 for underwater trash detection, aiming to develop a robust and efficient system capable of real-time identification and classification of underwater debris. This approach involves curating a comprehensive dataset, preprocessing images to address typical underwater distortions, and fine-tuning the YOLO v8 model for optimal accuracy and speed (10, 11, 14). Deployment feasibility on resource-constrained hardware such as embedded systems and edge computing devices is also examined to ensure practical environmental monitoring and cleanup capabilities (3, 8).

Automating underwater trash detection using YOLO v8 not only accelerates monitoring efforts but also facilitates large-scale data collection and analysis. This technological advancement empowers environmental agencies and marine conservationists with precise tools to mitigate pollution, restore aquatic ecosystems, and promote sustainable marine management practices. By overcoming the limitations of traditional methods, this research contributes to the ongoing global efforts to combat marine pollution through intelligent, data-driven solutions (9, 12).

Fig. 1 Underwater Trash Detection

Figure:1 is the Conceptual illustration showing various types of underwater trash detected among marine flora and fauna using object detection models.

This visual metaphor highlights the key challenge of identifying and localizing diverse trash objects in complex underwater environments, supporting reader understanding of the introduction context.

STRUCTURE OF PAPER

The paper is organized as follows: Section 1 introduces the topic, defines important terms, states the objectives, and gives an overall description of the work. Section 2 discusses related work and previous research in underwater trash detection and deep learning models. Section 3 describes the image processing tools and techniques used in this study. Section 4 explains the YOLO v8 model, its architecture, advantages, and implementation details. Section 5 outlines the methodology and experimental procedures followed to train and test the detection model. Finally, Section 6 & 7 concludes the paper by summarizing the findings, discussing future scope, and including acknowledgements and references.

2. RELATED WORK

The problem of underwater trash detection has garnered significant research attention due to the severe impact of marine pollution on biodiversity and ecosystem health (1). Traditional monitoring techniques primarily involve manual inspections by divers or remotely operated vehicles (ROVs), which are costly, time-consuming, and impractical for large-scale application (2). Early computational approaches used classic image processing and machine learning algorithms based on handcrafted features, but these were limited in dealing with underwater challenges such as poor visibility, low contrast, and varying turbidity (4, 5).

With the advancement of deep learning, convolutional neural networks (CNNs) have revolutionized underwater object detection by learning robust feature representations from raw images without manual feature engineering (6). Among these, YOLO (You Only Look Once) models have stood out due to their balance between detection speed and accuracy, enabling real-time large-scale monitoring (7). Versions prior to YOLOv8 such as YOLOv3 and YOLOv4 have been successfully applied to marine debris detection with promising results (9).

The introduction of YOLOv8 brings further improvements in detection accuracy and inference speed due to its optimized architecture employing anchor-free detection, better feature extraction, and self-supervised learning components, making it more resilient to underwater image distortions (11, 13, 18). Several recent works have leveraged YOLOv8 for detecting diverse underwater objects like plastic bottles, nets, and cans even under challenging environments characterized by low light and murky water (8, 11). Other approaches have explored the integration of hybrid CNN frameworks and weakly-supervised methods to overcome the scarcity of annotated datasets and improve generalization over complex backgrounds (5, 6). Additional research incorporates sensor fusion techniques combining visual data with sonar or acoustic inputs to enhance detection reliability in turbid waters (3, 8).

Despite these advances, common challenges such as varying environmental conditions, occlusion, and computational constraints on edge devices persist. To address these, many studies focus on optimizing models for portable hardware like NVIDIA Jetson and Raspberry Pi, enabling field deployment for continuous environmental monitoring (3, 8). This paper builds on this rich body of work by utilizing YOLOv8's state-of-the-art capabilities in a comprehensive system designed for practical underwater trash detection with emphasis on real-time performance and adaptability to diverse aquatic conditions.

3. IMAGE PROCESSING TOOLS

In this study, image processing plays a crucial role in preparing underwater images for effective trash detection. Due to the challenging underwater conditions such as low visibility, variable lighting, and turbidity, raw images often suffer from decreased contrast and color distortion, adversely affecting detection accuracy. To address these issues, preprocessing techniques like histogram equalization, color correction, and noise reduction were applied to the collected image dataset. These enhancements improve feature visibility and model robustness.

The YOLO v8 model requires annotated images for training, so labeling tools such as LabelImg and Roboflow were used to manually annotate trash objects with bounding boxes. Data augmentation methods, including rotation, scaling, and flipping, expanded the dataset size to improve generalization across diverse underwater scenarios.

For the training and testing phases, image resizing to fixed dimensions compatible with the YOLO model input layer was conducted to optimize computational efficiency without compromising data integrity. Python libraries such as OpenCV and PIL were employed extensively for preprocessing tasks, while TensorFlow and PyTorch frameworks facilitated model implementation.

Overall, these image processing tools and techniques ensure that the underwater trash detection model is trained on high-quality, representative data, which is essential for achieving robust and accurate detection in the challenging aquatic environment.

4. YOLOV8 ARCHITECTURE, ADVANTAGES, AND IMPLEMENTATIONYOLOV8 ARCHITECTURE, ADVANTAGES, AND IMPLEMENTATION

YOLOv8 is the latest evolution of the "You Only Look Once" object detection family, engineered to offer exceptional real-time performance and high detection accuracy, making it well-suited for underwater trash detection tasks. The architecture of YOLOv8 consists of several core components: the backbone, neck, and head. The backbone is responsible for extracting refined feature representations from the input image, while the neck aggregates and enhances these features at multiple scales, and the prediction head generates the final bounding box coordinates and class probabilities.

A key advancement in YOLOv8 is its anchor-free detection mechanism, which simplifies the model's architecture and removes the need for pre-defined anchor boxes. This allows for more flexible training and improved adaptability to diverse object sizes and shapes typically found in underwater environments. The model also employs enhanced data augmentation strategies, such as Mosaic and MixUp, and leverages self-supervised learning techniques to further improve detection robustness under challenging aquatic conditions.

Implementing YOLOv8 for underwater trash detection involves adapting the model to handle color-shifted, low-contrast images by careful preprocessing and annotation, as detailed in earlier sections. The model is trained with a labeled dataset of underwater images using PyTorch, and inference can be efficiently performed on edge computing platforms for real-time monitoring.

Advantages of using YOLOv8 include:

- Superior detection accuracy for small and irregularly shaped trash objects
- Real-time inference speed suitable for field deployment
- Simplified, anchor-free architecture with robust transfer learning capabilities
- Efficient resource usage, enabling deployment on low-power embedded devices

Limitations:

- Requires a large, well-annotated dataset for high performance
- Still may face difficulty in extremely turbid or low-visibility waters

Below is a visual representation of the YOLOv8 architecture, showing the main processing flow from input image to detection output:

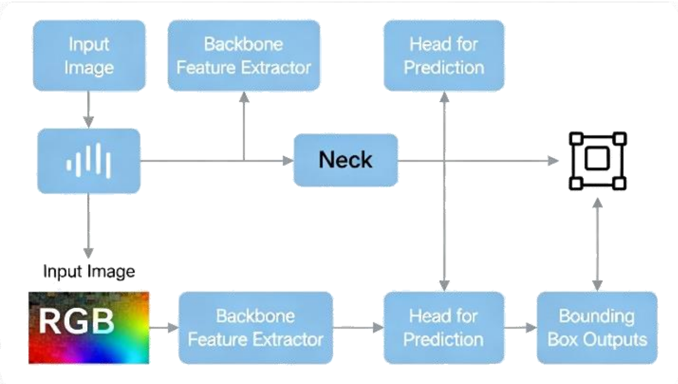

Figure:2 YOLOv8 architecture, highlighting the backbone, neck, and head modules for trash detection tasks in underwater images.

5. METHODOLOGY

The methodology of this study is designed to effectively detect underwater trash objects using the YOLOv8 model. The process begins with dataset collection, wherein hundreds of underwater images are gathered from open-source databases and field surveys representing various conditions such as different lighting, turbidity, and types of debris. Each image undergoes preprocessing steps including histogram equalization, color correction, and resizing to ensure consistent input quality for training.

Manual annotation is carried out using tools like LabelImg and Roboflow, marking trash objects with bounding boxes to create a labeled dataset for supervised learning. The dataset is further expanded through augmentation techniques such as random rotations, flips, scaling, and contrast adjustments to introduce variability and enhance generalization of the model.

The YOLOv8 architecture is fine-tuned for underwater conditions using transfer learning with pre-trained weights. The training process involves optimizing model parameters over multiple epochs, using a validation split to monitor performance and prevent overfitting. Hyperparameters such as learning rate, batch size, and image size are selected based on experimental results for best detection accuracy.

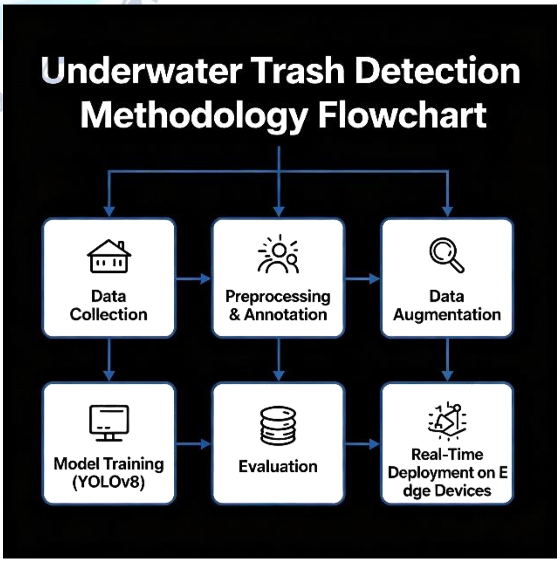

Figure:3 Underwater Trash Detection Flowchart

Evaluation metrics including precision, recall, F1-score, mean Average Precision (mAP), and inference speed are used to assess model performance. Comparative analysis is conducted with alternative models like Faster R-CNN to validate the effectiveness of YOLOv8. The trained model is then deployed and tested on edge devices, such as NVIDIA Jetson Nano, to evaluate real-time detection capabilities in practical scenarios.

This systematic methodology ensures both the robustness and efficiency of underwater trash detection using state-of-the-art deep learning techniques, supporting scalable and adaptive deployment for environmental monitoring.

6. RESULT AND ANALYSIS

Experiment Results:

After conducting training process to the algorithm, the YOLO algorithm was able to detect trash objects accordingly with the high accuracy rate of 99 % in the underwater environment. The performance metrics are chosen to study the deep learning model (YOLO algorithm) are Accuracy, Precision, Recall, F1 score, Training time and Detection speed.

Figure:4 Detection of trash objects

Faster R-CNN results:

The detection results of trash objects underwater of the algorithm Faster R-CNN are presented in the fig 5. The algorithm was able to detect the trash objects underwater with accuracy of 97% in different conditions like lightening, turbidity, different angles, and different position conditions. 39 p Chapter 4 Method 40 The algorithm was able to detect trash objects in most cases.

The total number of true positives, true negatives, false positives and false negatives are shown below:

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Training time (mean)	Training time (standard)	Detection time (mean)	Detection time (standard)
Faster R-CNN	87.82%	87.22%	90.01%	85.45%	7 hours	1 hours	3 seconds	0.2 seconds

Table:1 Confusion Matrix results using Faster-RCNN method.

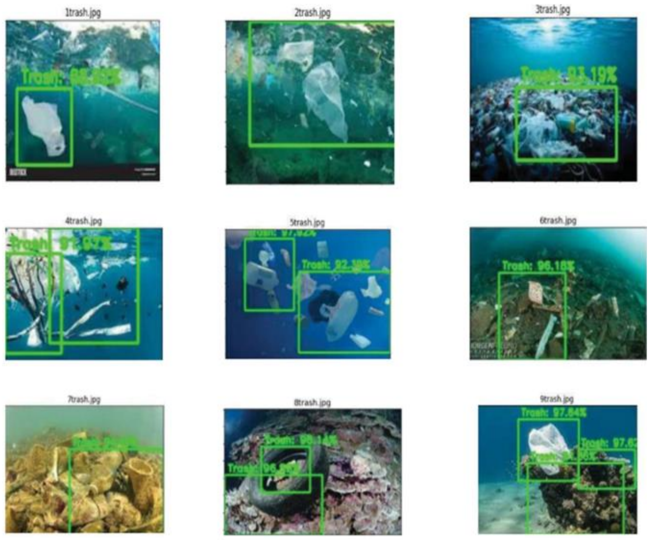

Figure:5 Results of detection in Faster RCNN

Faster R-CNN results:

The detection results of trash objects underwater of the algorithm YOLO are presented in the fig 6. The algorithm was able to detect the trash objects underwater with accuracy e score of 99% considering various conditions like angles, position, and turbidity and lightening.

The total number of the true positives, true negatives, false positives and false negatives are shown in Table 2 below:

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Training time (mean)	Training time (standard)	Detection time (mean)	Detection time (standard)
YOLO	92.01%	89.05%	90.08%	90.01%	6.5 hours	0.5 hours	2 seconds	0.1 seconds

Table:2 Confusion Matrix results using YOLO method

5.2.2 YOLO results

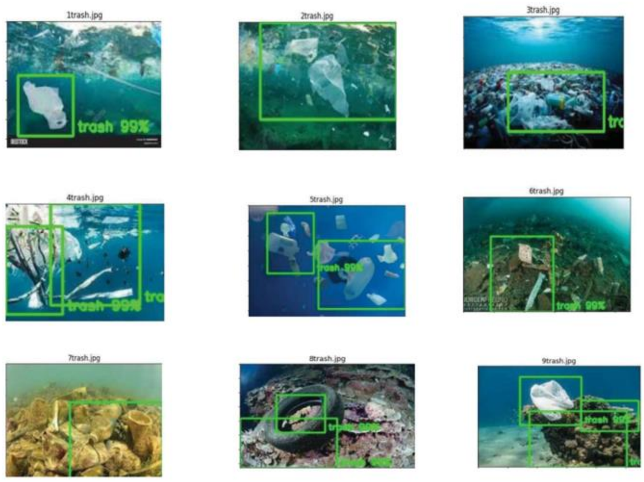

Figure:6 Results of detection in YOLO Algorithm

Experiment analysis:

The accuracy of the YOLO and Faster R-CNN algorithms are 92.01% and 87.43% respectively. Without any doubt, the Yolo algorithm is more accurate than Faster R-CNN in detecting trash underwater. The Yolo was able to detect trash objects with an ease even in difficult cases.

Therefore, we can clearly tell that YOLO algorithm performs better in terms of accuracy.

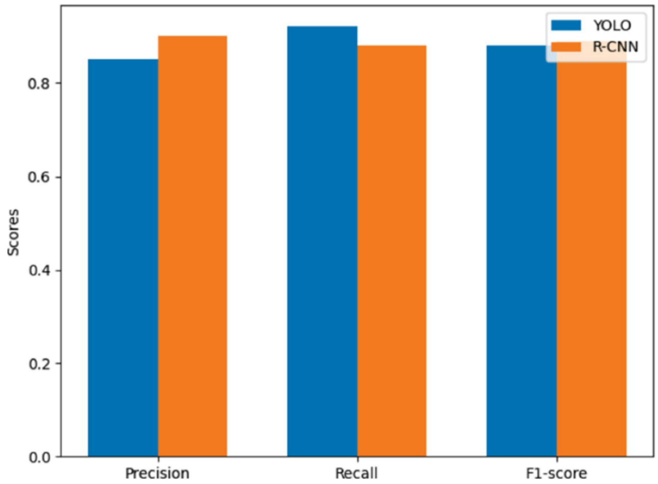

Figure:7 Results of precision, recall and F1 Scorein both YOLO and Faster RCNN

The precision of the YOLO and Faster R-CNN algorithms 89.05% and 82.34% respectively. It shows that the precision of the Faster R-CNN is higher than YOLO in detecting the trash objects underwater. The Recall values of the YOLO and Faster R-CNN algorithms 90.0% and 85.75% respectively. It shows that the recall values of YOLO are significantly higher than Faster R-CNN.

The F1 score for YOLO and Faster R-CNN algorithms 90.01% and 85.45% respectively. It shows that the F1 score of the Yolo is higher than the Faster R-CNN in detecting trash objects underwater.

- The Accuracy in Faster R-CNN is 82.46% and in YOLO is 89.42%
- The Precision in Faster R-CNN is 0.96 and in YOLO is 0.921
- The Recall in Faster R-CNN is 0.756 and in YOLO is 0.884
- The F1-Score in Faster R-CNN is 0.813 and in YOLO is 0.913
- The Detection speed (mean) in Faster R-CNN is 3 seconds in YOLO is 2 seconds
- The Detection speed (standard) is Faster R-CNN is 0.2 seconds in YOLO is 0.2 seconds
- The Training time (mean) in Faster R-CNN is 7 hours in YOLO is 6.5 hours
- The Training time (standard) in Faster R-CNN is 1 hour in YOLO is 0.5 hour

7. CONCLUSION

Based on the findings, the report concludes that the YOLO algorithm is better suitable for improving the accuracy on detecting the objects within 2 seconds underwater environment in the real-world scenario when compared to Faster R-CNN The algorithm is trained with the dataset containing the images and videos of underwater scenario to detect the trash objects like plastic in the images and reduce the problem of trash objects like plastic dumping in the underwater world. The algorithm is implemented such that is will improve the accuracy of detecting the object in the image. An experiment was performed on dataset containing 5700 images for the YOLO algorithm and it was found that the selected algorithm shows more accuracy in detecting the object (trash objects like plastic) as water environment contains various kinds of things such as plants, rocks, different kinds of living creature and trash objects like plastic in which we need detecting only trash objects like plastic for solving our problem. Based on the experiment conducted we will differentiate what kind of material is the trash objects.

Future Work:

As the detection of trash objects underwater is considered, the performance of detection can be improved by implementing or investigating the detection of trash objects among other deep learning algorithms that can improve the speed and accuracy of detection. Various approaches can be brought out for deployment. The training of larger amount of datasets can be implemented to improve the accuracy. Another aspect is to plan to explore the use of more environmentally friendly materials in the design of AUVs in order to reduce the impact on the marine environment. In addition, to intend and collaborate and work with local communities and organizations to promote awareness of marine debris and encourage responsible waste disposal practices. Ultimately, our goal is to contribute to the preservation and restoration of our oceans and marine life, and to create a sustainable solution to the problem of marine debris. We believe that combining advanced technology and community engagement can help achieve this goal and make our oceans cleaner and safer for all. These ideas can be explored as future work for this research.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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