

Automatic Underwater Plastics Detection Using YOLOv9

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Abstract— This paper presents a deep learning-based solution using the YOLOv9 object detection model to identify 15 distinct types of underwater debris. Namely Mask, Can, Cellphone, Electronics, GBottle, Glove, Metal, Net, PBag, PBottle, Plastic, Rod, Sunglasses, Tire, and Misc. We describe the dataset, preprocessing techniques, and training strategy employed in the development of this model. Experimental results demonstrate the model's ability to accurately detect various objects in challenging underwater environments, providing a valuable tool for environmental monitoring.

Keywords— *underwater plastic detection, YOLOv9, marine debris, object detection, image preprocessing*

I. INTRODUCTION

Plastic pollution has gained significant attention from governments and policymakers, emerging as a key focus area within the UN Decade of Ocean Science (2021–2030) and UN SDG 14, emphasizing the urgent need to decrease pollution, particularly from land-based sources. Plastic pollution is a transboundary issue; once it enters the surfaces of oceans and rivers, it can be carried over long distances by currents, eventually accumulating on the seabed as their final sink [1, 2]. Plastic litter has serious implications for the aquatic environment, including entanglement and ingestion [3, 4], where small-sized plastics like meso- and microplastics are easily ingested by marine organisms and transferred through trophic levels [3, 4]. Microplastics serve as a vector for pathogens, and inorganic and organic pollutants, posing risks to human health [5, 6]. Various socio-economic implications are associated with plastic pollution, affecting sectors such as fishing, navigation, and tourism [7].

Understanding flux and monitoring of marine litter are imperative for implementing effective remediation measures for plastic pollution, particularly since it has been linked to global warming [8]. Traditional monitoring methods are labor-intensive and insufficient for dealing with the vast scale of plastic pollution. Advancements in plastic pollution monitoring have integrated video camera technology, remote sensing, and deep learning algorithms for a reliable and feasible modeling of the spatiotemporal distribution and dynamics of plastic litter [9]–[11].

Advances in deep learning, particularly in object detection models, have paved the way for more effective environmental monitoring. Among these models, the You Only Look Once (YOLO) family of algorithms has demonstrated superior performance in real-time object detection across various domains [10], [11]. YOLO's ability to detect small, overlapping objects within complex backgrounds makes it particularly suited for underwater applications where debris often blends into the surrounding environment [12]. Previous research has utilized earlier versions of YOLO for detecting

objects in terrestrial environments, but relatively few studies have applied these models to underwater scenarios [13], [14].

The remainder of this paper is organized as follows: Section II reviews related work on underwater object detection and plastic pollution monitoring; Section III describes the dataset and preprocessing techniques used; Section IV outlines the methodology, including model selection and training; Section V presents the experimental results and analysis; and Section VI concludes with a discussion of future work.

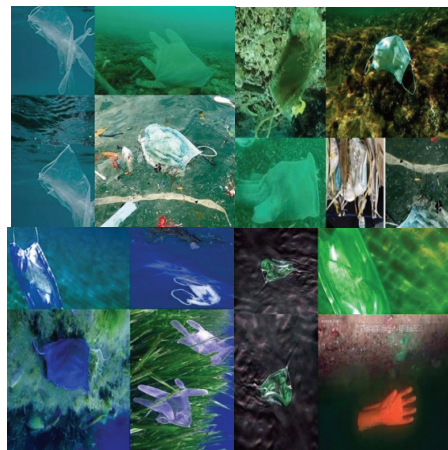


Fig. 1. Sample images ready for processing identification

II. RELATED WORK

Plastics debris as shown in Fig. 1, makes up a major portion of marine litter. The existing solutions to alleviate plastic pollution require improvement to meet environmental sustainability. There is a lack of comprehensive monitoring systems capable of accurately addressing the sources, pathways, and accumulation of plastic waste. There have been a variety of monitoring techniques to assess marine litter, such as on- ground surveys, bottom trawlers (for seabed litter) [15], manta net (for floating litter) [16], satellite sensors and optical devices (for floating litter) [17, 18], and echo-sounder and ROV for submerged litter [19, 20]. However, there is a need to process a large volume of data to effectively characterize marine litter items, which is time-consuming and labor-intensive. In this context, automated methods have provided rapid and smart solutions for marine litter identification [18]. Efforts in plastic pollution monitoring have advanced significantly in recent years by integrating AI, which has supported greatly marine litter research, including both macro and microplastics, through automatic recognition of items [21, 22].

In recent years, the integration of machine learning with autonomous systems has become a focus for developing

To address these limitations, we propose using the YOLOv9 model for underwater plastic detection (as shown in Fig 1). It improves feature extraction and a more efficient bounding box regression algorithm. The model better handle small objects and overlapping detections, making it particularly well-suited for detecting plastic waste in cluttered underwater environments. We use Dark Prior Channel to ensure the model performs well even in degraded underwater images.

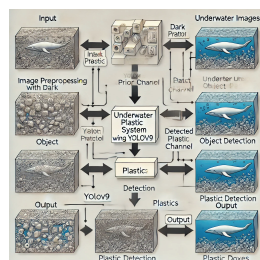


Figure 1 consists of four subplots. The top-left bar chart shows the number of instances for various materials: Mask (~1450), coin (~150), electronics (~250), glass (~350), metal (~100), wood (~50), rope (~550), bag (~1200), plastic (~200), not (~10), and fibre (~2000). The top-right heatmap shows a dense, circular distribution of points in a 10x10 grid. The bottom-left scatter plot shows a dense cluster of points in the center of a 1.0x1.0 coordinate system. The bottom-right scatter plot shows a dense cluster of points in the bottom-left corner of a 1.0x1.0 coordinate system.

Our methodology consists of (1) dataset preparation, (2) image preprocessing, (3) model selection, (4) training, and (5) evaluation.

The debris types include both small and large plastic items, which vary in size, shape, and material. To enhance the robustness of the model.

15 object classes: 'Mask', 'can', 'cellphone', 'electronics', 'gbottle', 'glove', 'metal', 'misc', 'net', 'pbag', 'pbottle', 'plastic', 'rod', 'sunglasses', and 'tire' are in each image and labeled with bounding box coordinates (x and y positions of the top-left corner and the width and height of each detected object)

To overcome poor visibility, we applied the Dark Prior Channel method for preprocessing, which significantly enhances image contrast and sharpness. It adjusts the image’s pixel values to better reveal objects that would otherwise be difficult to detect in low-visibility conditions.

Image augmentation techniques, such as random flips, rotations, and lighting adjustments, were also employed to improve the generalization ability of the model.

We selected YOLOv9 due to its superior performance in object detection tasks involving small and overlapping objects, which are common in underwater environments.

The performance of the YOLOv9 model was evaluated on the test set of 501 underwater images. Number of images for each class is shown in Fig 3, where (a) bar chart of the quantity of each class, (b) Size and quantity of grand truth box, (c) The position of the center point relative to the picture, (d) The ratio of height and width of the object relative to the picture. They contain a diverse set of plastic debris as shown in Fig 1. They vary in size, shape, and visibility, under different environmental conditions. The results proves the model's strengths in detecting underwater plastics.

The overall mean Average Precision (mAP) of 0.72 across the 15 object classes is shown in Table I, in terms of precision, recall, and F1 score for each class.

The application of the Dark Prior Channel preprocessing method had a significant impact on the model's ability to detect objects. Table II shows the performance difference between the model trained on raw images and those enhanced with the Dark Prior Channel. The use of this preprocessing

method led to a notable increase in both precision and recall, resulting in a higher mAP score (0.72 compared to 0.63 without preprocessing).

Table I: Performance Metrics for Each Object Class

Class	Precision	Recall	F1 Score
Mask	0.68	0.60	0.64
Can	0.75	0.70	0.72
Cellphone	0.73	0.65	0.69
Electronics	0.80	0.77	0.78
GBottle	0.83	0.75	0.79
Glove	0.65	0.58	0.61
Metal	0.79	0.72	0.75
Misc	0.70	0.66	0.68
Net	0.74	0.69	0.71
PBbag	0.81	0.77	0.79
PBottle	0.82	0.74	0.78
Plastic	0.78	0.72	0.75
Rod	0.77	0.70	0.73
Sunglasses	0.76	0.69	0.72
Tire	0.85	0.80	0.82

Table II: Comparison of Model Performance with and without Preprocessing

Image Preprocessing	mAP	Precision	Recall
Without Preprocessing	0.63	0.67	0.60
With Dark Prior Channel	0.72	0.76	0.71

During testing, the model maintained an average inference speed of 45 frames per second (FPS), which is more than sufficient for real-time monitoring applications in marine environments. This speed ensures that the system can efficiently scan large underwater areas without missing potential debris, significantly enhancing its operational value for marine pollution monitoring and cleanup missions.

The performance of the YOLOv9 model was evaluated using several key metrics: precision, recall, F1 score, and mean Average Precision (mAP) as follows: F1 score is the harmonic mean of precision and recall, providing a single metric to evaluate the balance between precision and recall as shown in Fig. 4.

Precision is the ratio of correctly predicted objects to all predicted objects, and it reflects the model's ability to minimize false positives as shown in Fig. 5 and Fig 6 where the F1 - Confidence Curve shows how the model's F1 score changes with different confidence thresholds. As the threshold increases, fewer false positives are detected, but this may also reduce true positives, affecting the balance between precision and recall. The curve helps assess the model's overall performance at different confidence levels. Recall is the ratio of correctly predicted objects to all actual objects, indicating the model's ability to detect all relevant objects in the scene as shown in Fig. 7. (The Precision-Confidence curve shows how precision changes with varying confidence thresholds. As the threshold increases, precision improves (fewer false

positives), but fewer detections may occur. This helps evaluate the trade-off between detection accuracy and the number of objects identified) and Fig. 8 (The Precision-Recall curve shows the trade-off between precision and recall at different detection thresholds. It helps evaluate how well the model detects relevant objects while minimizing false positives. A curve closer to the top-right corner indicates better performance.)

The Recall-Confidence curve shows how recall changes with different confidence thresholds. As the threshold increases, recall typically decreases, reflecting a trade-off between detecting more objects and minimizing false negatives. And finally, Mean Average Precision (mAP) measures the average precision across all object classes and provides an overall indication of the model's performance. The system achieved an mAP of 0.72 across all 15 classes as shown in Table 1. The overall performance is shown in Fig. 9. The Performance Graphs in YOLOv9 evaluate the model's object detection performance across various metrics. These include precision, recall, F1 score, and mean average precision (mAP), which help balance accuracy and efficiency at different confidence thresholds. The graphs show how performance evolves with training epochs, confidence levels, and object detection.

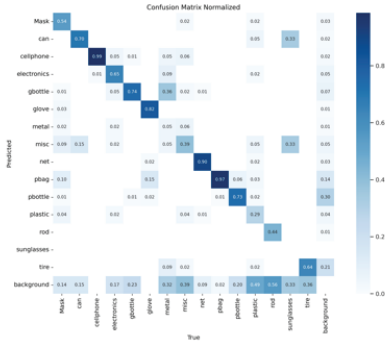


Fig. 4. Confidence Matrix

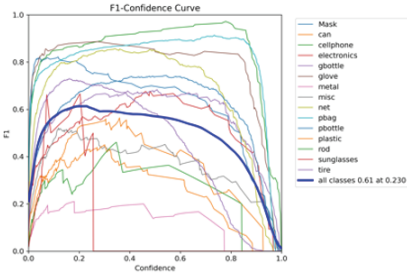


Fig. 5. F1 - Confidence Curve

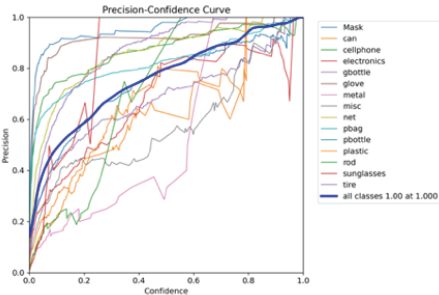


Fig. 6. Precision-Confidence curve

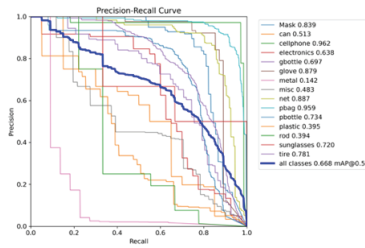


Fig. 7. Precision-Recall curve

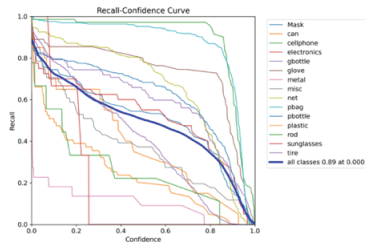


Fig. 8. Recall-Confidence curve

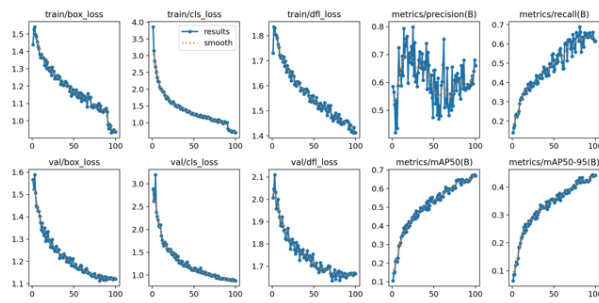


Fig. 9. The Performance Graphs

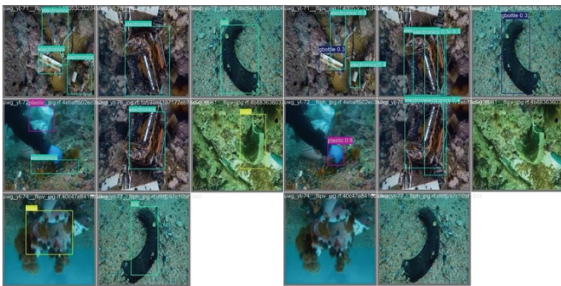


Fig. 10. Sample images with Yolov9 identification

CONCLUSION

In this paper, we presents a novel approach for underwater plastic detection using the YOLOv9 object detection model. It was trained and tested on a curated dataset of underwater images containing various types of plastic debris. It uses advanced image preprocessing techniques, including the Dark Prior Channel method to improve image quality in underwater environments to detect both large and small objects.

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