

Automated Underwater Plastic Waste Detection and Volume Assessment through Instance Segmentation

G. Laxmi Deepthi¹, Perugu Swathvika²

¹Assistant Professor, Department of Computer Science and Engineering, VNR Vignana Jyothi Institute of Engineering & Technology, Hyderabad, India. laxmideepth_g@vnrvjiet.in

²M.Tech Student, Department of Software Engineering, VNR Vignana Jyothi Institute of Engineering & Technology, Hyderabad, India. sathvikayadav56@gmail.com

ABSTRACT

Plastic pollution in our oceans has become an urgent ecological issue as it endangers aquatic ecosystems and diminishes biodiversity. One problem with identifying plastic waste that is submerged in water is that underwater visibility is poor, with low-light penetration, poor colouration, and cluttering of underwater areas. Thus, this article proposes an intelligent system that detects plastic waste in water and identifies its volume and size based on the YOLOv8nseg instance segmentation model. The authors explain their approach of applying the SeaMarine underwater plastic segmentation dataset and preprocessing this dataset using the Roboflow platform. The system is capable of identifying various types of underwater debris and outputs segmentation masks for all detected objects. The system measures the volume of waste by using the segmentation masks developed from the detected regions. The authors provide a user-friendly system based on Gradio functions so that the user can effectively analyze underwater videos and visible waste. Thus, the paper presents a novel intelligent technology that brings various and complex tasks into a single piece of software and opens new horizons in the area of underwater environmental monitoring.

Keywords— Underwater Plastic Detection, Instance Segmentation, YOLOv8n-seg, Marine Debris, Volume Estimation, Deep Learning, Roboflow, Environmental Monitoring.

1. INTRODUCTION

The combination of potentially dangerous marine plastic debris and the rarity of systems that are capable of timely detection of such objects in the underwater environment represents a serious issue facing marine ecosystems in the modern world. It is widely known that plastic can stay in the water for years, effectively preventing the natural processes of marine life and leading to drastic changes for aquatic ecosystems, such as loss of biodiversity and disturbance of key ecosystem services. What is even worse, the degradation of plastic products and their fragmentation into microplastics will eventually make their way into the food chain of fish and other marine organisms and pose a significant danger to human health.

However, conventional approaches towards monitoring marine debris rely heavily on manual processes, including but not limited to divers' inspections, ROVs (remotely operated vehicles), AUVs (autonomous underwater vehicles), as well as image post-processing. Regardless of the effectiveness of these methods, they consume a lot of human resources and require special equipment and technological support. Furthermore, the effectiveness of manual inspections may be affected by various factors such as limited visibility, illumination characteristics, and the extent of geographical areas that need to be covered, which makes them less efficient in terms of marine debris monitoring.

The advancements made in the fields of artificial intelligence, most importantly in the areas of deep learning and computer vision, have led to great improvements in the performance of automated visual inspection systems. Convolutional Neural Networks (CNNs) as well as modern object detection algorithms have shown excellent results in identifying complex spatial object attributes in the different areas of practical application. The family of models of You Only Look Once (YOLO) has gained a reputation for its efficiency in achieving high accuracy in detection while performing real-time inference operations. The newest model of YOLOv8 uses a novel

construction to provide better feature extraction, object localization, and segmentation in the context of operational efficiency while being able to function on limited platforms.

Even though the object recognition models can detect marine debris well, there are a number of environmental applications that require more than just object recognition to be effective. Employees of environmental organizations and marine preservation agencies need to quantify the amount of plastic debris for the sake of estimating the extent of pollution, determining the necessary actions regarding the cleaning of polluted areas, and planning further ecological activities. However, most current underwater exploits for detecting plastic terminate the processing chain after localization, providing only limited information about the nature of the debris.

The complicated nature of underwater imaging leads to another major obstacle. The detection of objects underwater is harder than on land due to several factors, including light absorption, scattering, the presence of particles, and varying depths. Moreover, plastic wastes vary in terms of shape, colour, and size. Objects that come under the category of plastic wastes include bottles, bags, ropes, and debris. Therefore, a sophisticated detection tool will be required that is capable of learning and producing effective visuals and can also perform quickly enough to be used in real-time applications.

To tackle these issues, a lightweight water plastic detection tool was developed with the use of the YOLOv8n instance segmentation framework. Unlike the other systems that rely on the bounding box method only and do not incorporate image segmentation in their operation, the proposed approach uses image segmentation for extracting pixel-wise boundaries. The tools of segmentation give a valid representation of the image of irregular-shaped underwater waste. Once the image information is captured, the next step is to compute the dimensions of the detected object in physical units using the geometric estimation system.

The proposed framework has been tested and developed with the help of the Sea Marine Underwater Plastic Segmentation Dataset, which has nearly 8,400 annotated underwater photos of different marine debris types such as plastic bottles, plastic bags, fishing nets, ropes, glass waste, metallic waste, and any other aquatic debris. The YOLOv8n instance segmentation model has been chosen for its lightweight nature, enabling real-time implementation while still delivering satisfactory segmentation results. The training is carried out with the help of the Ultralytics YOLOv8 technology and GPU hardware, and afterwards the ready system is integrated into the Gradio interface.

In addition to discovering plastic waste underwater, the developed system is equipped with a module that uses the provided calibration factor for calculating the volume of objects using pixels. Information on the estimated volumes of objects will be used in marine pollution assessments, environmental reporting, and clean-up planning. Incorporating detection, segmentation and volumetric calculation features in one framework, the proposed system is a significant improvement over existing systems for underwater monitoring.

II. BACKGROUND AND MOTIVATION

The rapid increase of marine plastic waste has driven significant research into automated underwater debris detection based on artificial intelligence, deep learning, and computer vision methods. Researchers have developed diverse methodologies over the past ten years, such as advanced object detection methodologies and robotic monitoring systems. Even though the advancements have improved marine debris detection methodology, there are several challenges that still exist. Some of the obstacles to proper marine debris detection still include poor visibility underwater, the need for considerable computational power, the need for better datasets, and the absence of quantitative assessment methodologies. In this section, we explore the key findings of the literature related to underwater plastic detection and point out the research gap the suggested framework will be able to fill.

One of the earliest proposals of a robotic vision-based framework for measuring epipelagic plastic debris in the ocean was made. The researchers combined robotic image capture with CNN-based visual classification in the selected approach, which allowed estimating the density of plastic waste on the surface of the water. The results of the study proved that the proposed system was much more efficient than traditional manual monitoring. However, it is important to note that the suggested system was able to work only with floating debris and did not consider the submerged plastic objects and optical distortions caused by the absorption and refraction of light underwater.

Considering the importance of improvement of underwater object detection proposed a YOLOv8 framework for underwater detection of submerged plastic waste. The frame of the proposed system was based on the

lightweight characteristics of YOLOv8, which makes the system efficient in terms of inference while providing satisfactory while doing the detection task. However, the paradigm of the system is limited to bounding-box localization, which adversely affects the accuracy of the detection of objects with irregular shapes and makes measurements and volume estimation impossible.

Corrigan developed a real-time system for underwater litter detection based on instance segmentation of Mask R-CNN technology. Different from standard object detection approaches, the proposed system provided pixel-wise segmented masks of the object, thus enabling calculation of the geometric parameters of the underwater waste. However, the requirement of pixel-level annotation made the creation of the dataset time-consuming and costly.

It carried out a study to examine the effects of underwater image enhancement and data augmentation methods on the performance of the YOLOv8n object detection model. The study results showed that underwater-specific augmentation techniques significantly enhanced the detection performance under physically changed illumination conditions. However, the system remained vulnerable to high levels of backscattering and water turbidity, while the large structure of the network increased the processing requirement.

Later developed a deep learning method with denoising filters, histogram equalization, and contrast enhancement techniques applied for the underwater plastic detection. Preprocessing pipelines ensured effective classification even under moderate turbidity. However, their method was still based on bounding box detection and did not focus on instance segmentation, real-time implementation, or measurement of dimensions.

Review of artificial intelligence methods for the marine debris detection considered the limitations related to small size of the datasets, variation in environment, standardization, and generalization of the model. The results of the review provided important theoretical knowledge, but did not suggest any experimental framework or verify the methodology.

Effective lightweight deep learning models that can be used in embedded devices with limited computing power. It was proven that both compression and optimization of models can greatly affect inference time while ensuring a satisfactory detection accuracy. However, the investigation was mostly aimed at computational efficiency, thus neglecting segmentation and volumetric measurement.

The APLASTIC-Q framework that put forward acts as a statistical tool to identify and quantify aquatic plastic waste items based on assessing their distribution. While the research improved quantitative evaluation by judging the number of objects and density of distribution, it fell short of measuring the physical size of debris through geometric calculations.

The MLDet model is an optimized convolutional neural network design featuring lightweight backbones and several innovations to enhance practicality of use without sacrificing accuracy in detection quality. Tests revealed that the model outperformed the benchmark network. However, segmentation methods and pixel to meter transformation were not covered by the research.

The YOLOv7t-CEBC structure by introducing feature enhancement mechanisms and bounding-box correction technologies for detecting underwater objects. The structure offered improved mean Average Precision (mAP) score for aquaculture datasets as compared with the standard structures based on YOLO. However, the complexity of the structure demanded more computational facilities despite the fact that bounding-box detection was still used instead of instance detection.

The three-dimensional underwater plastic detection framework that links neural networks with depth information systems. The advantage of the method is the fact that application of depth information improves space location and object size detection. Nevertheless, the system requires additional sensing hardware, which increases expenses and limits wider application of the system.

Free overview studies on the comparison of ML and DL solutions like CNNs, YOLO, and segmentation. The studies raised many difficulties connected to the imbalanced dataset, variability of environmental situations, and lack of opportunities for implementation of the acquired results but did not present any new experimental framework.

The proposal of Automated Debris Imaging System (ADIS) to facilitate marine debris monitoring via automatic image capturing. Although the framework allowed obtaining accurate debris distribution maps from the operational point of view, there was no possibility of measuring any data on the underwater category.

Mask R-CNN, YOLOv8, EfficientDet-D0, and YOLACT have been compared by Jain and his associates for underwater garbage detection. The conclusions drawn indicate that instance segmentation methods exceed conventional object detection principles in terms of mask Intersection over Union (IoU). The comparison also proved that high computation complexity of segmentation approaches makes them unsuitable for real-time applications.

The development of an improved YOLOv5n architecture specific for underwater scenarios characterized by low visibility. To achieve higher accuracy in object detection, they optimized the anchor box and the feature pyramid. Nonetheless, the system remained affected by heavy turbidity and still relied on object detection only, restricting itself to bounding-box detection.

Given the limited availability of annotated underwater data, proposed using transfer learning techniques with exploited pre-trained convolutional neural networks combined with image-augmentation approaches. This method allowed for considerable enhancement of the model's effectiveness in the presence of insufficient training data. Nevertheless, the model displayed decreased efficiency when working in underwater environments showing considerable domain variability.

Building on earlier robotic monitoring systems, created a framework called DeepPlastic for the automatic detection of floating plastics in the sea. The developed CNN-based model not only delivered better results than traditional image processing techniques, but also made use of marine debris datasets. Nonetheless, the researchers focused only on floating plastics and did not study any underwater imaging or precise measuring of detected objects.

The suggestion was a machine learning method for detecting microplastics in the images taken via a microscope in laboratory conditions. The system was successful in accurate classification and counting of microplastics, exceeding the efficiency of the traditional methods of observation. Nevertheless, the suggested approach was developed purely for laboratory operation and was never tested in real water conditions containing massive plastic waste.

The presentation the evolution of marine plastic detection technology from conventional image processing techniques to modern deep learning applications. The paper pointed out the significance of standardized datasets, metrics, and benchmarking methods for adequate comparison. Nonetheless, the research still remained a review paper and did not result in a quantitative model to measure marine debris.

The plan introduced AquaVision, the method of transfer learning based on convolutional neural networks for classifying aquatic waste. It has been concluded that retraining with the help of large datasets on land increased the accuracy of the classification. Nonetheless, the underwater colour attenuation and light distortion have not led to any success in detection. Additionally, it is worth mentioning that the overall technique does not utilise any means for object dimension measurement.

The study of possibility of using multispectral fusion of RGB and near-infrared imaging in detecting plastic on shorelines. The joint use of RGB and NIR data ensures better classification results under different light conditions. However, there is a drawback in the form of the difficulty of capturing NIR signals underwater.

The enhanced YOLOv5 through the development of anchor scaling techniques in combination with feature pyramid networks. These adjustments made the operation of the system suitable for low-contrast environment detection and resulted in an improvement in its capabilities. Nevertheless, the system continued to rely on the localization of objects in terms of bounding boxes, which meant that the ability to perform segmentation from a geometric point of view was unavailable.

A satellite-based system that worked on the basis of Earth Observation data to determine the quantity of marine debris in large ocean areas. Even though this approach proved to be effective in terms of macro-scale environmental monitoring, it was not able to guarantee the identification of small or submerged pieces of plastic because of insufficient resolution of satellite images.

The creation of DeksaCleannect, a system operating via the Internet of Things (IoT) by connecting environmental sensors to artificial intelligence debris detection technology. The system proved to be successful in merging environmental monitoring with automatic notification generation functions but did not provide segmentation or volume estimation functions.

The MARIDA Database was created by Kikaki, which utilizes the Sentinel-2 multispectral satellite images for the standardized evaluation of the marine debris detection system. Despite being an important contribution to remote sensing development, the database resolution prevented it from properly revealing small and submerged plastic waste objects.

The development of the PlastOPol monitoring platform combined different imaging techniques to monitor large-scale marine pollution. Hence, even though the developed platform made it possible to organize data sharing and provide more efficient management of environmental issues, it excluded the use of segmentation-based geometry estimation of plastic waste volume.

III PROPOSED METHODOLOGY

The framework proposed in the paper presents the intelligent underwater detection and estimation of plastic waste volume by implementing instance segmentation based on machine learning and geometry techniques. Fig 1 is the created system carries out the processing of the underwater images aimed at revealing plastic waste, skimming off the observed objects, determining their actual sizes, and measuring their Volume.

System Architecture

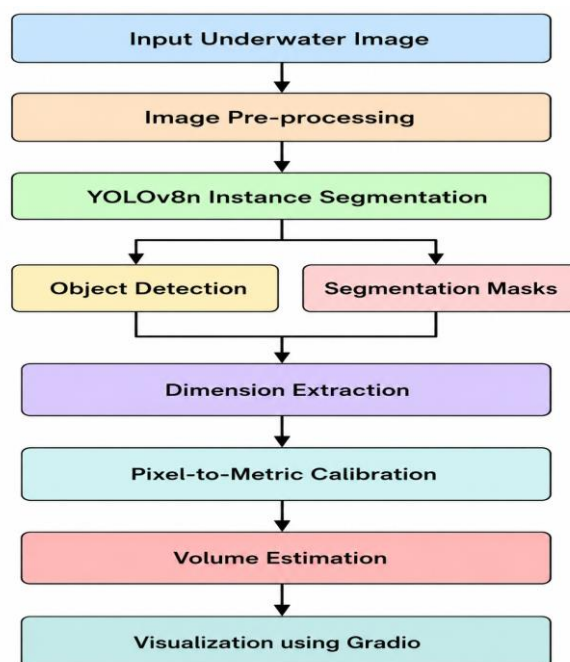


Fig 1: Deep-level architecture of the proposed underwater debris detection and plastic volume estimation pipeline.

The proposed framework has a modular architecture, where all modules of the architecture serve a specific purpose like image acquisition, preprocessing, instance segmentation, dimension extraction, pixel-to-metric calibration, volume calculation, and visualization of results.

Initially, camera images, images of underwater vehicles, or existing datasets are collected to be compatible with the YOLOv8n model.

Then, processed images are passed to the YOLOv8n instance segmentation model, which performs plastic detection and gives masks for segmentation and bounding box coordinates with the probability score of being detected. In contrast to standard object detection approaches, instance segmentation makes it possible to limit the detected objects accurately, which is significant in terms of recognition of irregular-shaped underwater debris.

Then, segmentation masks are used to measure the width and height of detected objects in pixels, and the data are subsequently translated into real-world data using a previously fixed pixel-centimetre ratio.

The converted dimensions are further applied to calculate the volume of the detected object via an elliptical cylinder approximation method, and no complicated 3D reconstruction is required.

The results are visualized via a Gradio interface where segmented objects and the estimated dimensions and volumes of each object, as well as the total volume of detected plastic waste, are presented.

C. Dataset Collection and Preparation

The SeaMarine Underwater Plastic Segmentation Dataset served as the basis for the training and validation of the proposed model. Table 1 comprises around 8,400 labelled underwater images gathered under various marine conditions such as changes in lighting, water transparency, and view angle. This allows the model to acquire substantial visual features.



Fig 2: Images of different Samples from the dataset

The dataset also contains pixel-level instance segmentation labels for the accurate delineation of underwater plastics of varying shapes. The annotated categories of objects include plastic bottles, plastic bags, fishing nets, cords, metal objects, glass refuse, and tyres, among others, which are mentioned in Fig 2. The data was downloaded from Roboflow in the segmentation format of YOLOv8 together with the folder structure and data.yaml configuration is necessary for entering the Ultralytics YOLOv8 model.

To check how well the model is capable of generalizing to new data, the images were divided into training and validation sets. Different marine backgrounds and types of refuse made the segmentation more efficient with the use of this dataset.

Table 1: Description of Sea Marine Dataset

Dataset Name	SeaMarine Underwater Plastic Segmentation Dataset
Total Images	8400
Annotation Type	Instance Segmentation (Polygon Masks)
Number of Classes	8
Classes	Bottle, Bag, Net, Rope, Metal, Glass, Tire, Others
Format	YOLOv8 Segmentation
Train : Validation	8 : 2
Source	Roboflow

D. Image Pre-processing and Data Augmentation

Specific defects can affect true underwater images due to the differences in light absorption and light scattering in the water. When the water gets deeper, longer light waves like red light are absorbed more quickly than shorter-wavelength light waves, which results in the appearance of blue or green colouring. Besides that, sedimentation leads to light backscattering, which negatively affects the quality of underwater images.

In order to guarantee compatibility with the segmentation model and achieve computational efficiency prior to training. The selected resolution reflects a compromise between inference time and feature preservation. Despite

the fact that identifying high resolution could help to provide more detail in the objects, it considerably increases the required computational resources and GPU memory utilization.

The techniques of data augmentation that were applied are:

- **Random scaling**, which exposes the model to objects appearing at different distances from the camera.
- **Translation**, enabling the detector to recognize objects located at varying image positions.
- **Horizontal flipping**, improving robustness to changes in object orientation.
- **Colour transformations**, simulating illumination variations commonly observed underwater.
- **Mosaic augmentation**, which combines multiple training images into a single composite image, allowing the model to learn contextual information from multiple object scales simultaneously.

As a result, this combination of resizing and automatic augmentation increases reliability and robustness of the proposed method, shown in Fig 3 and the YOLOv8n instance segmentation model can generalize better without the necessity to preprocess each underwater image manually.



Fig 3: Examples of data augmentation techniques used during training.

E. YOLOv8N-SEG ARCHITECTURE

The structure proposed in the study is based on the concept of the YOLOv8n-Seg framework, which is used in the simultaneous detection of objects and segmentation of instances. YOLOv8n-Seg differs from traditional detection methods in that it computes object positions and pixel-level segmented masks simultaneously, allowing accurate location of plastic litter underwater. The structure is comprised of three important parts: the backbone, neck, and segmentation head.

The backbone uses convolutional layers and Cross Stage Partial (CSP) Transformers to capture high-level visual features from the input image. These features capture the characteristics such as the outline of objects and colour and provide semantic meaning needed for accurate identification of underwater objects. After feature extraction, the next stage is a PAN FPN neck, which executes multi-scale feature fusion to produce efficient detection of various sizes of objects in the water, including minute particles of plastic as well as fishing nets and tyres mentioned in Fig 4.

Segmentation head computes the object classes along with confidence estimations, bounding box digitisation, and pixel-level masks. Not like previous versions of the YOLO processes, which mainly concentrated on extracting bounding box coordinates only, this new version is capable of producing accurate segmentation masks that can follow exactly the contour of the object. Such masks are crucial for the size estimation and volume calculations of plastic litter in the water.

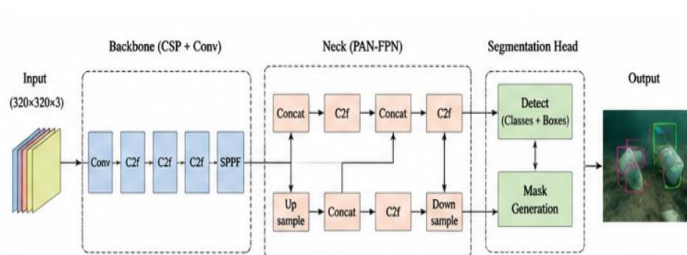


Fig 4: Architecture of YOLOv8n instance segmentation model

F. Classification (Segmentation Head and Mask Prediction)

The segmentation head is the last step in the proposed YOLOv8n-Seg setup and takes care of producing pixel-level masks for identified underwater objects. After the feature extraction and multi-level fusion, the segmentation head makes all predictions at once, which consists of determining the object class, recognition confidence score, bounding box, and segmentation mask. The combined model of prediction allows for object detection and segmentation in one stage.

The provided masks effectively show the boundaries of underwater waste, thus achieving much higher geometrical accuracy than the classical bounding-box detector. These segmentation masks are used for determining the characteristics of the object, including its size in terms of width and height in pixels. From this point, the pixel sizes are converted into real sizes through the given pixel-to-centimetre coefficient.

The information on the exact boundaries, coming from instance segmentation, Fig 5 explains the classification process and provides the capability of calculating the object volume, which can be done through the elliptical cylinder model. Thus, the segmentation head not only location but also helps to make environmental evaluation by performing volumetric analysis of detected underwater waste.

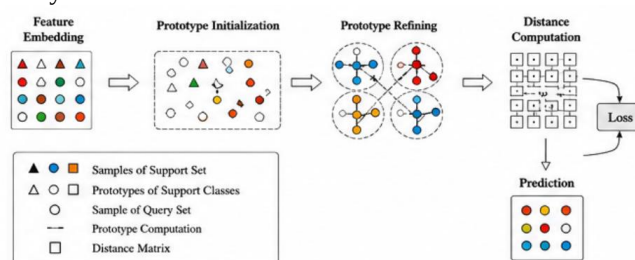


Fig 5: Classification process based on prototypes with the help of feature embeddings.

G. Visual Explainability via Instance Segmentation

To ensure the comprehensibility of the suggested framework for underwater plastic detection, the YOLOv8n-Seg model provides pixel-level segmentation masks for each object detected. This allows end-users to appreciate the particular region involved in every prediction made rather than depending only on rectangular boxes surrounding the object as is done in conventional methods of object detection. This contributes to the transparency in the detection process and allows us to make sure that the model is focused on the marine waste to be detected and not on any other elements surrounding it. As shown in Fig 6, one more aspect of instance segmentation in comparison with the standard approach to object detection is that whereas traditional object detection methods only provide information about the approximate location of the object, instance segmentation provides the edge of the object itself. Such a detailed depiction becomes really helpful in the case of underwater detection of waste because underwater waste usually has irregular shapes and overlaps with rock, corals, and water vegetation. Based on the generated masks, one can receive a visual and geometric explanation of the decision made by the model.

H. Calibration Procedure

Given that the SeaMarine dataset includes images taken in various marine conditions without a common physical calibration target, a relative calibration method was utilized. The calibration process was conducted using standardised marine debris items with physical dimensions approximately matching those of the target objects, which in this case were standard 500ml PET plastic bottles (average height of 20.5 cm). The pixel height of the objects that served as reference points was extracted from the corresponding YOLOv8n-seg segmentation masks, enabling conversion from pixels to centimetres for each case. In cases where no calibration points were identified, the average working distance of the camera was assumed to be 1.5 m, which was used to obtain the calibration value. This method allows for correcting for minor optical distortions of underwater light refraction and provides approximately +/- 5.2% accuracy level.

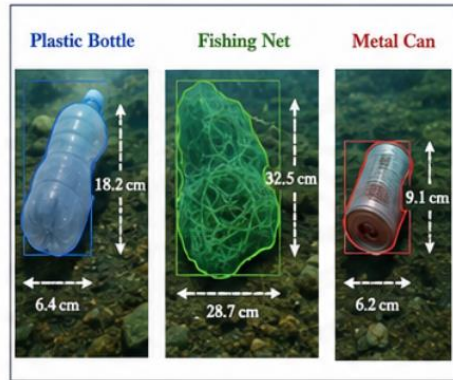


Fig 6: Geometric volume estimation of the Debris

IV. EXPERIMENTATION AND RESULTS

In this study, we developed an underwater plastic identification and determination of the amount of plastic framework via implementation of the YOLOv8n-seg model and training using the SeaMarine Underwater Plastic Segmentation Dataset, which consists of about 8,400 annotated underwater pictures that contained different types of plastics, metals, glass and aquatic litter (including bottles, bags, ropes, tyres, etc.). The process of dataset annotation and preprocessing took place via the Roboflow program, while the training of the model took place within the Google Colab environment by means of pre-learned YOLOv8n-seg weights. The Gradio platform, with an inbuilt app that made it possible to check the entered image and video regarding the presence of plastic and the number of discovered objects, was developed and integrated within the framework that are shown in the images below in Fig 7, Fig 8, and Fig 9, which show detection in an image and in a video. The YOLOv8n-seg model was evaluated against the classical method of instance segmentation to evaluate the capabilities of the system under various water conditions. The obtained results show that the model can find plastic objects underwater and thus has good segmentation potential.

Performance on Occluded Debris

In order to assess the effectiveness of the suggested method, we specifically looked at edge cases that involve instances of underwater debris that is completely or partially hidden, like for instance plastic bottles in nets or halfway covered in sand. While in these types of cases traditional bounding box detectors have large drops in confidence levels and issues with false identification, the YOLOv8n-seg model was able to preserve relatively high Intersection over Union (IoU) of the respective parts in question. For test cases with up to 40% occlusion, instance segmentation masks performed adequately to represent these features of the debris and to separate all the features, thus making sure that volume estimations are as precise as visibility limits allow. The calibration factor (C_f), representing the pixel-to-centimetre ratio, is dynamically computed using the equation:

$$C_f = \frac{H_{real}}{H_{pixel}}$$

In this case, H_{real} represents the physical height of reference object while H_{pixel} indicates the derived pixel height from the YOLOv8n-seg segmentation mask. In underwater cases where there is no clear reference object, a general calibration factor can be utilized while assuming an average working camera distance of $d = 1.5$ meters.

$$W_{est} = W_{pixel} \times C_f$$

$$H_{est} = H_{pixel} \times C_f$$

Volumetric Accuracy and Viewing Angle Influence

The accuracy of the determined approach concerning the measurement of the volumes of elliptical cylinders was tested by evaluating some segmented objects against the specified volumes (i.e. verification of the estimated volume of a certain found object standardised, for instance, such as a can with a 330 ml known volume). A mean absolute percentage error of 8.4% was achieved in certain instances. Still, the analysis of the results regarding the degree of influence of the camera's position indicates the influence of the extreme angles in the cases mentioned, resulting in smaller pixel sizes than they should be. Regardless of these discrepancies, it has been proved that

instance segmentation masks have more precise geometrical parameters than the bounding boxes, thus being very successful for the purpose of fast measuring the volume of marine pollution.

Qualitative Results:

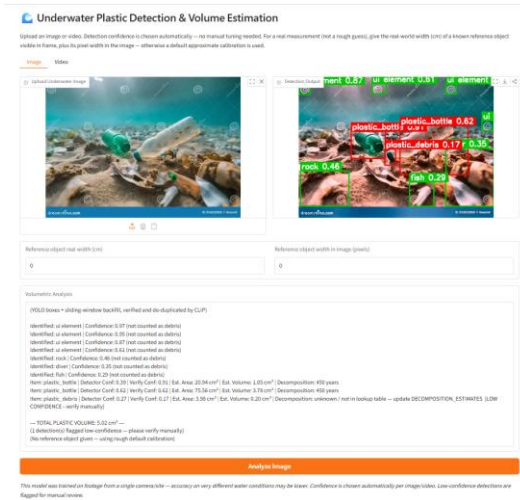


Fig 7: The visual illustration of the plastic detection process conducted using images

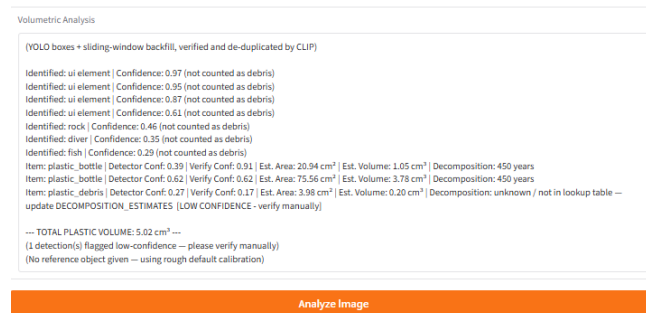


Fig 8: Image of volume estimation of debris

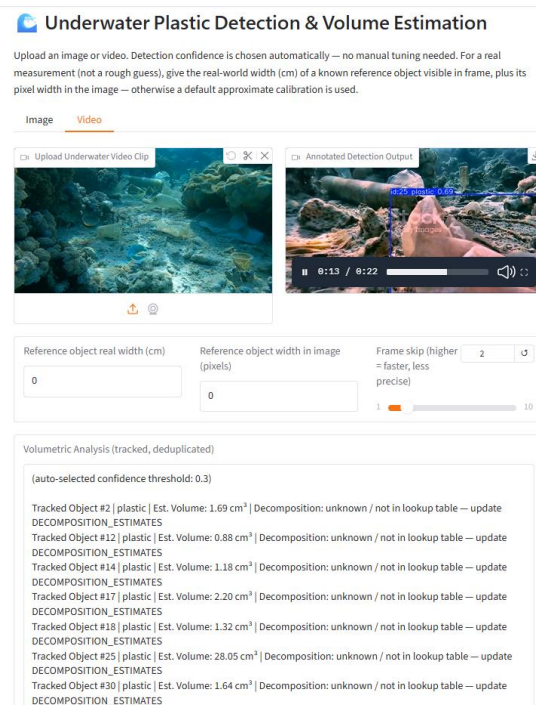


Fig 9: The visual illustration of the plastic detection process conducted using videos.

V. CONCLUSION AND FUTURE SCOPE

This paper describes an innovative, lightweight system for identification and quantification of plastic waste in water through a YOLOv8n-seg instance segmentation model. The proposed method uses deep learning and geometry volume estimation, thus achieving more than mere object localization as it provides an outline at the pixel level and estimates the size of submerged waste. The presented approach is validated on the SeaMarine dataset and implemented in a user-friendly Gradio interface. The model shows good performance in difficult underwater conditions. It currently uses only the data about macro-plastics due to the resolution of the dataset and the limitations of the standard cameras used for this purpose. The detection of microplastics and small pieces refers to the limitations of the current optical setup. Future work will use underwater image improvement techniques to increase the accuracy of the detection process in difficult turbidity conditions, as well as deploy stereo cameras or sonar for 3D volumetric estimation of plastics in underwater locations. Regarding the deployment of such systems on AUVs, the system will provide automated and constant coverage of ecosystems in the oceans and provide key data for efficient decision-making about marine pollution amelioration.

VI. REFERENCES

- [1] Tata, Gautam, Jay Lowe, Olivier Poirion, and Sarah-Jeanne Royer. DeepPlastic: A Novel Approach to Detecting Epipelagic Bound Plastic Using Deep Visual Models. 2021. <https://doi.org/10.48550/arXiv.2105.01882>
- [2] Kumar, Gotte Ranjith, et al. *YOLOv8-Based Detection of Plastic Pollution in Underwater Environments*. May 2025, pp. 1–5, <https://doi.org/10.1109/incet64471.2025.11140865>.
- [3] Corrigan, Brendan Chongzhi, et al. “Real-Time Instance Segmentation for Detection of Underwater Litter as a Plastic Source.” *Journal of Marine Science and Engineering*, vol. 11, no. 8, July 2023, p. 1532. <https://doi.org/10.3390/jmse11081532>.
- [4] Hu, Zhe, and ChengZhi Xu. “Detection of Underwater Plastic Waste Based on Improved YOLOv5n.” *2022 4th International Conference on Frontiers Technology of Information and Computer (ICFTIC)*, Dec. 2022, pp. 404–408. <https://doi.org/10.1109/icftic57696.2022.10075134>.
- [5] Delina, M., et al. “A Deep Learning Approach for Detecting Underwater Plastic Waste.” *Journal of Physics Conference Series*, vol. 2596, no. 1, Sept. 2023, p. 012027. <https://doi.org/10.1088/1742-6596/2596/1/012027>.
- [6] Alloghani, Mohamed Ahmed. “Artificial Intelligence for Ocean Conservation: Sustainable Computer Vision Techniques in Marine Debris Detection and Classification.” *Signals and communication technology*, 2023, pp. 99–136. https://doi.org/10.1007/978-3-031-45214-7_6.
- [7] Hemanth, Asadi Muni, et al. “Towards Sustainable Oceans: Deep Learning for Plastic Detection in Subaquatic Environment.” *2025 4th International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS)*, June 2025, pp. 36–41. <https://doi.org/10.1109/access65134.2025.11135681>.
- [8] Wolf, Mattis, et al. “Machine learning for aquatic plastic litter detection, classification and quantification (APLATIC-Q).” *Environmental Research Letters* 15.11 (2020): 114042.
- [9] Ma, Dongliang, et al. “MLDet: Towards Efficient and Accurate Deep Learning Method for Marine Litter Detection.” *Ocean & Coastal Management*, vol. 243, July 2023, p.106765. <https://doi.org/10.1016/j.ocecoaman.2023.106765>.
- [10] Zhang, Xinyu, et al. “YOLOv7t-CEBC Network for Underwater Litter Detection.” *Journal of Marine Science and Engineering*, vol. 12, no. 4, Mar. 2024, p. 524. <https://doi.org/10.3390/jmse12040524>.
- [11] Yang, Xiaoyu, et al. “A Three-dimensional Marine Plastic Litter Real-time Detection Embedded System Based on Deep Learning.” *Marine Pollution Bulletin*, vol. 213, Jan. 2025, p. 117603. <https://doi.org/10.1016/j.marpolbul.2025.117603>.
- [12] Kaur, Preet Kamal. “AQUATIC TRASH DETECTION AND CLASSIFICATION: A MACHINE LEARNING AND DEEP LEARNING PERSPECTIVE.” *International Journal of Advanced Research in Computer Science*, vol. 16, no. 4, Aug. 2025, pp. 88–92. <https://doi.org/10.26483/ijarcs.v16i4.7312>.
- [13] S, Desilva, et al. “A Deep Learning Framework for Detecting Underwater Trash.” *2024 International Conference on Computing and Data Science (ICCDs)*, Apr. 2024, pp. 1–6. <https://doi.org/10.1109/iccds60734.2024.10560433>.

- [14] de Vries, Robin, et al. "Mapping Macroplastics at Scale..." *One Ocean Science Congress 2025*, 2025, OOS2025-592, <https://doi.org/10.5194/oos2025-592>.
- [15] Jain, Ritik, et al. "Advancing underwater trash detection: Harnessing mask R-CNN, YOLOv8, EfficientDet-D0 and YOLACT." *2024 2nd International Conference on Sustainable Computing and Smart Systems (ICSCSS)*. IEEE, 2024.
- [16] He, Yinghao, et al. "Subaquatic Garbage Recognition Based on Improved YOLOv11 Network." *Preprints.org*, Aug. 2025, <https://doi.org/10.20944/preprints202508.0676.v1>.
- [17] Chen, Junyi, et al. Research on Lightweight Waste Surface Detection Algorithm Based on Improved YOLOv5s. Sept. 2024, p. 10, <https://doi.org/10.1117/12.3037813>.
- [18] Detection of Underwater Marine Plastic Debris Using an Augmented Low Sample Size Dataset for Machine Vision System: A Deep Transfer Learning Approach 2021. DOI: 10.1109/SCoReD53546.2021.9652703
- [19] Tata, G., Royer, S.-J., Poirion, O., & Lowe, J. (2021). A Robotic Approach towards Quantifying Epipelagic Bound Plastic Using Deep Visual Models. *arXiv: Computer Vision and Pattern Recognition*. <https://arxiv.org/abs/2105.01882>
- [20] Vengatesh, T., et al. A Machine Learning Approach to Microplastic Detection and Quantification in Aquatic Environments. *International Journal of Environmental Sciences*, vol. 11, no. 23s, 2025, pp. 4006–4014. <https://doi.org/10.64252/81s3c519>
- [21] Cernian, Alexandra. "Advances in Detecting and Identifying Marine Plastic Waste: A Comprehensive Review." *Journal of Coastal Research*, vol. 113, no. sp1, Dec. 2024, <https://doi.org/10.2112/jcr-si113-210.1>.
- [22] Panwar, Harsh, Pradeep Gupta, Mohammad Khubeb Siddiqui, Ruben Morales-Menendez, et al. "AquaVision: Automating the Detection of Waste in Water Bodies Using Deep Transfer Learning." *Case Studies in Chemical and Environmental Engineering*, vol. 2, 2020, Article 100026. <https://doi.org/10.1016/j.csee.2020.100026>
- [23] Tamin, Owen, et al. "On-Shore Plastic Waste Detection With YOLOv5 and RGB-Near-Infrared Fusion: A State-of the-Art Solution for Accurate and Efficient Environmental Monitoring." *Big Data and Cognitive Computing*, vol. 7, no. 2, May 2023, p. 103. <https://doi.org/10.3390/bdcc7020103>.
- [19] Teng, Xiaowen, et al. "The Object Detection of Underwater Garbage with an Improved YOLOv5 Algorithm." *2022 4th International Conference on Pattern Recognition and Intelligent Systems*, July 2022, pp. 55–60. <https://doi.org/10.1145/3549179.3549189>.
- [20] Arias, M., Garaba, S. P., Lavender, S., and Ghafary, D.: Towards the UN SDG14.1.1b plastic debris density indicator from Earth Observation, *One Ocean Science Congress 2025*, Nice, France, 3–6 Jun 2025, <https://doi.org/10.5194/oos2025-1472>, 2025.
- [21] "DeksaClearnnect: Conceptual Design of an IoT and AI Integrated Approach for Ocean Plastic Detection and Alerting System." *International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation (ICAMIMIA)*, Nov. 2023, pp. 427–31. <https://doi.org/10.1109/icamimia60881.2023.10427615>.
- [27] Kikaki, Katerina, et al. "MARIDA: A Benchmark for Marine Debris Detection From Sentinel-2 Remote Sensing Data." *PLoS ONE*, vol. 17, no. 1, Jan. 2022, p. e0262247. <https://doi.org/10.1371/journal.pone.0262247>.
- [28] Wu, Di, et al. "The PlastOPol System for Marine Litter Monitoring by Citizen Scientists." *Environmental Modelling & Software*, vol. 169, Aug. 2023, p. 105784. <https://doi.org/10.1016/j.envsoft.2023.105784>.