

Deep Dive into Marine Pollution Segmentation: Unveiling the Power of Deep Learning for Effective Trash Detection

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ABSTRACT

Marine pollution, particularly plastic debris, poses a significant threat to marine ecosystems, requiring efficient and accurate methods for detection and mitigation. Traditional methods for identifying marine trash have limitations in scalability and precision, especially in underwater environments. This paper explores the application of deep learning-based segmentation models, with a specific focus on YOLOv8, for the segmentation of marine debris in underwater imagery. The study investigates the potential of YOLOv8 to not only detect but also segment various types of marine trash in complex environments. Through extensive experimentation, we evaluate the model's performance based on metrics such as precision, recall, Mean Average Precision (mAP), and accuracy. The results demonstrate that YOLOv8 excels in real-time applications, making it suitable for scalable and automated environmental monitoring. This research highlights the potential of YOLOv8 in enhancing marine pollution monitoring, providing a foundation for real-time, efficient environmental assessments.

Keywords: Marine Pollution, Marine Trash Detection, Segmentation, Deep Learning, Object Detection, YOLOv8, Underwater Imagery, Precision, Recall, mAP, Environmental

1. INTRODUCTION

Monitoring, Automated Detection, Marine Ecosystems Marine pollution, particularly in the form of plastic waste, debris, and other contaminants, has become one of the most pressing environmental issues worldwide. It threatens marine biodiversity, disrupts ecosystems, and poses significant risks to human health. While the magnitude of this issue is well recognized, the challenge of effectively detecting, monitoring, and quantifying marine trash remains a significant obstacle. Traditional methods of detecting and assessing marine debris, such as manual surveys, visual inspections, and satellite imagery, often fall short in terms of scalability, real-time application, and accuracy, especially when dealing with underwater environments.

The vast and often inaccessible nature of marine ecosystems, combined with challenging conditions such as murky waters, varying depths, and dynamic environments, makes it even more difficult to track and manage marine debris effectively. In response to these challenges, the field of

deep learning has emerged as a powerful tool for automated object detection and segmentation, offering a promising solution to address the growing need for efficient marine debris monitoring.

In particular, segmentation models have gained attention for their ability to provide pixel-level precision in identifying and delineating objects within complex images. While object detection models focus on locating and classifying objects within a bounding box, segmentation models offer a more refined approach by outlining the exact shape and boundaries of each object, which is crucial for assessing the scale and impact of pollution. This level of detail is essential for applications such as assessing the volume of marine debris, tracking specific pollutants, and developing targeted interventions for environmental protection.

Among the various deep learning models designed for object detection and segmentation, YOLOv8 (You Only Look Once, version 8) stands out as one of the most advanced and efficient models available. YOLOv8 is known for its speed, real-time performance, and high accuracy, making it particularly suited for applications that require rapid processing and decision-making. It achieves impressive performance by simultaneously handling both object detection and segmentation tasks, which is especially useful in dynamic environments like underwater scenes. The model's architecture is optimized for high-speed processing, enabling real-time detection of objects and their precise segmentation, even in challenging conditions like low light, occlusions, and cluttered scenes.

This study investigates the use of YOLOv8 for marine trash segmentation, focusing on its application in underwater imagery. The model is evaluated based on its ability to accurately segment marine debris, including various types of trash such as plastics, nets, and other pollutants. Special attention is given to the model's robustness in dealing with the complexities of underwater environments, such as varying object sizes, overlapping debris, and complex backgrounds. The goal of this research is to demonstrate the effectiveness of YOLOv8 in providing a scalable, real-time solution for marine pollution monitoring and to highlight its potential as a tool for safeguarding marine ecosystems. By leveraging YOLOv8's advanced segmentation capabilities, this study aims to contribute to more efficient and accurate methods for assessing

and managing marine debris, ultimately supporting global efforts to combat marine pollution.

2. RELATED WORK

Marine trash segmentation has been a focal point of research, especially with the need to provide detailed, pixel-level information about debris in underwater environments. Traditional object detection and segmentation methods, although effective in other domains, faced challenges due to the murky waters and the complexity of the underwater scene. Among various methods, YOLO (You Only Look Once) has emerged as a powerful model for real-time object detection and segmentation. YOLO, particularly in its later versions, has made significant strides in providing high-speed and accurate results, making it suitable for dynamic, time-sensitive applications such as marine debris detection.

One of the main advantages of YOLO for marine debris segmentation is its efficiency and speed. YOLO processes images in real-time, making it ideal for use in underwater robots or drone surveillance systems that monitor marine pollution continuously. Earlier work on YOLO focused primarily on object detection, but recent adaptations have enabled the model to handle segmentation tasks as well. YOLOv8, the latest iteration, is particularly well-suited for marine trash segmentation due to its improved architecture, which provides a balance between speed and accuracy. This allows YOLOv8 to segment marine debris effectively, even in cluttered and dynamic underwater environments where traditional methods may fail.

A key challenge in underwater debris segmentation lies in the high variance of objects, such as plastic bags, nets, and other pollutants, which can be partially obscured or overlapped. YOLOv8's real-time detection capabilities make it effective in identifying and segmenting these objects even under such conditions. Researchers have used YOLO models to detect and segment marine debris in complex underwater scenes, such as coral reefs and seafloor environments, with promising results. The model's ability to handle overlapping objects and perform segmentation in real-time significantly enhances its utility in operational settings, such as environmental monitoring and underwater cleanup missions.

Recent advancements also highlight YOLO's use in fine-tuning and transfer learning. By fine-tuning pre-trained YOLO models on domain-specific underwater datasets, researchers have managed to improve its performance in marine trash segmentation, even in environments with limited annotated data. For instance, models pre-trained on large datasets like COCO or ImageNet have been adapted for underwater tasks, allowing for better detection of marine debris. The success of these models suggests that YOLO's flexibility and robustness can be further enhanced through fine-tuning and

transfer learning, improving segmentation accuracy without requiring vast amounts of new labeled data.

Additionally, YOLO's integration into hybrid architectures has also shown promise. Combining YOLO with other models, such as U-Net for precise segmentation boundaries or Mask R-CNN for better handling of occlusions and overlapping objects, could potentially enhance its performance for marine trash segmentation. These hybrid models can combine the speed of YOLO with the precision of segmentation networks to offer an even more robust solution for marine debris monitoring.

Despite these successes, challenges remain, particularly in dealing with small or fragmented debris that may be difficult to segment accurately. YOLO's reliance on bounding boxes for detection, rather than pixel-level precision, can sometimes limit its segmentation capabilities in cases where fine detail is required. However, ongoing improvements to the YOLO architecture, such as more refined segmentation masks and hybrid solutions, continue to address these issues.

YOLO has proven to be a valuable tool for marine trash segmentation due to its speed, adaptability, and real-time performance. While challenges in fine-grained segmentation remain, the ongoing evolution of YOLO models, particularly YOLOv8, promises to provide effective solutions for the real-time detection and segmentation of marine debris. With continued advancements, YOLO's ability to support underwater environmental monitoring and pollution mitigation efforts is expected to grow, making it a crucial tool in the fight against marine pollution.

3. EXPERIMENTAL SETUP

Dataset

The dataset used in this study contains underwater images of marine trash with pixel-wise annotations for segmentation. Each image is labeled with a corresponding segmentation mask, indicating the boundaries of different marine trash objects. These images were pre-processed into the TFRecord format, allowing efficient handling of large-scale data during model training. The dataset was divided into two subsets: the training set and the validation set. The training set was used to teach the models to segment various types of marine trash, while the validation set helped assess the model's ability to generalize.

Each image was resized to a standard 224x224 pixels, and pixel values were normalized to the range [0, 1]. The segmentation masks were one-hot encoded, where each pixel corresponds to a class (such as plastic, bio-debris, or background). The dataset contains a diverse range of marine trash objects, ensuring the model could learn to handle a variety of shapes, sizes, and materials.

Data Pipeline

For model training, a data pipeline was built using TensorFlow's TFRecordDataset, enabling efficient reading and preprocessing of images and corresponding segmentation masks. The images were decoded, resized to 224x224 pixels, and normalized. Simultaneously, the segmentation masks were processed to match the dimensions of the images. This pipeline streamlined the workflow, making the process of training and evaluating the models faster and more efficient. The segmentation task focuses on accurately predicting pixel-wise masks for different debris types, rather than detecting bounding boxes.

Feature Extraction

The features used for segmentation consist of the pixel-wise annotations provided in the segmentation masks. These masks include labeled regions of various types of trash, such as plastic, bio-debris, and metal, which the models use to learn the characteristics of each class. The goal of the segmentation models is to generate pixel-level predictions that accurately match the ground truth masks for each type of trash.

Table - 1 explainsthe detailsofthefeature.

Table – 1: Details of feature

S. No	Attribute Name
1	Trash
2	Bio
3	Plastic

YOLOv8

YOLO (You Only Look Once) is a powerful and efficient object detection model known for its real-time processing capabilities. Initially designed for object detection, YOLO has been applied to various domains, including marine trash segmentation, by leveraging its fast and accurate processing to detect and segment marine debris in underwater environments. The key feature of YOLO is its single-pass, end-to-end architecture that divides the input image into a grid, allowing the model to predict multiple objects simultaneously. This feature is particularly useful for marine trash segmentation, where detecting a variety of trash objects within the same image is crucial.

YOLO's standard output of bounding boxes is adapted to output pixel-wise classification, treating the pixels of the image as part of the trash object class. YOLO's architecture remains unchanged; instead, the model is trained to recognize and label different marine debris, such as plastics, bio-debris, and other types of trash, as distinct categories. This allows

YOLO to perform segmentation at the pixel level while maintaining its real-time capabilities.

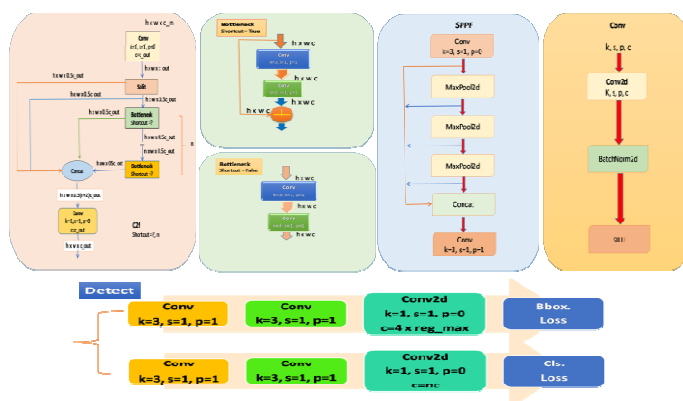


Figure-1 YOLOv8 Architecture

The model's training involved fine-tuning a pre-trained YOLO model, which had previously been trained on large, general datasets such as COCO or VOC, on a custom marine trash dataset. Transfer learning played a key role in adapting YOLO for marine trash segmentation, significantly reducing the amount of training data required while enhancing the model's accuracy and ability to generalize across various types of underwater debris.

YOLO's efficiency allows for fast inference, which is critical in real-time applications like drone-based marine monitoring or autonomous underwater vehicles (AUVs). It can handle large datasets in real-time, providing immediate feedback on the presence and location of marine trash, which is essential for timely decision-making in environmental monitoring and marine conservation efforts. Despite its strengths in speed and efficiency, YOLO might face challenges in highly cluttered or complex environments where very fine segmentation is required. Nonetheless, it remains an ideal solution for quick, reliable detection of marine trash in dynamic settings.

Performance Metrics

Precision measures the accuracy of the model's predictions. In segmentation tasks, precision is defined as the ratio of true positive pixels (correctly predicted pixels as part of the trash object) to the total number of predicted positive pixels (true positives + false positives). A high precision value indicates that the model makes few false positive predictions.

Precision =

Precision is especially important in segmentation tasks to ensure that the predicted pixels that are labeled as trash are actually trash pixels, minimizing the presence of false positives.

Recall, in the context of segmentation, measures the model's ability to correctly identify all relevant pixels (i.e., trash pixels) in the image. It is calculated as the ratio of true positive pixels to the sum of true positives and false negatives. A high recall value indicates that the model is able to detect most of the trash pixels, even if it includes some false positives..

Recall =

Recall is particularly important for ensuring that the model does not miss any trash objects, especially in cases where debris is fragmented or partially occluded.

Mean Average Precision (mAP)mAP is a more comprehensive metric that is often used in segmentation tasks to evaluate the model's performance at various thresholds of IoU. mAP averages the precision values across different recall levels, providing a balanced evaluation of the model's performance. For segmentation tasks, mAP is typically computed over different IoU thresholds (e.g., mAP@0.5, mAP@0.50:0.95), which reflects the model's ability to correctly segment the trash objects with varying levels of overlap between the predicted and ground truth masks.

mAP = $\frac{1}{N} \sum AP_i$

Here, AP_i represents the Average Precision for each class (e.g., plastic, bio-debris) at various IoU thresholds.

Accuracy in segmentation tasks refers to the proportion of correctly classified pixels (both trash and non-trash) to the total number of pixels. This metric gives a general indication of the model's ability to identify and classify all objects across the image.

Accuracy = $\frac{TP}{TP + FN}$

These metrics collectively allow for a detailed evaluation of the model's performance in marine trash segmentation, ensuring that it can accurately segment and classify trash objects from underwater imagery.

4. RESULTS

YOLOv8 demonstrates exceptional performance in real-time marine trash segmentation, offering fast and efficient inference. Its strength lies in its lightweight architecture, optimized for rapid processing, making it ideal for live monitoring of marine environments and underwater debris. The model's ability to segment large-scale objects quickly makes it particularly effective for operational applications like hazard detection or emergency response.

YOLOv8 excels in processing large datasets in real-time, enabling swift detection of marine trash in dynamic environments. However, there is a noticeable trade-off between speed and segmentation accuracy. YOLOv8's lower recall of 0.463 indicates that some trash objects, especially smaller or overlapping ones, might be missed, particularly in cluttered underwater scenes. This lower recall may affect its performance in highly detailed research tasks that require complete and accurate object segmentation.

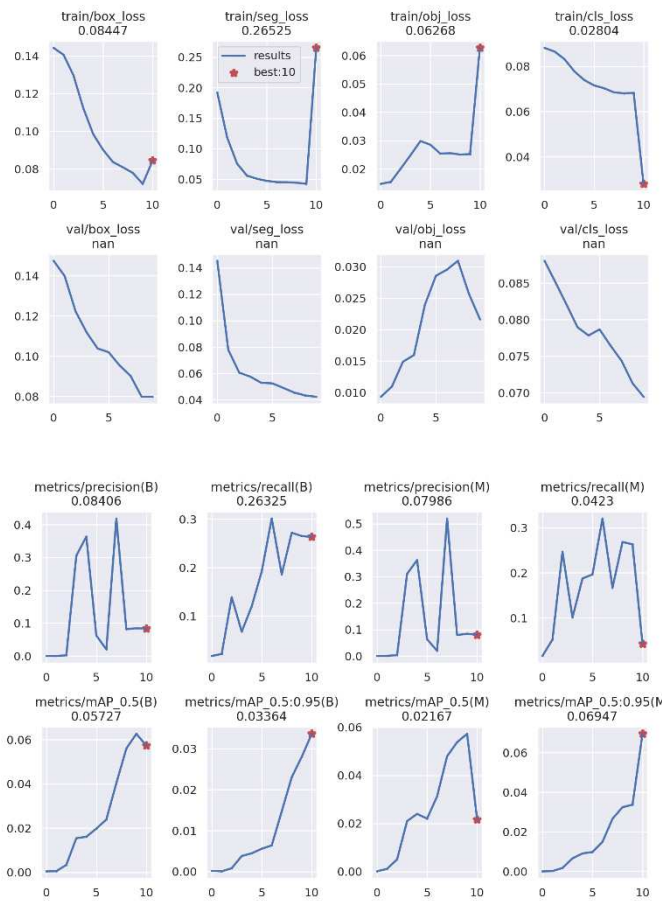


Figure-2 Graphs of YOLOv8

Despite this, YOLOv8's real-time capabilities make it an ideal choice for scenarios where immediate feedback is required. For example, in drone-based underwater imaging systems or autonomous underwater vehicles, fast processing is critical for monitoring and responding to marine debris. However, for research-focused tasks requiring high precision and the detection of all relevant objects, YOLOv8 may not be the best fit due to its lower recall and segmentation accuracy.

YOLOv8's real-time segmentation capabilities make it the preferred choice for applications where speed and

efficiency are paramount. While it sacrifices some accuracy and recall for faster processing, its ability to detect large-scale marine trash objects in dynamic environments makes it invaluable for operational uses such as live hazard detection or emergency response.

The following output images demonstrate YOLOv8’s ability to detect and segment marine trash in underwater environments. The bounding boxes highlight detected objects, and the approximate percentage of trash detected is indicated on each box.

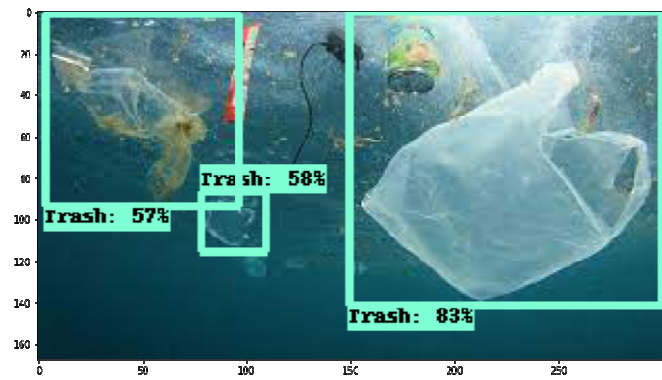
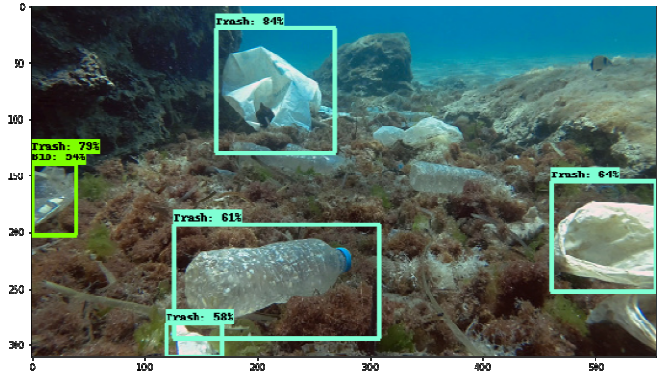


Figure-3 Output Images of Detected Trash

These images showcase YOLOv8's capability to process and segment trash in real-time underwater images, offering valuable insights for operational monitoring.

For research applications that demand high precision and thorough segmentation, YOLOv8 might not be the optimal choice due to its lower recall. However, its computational efficiency and fast inference make it highly effective for practical, real-time deployment scenarios where real-time processing is critical, such as monitoring marine debris during live surveillance or rapid assessments.

This result highlights YOLOv8’s suitability for real-time marine trash segmentation tasks, emphasizing its quick processing capabilities over detailed accuracy, making it ideal for operational use but less suited for tasks requiring high precision and recall.

Table – 2: Accuracy, Precision, Recall and mAP@0.5

Model	Accuracy	Precision	Recall	mAP@0.5
YOLOv8	89.4%	0.738	0.463	0.560

5. CONCLUSION

This study focused on evaluating YOLOv8 for marine trash segmentation, emphasizing its suitability for real-time applications. YOLOv8 achieved an accuracy of 89.4% and an mAP@0.5 of 0.560, demonstrating its ability to process images rapidly and effectively. Although the model showed a good precision of 0.738, its recall of 0.463 suggests that it may miss certain objects, particularly those that are smaller or occluded. Despite this, YOLOv8 remains ideal for time-sensitive tasks, such as real-time underwater monitoring or autonomous vehicle navigation, where quick detection is more important than perfect accuracy. For applications requiring higher precision and recall, additional model optimizations could be considered to improve its performance in complex environments. Future work might focus on enhancing the recall while maintaining YOLOv8's strength in real-time

detection, making it a more reliable tool for marine trash segmentation in diverse underwater conditions.

References:

[1] I. M. J. van den Beld, B. Guillaumont, L. Menot, C. Bayle, S. Arnaud-Haond, and J.-F. Bourillet, "Marine litter in submarine canyons of the Bay of Biscay," *Deep-Sea Res. Part II-Topical Studies Oceanogr.*, vol. 145, no. SI, pp. 142–152, Nov. 2017.

[2] F. Galgani and B. Andral, "Methods for evaluating debris on the deep seafloor," in *Proc. Conf. IEEE Oceanic Eng. Soc.*, 1998, pp. 1512–1524.

[3] S. Chiba et al., "Human footprint in the abyss: 30 year records of deep-seaplastic debris," *Mar. Policy*, vol. 96, pp. 204–212, Oct. 2018.

- [4] W. C. Li, H. F. Tse, and L. Fok, "Plastic waste in the marine environment: review of sources, occurrence and effects," *Sci. Total Environ.*, vol. 566, pp. 333–349, Oct. 2016.
- [5] K. Schlining et al., "Debris in the deep: Using a 22-year video annotation database to survey marine litter in Monterey Canyon, Central California, USA," *Deep-Sea Res. Part I-Oceanogr. Res. Papers*, vol. 79, pp. 96–105, Sep. 2013.
- [6] M. Valdenegro-Toro, "Deep neural networks for marine debris detection in sonar images," 2019, arXiv preprint arXiv:1905.05241. [Online]. Available: <https://arxiv.org/abs/1905.05241>
- [7] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 770–778.
- [8] C. Szegedy et al., "Going deeper with convolutions," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2015, pp. 1–9.
- [9] S.-H. Wang, V. V. Govindaraj, J. M. Gorriz, X. Zhang, and Y.-D. Zhang, "COVID-19 classification by FGNet with deep feature fusion from graph convolutional network and convolutional neural network," *Inf. Fusion*, vol. 67, pp. 208–229, Mar. 2021.
- [10] Y.-D. Zhang, S. C. Satapathy, D. S. Guttery, J. M. Gorriz, and S.-H. Wang, "Improved breast cancer classification through combining graph convolutional network and convolutional neural network," *Inf. Process. Manage.*, vol. 58, no. 2, Mar. 2021, Art. no. 102439.
- [11] C. Qiu, S. Zhang, C. Wang, Z. Yu, H. Zheng, and B. Zheng, "Improving transfer learning and squeeze-and-excitation networks for small-scale fine-grained fish image classification," *IEEE Access*, vol. 6, pp. 78503–78512, 2018.
- [12] P. L. D. Roberts, J. S. Jaffe, and M. M. Trivedi, "Multiview, broadband acoustic classification of marine fish: A machine learning framework and comparative analysis," *IEEE J. Ocean. Eng.*, vol. 36, no. 1, pp. 90–104, Jan. 2011.
- [13] A. Mahmood et al., "Deep image representations for coral image classification," *IEEE J. Ocean. Eng.*, vol. 44, no. 1, pp. 121–131, Jan. 2019.
- [14] X. Tang, F. Lin, S. Samson, and A. Remsen, "Binary plankton image classification," *IEEE J. Ocean. Eng.*, vol. 31, no. 3, pp. 728–735, Jul. 2006.
- [15] T. Luo et al., "Recognizing plankton images from the shadow image particle profiling evaluation recorder," *IEEE Trans. Syst., Man, Cybern., Part B (Cybern.)*, vol. 34, no. 4, pp. 1753–1762, Aug. 2004.
- [16] J. J. Hall, M. R. Azimi-Sadjadi, S. G. Kargl, Y. Zhao, and K. L. Williams, "Underwater unexploded ordnance (UXO) classification using a matched subspace classifier with adaptive dictionaries," *IEEE J. Ocean. Eng.*, vol. 44, no. 3, pp. 739–752, Jul. 2019.
- [17] H.-T. Nguyen, E.-H. Lee, and S. Lee, "Study on the classification performance of underwater sonar image classification based on convolutional neural networks for detecting a submerged human body," *Sensors*, vol. 20, no. 1, Jan. 2020, Art. no. 94.
- [18] G. Huo, Z. Wu, and J. Li, "Underwater object classification in sidescan sonar images using deep transfer learning and semisynthetic training data," *IEEE Access*, vol. 8, pp. 47407–47418, 2020.
- [19] M. Arii, M. Koiwa, and Y. Aoki, "Applicability of SAR to marine debris surveillance after the great East Japan earthquake," *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.*, vol. 7, no. 5, pp. 1729–1744, May 2014.
- [20] G. Goncalves, U. Andriolo, L. Goncalves, P. Sobral, and F. Bessa, "Quantifying marine macro litter abundance on a sandy beach using unmanned aerial systems and object-oriented machine learning methods," *Remote Sens.*, vol. 12, no. 16, Aug. 2020, Art. no. 2599.
- [21] T. Acuna-Ruz et al., "Anthropogenic marine debris over beaches: Spectral characterization for remote sensing applications," *Remote Sens. Environ.*, vol. 217, pp. 309–322, Nov. 2018.
- [22] S. W. Jang, S. K. Lee, D.-H. Kim, and Y. Hong-Joo, "The application of unmanned aerial photography for effective monitoring of marine debris," *J. Korean Soc. Mar. Environ. Saf.*, vol. 17, no. 4, pp. 307–314, 2011.
- [23] K. Topouzelis, D. Papageorgiou, A. Karagaitanakis, A. Papakonstantinou, and M. A. Ballesteros, "Plastic litter project 2019: Exploring the detection of floating plastic litter using drones and Sentinel 2 satellite images," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2020, pp. 6329–6332.
- [24] K. Themistocleous, C. Papoutsas, S. Michaelides, and D. Hadjimitsis, "Investigating detection of floating plastic litter from space using Sentinel-2 imagery," *Remote Sens.*, vol. 12, no. 16, Aug. 2020, Art. no. 2648.
- [25] K. Topouzelis, A. Papakonstantinou, and S. P. Garaba, "Detection of floating plastics from satellite and unmanned aerial systems (Plastic Litter Project 2018)," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 79, pp. 175–183, Jul. 2019.
- [26] G. Goncalves, U. Andriolo, L. Pinto, and D. Duarte, "Mapping marine litter with unmanned aerial systems: A showcase comparison among manual image screening and

machine learning techniques,” Mar. Pollut. Bull., vol. 155, Jun. 2020, Art. no. 111158.

[27] J. Lorenzo-Navarro et al., “SMACC: A system for microplastics automatic counting and classification,” IEEE Access, vol. 8, pp. 25249–25261, 2020.

[28] L. Fallati, A. Polidori, C. Salvatore, L. Saponari, A. Savini, and P. Galli, “Anthropogenic marine debris assessment with unmanned aerial vehicle imagery and deep learning: A case study along the beaches of the Republic of Maldives,” Sci. Total Environ., vol. 693, Nov. 2019, Art. no. 133581.

[29] S. Kako, S. Morita, and T. Taneda, “Estimation of plastic marine debris volumes on beaches using unmanned aerial vehicles and image processing based on deep learning,” Mar. Pollut. Bull., vol. 155, Jun. 2020, Art. no. 111127.

[30] M. Valdenegro-Toro, “Submerged marine debris detection with autonomous underwater vehicles,” in Proc. Int. Conf. Robot. Autom. Humanitarian Appl., 2016, pp. 1–7.

[31] Duarte, M.M., Azevedo, L., “Automatic detection and identification of floating marine debris using multispectral satellite imagery,” IEEE Trans. Geosci. Remote Sens., 61, 1–15, 2023.

[32] Andriolo, U., Topouzelis, K., van Emmerik, T.H.M., Papakonstantinou, A., Monteiro, J.a.G., Isobe, A., Hidaka, M., Kako, S., Kataoka, T., Gonçalves, G. “Drones for litter monitoring on coasts and rivers: suitable flight altitude and image.” Resolution 195, 115521, 2023.