

Underwater Debris Detection, Categorization, Tracking and Geospatial Mapping using Deep Learning and Low-Level Computer Vision Techniques for Enhanced Ocean Clean up

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Abstract:

The escalating concern of underwater debris demands innovative approaches for effective ocean cleanup. This study presents a comprehensive framework utilizing deep learning methods to detect, categorize, track, and geospatially map underwater debris. By amalgamating cutting-edge object detection models, the system extracts real-time insights from underwater sensor data, facilitating the identification and categorization of debris based on various attributes. The incorporation of advanced tracking algorithms enables the monitoring of debris dynamics, contributing to predictive capabilities.

Furthermore, geospatial mapping techniques are employed to project identified debris onto world maps, using latitude and longitude coordinates. This mapping feature aids in locating debris accumulation areas, thereby enabling strategic and efficient cleanup efforts. Through meticulous experimentation on authentic underwater debris datasets, our framework demonstrates its potential in precisely detecting, tracking, and mapping debris. This approach holds promise for revolutionizing ocean conservation endeavors by providing valuable insights for targeted and ecologically-aware removal of underwater debris.

Keywords: *Underwater debris, deep learning, object detection, tracking, geospatial mapping, ocean conservation.*

Literature Survey:

1. Sánchez-Ferrer, Alejandro, et al. "The CleanSea set: a benchmark corpus for underwater debris detection and recognition." Iberian Conference on Pattern Recognition and Image Analysis. Cham: Springer International Publishing, 2022.
Link: https://link.springer.com/chapter/10.1007/978-3-031-04881-4_49
Summary: Introduces the CleanSea dataset for underwater debris detection and recognition, offering bounding box and contour annotations. Employs a Reference Mask Object-Based Convolution Neural Network for benchmarking.
2. Watanabe, Jun-Ichiro, Yang Shao, and Naoto Miura. "Underwater and airborne monitoring of marine ecosystems and debris." Journal of Applied Remote Sensing 13.4 (2019): 044509.
Link: <https://www.spiedigitallibrary.org/journals/journal-of-applied-remote-sensing/volume-13/issue-04/044509/Underwater-and-airborne-monitoring-of-marine-ecosystems-and-debris/10.1117/1.JRS.13.044509.full?SSO=1>
Summary: Presents YOLO V3 for detecting underwater sea life and ocean surface debris. Achieves mAP of 69.6% and 77.2% for distinct classes.
3. Huang, Baoxiang, et al. "Instant deep sea debris detection for maneuverable underwater machines to build sustainable ocean using deep neural network." Science of the Total Environment 878 (2023): 162826.
Link: <https://www.sciencedirect.com/science/article/abs/pii/S0048969723014420>
Summary: Proposes DSDebrisNet using a lightweight neural network architecture for instant deep-sea debris detection, contributing to sustainable ocean practices.
4. Moorton, Zoe, Zeyneb Kurt, and Wai Lok Woo. "Is the use of deep learning an appropriate means to locate debris in the ocean without harming aquatic wildlife?" Marine Pollution Bulletin 181 (2022): 113853.
Link: <https://www.sciencedirect.com/science/article/pii/S0025326X22005355>
Summary: Utilizes VGG-16 on 1644 underwater images for binary classification of synthetic material and aquatic life, addressing potential harm to marine ecosystems.

5. Wang, Puze, et al. "Exploring the application of artificial intelligence technology for identification of water pollution characteristics and tracing the source of water quality pollutants." *Science of the Total Environment* 693 (2019): 133440.
Link: <https://www.sciencedirect.com/science/article/abs/pii/S0048969719333601>
Summary: Explores water pollution identification and source tracing using LSTM, cross-correlation, and association rules, advancing water quality monitoring.
6. Sánchez-Ferrer, Alejandro, et al. "An experimental study on marine debris location and recognition using object detection." *Pattern Recognition Letters* 168 (2023): 154-161.
Link: <https://www.sciencedirect.com/science/article/pii/S0167865522003889>
Summary: Applies Mask RCNN on the CleanSea Corpus to study marine debris location and recognition, leveraging advanced object detection techniques.
7. Sudaroli Sandana, J., et al. "Deep Sea Debris Detection Using YOLOIncep Network." *International Conference on Computational Intelligence*. Singapore: Springer Nature Singapore, 2022.
Link: https://link.springer.com/chapter/10.1007/978-981-99-2854-5_9
Summary: YOLOIncep network on JAMSTEC dataset, mAP @0.5 of 0.979
8. Naik, Vritika Vijaylal, and Sadaf Ansari. "Underwater Acoustic Image Processing for Detection of Marine Debris." *International Conference on Artificial Intelligence and Sustainable Engineering: Select Proceedings of AISE 2020, Volume 1*. Singapore: Springer Nature Singapore, 2022.
Link: https://link.springer.com/chapter/10.1007/978-981-16-8542-2_44
Summary: VisuShrink a wavelet transformation technique for restoring and enhancing underwater acoustic images of marine debris
9. Escobar-Sánchez, Gabriela, et al. "Aerial and underwater drones for marine litter monitoring in shallow coastal waters: factors influencing item detection and cost-efficiency." *Environmental monitoring and assessment* 194.12 (2022): 863.
Link: <https://link.springer.com/article/10.1007/s10661-022-10519-5>
Summary: Testing potential of UAVs and ROVs for marine litter monitoring. And study the effects of water conditions, item characteristics and method settings(depth/height) on detection accuracy.
10. Sarkar, Pratima, Sourav De, and Sandeep Gurung. "A survey on underwater object detection." *Intelligence Enabled Research: DoSIER 2021*. Singapore: Springer Singapore, 2022. 91-104.
Link: https://link.springer.com/chapter/10.1007/978-981-19-0489-9_8
Summary: Review of deep learning and non-deep learning based techniques for underwater object detection on regular and sonar images. also covers object related confusion.
11. Yang, Jing, James P. Wilson, and Shalabh Gupta. "DARE: Diver Action Recognition Encoder for Underwater Human-Robot Interaction." *IEEE Access* (2023).
Link: <https://ieeexplore.ieee.org/abstract/document/10190624>
Summary: AUV diver interaction using deep learning techniques, uses computer vision to understand hand gestures of divers and perform accordingly, trained on the CADDY dataset.
12. Abdu, Haruna, and Mohd Halim Mohd Noor. "A Survey on Waste Detection and Classification Using Deep Learning." *IEEE Access* 10 (2022): 128151-128165.
Link: <https://ieeexplore.ieee.org/abstract/document/9970346>
Summary: Survey of various trash datasets and various classification and object detection neural network architectures.
13. Chia, Kai Yuan, Cheng Siong Chin, and Simon See. "Deep Transfer Learning Application for Intelligent Marine Debris Detection." *International Conference on Engineering Applications of Neural Networks*. Cham: Springer Nature Switzerland, 2023.
Link: https://link.springer.com/chapter/10.1007/978-3-031-34204-2_39
Summary: YOLOV5s on marine debris dataset with accuracy score of 91.2%

14. Merrifield, Sophia T., et al. "Wide-Area Debris Field and Seabed Characterization of a Deep Ocean Dump Site Surveyed by Autonomous Underwater Vehicles." *Environmental Science & Technology* (2023).
Link: <https://pubs.acs.org/doi/full/10.1021/acs.est.3c01256>
Summary: Sonar survey using AUVs to detect and map underwater debris and also perform sediment analysis.

15. Alkema, Lise M., et al. "Maximizing realism: mapping plastic particles at the ocean surface using mixtures of normal distributions." *Environmental Science & Technology* 56.22 (2022): 15552-15562.
Link: <https://pubs.acs.org/doi/full/10.1021/acs.est.2c03559>
Summary: Characterizing plastic debris on ocean surface using Gaussian Mixture Models, small debris show high correlation whereas large show low correlation.

16. McEver, R. Austin, et al. "Context-Driven Detection of Invertebrate Species in Deep-Sea Video." *International Journal of Computer Vision* 131.6 (2023): 1367-1388.
Link: <https://link.springer.com/article/10.1007/s11263-023-01755-4>
Summary: DUSIA(Dataset for Underwater Substrate and Invertebrate Analysis) that contains four underwater substrates as well as 59 underwater invertebrate species. over 10 hours of footage, along with baseline object detection model

17. Dasgupta, Susmita, Maria Sarraf, and David Wheeler. "Plastic waste cleanup priorities to reduce marine pollution: A spatiotemporal analysis for Accra and Lagos with satellite data." *Science of the Total Environment* 839 (2022): 156319.
Link: <https://www.sciencedirect.com/science/article/abs/pii/S0048969722034167>
Summary: Analysis of marine pollution hotspots and flow of waste from inland to oceans to seasonal activity using publicly available information.(No deep learning involved)

18. Ma, Dongliang, et al. "MLDet: Towards efficient and accurate deep learning method for Marine Litter Detection." *Ocean & Coastal Management* 243 (2023): 106765.
Link: <https://www.sciencedirect.com/science/article/abs/pii/S0964569123002909>
Summary: MLDet , a detection algorithm for recognizing marine litter, uses transfer learning and data augmentation.

19. Hidaka, Mitsuko, et al. "Pixel-level image classification for detecting beach litter using a deep learning approach." *Marine Pollution Bulletin* 175 (2022): 113371.
Link: <https://www.sciencedirect.com/science/article/abs/pii/S0025326X22000534>
Summary: Semantic Segmentation of beach litter, aka pixel wise classification.

20. Teng, Cathy, Kyriaki Kylili, and Constantinos Hadjistassou. "Deploying deep learning to estimate the abundance of marine debris from video footage." *Marine Pollution Bulletin* 183 (2022): 114049.
Link: <https://www.sciencedirect.com/science/article/abs/pii/S0025326X22007317>
Summary: Mildly similar to our objective due to the presence of counting, counting based on ROI line and centroid of object and image classifier to classify the object. Utilized YOLOv5 for identification and localization.

Note: Most papers are taken from articles after 2020 and from reputed publishing houses like Elsevier, IEEE CVF, ACCESS, ACS, Springer.etc