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AQUATIC TRASH DETECTION AND CLASSIFICATION: A MACHINE LEARNING AND DEEP LEARNING PERSPECTIVE

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Abstract: The escalating volume of pollutants flowing into the oceans and waterways is an alarming concern, not only to marine ecosystems but also to the health and livelihoods of communities worldwide. The rate at which aquatic trash is accumulating far outpaces its' slow degradation, creating a persistent and growing problem. Both prevention and cleanup are essential for restoring and maintaining healthy aquatic environments. Advanced technology combining machine learning and deep learning algorithms with autonomous underwater vehicles (AUVs) is creating intelligent, automated solutions for detecting and removing trash from the waterways. This approach simplifies the cleanup process and is more efficient than manual methods. This paper examines the crucial role of machine learning and deep learning in detecting various types of aquatic trash. It offers a comprehensive analysis of recent research in the field, comparing different studies based on a variety of parameters. The study also discusses the challenges of trash detection in dynamic aquatic environments, highlighting scope for the future research.

Keywords: trash, detection, classification, machine learning, deep learning, attenuation, scattering, occlusion

I. INTRODUCTION

Approximately 71% of the Earth's surface is covered by water. Aquatic ecosystems are vital to the planet, playing key roles in climate regulation, transportation, employment, economic development, recreation and supporting rich biodiversity as well as habitat. They also provide essential resources such as renewable energy, food, medicinal products, raw materials, etc. [1]-[3]. Oceans generate over half of the world's oxygen and store fifty times more carbon dioxide than the atmosphere, making them critical for maintaining environmental balance. According to SDG 14 "Life Below Water," supporting global sustainable development requires a shared objective to responsibly utilize seas, oceans, and their resources while minimizing marine pollution [4]-[5].

Source from which the source is generated	*Type of waste*
Commercial and industrial	Chemicals, glass, wood, plastics (thick and thin), metals, food and packaging waste, paper, ashes, cardboard, fabric, electrical and electronic waste etc.
Institutional	Waste generated from government, educational, sporting, financial (& many more) organisations which may include wood, plastic, food, electronics, metals, cardboard, paper etc.
Residential	Glass, metals, plastic, cardboard, paper, leather, food and yard wastes, ashes, tires, batteries, packaging items such as cans, miscellaneous material like old shoes, mattresses, bags, broken cooking pots, baskets etc.
Agricultural	Waste from forests, residues of crops, weeds, pesticide containers, leaf litter, sawdust, spoiled food, fertilizers, animal waste, litter from poultry etc.
Health Care Facilities	Bandages, syringes, masks, gloves, drugs, napkins, plastic, diapers, urine bags, paper, food waste etc.
Construction and Demolition	Copper wires, steel, concrete, bricks, dirt, rubber, glass, plastic, plasters, metal, ceramics etc.

Fig. 1: Types and Sources of Waste

In today's world, rapid growth of the human population is accompanied by a significant increase in waste generation from anthropogenic activities. Figure 1 illustrates the different types of waste with their corresponding sources [6]-[7]. Aquatic trash or marine litter is any unwanted, discarded or disposed solid substance (either manufactured or treated) that floats and ultimately ends up in coastal or aquatic environment [8]. Upon entering the aquatic environment, waste not only spreads across the surface but also sinks to deeper layers and may even settle on the seabed. Various materials such as metal, plastic, radio-active substances and rubber are highly resistant to decomposition and take a significant amount of time to break down. Accumulation of underwater waste leads to numerous critical consequences including ingestion by animals, entanglement, habitat destruction, economic loss, navigational hazard, unforeseen climatic changes, effect on human health and more [9]-[11]. Proper collection and management of aquatic litter is a challenging yet crucial task that must be carried out timely. Manually cleaning water reservoirs is highly labor-intensive, time-consuming and costly. Here's where automation comes into the picture.

Image-based automation is becoming a key approach to combat aquatic trash. However, the complexities of the underwater environment pose significant challenges for object identification. Attenuation, absorption, scattering, and artificial lighting degrade image quality by introducing noise, reducing contrast, blurring the details and causing inconsistent illumination [12]-[13]. Therefore, pre-processing is essential to enhance the clarity of litter images. To develop robust and high-performing models, datasets undergo augmentation using various transformations. Subsequently, key features are extracted using either conventional techniques (e.g., HOG, SIFT, LBP) or modern intelligent methods [14]-[15]. These extracted features are then used to classify, locate or detect litter within water bodies.

Exploring the cutting edge of aquatic trash detection and classification, this paper delves into machine learning and deep learning advancements. Latest papers published in the last half-decade have been analyzed, identifying significant techniques, emerging trends and key challenges confronting the field.

II. MACHINE LEARNING AND DEEP LEARNING FOR AQUATIC TRASH DETECTION

Underwater environment itself significantly complicates detection efforts due to phenomena like light scattering, absorption and attenuation which degrade image quality. Furthermore, turbidity and non-uniform illumination severely hinder clear visibility, making manual recognition incredibly time-consuming and often impractical. These obstacles underscore the critical need for timely, automated solutions to accurately detect and classify aquatic waste. Machine Learning as well as deep learning-based approaches [14] have emerged as groundbreaking technologies for the real-time object detection and identification purposes, advancing ahead the struggle against mounting marine pollution. However, the perception and criteria of both machine and deep learning is fundamentally different.

Traditional machine learning models require a user expertise to define the visual characteristics of trash like its' color, texture and shape through a process called feature engineering [15]. Some of the handcrafted feature extractors are Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT), Local Binary Pattern (LBP), etc. These predetermined features are then fed to train an algorithm (such as a Decision Tree, K-Nearest Neighbor, Support Vector Machine) to perform the final classification [16]. Figure 2 depicts the concept of machine learning algorithm:

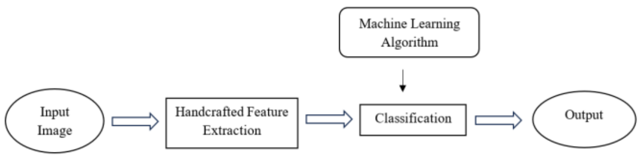

Fig. 2: Concept of Machine Learning

In contrast, deep learning's power lies in its' ability to learn these features automatically. Its multi-layered architecture progressively extracts features from an image, with the initial layers recognizing basic elements like edges, colors and the deeper layers synthesizing these elements to understand the complete, complex form of an object. This automated and end-to-end learning gives deep learning the superior performance in complex environments. For image classification, popular architectures include the foundational Convolutional Neural Network (CNN) and advanced models built upon it, such as AlexNet, ResNet, VGG (Visual Geometric Group), MobileNet, EfficientNet, Inception, etc. [17]. Figure 3 shows the basic process of deep learning:

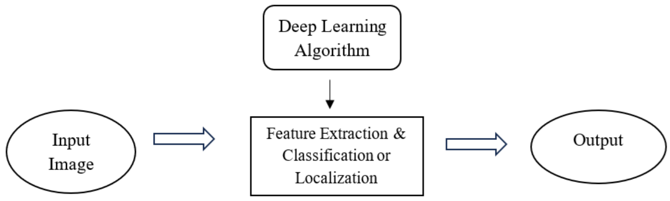

Fig. 3: Concept of Deep Learning

When the goal is not just to classify an image but to locate objects within it, object detection models are used. These are typically divided into two categories: - two-stage detectors [18] like R-CNN and its more refined versions like Fast R-CNN and Faster R-CNN, which are known for their high accuracy; and single-stage detectors [19] such as YOLO, SSD and RetinaNet, which are popular for their speed and real-time performance.

III. ANALYSIS OF LITERATURE

Table I provides a comprehensive overview of recent research papers on waste classification, focusing on studies published within the last five years. The table systematically compares these papers based on three key criteria: the technique's functionality (e.g., the specific deep learning or machine learning models used), the evaluation parameters applied (accuracy, precision, recall, F1-score, mean average precision, etc.), and the classes of waste considered in each study. Structured analysis helps to quickly identify the methods, metrics and waste types addressed in the current literature.

Table I. Comprehensive analysis of recent research in the field

Author	*Year*	*Technique(s) applied*	*Classes of litter*	*Evaluation parameter*
Marin et al. [20]	2021	Evaluates the performance of VGG19, Inception-ResNetV2, InceptionV3, ResNet50, MobileNetV2, DenseNet121	Plastic, Metal, Rubber, Glass, Other trash, No trash	Precision, recall, accuracy, F1-score
Rehman et al. [21]	2025	YOLOv8s with OFAT (One factor at a time) optimization strategy for fine tuning	Cans, masks, gloves, bottles, electronics, plastic bags, rods, tires, general debris, metal objects	Precision, F1-score, recall, mAP
Sarkar et al. [22]	2025	Underwater-YOLOv3: modified YOLOv3 by using k-means++ clustering, SPP for feature aggregation, resizing features MIRNet for image enhancement	Classes in Trash-ICRA: Plastic, ROV, Bio Classes in Brackish dataset: crabs, small fish and other aquatic animals	Precision, recall, F1-score, Intersection over Union (IoU), mAP
Demir and Yaman	2024	Feature generator: ResNet101	Garbage, Sea Animals	Precision, accuracy,

[23]		Feature selector: NCA (Neighborhood Component Analysis) Classifier: k-NN (k-nearest neighbor)		sensitivity, geometric mean, and F-score
Sumallika et al. [24]	2023	ResNet (combined with enhancement, normalization, augmentation, feature analysis)	Metal, glass, rubber, cloth, plastic, natural debris, ropes, nets	Accuracy
Gupta et al. [25]	2023	Multi feature based pyramid network (ResNet-101 for feature extraction)	Marine debris, ship, organic material, waves, foam, clouds, etc.	MIoU, F1-score, Accuracy
Aleem et al. [26]	2022	Pre-processing: Histogram equalization, Median Filtering Detector: Faster R-CNN with ResNet	Can, Bottle, Hook, Propeller, Chain, Tire, Valve, Drink-carton, shampoo-bottler, standing-bottle	Accuracy, recall, Mean IoU
Guan and Guo [27]	2025	Improved YOLOv5 (integration of attention mechanism and lightweight convolution layers)	trash bottle, boot trash, trash bag, other trash	mAP, detection time
Cai et al. [28]	2024	YOLOv8-RepGhost-EMA (Improvement of YOLOv8 using GhostNet)	Plastic, biological material, ROVs	Precision, recall, mAP
Demir and Yaman [29]	2024	HOG (Histogram of Oriented Gradient) as feature extractor k-NN, linear discriminant, decision tree, SVM and naïve bayes for classification.	Biological material, ROV, plastic	Accuracy, precision, recall
Aminurrashid et al. [30]	2024	YOLOv5 Integration on embedded platform as well	Plant, animal, different subclasses of plastic and non-plastic trash	F1-confidence curve, confusion matrix, testing in challenging conditions
Sánchez-Ferrer et al. [31]	2023	Mask R-CNN	Plastic bag, bottle, fishing net, rope, wood, can, tire, bumper, gloves, etc. (total 17 classes)	mAP, IoU
Yang et al. [32]	2024	Improvements in base VGG-16, parameter tuning, transfer learning	Subcategories of natural degradation, textile-based products, plastic products, other objects (total 15 classes)	Precision, recall, accuracy, f1-score
Lin et al. [33]	2021	FMA-YOLOv5s (feature map attention added to backbone of YOLO), mosaic data augmentation	Floating debris from waterways (bottle, milk box, branch, grass, leaf, ball, plastic garbage, plastic bags)	mAP, frames per second
Assem et al. [34]	2024	Modified VGG-Net Compares the performance of a modified VGG-Net with CNN using transfer learning and Fast RCNN	Tire, Plastic bottle, rope, plastic_bag, glass bottle, metal_ladder, metal_chain, metal_container, etc. (total 15 classes)	Accuracy
Jain et al. [35]	2024	Mask R-CNN, YOLOv8, YOLACT, EfficientDet-DO	Plastic, biological material, ROV	Recall, mAP, F1-score
Saji et al. [36]	2024	YOLOv8n	Debris, non-debris	Precision, recall, mAP, computational load
Xue et al. [37]	2021	Hybrid Shuffle-Xception network	fishing net and rope, plastic, metal, rubber, glass, cloth, natural debris.	Recall, precision, F1-score
Kshirsagar et al. [38]	2021	Pre-processing: RGB-Gray scale, equalization, normalization Feature extraction: DWT and GLCM Classification: Feed forward Neural network	Dead reef, oil spills, plastic, fishing net	Accuracy
Musić et al. [39]	2020	Custom-based CNN Transfer learning using pre-trained weights from ResNet, VGG16, Xception, YOLOv4	Metal, Plastic, Glass, Cardboard, etc.	Validation and Test accuracy
Kylili et al. [40]	2021	Annotation: VGG Detection: YOLOACT++, YOLOv5	Wrappings, bags, buckets, bottles, straws, nets	IoU, Accuracy, Precision, Recall
Lee et al. [41]	2023	YOLOv5 (hyper-parameters optimized using GA)	Bottle, rope, net, glass, metal, Styrofoam piece or box, etc.	mAP, Inference speed

Panwar et al. [42]	2020	RetinaNet (ResNet and feature pyramid network as backbone)	Paper, plastic, glass, cardboard	IoU, Average precision, Recall
Fulton et al. [43]	2019	Object detection networks: YOLOv2 (darknet-19 as custom network), Tiny-YOLO, Faster RCNN with Inception v2, SSD (Multi-Box) with MobileNet v2	Plastic as main debris category (like plastic bottles, grocery bags, etc.), other classes such as plants, animals, ROVs included so that resulting model does not confuse them with plastic.	mAP, IoU

IV. CHALLENGES

Optical properties of water change the way light behaves. This leads to a range of problems in underwater imaging, including attenuation, scattering (forward and backward) and non-uniform illumination. Consequently, captured images suffer from low contrast, pervasive color cast and loss of sharpness [12]-[13]. Aquatic environment causes trash objects to deform, resulting in irregular and often unrecognizable shapes. Additionally, these objects are frequently occluded by other debris or entangled with natural vegetation [43][44]. Occlusion possesses a challenge for detection and classification models, as it complicates the task of differentiating individual items from the background or from each other. Presence of marine organisms in the water can confuse the models, leading them to mistakenly identify these organisms as trash objects. Another matter of concern is the scarcity of large, high-quality and well-labelled datasets [20][37]. Since machine learning and deep learning models are highly dependent on data, lack of sufficient ground-truth data leads to poor generalization capabilities and limits their performance on computer vision tasks.

V. CONCLUSION

For classification or detection of aquatic trash, deep learning models have been more effective than classical machine learning, mainly because deep learning models can automatically learn complicated features from visual data, avoiding the drawbacks of manual feature engineering. However, performance of both approaches is limited by several factors inherent to the aquatic environment. These include the degradation of image quality from phenomena like light attenuation and scattering, complexity of recognizing deformed or occluded objects and a major bottleneck stemming from the scarcity of large, high-quality and labelled datasets. Ultimately, advancement of aquatic trash classification and detection requires a multifaceted approach that integrates a deep understanding of both environmental variables and technological capabilities to deliver effective, AI-driven solutions to the global marine pollution crisis.

VI. REFERENCES

[1] K. Katiyar, "Marine resources: Plethora of opportunities for sustainable future," in *Marine Biomass Biorefinery and Bioproducts: Environmental Bioremediation*, R. T. Kapoor, M. Rafatullah, and N. Ismail, Eds., Berlin, Germany: De Gruyter, 2024, pp. 367–388.

[2] C. M. Duarte, "Rebuilding marine life," *UNESCO Cour.*, vol. 2021, no. 1, pp. 13–15, 2021.

[3] E. Sala et al., "Protecting the global ocean for biodiversity, food and climate," *Nature*, vol. 592, no. 7854, pp. 397–402, 2021.

[4] C. Mohan, J. Robinson, L. Vodwal, and N. Kumari, "Sustainable Development Goals for addressing environmental challenges," in *Green Chemistry Approaches to Environmental Sustainability: Status, Challenges and Prospective*, V. K. Garg, A. Yadav, C. Mohan, S. Yadav, and N. Kumari, Eds. San Diego, CA, USA: Elsevier, 2023, pp. 357–374.

[5] B. Singh, C. Kaunert, and G. Singh, "Scaling Legal Framework for Plastic Pollution and Advancing Cutting Edge Water Governance: Reducing and Eliminating Marine Pollution in Alignment With SDG 14 (Life Below Water)," in *Societal and Environmental Ramifications of Plastic Pollution*, N. Gaur, E. Sharma, T. A. Nguyen, M. Bilal, and N. P. Melkania, Eds. Hershey, PA, USA: IGI Global, 2025, pp. 197–222.

[6] S. Nanda and F. Berruti, "Municipal solid waste management and landfilling technologies: a review," *Environ. Chem. Lett.*, vol. 19, no. 2, pp. 1433–1456, 2021.

[7] P. Agamuthu et al., "Marine debris: A review of impacts and global initiatives," *Waste Manage. Res.*, vol. 37, no. 10, pp. 987–1002, 2019.

[8] F. S. Islam, "The Effects of Plastic and Microplastic Waste on the Marine Environment and the Ocean," *Eur. J. Environ. Earth Sci.*, vol. 6, no. 3, pp. 1–9, 2025.

[9] D. Dadheech, A. S. Paul, S. Vyas, and A. Malakar, "Revolutionizing Ocean Cleanup: AI and Robotics Tackle Pollution Challenges," in *Artificial Intelligence and Edge Computing for Sustainable Ocean Health*, D. De, D. Sengupta, and T. A. Tran, Eds. Cham, Switzerland: Springer Nature Switzerland, 2024, pp. 343–358.

[10] N. van Truong and C. BeiPing, "Plastic marine debris: sources, impacts and management," *Int. J. Environ. Stud.*, vol. 76, no. 6, pp. 953–973, 2019.

[11] M. Angiolillo and T. Fortibuoni, "Impacts of marine litter on Mediterranean reef systems: from shallow to deep waters," *Front. Mar. Sci.*, vol. 7, Art. no. 581966, 2020.

[12] Y. M. Alsakar, N. A. Sakr, S. El-Sappagh, T. Abuhmed, and M. Elmogy, "Underwater image restoration and enhancement: a comprehensive review of recent trends, challenges, and applications," *Vis. Comput.*, pp. 1–49, 2024.

[13] M. Jian, X. Liu, H. Luo, X. Lu, H. Yu, and J. Dong, "Underwater image processing and analysis: A review," *Signal Process. Image Commun.*, vol. 91, Art. no. 116088, 2021.

[14] R. B. Hegde, K. Prasad, H. Hebbar, and B. M. K. Singh, "Feature extraction using traditional image processing and convolutional neural network methods to classify white blood cells: a study," *Australas. Phys. Eng. Sci. Med.*, vol. 42, pp. 627–638, 2019.

[15] N. Hussain et al., "A deep neural network and classical features based scheme for objects recognition: an application for machine inspection," *Multim. Tools Appl.*, pp. 1–23, 2024.

[16] G. G. Rajput and V. B. Doddamani, "Disease Identification and Categorization in Pigeon Pea Leaves Using LBP and HOG Features," in *Congress on Intelligent Systems*. Singapore: Springer Nature, 2024, pp. 133–145.

[17] S. Deepa, J. L. Zeema, and S. Gokila, "Exploratory architectures analysis of various pre-trained image

classification models for deep learning," *J. Adv. Inf. Technol.*, vol. 15, no. 1, pp. 66–78, 2024.

[18] W. Li, "Analysis of object detection performance based on Faster R-CNN," *J. Phys.: Conf. Ser.*, vol. 1827, no. 1, Art. no. 012085, 2021.

[19] B. Srishailam, P. Khammampati, M. N. Gopagani, M. R. Reddy, and M. A. Khader, "Enhancing Image Classification and Detection with RetinaNet and SSD: A Comparative Analysis," *Front. Collabor. Res.*, vol. 2, no. 1s, pp. 36–42, 2024.

[20] I. Marin, S. Mladenović, S. Gotovac, and G. Zaharija, "Deep-feature-based approach to marine debris classification," *Appl. Sci.*, vol. 11, no. 12, Art. no. 5644, 2021.

[21] F. Rehman, M. Rehman, M. Anjum, and A. Hussain, "Optimized YOLOV8: An efficient underwater litter detection using deep learning," *Ain Shams Eng. J.*, vol. 16, no. 1, Art. no. 103227, 2025.

[22] Sarkar, S. De, and S. Gurung, "U-YOLOv3: A Model Focused on Underwater Object Detection," *Informatica*, vol. 49, no. 6, 2025.

[23] K. Demir and O. Yaman, "Projector deep feature extraction-based garbage image classification model using underwater images," *Multim. Tools Appl.*, pp. 1–15, 2024.

[24] T. Sumallika, K. Anusha, G. D. S. Kiran, G. LayaSri, and K. S. Kumar, "Deep Sea Debris Detection," *A Journal for New Zealand Herpetology*, vol. 12, no. 2, 2023.

[25] S. Gupta, Y. Khurana, J. Atrey, S. Gupta, and P. Krishnamoorthy, "Marine debris detection using a multi-feature pyramid network," *Remote Sens. Lett.*, pp. 231–241, 2023.

[26] A. Aleem, S. Tehsin, S. Kausar, and A. Jameel, "Target Classification of Marine Debris Using Deep Learning," *Intell. Autom. Soft Comput.*, vol. 32, no. 1, 2022.

[27] J. Guan and B. Guo, "An improved YOLOv5 algorithm for underwater garbage recognition," *J. Comput. Methods Sci. Eng.*, vol. 25, no. 2, pp. 1136–1146, 2025.

[28] D. Cai, K. Li, and B. Hou, "YOLOv8-RepGhostEMA: An efficient underwater trash detection model," *J. Phys.: Conf. Ser.*, vol. 2906, no. 1, Art. no. 012019, 2024.

[29] K. Demir and O. Yaman, "A HOG Feature Extractor and KNN-Based Method for Underwater Image Classification," *Firat Univ. J. Exp. Comput. Eng.*, vol. 3, no. 1, pp. 1–10, 2024.

[30] A. R. Aminurrashid and M. N. S. M. Sayuti, "A CNN Plastic Detection Model for Embedded Platform of ROV," *ITM Web Conf.*, vol. 63, Art. no. 01003, 2024.

[31] A. Sánchez-Ferrer, J. J. Valero-Mas, A. J. Gallego, and J. Calvo-Zaragoza, "An experimental study on marine debris location and recognition using object detection," *Pattern Recognit. Lett.*, vol. 168, pp. 154–161, 2023.

[32] J. Yang, Z. Li, Z. Gu, and W. Li, "Research on floating object classification algorithm based on convolutional neural network," *Sci. Rep.*, vol. 14, no. 1, Art. no. 32086, 2024.

[33] F. Lin, T. Hou, Q. Jin, and A. You, "Improved YOLO based detection algorithm for floating debris in waterway," *Entropy*, vol. 23, no. 9, Art. no. 1111, 2021.

[34] M. Assem, I. M. Hassab-Allah, M. E. Eltaib, and M. Abdelrahim, "Identification of Unknown Marine Debris by ROVs Using Deep Learning and Different Convolutional Neural Network Structures," *JES. J. Eng. Sci.*, vol. 52, no. 1, pp. 36–51, 2024.

[35] R. Jain, S. Zaware, N. Kacholia, H. Bhalala, and O. Jagtap, "Advancing Underwater Trash Detection: Harnessing Mask R-CNN, YOLOv8, EfficientDet-D0 and YOLACT," in *2024 2nd Int. Conf. Sustainable Comput. Smart Syst. (ICSCSS)*, Coimbatore, India, July 2024, pp. 1314–1325.

[36] S. Saji, M. S. Manikandan, J. Zhou, and L. R. Cenkeramaddi, "Underwater Debris Detection Using Visual Images and YOLOv8n for Marine Pollution Monitoring," in *2024 IEEE 19th Conf. Ind. Electron. Appl. (ICIEA)*, Singapore, Aug. 2024, pp. 1-6.

[37] B. Xue, B. Huang, G. Chen, H. Li, and W. Wei, "Deep-sea debris identification using deep convolutional neural networks," *IEEE J. Sel. Topics Appl. Earth Observations Remote Sens.*, vol. 14, pp. 8909–8921, 2021.

[38] S. Kshirsagar, S. Ghodke, and R. Shriram, "Ocean pollution detection using image processing," in *2021 Int. Conf. Emerg. Smart Comput. Inf. (ESCI)*, Pune, India, March 2021, pp. 408–412.

[39] J. Musić, S. Kružić, I. Stančić, and F. Alexandrou, "Detecting underwater sea litter using deep neural networks: an initial study," in *2020 5th Int. Conf. Smart Sustainable Technol. (SpliTech)*, Split, Croatia, Sept. 2020, pp. 1–6.

[40] K. Kylili, A. Artusi, and C. Hadjistassou, "A new paradigm for estimating the prevalence of plastic litter in the marine environment," *Mar. Pollut. Bull.*, vol. 173, Art. no. 113127, 2021.

[41] T. Y. Lee, S. B. Jeon, and M. H. Jeong, "Marine Debris Detection Using Optimized You Only Look Once Version 5," *Sens. Mater.*, vol. 35, 2023.

[42] H. Panwar et al., "AquaVision: Automating the detection of waste in water bodies using deep transfer learning," *Case Stud. Chem. Environ. Eng.*, vol. 2, Art. no. 100026, 2020.

[43] M. Fulton, J. Hong, M. J. Islam, and J. Sattar, "Robotic detection of marine litter using deep visual detection models," in *2019 Int. Conf. Robot. Autom. (ICRA)*, Montreal, QC, Canada, 2019, pp. 5752-5758.

[44] J. S. Walia, K. Haridass, and L. K. Pavithra, "Deep learning innovations for underwater waste detection: An in-depth analysis," *IEEE Access*, vol. 13, pp. 88917-88929, 2025.