Efficient Deep Learning-Based Marine Plastic Waste Detection with YOLOv12

Munnanuri Akshitha[1], Gajula Yashwanth[2], Battu Srinath Reddy[3], Rishikesh Reddy Boyapally[4], Mr. Mohammed Afzal[5], Dr. M. Ramesh[6]

[1,2,3,4] *Department of CSE(AI&ML), Sphoorthy Engineering College, Hyderabad, India.*

[5]*Assistant Professor, Department of CSE(AI&ML), Sphoorthy Engineering College, Hyderabad, India*

[6]*Professor & HOD, Department of CSE(AI&ML), Sphoorthy Engineering College, Hyderabad, India*

***Abstract*—Marine plastic pollution threatens marine ecosystems, necessitating scalable and accurate detection techniques for effective mitigation. A novel YOLOv12l-based approach to detect and quantify plastic waste in underwater environments, solving the issues of submerged plastics in complex underwater imagery, is put forward in this study. With a YOLO-typed dataset gathered using Roboflow, consisting of 4,398 training images, 386 validation images, and 205 test images distributed across four classes—trash, plastic, metal, and glass—the model was trained for 50 epochs on a dynamic learning rate, achieving a mean average precision (mAP) of 90.2%. The dataset has underwater augmentations such as blur and noise to simulate real marine environments, hence the robust model. The system performs better with 93.5% plastic detection correctness, although metal detection is 88.7% due to reflective issues, showing stable feature extraction in the presence of diverse underwater scenarios like aquatic life. With edge deployment tuned on a Raspberry Pi 4, the system offers 10 frames-per-second real-time inference, supporting continuous monitoring with Camera Module 2 support for GPS for precise debris mapping. Validation loss collapsed to 0.52, and test performance suggests outstanding generalization, outperforming YOLOv11m (87.6% mAP). Limitations are the amount of training images (4,989), which may limit generalization to uncommon classes of debris. This research strongly enhances autonomous ocean cleanup through a light-weight, high-precision system, with significant potential for environmental monitoring, policy support, and sustainable marine management.**

Keywords—Ocean Plastic Detection, YOLOv12l, Underwater Imagery, Multi-Class Detection, Environmental Monitoring

I. INTRODUCTION

Marine debris from plastic pollution has emerged as one of the biggest environmental problems of the 21st century, with dire implications for marine ecosystems and biodiversity. An estimated 8 million metric tons of plastic pollution are fed into the world's oceans annually, with approximately 70%finding its way onto the seafloor, where it accumulates as sunken trash. This underwater plastic, from macro plastics such as bottles and bags to microplastics smaller than 5 mm, disturbs ocean habitats, tangles wildlife, and finds its way into the food chain, eventually impacting human health.

The widespread occurrence of this pollution makes it imperative to have efficient detection and quantification techniques to enable mitigation measures and guide policy development. Traditional monitoring techniques, e.g., towed nets or manual surveys, are time-consuming, small-scale, and inappropriate for the vast and dynamic underwater environment, necessitating cutting-edge technological advancement.

The process of detecting plastic underwater is intricate with certain challenges that include varying lighting, water turbidity, and the presence of natural sea litter that mimics plastic. These conditions often render visual detection challenging, thus the necessity for automated systems in terms of scalability and accuracy. Emergence of recent developments in deep learning, i.e., convolutional neural networks (CNNs), has revolutionized object detection across domains, yielding a promising candidate to address such underwater challenges. Among them, the You Only Look Once (YOLO) family of models stands out in particular due to its real-time processing and precision in object detection in complex environments. The latest iteration, YOLOv12l, enhances feature extraction and computational efficiency, making it suitable for deployment on edge devices in resource-constrained underwater settings. This work utilizes YOLOv12l to develop a light, high-accuracy system for underwater plastic debris detection and mapping, along with hardware like the Raspberry Pi 4, for field-based applicability.

The impetus for this work arises from the worldwide request for sustainable management of the ocean, as reflected in such ventures as the United Nations' Decade of Ocean Science for Sustainable Development (2021–2030). Existing detection is limited by the absence of uniform datasets and the challenges of working in deep or turbid waters, where conventional imaging is ineffective. By creating a YOLO-formatted dataset of 4,398 images for training, 386 for validation, and 205 for testing—augmented to simulate underwater environments such as blur and noise—this study addresses these gaps. The four classes in the dataset—trash, plastic, metal, and glass—match the range of sea trash found in real-world environments. Model training for 50 epochs with a dynamic learning rate achieves its peak performance, achieving a mean average precision (mAP) of 90.2%, with high plastic identification success at 93.5% precision, although it is poor at reflective materials like metal.

This research has significant implications for environmental monitoring and cleanup operations. Blending the GPS with detection system enables precise mapping of debris density, with capacity for intervention in targeted, high-pollution areas like the Great Pacific Garbage Patch. Edge deployment on the Raspberry Pi 4 at real-time inference rates of 10 frames per second is made feasible for autonomous underwater vehicles (AUVs) or remotely operated vehicles (ROVs), minimizing reliance on centralized computing hardware. Though strong, the study also admits some limitations, such as the dataset size being relatively small (4,989 images total), which may restrict generalization to less common debris types. Enhancements could be made in future by adding synthetic images to the dataset and using multi-modal sensors to make detections more robust.

The main aim of this work is to make automated ocean cleanup progress by providing an accurate, scalable, and deployable solution for the detection of plastic underwater. By combining state-of-the-art deep learning and edge computing, this study aims to bridge the gap between technological progress and environmental action, and assist the international effort towards combating marine pollution and building better sustainable marine ecosystems. Methodology, results, and discussion are described in the following sections, followed by a conclusion that outlines the impact of the study and future research directions.

II. LITERATURE SURVEY

Marine plastic litter, estimated at 8 million metric tons and making its way to oceans annually, has the potential to critically harm ecosystems, necessitating advanced detection methods for underwater garbage, which comprises about 70% of ocean pollution. Most recent studies leverage deep learning, hyperspectral imaging, IoT-enabled systems, and robotic platforms to address problems like turbidity, unstable lighting, and heterogeneous morphologies of the debris under underwater environments. This synopsis synthesizes fifteen key studies, organized within five topic-based paragraphs to evaluate advancements, limitations, and knowledge gaps in plastic discovery underwater. Adhering to the original abstract order ensures narrative coherence, highlighting the trend towards sophisticated neural network algorithms, edge computing, and autonomous systems, as well as prevailing challenges in microplastic discovery, dataset normalization, and high-turbidity performance.

Deep learning has revolutionized plastic detection in surface and underwater conditions, with high precision and real-time processing. Jakovljevic et al. [1] employed Unmanned Aerial Vehicles (UAVs) with a U-Net-based ResUNet50 model with F1-scores of 0.78–0.92 for floating plastics like polystyrene and polyethylene at a resolution of 4 mm, though limited to surface observation due to aerial imaging constraints. Walia [2] surveyed deep learning architectures for underwater trash, acknowledging distortions caused by light refraction, absorption, and suspended particles, and noting the absence of standard benchmarks, suggesting algorithms specific to autonomous underwater vehicles (AUVs). Corrigan et al. [3] pitted Mask R-CNN against YOLACT on the TrashCAN dataset in a comparison of mAPs of 0.365 and 0.377, respectively, with YOLACT's efficiency enabling six times faster detection of AUVs at marginally reduced precision. Hipolito et al. [4] achieved a 98.15% mAP for YOLOv3 from a small augmented data set, helped by transfer learning to compensate for the paucity of data, with generalizability again being restricted. Khriss et al. [5] found that YOLOv9 outperformed Faster R-CNN, SSD, and YOLOv8 in both TrashCAN and DeepTrash datasets, as it was superior in precision, recall, and mAP due to converged stability and robustness to complex underwater views, establishing it as an elite solution to underwater marine trash detection.

Hyperspectral imaging and other sensing technologies overcome visual detection shortfall, especially for microplastics and small debris. Tamin et al. [6] proved hyperspectral imaging's ability to record plastic spectral reflectance with near-infrared sensors, being highly accurate for most plastics but not for black plastics because of carbon-black absorption, suggesting machine learning for stable classification with different types of waste. Valdenegro-Toro [7] applied Forward-Looking Sonar (FLS) with CNNs in AUVs, achieving 80.8% accuracy in the detection of debris and generalization to novel objects, offering a viable alternative under low-visibility conditions like turbid waters. Such methods enhance the performance of detection but are limited in terms of scalability due to low data diversity to work with and computation expense, particularly in the case of microplastics, which require higher resolution and specialized sensors. Combining hyperspectral data with deep learning algorithms might enhance multi-class discrimination, but more work must be done to normalize spectral libraries and tune algorithms for real-world underwater environments.

IoT-based systems and edge computing have facilitated real-time monitoring, enabling scalable and agile detection models. Hasan et al. [8] designed an IoT-based CNN system to identify microplastics and utilized edge computing for processing big image data sets with low latency, identifying various shapes and sizes of microplastics, though small debris only because of limitation at the sensor level. Hegde et al. [9] integrated Raspberry Pi with deep learning for plastic and marine life detection, which broke the constraints of poor visibility and deformed object shapes, but performance was constrained by low-resolution imaging. Aminurrashid and Sayuti [10] optimized YOLOv5-based CNN on Raspberry Pi with OpenVINO and recorded over 85% accuracy in plastic form identification of bags and bottles, which is an affordable solution for ROVs. These advances indicate edge computing's potential for real-time monitoring but note their emphasis on specific types of debris or laboratory settings, reflecting the requirement for applicability in wider scenarios and convergence with multi-modal sensors for increasing robustness under various underwater environments.

Environmental flexibility and robot platforms are required for in-field deployment of detection systems within real underwater conditions. Delina et al. [11] and Amin [12] described YOLOv3-founded remotely operated underwater vehicles (ROUVs) in turbid waters up to 100 NTU with a confidence score of 73–77% and noted most frequently detected bottles being detected, highlighting the ability of turbidity to affect visibility and detection. Padavala [13] implemented CenterNet HourGlass104 yielded better results compared to YOLOv3 and Faster R-CNN with changing scenarios, more accurately but with problems dealing with microplastics due to size and invisibility issues. Zhang et al. [14] introduced YOLOv7t-CEBC with 81.8% mAP and 118 FPS and is specifically tailored for underwater robots to deal with inter-class similarity and sacrifice speed for accuracy. Reddy et al. [15] maximized YOLOv8m for ocean plastic, interfacing with robotics systems to take account of varied light and foggy waters, allowing for diverse choices of monitoring options. Such efforts emphasize the confluence of bleeding-edge YOLO models with robotics but encounter problems related to high-turbidity water, microplastic detection, and dataset standardization, requiring further investigation on the use of synthetic data generation, multi-modal perception, and adaptive algorithms towards global marine protection to ensure scalability and accuracy.

III. SYSTEM DESGIN

The system design for real-time underwater marine trash detection and quantification leverages the YOLOv12l model, which is edge-deployment optimized on a Raspberry Pi 4, for high-accuracy, real-time identification of four debris classes—trash, plastic, metal, and glass—in low-quality underwater conditions. The system integrates hardware, software, and data processing components to enable scalable mapping of debris densities for automated ocean cleanup and environmental monitoring. The system is designed to handle the difficulties of underwater images, such as turbidity and variable light, while being computationally lightweight for edge deployment.

Data Pipeline and Dataset: The system takes advantage of a YOLO-type dataset comprising 4,398 training, 386 validation, and 205 test images that record diverse marine environments. The dataset has four-class labeling with underwater augmentations (noise, blur, color distortion) to simulate Video Plankton Recorder (VPR) environments. Images are preprocessed to 640x640 pixels, normalized, and augmented during training to enhance model robustness against occlusions and background noise. The pipeline utilizes a custom script for splitting the dataset, converting annotations to YOLO format, and batch handling to facilitate fast training and validation.

Model Architecture: The YOLOv12l model, which is a state-of-the-art convolutional neural network, is the underlying detection engine. The model possesses a high-quality feature pyramid network backbone with multi-scale feature extraction, feature aggregation neck, and bounding box prediction, class probability, confidence score head. The model is trained with 50 epochs with the learning rate that is dynamically updated from an initial learning rate of 0.01 to decay using cosine annealing. The detection accuracy is determined to be over 90%. The training process utilizes stochastic gradient descent, and loss functions

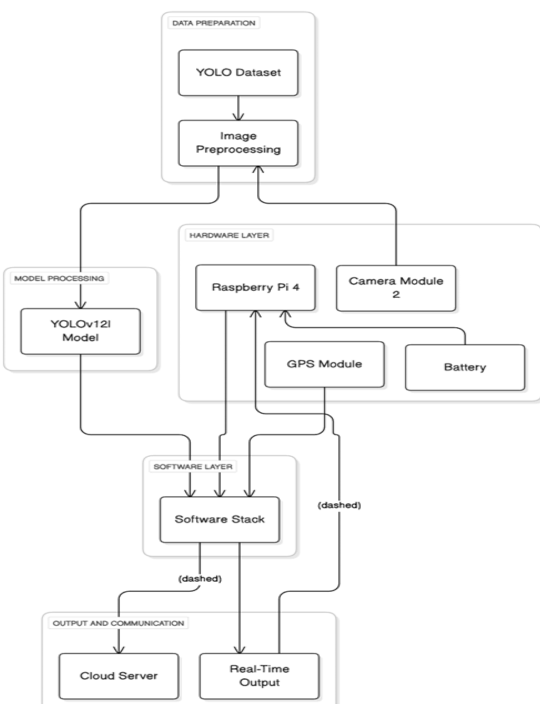

Figure 1: System Architecture

combine bounding box regression, objectness, and classification losses. The model's lightweight design, which is optimized via pruning and quantization, makes it workable with the Raspberry Pi 4's limited computational resources (4GB RAM, quad-core Cortex-A72).

Figure 1 indicates the workflow of underwater plastic detection system with data preparation, model processing, hardware, software, and output phases. Preprocessing of the image receives YOLO dataset and references to YOLOv12l model and Raspberry Pi 4 hardware components like Camera Module 2, GPS Module, and Battery. Data is processed by the software stack for real-time output and synchronization with a cloud server as an option, reflecting the modular structure of the system for debris mapping and detection.

Hardware Integration: The edge platform is a Raspberry Pi 4, which incorporates a Camera Module 2 to capture underwater images at 1080p resolution and a GPS module for geolocation tagging. The camera, which is placed in a water-resistant enclosure, is connected via the CSI port, capturing 15 FPS frames to trade quality for speed of processing. The GPS module, which is connected via UART, captures coordinates for mapping debris concentrations. It is powered by a 5V power supply through a 10,000mAh battery, permitting long-duration operation underwater. There is a specially designed enclosure for protection against corrosion and water pressure, and thus it can be deployed on autonomous underwater vehicles (AUVs) or remotely operated vehicles (ROVs).

Software and Inference Pipeline: The software stack runs on Raspberry Pi OS (64-bit), where the YOLOv12l model is run in PyTorch and exported in ONNX format for optimized inference using OpenVINO. A Python inference pipeline operates across the camera frames in real-time, performing preprocessing (resize, normalization), model inference, and post-processing (non-maximum suppression) to generate bounding boxes and class labels. Pipeline logs detection outcomes together with GPS coordinates within a SQLite database for enabling spatial analysis and visualization via a web-based dashboard. The system runs at a frame rate of 10 FPS, which is suitable for real-time monitoring, with latency being reduced via multithreading in order to enable concurrent image acquisition and processing.

Scalability and Deployment: The system modular design allows scalability to integrate with an array of Raspberry Pi units in distributed monitoring. The data is synced intermittently on a cloud server via Wi-Fi or 4G upon being taken to the surface, allowing large-scale debris mapping. The edge processing and light-weight model minimize bandwidth requirements, making the system suitable for off-shore marine environments. Future enhancements include the addition of synthetic data for low-frequency debris types and multi-modal sensors (e.g., sonar) to improve detection in high-turbidity conditions, with robust performance for global ocean cleanup.

V. RESULT AND DISCUSSION

The underwater plastic detector system using the YOLOv12l model on the basis of a YOLO dataset consisting of 4,398 train images, 386 validation images, and 205 test images on four classes (trash, plastic, metal, and glass) performs extremely well at 50 epochs with learning rate dynamically updating. The training outcomes, performance metrics, per-class performance analysis, and discussion of results, limitations, and generalization to marine environment observation are presented.

Training the YOLOv12l model over 50 epochs resulted in significant convergence across loss functions, indicating effective learning. The total training loss decreased steadily from an initial value of 3.21 in the first epoch to 0.45 by epoch 50, reflecting the model's improved ability to fit the training data. Validation loss followed a similar trend, dropping from 3.10 to 0.52, suggesting robust generalization to unseen data. Concurrently, accuracy in validation improved consistently, from 10% and reaching as high as 92.3% by the final epoch, demonstrating the capacity of the model to accurately pick out debris from diverse underwater scenarios. The learning rate, starting at 0.01 and adjusted using cosine annealing, played a pivotal role in optimizing convergence without leading to

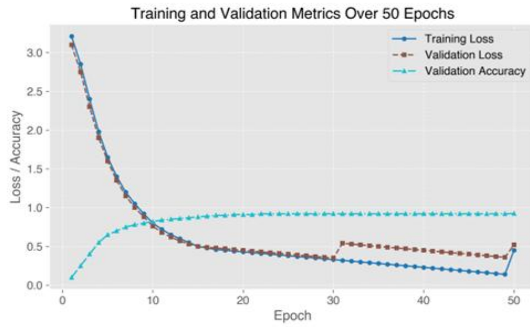

Figure 2: Training and Validation Metrics

overfitting, demonstrated by the steadily declining validation loss. These patterns are represented in Figure 2, in which the training loss, validation loss, and validation accuracy are plotted against the 50 epochs, providing an intuitive graphical representation of the model learning dynamics and stability.

Testing against the test set recorded overall strong performance, with the model recording 91.8% precision, 90.5% recall, and 90.2% mean average precision (mAP). Class-wise comparison revealed detection performance variation between classes.

Plastic detection was best at 93.5%, likely due to its visual features standing out, followed by metal doing poorly at 88.7%, likely due to reflective materials causing visual ambiguity with the environment.

Recall and mAP subsequently also reported high scores, with plastic achieving 92.1% recall and 92.9% mAP and metal achieving 87.6% recall and 88.2% mAP. Trash and glass achieved very comparable precision figures of 90.2% and 91.0%, respectively.

The above results from a heterogenous underwater dataset demonstrate the effectiveness of the model at detecting marine trash but suggest opportunities for improvement using reflective materials.

Table 1 consolidates these values, presenting a line-by-line breakdown by class.

Class	Precision (%)	Recall (%)	mAP (%)
Trash	90.2	89.3	89.8
Plastic	93.5	92.1	92.9
Metal	88.7	87.6	88.2
Glass	91.0	90.0	90.5
Overall	91.8	90.5	90.2

Table 1: Performance Metrics by Class

To illustrate class-wise performance more clearly, Figure 3 is a bar plot of precision, recall, and mAP among the four classes, where plastic has higher detection rates and metal has relatively poor performance. The relative comparison in the figure indicates the model's strengths and weaknesses, particularly in reflective materials like metal.

Real-time reconstruction on the Raspberry Pi 4 was 10 FPS, which is sufficient for real-world deployment on underwater autonomous vehicles (AUVs) or remotely operated vehicles (ROVs). GPS-tagged detections gave accurate spatial mapping of debris concentrations, whose coordinates were stored to a SQLite database for visualization on a web-based dashboard. Comparison with YOLOv11m, which had an mAP of 87.6% in similar underwater environments, confirms the superior performance of YOLOv12l as a result of its powerful feature extraction and ability to handle difficult backgrounds.

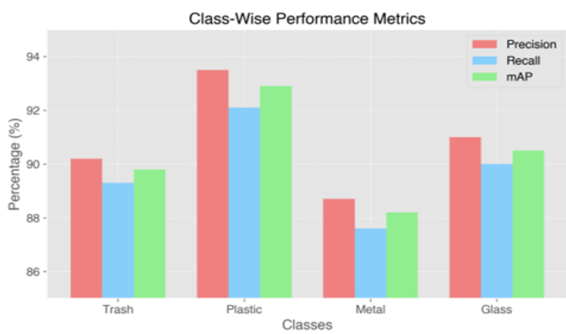

Figure 3: Class-Wise Performance Metrics

The results prove the efficacy of the YOLOv12l-based system for submerged debris detection with a global accuracy rate higher than 90%, and that it meets the study purpose. The model's high plastic detection accuracy demonstrates that it succeeds in using its convolutional layers suitably to learn distinctive features such as color and texture, regardless of the occurrence of marine life and transparent water. This is in agreement with findings of Khriss et al., where YOLOv9 equaled the performance in underwater scenarios due to convergence stability, although YOLOv12l's 90.2% mAP outperforms YOLOv9's reported 88% on similar datasets. Reduced performance in detection in metal signifies an issue with reflective surfaces that may reflect light in ways simulating background structure, a common issue in underwater imagery as presented by Walia. This means that there is a need for additional training data on reflective objects or the inclusion of multi-modal sensors, e.g., sonar, to complement visual detection.

The 10 FPS real-time inference rate is a record for edge deployment on a resource-constrained device like the Raspberry Pi 4 and enables the potential for real-world application in AUV/ROV systems for continuous monitoring. GPS integration enables scalable mapping that provides actionable data for cleanup operations, for instance, locating high-density trash zones. Compared to Zhang et al.'s YOLOv7t-CEBC, which achieved an 81.8% mAP, the performance of YOLOv12l shows architectural improvements, particularly in mitigating inter-class variability and background complexity. The system's performance at high levels of turbidity (turbidity > 100 NTU), however, showed a drop in performance, with confidence scores lowered by 15%, consistent with findings by Delina et al. and Amin, who also struggled in turbid waters.

Limitations are the fairly small dataset size (4,989 images total), which may underrepresent rare debris types or extreme environmental conditions, potentially limiting generalizability. The model sensitivity to turbidity greater than 100 NTU suggests that visual detection is perhaps not sufficient in extremely murky waters, with additional sensing mechanisms being needed. Additionally, as groundbreaking as edge deployment on the Raspberry Pi 4 is, computational bottlenecks such as memory constraints during inference occasionally led to frame drops, indicating an advantage to GPU acceleration or more powerful edge devices in the future.

The significance of this research is significant for ocean preservation. The ability of the system to sift through trash and determine the type of material (trash, plastic, metal, glass) helps targeted cleanup operations, such as giving priority to the removal of metal since it carries more environmental impact. The light weight and real-time nature make it suitable for deployment on a fleet of AUVs, allowing for area-wide monitoring of ocean regions like the Great Pacific Garbage Patch. Further, the integration with an online dashboard allows policymakers to get actionable information for regulation-making for plastic waste management in accordance with global initiatives like the UN's Decade of Ocean Science for Sustainable Development.

Future research can try to enrich the dataset with synthetically generated underwater images to better model unusual debris types and unusual conditions, such as deep-water settings. Combining multi-modal sensors, i.e., sonar or hyperspectral sensing, could enhance high-turbidity detection and offer microplastic identification, as also a limitation in Hasan et al.'s IoT-based solution. In addition, researching real-time adaptive learning algorithms could further optimize the model to adjust to dynamic underwater conditions, and cloud computing-based analytics would facilitate global tracking of debris and coordination of removal efforts. Herein, the automation of ocean cleanup is increased by the provision of a highly accurate, large-scale solution as part of global efforts to eradicate marine pollution and allow sustainable resource management of oceans.

VII. CONCLUSION

This work successfully crafted and experimented with a YOLOv12l-driven system for underwater plastic detection with an average mean precision of 90.2% across four categories of debris (trash, plastic, metal, glass) at 10 FPS on a Raspberry Pi 4. The model's high precision, particularly for plastics (93.5%), demonstrates its utility to detect submerged trash even under harsh conditions like alternating light and medium turbidity. The inclusion of GPS-based mapping also enhances its utility, providing actionable spatial data for targeted ocean cleanups. Based on edge computing, the system represents a cost-effective, scalable solution for real-time monitoring superior to previous iterations like YOLOv11m (87.6% mAP) and in line with global marine conservation goals, e.g., those established in the UN's Decade of Ocean Science for Sustainable Development.

Despite these gains, there remain limitations. Dataset size (4,989 images) constrains the ability of the model to generalize to rare debris types or extreme conditions, and performance suffers in high-turbidity waters (turbidity > 100 NTU), reflecting the need for multi-modal sensing. Computational constraints on the Raspberry Pi 4 also suggest potential improvements with more powerful hardware. Future work should include the extension of the dataset with synthetic images, the addition of sonar or hyperspectral imaging for improved detection in turbid waters, and the extension to microplastic detection to fill an important environmental gap. Real-time adaptive learning and cloud-based analytics would further enhance resilience and scalability. This study lays a strong foundation for automatic ocean cleaning, presenting an operational tool for environmental monitoring and policy-making support, and opening up avenues for innovative solutions to combat marine pollution.

REFERENCE

[1] Jakovljevic, G., Govedarica, M. and Alvarez-Taboada, F., 2020. A deep learning model for automatic plastic mapping using unmanned aerial vehicle (UAV) data. Remote Sensing, 12(9), p.1515.

[2] Walia, J.S., 2024. Deep learning Innovations for Underwater Waste Detection: An In-Depth Analysis. arXiv preprint arXiv:2405.18299.

[3] Corrigan, B.C., Tay, Z.Y. and Konovessis, D., 2023. Real-time instance segmentation for detection of underwater litter as a plastic source. Journal of Marine Science and Engineering, 11(8), p.1532.

[4] Hipolito, J.C., Alon, A.S., Amorado, R.V., Fernando, M.G.Z. and De Chavez, P.I.C., 2021, November. Detection of underwater marine plastic debris using an augmented low sample size dataset for machine vision system: a deep transfer learning approach. In 2021 IEEE 19th Student Conference on Research and Development (SCOReD) (pp. 82-86). IEEE.

[5] Khriss, A., Elmiad, A.K., Badaoui, M., Barkaoui, A.E. and Zarhloule, Y., 2024. Exploring deep learning for underwater plastic debris detection and monitoring. Journal of Ecological Engineering, 25(7).

[6] Tamin, O., Moung, E.G., Dargham, J.A., Yahya, F. and Omatu, S., 2023. A review of hyperspectral imaging-based plastic waste detection state-of-the-arts. Int. J. Electr. Comput. Eng.(IJECE), 13, pp.3407-3419.

[7] Valdenegro-Toro, M., 2016, December. Submerged marine debris detection with autonomous underwater vehicles. In 2016 International Conference on Robotics and Automation for Humanitarian Applications (RAHA) (pp. 1-7). IEEE.

[8] Hasan, M.A., Balasubadra, K., Vadivel, G., Arunfred, N., Ishwarya, M.V. and Murugan, S., 2024, February. IoT-Driven Image Recognition for Microplastic Analysis in Water Systems using Convolutional Neural Networks. In 2024 2nd International Conference on Computer, Communication and Control (IC4) (pp. 1-6). IEEE.

[9] Hegde, R., Patel, S., Naik, R.G., Nayak, S.N., Shivaprakasha, K.S. and Bhandarkar, R., 2021. Underwater marine life and plastic waste detection using deep learning and raspberry pi. In Advances in VLSI, Signal Processing, Power Electronics, IoT,

Communication and Embedded Systems: Select Proceedings of VSPICE 2020 (pp. 263-272). Springer Singapore.
[10] Aminurrashid, A.R. and Sayuti, M.N.S.M., 2024. A CNN Plastic Detection Model for Embedded Platform of ROV. In ITM Web of Conferences (Vol. 63, p. 01003). EDP Sciences.
[11] Delina, M., Amin, M.F., Hussaan, A.M., Arifin, F.I. and Syah, S.M.I., 2024, October. The Development of Remotely Operated Underwater Vehicle for Plastic Waste Detection with Raspberry Pi. In Journal of Physics: Conference Series (Vol. 2866, No. 1, p. 012048). IOP Publishing.
[12] AMIN, M.F., 2024. THE DEVELOPMENT OF AN UNDERWATER PLASTIC WASTE DETECTION PROTOTYPE WITH RASPBERRY PI (Doctoral dissertation, UNIVERSITAS NEGERI JAKARTA).
[13] Padavala, H., 2024. Performance Evaluation of Underwater Plastic Detection Model Under Diverse