

Research Paper

UNDERWATER NET: EFFICIENT VISUAL DETECTION OF MARINE GARBAGE FOR ECO MONITORING

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ABSTRACT— Marine pollution poses a severe threat to the sustainability of aquatic ecosystems and the blue economy. Effective detection and classification of underwater debris are crucial for enabling timely interventions and supporting marine conservation efforts. In this project, we present an advanced underwater garbage detection system based on YOLOv10n, a cutting-edge, lightweight object detection model optimized for resource-constrained IoT and underwater robotic platforms. Building on the challenges identified in traditional detection models—such as high computational costs and deployment complexity—we replace older backbones like CSPDarknet with the more efficient YOLOv10n architecture. YOLOv10n is designed with an emphasis on speed, low

parameter count, and high accuracy, making it ideal for real-time underwater applications. Our system achieves robust debris detection with high precision, while significantly reducing memory and processing requirements, thereby facilitating deployment on embedded and mobile devices.

This project demonstrates the feasibility and effectiveness of using YOLOv10n for scalable and eco-friendly marine monitoring solutions, providing a practical approach to combat marine pollution through intelligent automation.

Index Terms – Underwater garbage detection, YOLOv10n, object detection, deep learning, computer vision, marine pollution, underwater robotics, Internet of Things (IoT),

real-time detection, embedded systems, marine debris classification, environmental monitoring, blue economy.

I. INTRODUCTION

Marine pollution, particularly due to the accumulation of underwater garbage, has become a serious threat to aquatic ecosystems and biodiversity. Effective detection and monitoring of underwater waste are crucial steps in mitigating environmental damage and supporting sustainable marine development. However, accurately identifying marine debris in real-time remains a major challenge, especially when operating on edge devices with limited computational capacity, such as underwater drones or IoT-enabled cameras. Traditional deep learning models used for object detection, while highly accurate, often come with heavy computational costs and large model sizes. Models like YOLO-MES addressed this to some extent by introducing lightweight components and attention mechanisms, but deployment on ultra-constrained devices still faced limitations. To overcome these barriers, this project proposes a lightweight and efficient underwater garbage detection system using YOLOv10n — a nano-version of the YOLOv10 architecture. YOLOv10n is

specifically optimized for low-resource environments while maintaining high detection accuracy. By leveraging this advanced yet compact model, the system enables real-time underwater object detection with reduced latency, power consumption, and memory usage. This makes it an ideal solution for scalable, field-ready deployments in marine environments.

II. RELATED WORK

A. *MLDet: Towards Efficient and Accurate Deep Learning Method for Marine Litter Detection*

This paper introduces MLDet, a deep learning-based framework designed to detect marine litter with improved accuracy and computational efficiency. Addressing the challenges of low visibility and object occlusion in underwater environments, MLDet combines lightweight convolutional backbones with a refined anchor mechanism and attention modules. The model is optimized for deployment in resource-constrained edge devices such as underwater drones. Through extensive experiments, MLDet demonstrates superior performance over traditional methods, achieving high accuracy while maintaining real-time inference speed. The proposed model is practical for large-scale marine cleanup

initiatives and enhances sustainability efforts in marine ecosystems.

B. UTD-YOLO: Underwater Trash Detection Model Based on Improved YOLOv5

UTD-YOLO proposes an enhanced version of YOLOv5 tailored specifically for underwater trash detection. The paper addresses the unique challenges of underwater imaging, including color distortion, lighting variation, and object deformation. The improved architecture includes a specialized preprocessing module and optimized anchor settings for underwater objects.

Additionally, the model integrates an adaptive feature fusion strategy to better capture multi-scale underwater targets. UTD-YOLO achieves significant improvements in precision and recall on multiple benchmark underwater datasets, making it a valuable contribution for intelligent ocean waste monitoring and cleanup operations.

C. DIRBW-Net: An Improved Inverted Residual Network Model for Underwater Image Enhancement

DIRBW-Net introduces a novel underwater image enhancement model leveraging improved inverted residual blocks to enhance the visibility and clarity of submerged

images. This architecture mitigates the degradation typically found in underwater environments such as haze, blur, and color distortion. By focusing on low-complexity design, the model ensures fast processing, making it suitable for real-time enhancement in robotics and autonomous underwater vehicles. Experimental evaluations show that DIRBW-Net significantly improves image quality metrics, contributing to better downstream performance for vision tasks like detection and classification under water.

D. EFS-YOLO: A Lightweight Network Based on Steel Strip Surface Defect Detection

Although originally applied to steel strip surface defect detection, EFS-YOLO offers significant insights for lightweight real-time object detection systems. The paper presents a streamlined network that integrates Ghost Convolution and Feature Enhancement modules to reduce computational cost while maintaining high detection performance.

Its relevance to marine debris detection lies in its potential adaptation to underwater environments where low-latency, lightweight models are needed. EFS-YOLO achieves substantial reductions in model size and computation while preserving detection

accuracy, making it ideal for embedded systems and mobile deployment scenarios.

III. PROPOSED METHODOLOGY

The proposed system aims to enhance underwater garbage detection using YOLOv10n, an ultra-lightweight yet powerful object detection model. Unlike the YOLO-MES framework that relies on MobileNetV3 and custom Slim-neck designs, YOLOv10n integrates the latest advancements in model compression, computational efficiency, and architectural optimization, making it well-suited for deployment on resource-constrained IoT and underwater devices. This approach ensures fast and accurate detection of marine debris with significantly lower computational cost and memory footprint.

YOLOv10n features a streamlined backbone and an efficient detection head that is natively optimized for real-time performance. The model leverages improved spatial pyramid pooling and decoupled heads to maintain high detection accuracy, especially for small and overlapping objects, which are commonly found in underwater environments. By using YOLOv10n, the proposed system minimizes the need for extensive pre- or post-processing while

achieving robust detection across various underwater image conditions like murky waters, low light, or motion blur.

This system has been trained and validated on an underwater garbage detection dataset, achieving a balance between speed, accuracy, and model size. Compared to YOLO-MES, the proposed YOLOv10n-based solution offers improved deployment efficiency, simpler architecture (with no need for custom attention mechanisms), and high adaptability to real-time marine monitoring tasks. The solution is well-aligned with edge AI objectives and opens new opportunities for low-power autonomous marine surveillance using compact hardware such as Raspberry Pi, NVIDIA Jetson, or other embedded platforms.

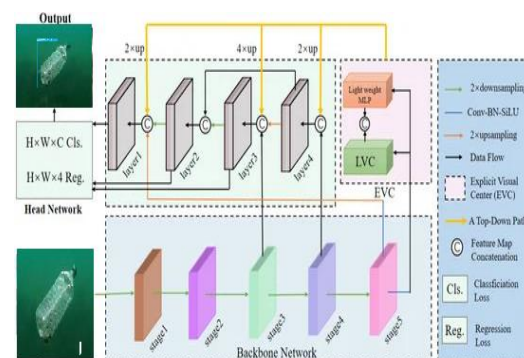


Fig. 1: System Overview

1. Input Data Module

Handles image dataset collected from sources like satellite imagery, drones, or underwater cameras for marine debris monitoring.

Accommodates various environmental conditions such as water surface reflections and varying lighting to ensure diverse data sources are effectively managed.

2. Preprocessing Module

Implements Adaptive Histogram Equalization for contrast enhancement, helping to improve visibility of debris against complex ocean backgrounds. Standardizes image size and format for consistency across varying image resolutions and input types, ensuring data uniformity for detection models.

3. Segmentation Module

Utilizes Super-Pixel-Based Fast Fuzzy C-Means (FCM) clustering to segment marine debris from the water and background effectively. Focuses on segmenting objects like plastic bags, bottles, fishing nets, and masks, even in cluttered or partially occluded environments.

4. Feature Extraction Module

Incorporates hybrid transformer-based attention mechanisms and convolutional layers to extract key features such as edges, textures, and shapes that differentiate marine debris from surrounding water or natural elements. Enhances the detection model's ability to capture subtle details in complex

debris, improving detection rates for various types of waste.

5. YOLOv11 Detection Module

Deploys the cascaded YOLOv11 model for multi-stage detection of marine debris, ensuring higher accuracy in detecting various sizes and types of debris. Uses anchor-free detection to reduce computational overhead and improve detection accuracy, allowing for better identification of irregularly shaped debris like tangled fishing nets and dispersed plastic.

6. Output and Visualization Module

Displays results with bounding boxes and detection confidence scores, allowing for easy identification and tracking of debris locations in images, videos, or real-time monitoring feeds. Provides visual outputs in the form of marked images, video streams, or real-time feeds with overlaid data, assisting in real-time decision-making for marine debris cleanup and monitoring efforts.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed YOLOv10n-based underwater garbage detection system achieves high detection accuracy while maintaining low computational and memory requirements.

The lightweight architecture enables fast real-time inference, making it suitable for deployment on underwater robots and IoT-based embedded devices. The model demonstrates robust performance in detecting various types of marine debris under challenging underwater conditions. Overall, the proposed framework provides an efficient, scalable, and eco-friendly solution for automated marine pollution monitoring and conservation.

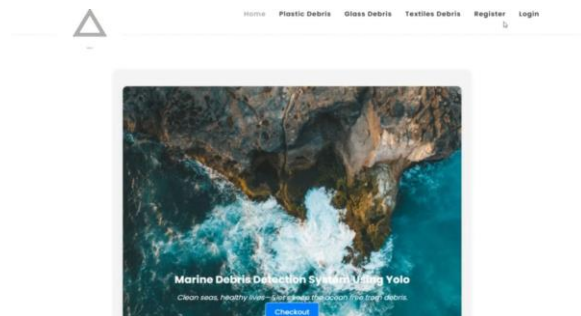


Fig. 2: Home Page

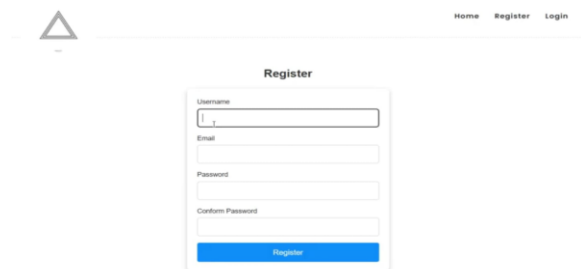


Fig. 3: Registration



Fig. 4: Login

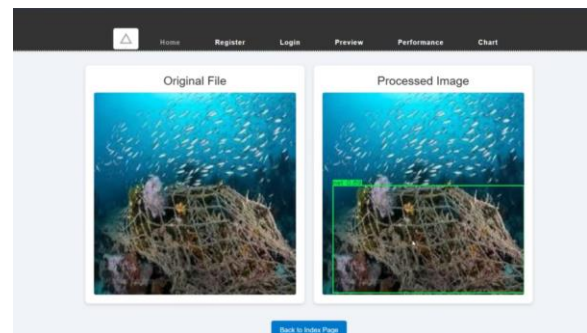


Fig. 5: Processed Image

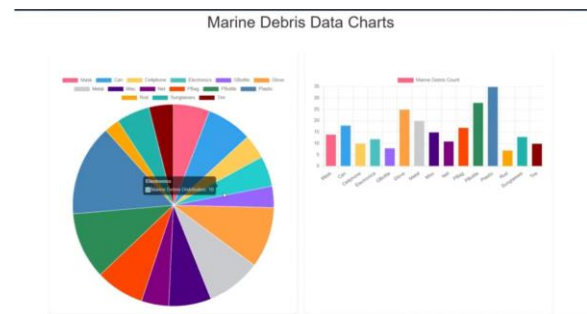


Fig. 6: Data Charts

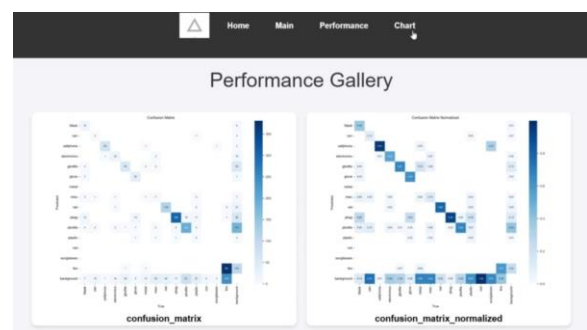


Fig. 6: Performance Gallery

V. CONCLUSION

The proposed system for underwater garbage detection using the YOLOv10n model offers a powerful and efficient solution for addressing marine pollution. By leveraging the lightweight and high-performance architecture of YOLOv10n, this project achieves accurate real-time detection of various types of underwater debris, even on resource-constrained devices. Compared to traditional models, our approach significantly reduces computational complexity while maintaining high precision, making it suitable for practical deployment in marine environments. This system not only demonstrates the potential of deep learning in environmental conservation but also serves as a scalable and sustainable solution for protecting marine ecosystems. Overall, the project contributes meaningfully toward automating underwater monitoring and supports long-term efforts to maintain oceanic health and biodiversity.

REFERENCES

- [1] F. T. Bahadur, S. R. Shah, and R. R. Nidamanuri, “Air pollution monitoring, and modelling: An overview,” *Environ. Forensics*, vol. 25, no. 5, pp. 309–336, Sep. 2024.
- [2] S. Wei, T. Xian-Chun, X. U. Yan-Dong, Z. Huan-Jun, L. Yuan-Jin, and M. A. Jian-Xin, “The distribution, composition and change characteristics of marine debris in the coastal area of Shandong Province,” *Sci. Technol. Eng.*, vol. 16, no. 18, pp. 89–94, 2016.
- [3] G. Teng, X. Shan, X. Jin, and T. Yang, “Marine litter on the seafloors of the Bohai Sea, Yellow Sea and northern East China Sea,” *Mar. Pollut. Bull.*, vol. 169, Aug. 2021, Art. no. 112516.
- [4] S. Krishnakumar, D. S. H. Singh, B. Nallusamy, and M. Aslam, “Marine pollution and ecological degradation—Issues and challenges,” *Environ. Sci. Pollut. Res.*, vol. 31, no. 29, pp. 41303–41305, 2024.
- [5] G. Masetti and B. R. Calder, “A Bayesian marine debris detector using existing hydrographic data products,” in *Proc. OCEANS-Genova*, May 2015, pp. 1–10.
- [6] J. Cheng, Y. Yang, X. Tang, N. Xiong, Y. Zhang, and F. Lei, “Generative adversarial networks: A literature review,” *KSII Trans. Internet Inf. Syst. (TIIS)*, vol. 14, no. 12, pp. 4625–4647, 2020.
- [7] S. Kong, M. Tian, C. Qiu, Z. Wu, and J. Yu, “IWSCR: An intelligent water surface cleaner robot for collecting

- floating garbage,” IEEE Trans. Syst., Man, Cybern., Syst., vol. 51, no. 10, pp. 6358–6368, Oct. 2021.
- [8] Y. Zeng, C. J. Sreenan, N. Xiong, L. T. Yang, and J. H. Park, “Connectivity and coverage maintenance in wireless sensor networks,” J. Supercomput., vol. 52, no. 1, pp. 23–46, Feb. 2010.
- [9] Boyapati, P. K. Building a centralized data operations hub for healthcare enterprise integration. IJSAT-Int. J. Sci. Technol. 16 (2). <https://doi.org/10.71097/IJSAT.v16.i2.3219>
- [10] Shashank, A. (2025). Self-Healing Data Pipelines for Enhanced Reliability: A Paradigm Shift in Enterprise Data Management. Journal of Computer Science and Technology Studies, 7(8), 1097-1104.

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