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Under Water Net: Efficient Visual Detection of Marine Garbage for Eco Monitoring

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Abstract: Marine pollution significantly threatens aquatic ecosystems, biodiversity, and the blue economy due to the accumulation of debris like plastics and fishing nets. Effective detection and monitoring are essential for conservation and cleanup efforts. This project proposes an advanced underwater garbage detection system using YOLOv10n, a lightweight model optimized for IoT devices and robotic platforms such as AUVs and ROVs. Unlike traditional methods and older deep learning models, it offers improved accuracy, faster inference, and lower computational requirements. The system efficiently detects small and occluded debris in real time, enabling continuous monitoring and supporting scalable, eco-friendly solutions for marine conservation and sustainable underwater ecosystem management.
Keywords: YOLO; Underwater Garbage Detection; Marine Pollution Monitoring; Object Detection

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 optimised for low-resource environments while maintaining high detection accuracy.

I. LITERATURE SURVEY

Jaskaran Singh Walia , Kavitha Haridas L. K. Pavithra (2025),This paper presents a novel deep learning framework for real-time underwater waste detection, aiming to address the growing environmental concern of marine pollution through advanced computer vision techniques. The framework is designed to operate effectively under challenging underwater conditions by leveraging state-of-the-art object detection algorithms. A key contribution of the study is the development of a manually annotated custom dataset, which includes images collected from various water bodies such as oceans, rivers, and lakes.

Ravinder Kumar, Dimpal Sharma, Ajay Kumar, Naveen Hemrajani, Ramesh Chandra Poonia (2025), This article proposes the use of YOLOv8 (You Only Look Once version 8), a state-of-the-art deep learning architecture widely recognised for its exceptional speed, efficiency, and high-accuracy object detection capabilities. As an advanced evolution of the YOLO family, YOLOv8 introduces several architectural enhancements, including decoupled detection heads, improved feature extraction modules, and optimised training strategies.

Yangke Le, Xinman Zhang (2024):This article describes a novel lightweight multi-scale cross-level segmentation network designed for automatic underwater waste detection using sonar imagery. With the rapid accumulation of marine debris posing serious threats to ecological balance and water quality, traditional manual recovery methods have become inefficient, labor-intensive, and risky. These conventional approaches often fail to operate effectively in deep or hazardous underwater environments, where visibility is limited and human intervention is challenging.

Y.An,Y.Feng,N.Yuan,Z.Ji, and I. Ganchev (2024): This paper introduces DIRBW-Net a novel underwater image enhancement model that leverages improved inverted residual blocks to significantly enhance the visibility and clarity of submerged images. Underwater environments often suffer from various forms of image degradation, including haze, blur, low contrast, and severe color distortion caused by light absorption and scattering. These challenges negatively impact the performance of computer vision systems, making accurate detection and classification of underwater objects more difficult. To address these issues, DIRBW-Net is designed as an efficient and robust solution for improving underwater image quality.

II. EXISTING SYSTEM

The current methods for detecting underwater debris largely rely on manual surveillance, sonar imaging, or traditional computer vision approaches using handcrafted features. These techniques are time-consuming, error-prone, and require significant human effort for monitoring and labelling. Additionally, the underwater environment poses several challenges such as low visibility, varying light conditions, and complex backgrounds, which further reduce the reliability of conventional approaches in identifying debris accurately and consistently.

Existing System Disadvantages

- High dependency on manual effort
- High processing delay
- Inefficiency of lightweight alternatives

Proposed System

The proposed system aims to enhance underwater garbage detection by leveraging YOLOv10n, an ultra-lightweight yet highly efficient object detection model tailored for low-power and resource-constrained environments. In contrast to earlier approaches such as YOLO-MES, which rely on MobileNetV3 backbones and specialised Slim-neck designs, YOLOv10n integrates recent advancements in model compression, architectural optimisation, and computational efficiency. This makes it highly suitable for deployment on IoT-enabled underwater devices, autonomous underwater vehicles, and energy-constrained marine sensors, delivering fast and accurate debris detection with minimal resource consumption.

Proposed System Advantages:

- Highly lightweight and efficient architecture
- Real-time detection performance
- Improved accuracy for small and overlapping objects
- Low memory usage and energy efficiency

III. SYSTEM ARCHITECTURE

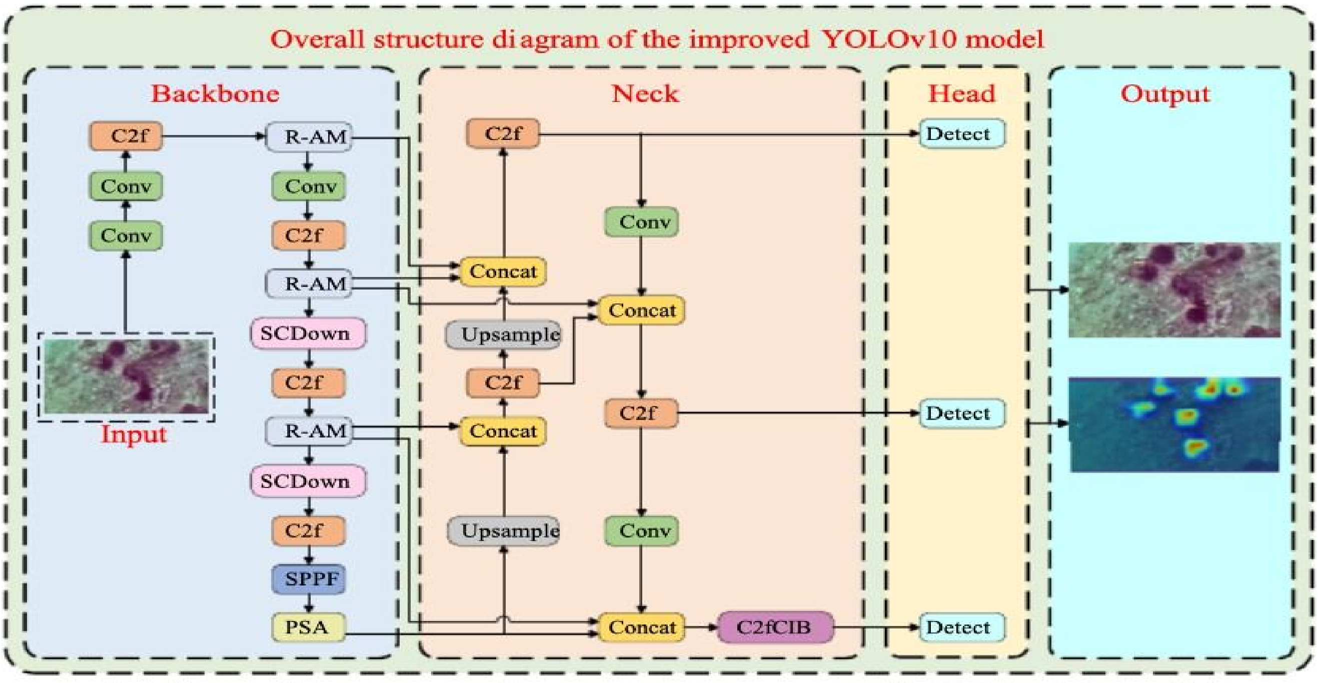

Figure 1: System Architecture

The system architecture for underwater garbage detection using YOLOv10n consists of several key components that work together to identify and classify marine debris efficiently. The architecture begins with data collection from underwater sources such as cameras mounted on AUVs, ROVs, or smart buoy systems. The collected images and video frames undergo preprocessing techniques like resizing, normalization, and enhancement to address issues such as low visibility and noise. The processed data is then fed into the YOLOv10n model, which performs real-time object detection by extracting features and identifying debris in a single pass. The model detects and classifies various types of waste such as plastics, fishing nets, and metals, even in complex underwater conditions. The output includes labeled bounding boxes indicating detected objects, which are stored for analysis and monitoring.

Modules Name:
- Underwater Data Acquisition
- Data Preprocessing & Annotation
- Model Selection and YOLOv10 Configuration
- Training the YOLOv10 Model
- Cloud Synchronisation& Storage

1. Underwater Data Acquisition: The system begins with collecting underwater images and video frames captured by an AUV,ROV, underwater drone, or stationary underwater camera. The dataset includes various underwater conditions such as murky water, low light, motion blur, and diverse types of debris (plastic bags, bottles, fishing nets, metal objects). Both publicly available datasets and custom- captured data are used to ensure dataset diversity and robustness.

2. Data Preprocessing & Annotation: Captured images undergo preprocessing steps such as colour correction, denoising, histogram equalisation, and resolution normalisation to reduce underwater distortions. The images are manually annotated using tools like LabelImg or Roboflow to mark debris objects with bounding boxes and class labels. The annotated dataset is split into training, validation, and test sets.

3. Model Selection and YOLOv10 Configuration: YOLOv10-n (nano version) is selected for its lightweight architecture, fast inference, and suitability for edge devices such as Raspberry Pi, NVIDIA Jetson Nano, and embedded marine platforms. Model configuration includes defining batch size, image size, learning rate, augmentation settings, and anchor-free detection parameters. YOLOv10's improved backbone, feature fusion neck, and decoupled head enable better small-object detection essential for underwater debris.

4. Training the YOLOv10 Model: The model is trained on annotated underwater images using GPU acceleration. During training, techniques like mosaic augmentation, mixup, random cropping, rotation, and brightness adjustment are applied to increase model robustness. The training process generates loss curves, precision-recall curves, and evaluates metrics such as mAP50, mAP50-95, precision, recall, and F1-score to monitor performance.

5. Cloud Synchronisation& Storage: Detection results are uploaded to a cloud server for remote access, backup, and large-scale data analysis. This enables centralised monitoring for marine protection agencies and research teams. tifies cleanup teams through alert mechanisms. This ensures timely intervention to prevent ecosystem damage.

IV. IMPLEMENTATION

This project is a web-based intelligent system designed to detect underwater garbage using advanced computer vision with the YOLOv10n model. When the application runs, it loads a pre-trained YOLOv10n model optimized for lightweight and real-time object detection. When an underwater image or video frame is provided, the system first performs preprocessing steps such as resizing, noise reduction, and color correction to handle challenges like low visibility and distortion. The processed input is then passed to the model, which converts the visual data into feature maps and analyzes spatial patterns. Unlike traditional methods, YOLOv10n detects objects in a single pass, enabling faster and more accurate identification of debris. The model identifies various types of underwater waste such as plastics, fishing nets, and metal objects, even if they are small, overlapping, or partially hidden. Based on learned features, the system classifies and localizes the detected garbage with bounding boxes. The final output is displayed on the web interface with clear labels and detection results, enabling efficient monitoring and supporting marine conservation efforts.

V. EXPERIMENTAL RESULTS

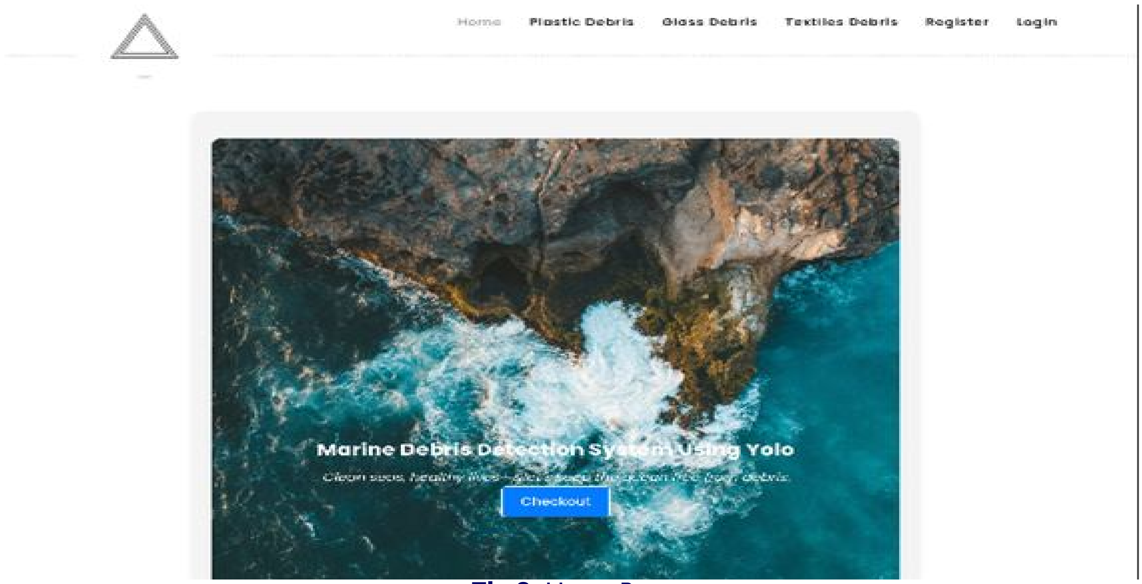

Fig 2: Home Page

The homepage presents a clean and modern interface for the Marine Debris Detection System using YOLO. At the top, a navigation bar is displayed with menu options such as Home, Plastic Debris, Glass Debris, Textiles Debris, Register, and Login, allowing users to easily navigate through different sections of the application. A minimalistic logo is placed on the left side, giving the website a professional appearance.

Existing Algorithm

The current methods for detecting underwater debris largely rely on manual surveillance, sonar imaging, or traditional computer vision approaches using handcrafted features. These techniques are time-consuming, error-prone, and require significant human effort for monitoring and labelling. Additionally, the underwater environment poses several challenges such as low visibility, varying light conditions, and complex backgrounds, which further reduce the reliability of conventional approaches in identifying debris accurately and consistently.

Proposed Algorithm

The proposed system aims to enhance underwater garbage detection by leveraging YOLOv10n, an ultra-lightweight yet highly efficient object detection model tailored for low-power and resource-constrained environments. In contrast to earlier approaches such as YOLO-MES, which rely on MobileNetV3 backbones and specialised Slim-neck designs, YOLOv10n integrates recent advancements in model compression, architectural optimisation, and computational efficiency.

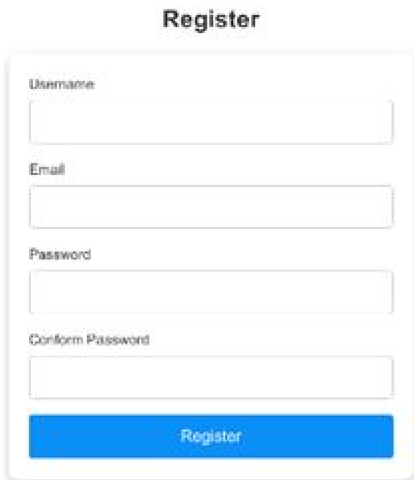

Fig 3: Registration Page

This page represents the User Registration Interface of the Marine Debris Detection System. It follows a clean and minimal design, ensuring ease of use and clarity for new users.At the top, a simple navigation bar is displayed with options such as Home, Register, and Login, along with a logo on the left side, maintaining consistency with the overall website design.

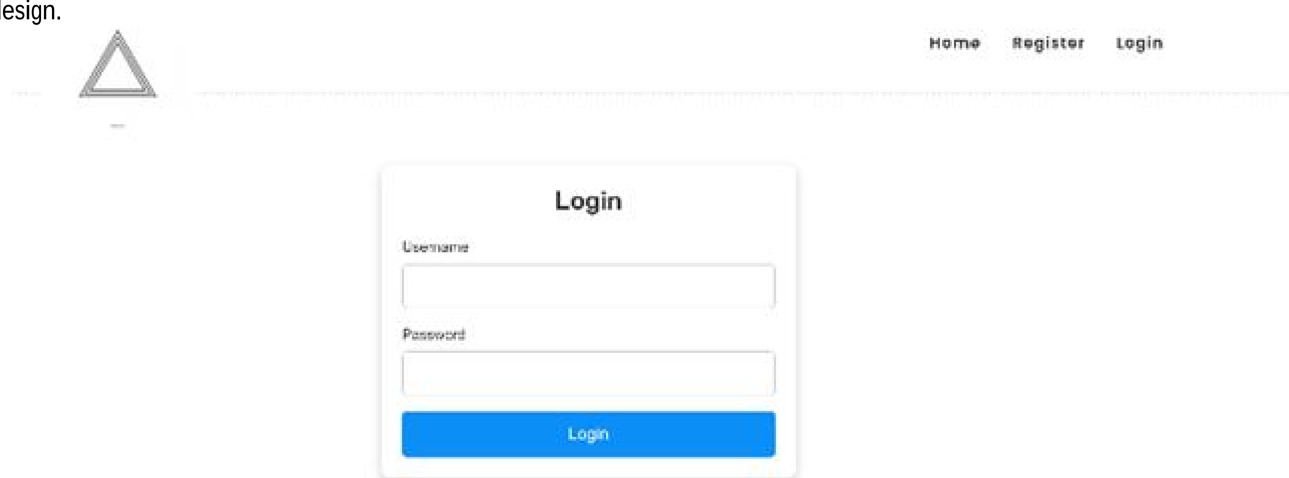

Fig 4: Login Page

This page represents the User Login Interface of the Marine Debris Detection System, designed with a clean and simple layout for easy access. At the top, a navigation bar is present with options such as Home, Register, and Login, along with a minimal logo on the left, maintaining consistency with the overall website design. The detection page shows the main prediction page of the marine garbage detection system after user login. It shows us that the image which we captured in the underwater and uploaded in our system it has detected a plastic glove and has also provided us with binding boxes around that garbage. The image shows the data charts which represents the type of debris found in the ocean according to our collected images dataset. As we can see there is a bar graph showing the types of debris found. This is very important to analyse which type of debris is found most and what type of measures to be taken.

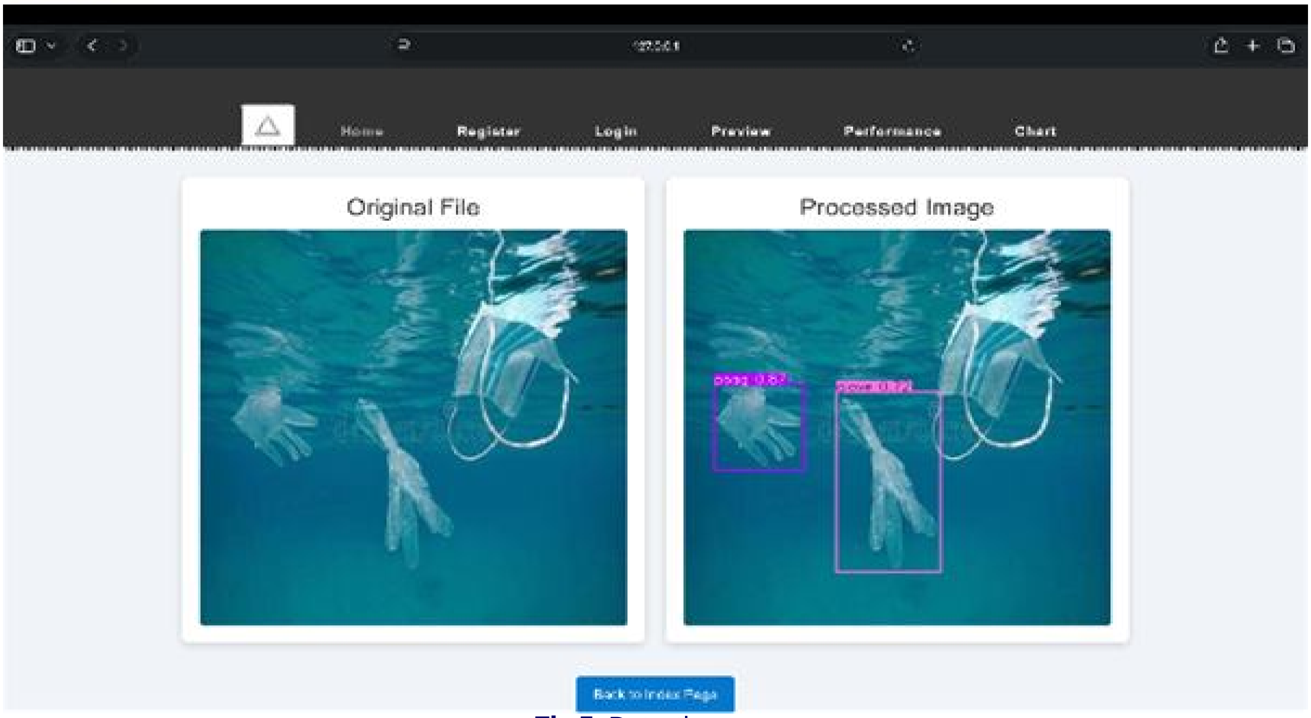

Fig 5: Detection page

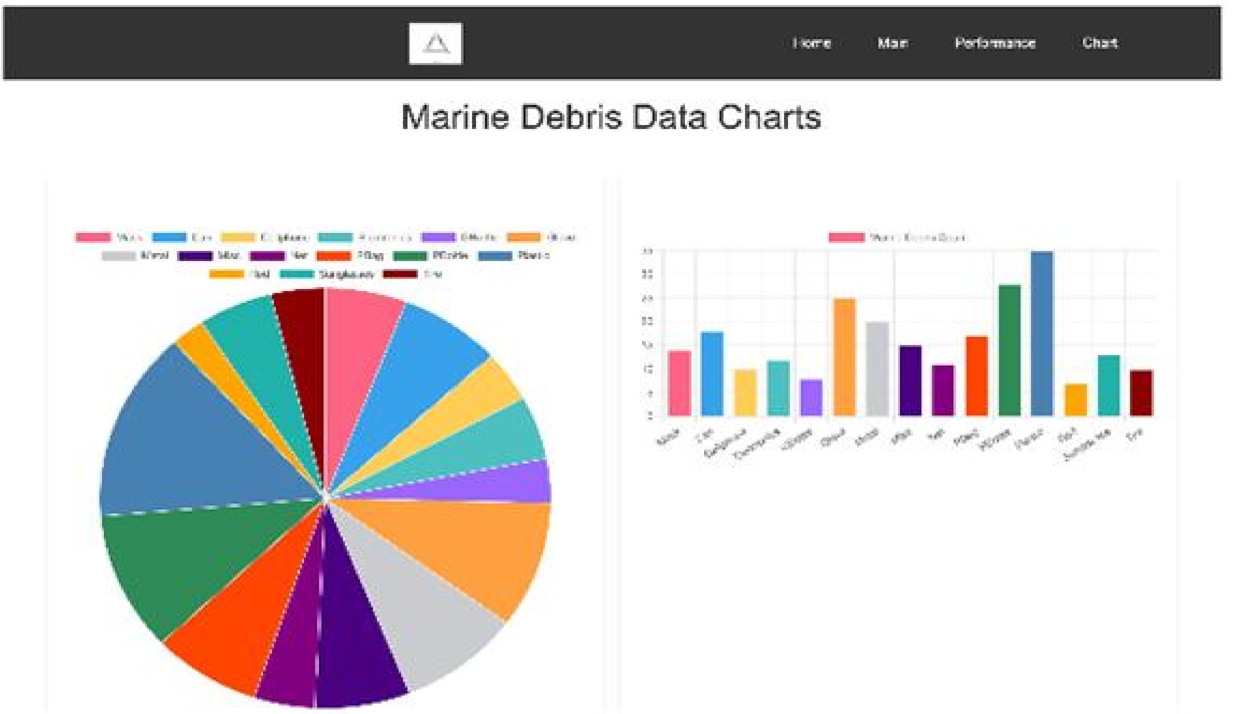

Fig 6: Debris detection dashboard

VI. CONCLUSION

In conclusion, the proposed YOLOv10-based underwater marine debris detection system offers an effective, efficient, and scalable approach to tackling the growing issue of marine pollution by enabling early and accurate identification of underwater waste. By combining advanced deep learning methods, image preprocessing techniques, and real-time detection pipelines, the system overcomes the shortcomings of conventional manual and vision-based approaches, especially in challenging underwater conditions such as low visibility and murky environments. Leveraging the strengths of the YOLOv10 architecture its lightweight structure, high processing speed, and strong detection accuracy the system achieves an optimal balance between performance and computational efficiency, making it well-suited for deployment on resource-limited platforms like AUVs, IoT devices, and underwater drones.

VII. FUTURE ENHANCEMENT

In the future, the system can be enhanced to support multiple types of debris , cross-platform analysis, and real-time integration, real time autonomous deployment , integration with sonar and sensor , cloud based monitoring and analytics.

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