Underwater Net: Efficient Visual Detection Of Marine Garbage For Eco Monitoring

Mr.CH.Gopi[1] ,A.Manogna[2], G.Dheeraj Narasimha[3], K.Archana[4]

[1]Assistant Professor; Department Of Information Technology Guru Nanak Institutions Technical Campus, Hyderabad, India

[2,3,4]B.Tech Students; Department Of Information Technology Guru Nanak Institutions Technical Campus, Hyderabad, India

Mail Id; Dheerajgaddam11@gmail.com[3]

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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.

Keywords— *Marine Pollution, YOLOv10n, Underwater Garbage Detection, Object Detection, Deep Learning, IoT, Real-Time Monitoring, Underwater Robotics.*

Introduction

Marine pollution caused by the accumulation of underwater debris has emerged as a significant environmental concern, threatening aquatic ecosystems, marine biodiversity, and the sustainability of the blue economy. Plastic waste, metal fragments, and other submerged materials negatively impact marine organisms and disrupt natural habitats. Therefore, accurate detection and monitoring of underwater garbage are essential for enabling timely intervention and promoting sustainable marine management. However, identifying underwater debris in real time remains challenging due to complex environmental factors such as poor visibility, varying illumination, water turbidity, and background clutter. These challenges are further intensified when deploying detection systems on edge devices, including underwater drones and IoT-based cameras, which have limited computational and energy resources.

Traditional deep learning–based object detection models provide high accuracy but often require substantial computational power and memory. Although earlier lightweight frameworks attempted to reduce complexity by integrating compact backbones and attention mechanisms, their deployment on ultra-constrained hardware still posed limitations. To address these issues, this project proposes an efficient underwater garbage detection system based on the YOLOv10n architecture, which represents a nano version of the YOLOv10 family. YOLOv10n is specifically designed for low-resource environments while maintaining competitive detection performance. By adopting this lightweight architecture, the proposed system achieves real-time detection with reduced latency, lower energy consumption, and minimal memory usage. Consequently, the system becomes suitable for scalable deployment in real-world marine environments using embedded and mobile platforms.

Scope of the Project

The scope of this project focuses on the development of a lightweight and real-time underwater garbage detection system using the YOLOv10n object detection algorithm. The system is intended for deployment on low-power IoT devices, underwater robotic platforms, and edge computing units operating in marine environments. By targeting underwater debris detection, the proposed solution contributes to environmental monitoring, pollution assessment, and marine conservation activities. The system is capable of

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identifying various categories of underwater waste, including plastic materials, metallic objects, and organic debris. This capability allows environmental agencies and researchers to monitor pollution levels efficiently and respond promptly to contamination threats.Furthermore, the compact design of the YOLOv10n model enables deployment in scenarios with limited computational resources and strict energy constraints. This improves scalability and supports long-term ecological monitoring. The system can also be integrated with autonomous underwater vehicles, drones, or stationary monitoring devices, thereby enabling continuous observation and supporting automated cleanup operations. Overall, the project offers a practical solution for sustainable marine ecosystem management through intelligent and lightweight detection mechanisms.

Objective

The main objective of this project is to design and implement an efficient and lightweight underwater garbage detection system using the YOLOv10n object detection framework. The system aims to accurately detect and classify various types of marine debris in real time, even when deployed on resource-constrained platforms such as IoT-enabled underwater drones and edge devices. Another key objective is to reduce computational complexity and model size while preserving high detection accuracy. By leveraging the optimized architecture of YOLOv10n, the project seeks to achieve faster inference and lower energy consumption. Ultimately, the proposed system supports sustainable marine ecosystem management by enabling rapid pollution identification, assisting cleanup operations, and protecting aquatic biodiversity.

Existing System

Existing approaches for underwater debris detection primarily rely on manual inspection, sonar-based imaging, or conventional computer vision techniques that utilize handcrafted features. These methods are often labor-intensive, time-consuming, and prone to human error. Moreover, underwater environments introduce additional challenges such as reduced visibility, uneven lighting, and complex backgrounds, which significantly affect detection reliability. As a result, traditional approaches struggle to provide consistent and accurate identification of marine debris.

Recent developments in deep learning have introduced object detection models such as Faster R-CNN, SSD, and various versions of YOLO for automated marine debris detection. These models demonstrate improved performance compared to traditional techniques; however, they typically require high computational resources and large memory capacity. Such requirements limit their applicability in real-time scenarios involving embedded systems or battery-powered underwater devices. Although lightweight models like YOLOv5 and YOLOv8 offer improved speed, achieving an optimal balance between accuracy and efficiency remains difficult. Some modified architectures attempted to reduce model size by incorporating mobile backbones and attention mechanisms, but these solutions still require further optimization for practical deployment. Therefore, there is a need for a more efficient and lightweight system tailored specifically for underwater garbage detection.

Literature Survey

Several studies have explored deep learning techniques for underwater debris detection and related applications. A framework known as MLDet introduced an efficient deep learning approach for marine litter detection by combining lightweight convolutional backbones with refined anchor mechanisms and attention modules. Research on underwater image enhancement has also contributed to improving detection performance. An improved inverted residual network model was developed to enhance underwater image clarity by reducing haze and color distortion. The model achieved better image quality, thereby improving downstream detection tasks. Additionally, lightweight detection frameworks developed for industrial applications introduced techniques such as Ghost convolution and feature enhancement modules, which significantly reduced computational cost while maintaining accuracy. These concepts are applicable to underwater detection systems requiring low-latency performance. Furthermore, decentralized federated learning frameworks have been proposed to improve collaboration among edge devices. Although primarily designed for AIoT environments, such approaches can be adapted for distributed underwater monitoring systems to enhance scalability and reliability.

Proposed System

The proposed system introduces an advanced underwater garbage detection approach based on the YOLOv10n architecture. Unlike previous lightweight models that rely on custom modifications, YOLOv10n incorporates built-in optimization strategies for computational efficiency and reduced parameter count. This architecture enables accurate and fast detection while maintaining a small model size, making it suitable for deployment on IoT devices and underwater robots. The model utilizes an optimized backbone and detection head designed for real-time performance. These components enhance feature extraction and improve detection accuracy, particularly for small and overlapping objects commonly observed in underwater environments.

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The system is trained using an underwater garbage dataset and evaluated to achieve a balance between speed, accuracy, and computational efficiency. Compared to earlier frameworks, the proposed YOLOv10n-based approach simplifies architecture design and eliminates the need for additional attention modules. This results in improved deployment efficiency and adaptability to different underwater conditions, including low-light and murky water scenarios. The solution supports edge AI deployment on compact hardware platforms such as embedded computing boards and low-power devices. Consequently, the proposed system offers a scalable and practical solution for autonomous marine monitoring and pollution control.

PROJECT DESCRIPTION

Marine pollution caused by floating and submerged debris presents a serious challenge to marine ecosystems, fisheries, and coastal economies. Detecting and classifying marine litter using automated systems can significantly improve monitoring and cleanup efficiency. This project focuses on developing a deep learning–based marine debris detection system capable of identifying various types of waste from underwater and surface-level imagery. The system leverages modern object detection architectures and lightweight neural network designs to achieve both high accuracy and computational efficiency.

The model is trained using annotated datasets containing different categories of marine debris such as plastics, metals, fishing nets, and organic materials. Advanced computer vision techniques, including convolutional neural networks, feature pyramid networks, and attention-based feature enhancement, are utilized to improve detection performance in complex underwater conditions. Evaluation metrics such as precision, recall, F1-score, and inference speed are used to measure system performance. Additionally, the project emphasizes lightweight model deployment for embedded platforms such as underwater robots, IoT devices, and unmanned aerial vehicles. The proposed solution contributes to global marine conservation efforts by enabling automated pollution monitoring and supporting sustainable ocean management.

Methodologies

Modules

The proposed system consists of multiple functional modules including input data acquisition, preprocessing, segmentation, feature extraction, detection, and output visualization. These modules work sequentially to ensure efficient marine debris detection.

Module Description

The input data module is responsible for collecting images from underwater cameras, drones, and publicly available datasets. The module supports diverse environmental conditions, including low-light scenarios, surface reflections, and varying water clarity. This ensures the system is trained on diverse real-world data and improves generalization capability.The segmentation module focuses on separating potential debris from the background. Clustering-based segmentation methods help isolate objects such as plastic bottles, bags, and fishing nets even in cluttered environments. This improves the model's ability to focus on relevant regions within the image.The feature extraction module utilizes convolutional layers combined with attention mechanisms to capture essential visual patterns such as edges, textures, and shapes. These features enable accurate differentiation between marine debris and natural underwater elements such as rocks or vegetation. The extracted features are then forwarded to the detection network.The detection module employs the YOLOv10n architecture for real-time object detection. The lightweight model visualization module displays the detection results by overlaying bounding boxes and confidence scores on the input image. The results can be visualized in real-time video streams or stored for further analysis. This module assists users in monitoring pollution levels and supports decision-making for cleanup operations.

Technique Used

Existing Technique

Traditional underwater debris detection methods rely heavily on manual observation, sonar imaging, or classical image processing techniques based on handcrafted features. These approaches are inefficient and often produce inconsistent results due to environmental challenges such as poor visibility and background complexity. To address these limitations, deep learning–based object detection models such as Faster R-CNN, SSD, and YOLO variants have been introduced. These models provide improved detection accuracy but require substantial computational resources.

Although lightweight versions such as YOLOv5 and YOLOv8 reduce inference time, they still struggle to balance efficiency and accuracy on low-power devices. Some research introduced modified architectures with mobile backbones and attention modules to reduce complexity. However, these models often depend on custom components and lack optimization for real-time embedded deployment. As a result, existing approaches remain unsuitable for resource-constrained underwater monitoring systems.

Drawbacks of Existing Techniques

Existing systems exhibit limited real-time capability on low-power devices, dependency on customized

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architectures, sensitivity to dataset variations, and lack of optimized post-processing mechanisms. These factors reduce performance in real-world deployment scenarios.

Proposed Technique

The proposed system utilizes YOLOv10n, a nano-scale version of the YOLOv10 architecture designed specifically for efficient real-time object detection. YOLOv10n incorporates a redesigned backbone, improved feature pyramid structure, and decoupled detection heads that enhance feature reuse and gradient propagation. Despite its compact size, the model maintains competitive detection accuracy.

The lightweight nature of YOLOv10n significantly reduces computational overhead, making it suitable for deployment on embedded and IoT-based underwater devices. The architecture eliminates the need for additional attention modules while achieving robust detection performance. This enables faster inference, reduced power consumption, and efficient deployment in marine environments.

REQUIREMENTS ENGINEERING

Requirement engineering defines the functional and operational needs of the proposed system. The system is designed to achieve high detection accuracy while maintaining computational efficiency. Experimental observations indicate that the model achieves competitive performance compared to existing approaches, demonstrating strong classification capability and reliable detection accuracy across datasets.

Hardware Requirements

The hardware configuration required for implementing the proposed system includes a dual-core processor, minimum 4 GB RAM, and at least 250 GB storage. These specifications are sufficient for model training, testing, and deployment. The system can also be extended to embedded hardware such as edge computing devices for real-time inference.

Software Requirements

The software environment consists of a Windows-based operating system, Python programming language, and development platforms such as Jupyter Notebook or Spyder IDE. Required libraries include deep learning frameworks and image processing tools. These software components provide flexibility for model training, evaluation, and deployment.

Functional Requirements

The system should accept input images or video streams, preprocess the data, detect marine debris, classify detected objects, and display results with bounding boxes and confidence scores. The system should also store detection outputs for further analysis and support real-time monitoring functionality.

DESIGN ENGINEERING

Design engineering defines the structural and behavioral representation of the proposed system using UML diagrams. These diagrams help visualize system architecture, module interactions, and workflow processes. The design phase translates system requirements into a structured representation that guides implementation.

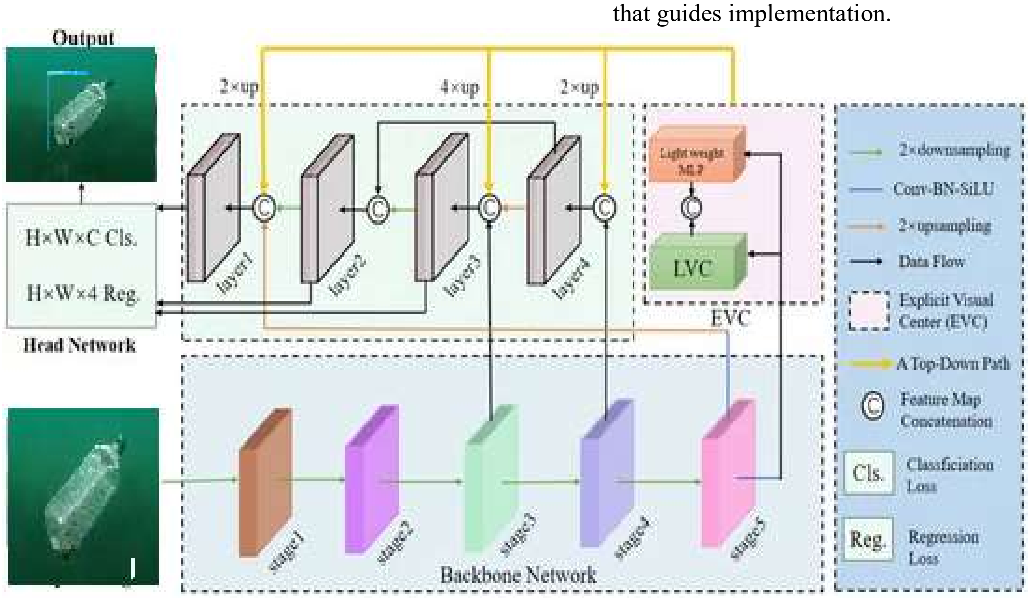

Fig 1; System Architecture

UML Diagrams

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The system design is represented using standard UML diagrams including use case, class, object, state, activity, sequence, collaboration, component, deployment, and data flow diagrams. The use case diagram illustrates interactions between the user and the system. The class diagram defines classes, attributes, and methods involved in the detection pipeline. The object diagram represents relationships among system objects during execution.

The state diagram describes different operational states such as input processing, detection, and output generation. The activity diagram shows workflow steps from data acquisition to result visualization. The sequence diagram explains message flow between modules during detection. The collaboration diagram illustrates communication among system components.The component diagram highlights modular architecture, including preprocessing, detection, and visualization components. The data flow diagram represents movement of data across modules, while the deployment diagram shows hardware and software mapping. These diagrams collectively define the architecture of the marine debris detection system.

SOFTWARE TESTING

Software testing plays a critical role in ensuring the reliability and correctness of the proposed underwater garbage detection system. The primary objective of testing is to identify defects and verify that the developed application performs according to specified requirements. Testing involves evaluating individual modules, integrated components, and the complete system to confirm functional correctness and operational stability. Through systematic validation, the testing process ensures that the software meets user expectations, produces accurate detection results, and performs consistently under different environmental conditions. Various testing strategies are employed to examine different aspects of system performance and functionality.

Developing Methodologies

The testing process begins with the creation of a comprehensive test plan designed to evaluate both general functionality and specific features of the system. The plan includes testing across different datasets, input conditions, and deployment scenarios. Quality assurance procedures are applied throughout the testing phase to ensure the model meets the requirements specified in the system design. The testing framework verifies detection accuracy, computational efficiency, and system responsiveness. These methodologies ensure that the application remains stable, efficient, and reliable for real-time marine monitoring.

Types of Tests

Unit Testing

Unit testing is performed to validate the functionality of individual modules such as preprocessing, feature extraction, detection, and visualization. Each module is tested independently to ensure correct input-output behavior. This testing verifies internal logic, data flow, and algorithm execution. By isolating modules, unit testing helps identify errors at an early stage, improving system robustness.

Functional Testing

Functional testing evaluates whether the system operates according to defined functional requirements. This includes verifying valid inputs, handling invalid data, executing detection functions, and generating appropriate outputs. The testing process ensures that the system correctly detects marine debris, classifies objects, and displays bounding boxes with confidence scores. Interaction between modules is also validated during functional testing.

System Testing

System testing is conducted after integrating all modules to verify complete system functionality. This testing evaluates the end-to-end workflow, including image input, preprocessing, detection, and output visualization. The objective is to ensure that the integrated system produces reliable and consistent results under different input conditions.

Performance Testing

Performance testing measures system efficiency in terms of response time, detection speed, and computational overhead. The evaluation ensures that the system produces outputs within acceptable time limits and supports real-time deployment. Metrics such as inference time, frame processing rate, and memory usage are considered during performance evaluation.

Future Enhancements

The proposed marine debris detection system can be extended in several directions to improve performance and practical applicability. Future work may include integration with autonomous underwater vehicles and aerial drones for large-scale ocean monitoring. Such integration would enable continuous data collection across coastal and offshore regions. Additionally, deploying optimized lightweight variants of object detection models on edge devices can further improve detection speed and energy efficiency.

The system may also be enhanced by incorporating multi-modal sensing technologies such as sonar, infrared imaging, or LiDAR. These additional data sources can improve detection performance in challenging underwater conditions including low visibility and turbid water. Integration with geographic information systems and IoT platforms can support visualization of pollution hotspots and

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enable predictive analytics for long-term monitoring.

Another potential improvement involves combining the detection system with robotic cleanup mechanisms. Autonomous robots equipped with manipulators could collect detected debris, enabling an end-to-end automated monitoring and cleanup pipeline. These enhancements would contribute to scalable marine conservation solutions and support decision-making for environmental protection.

Conclusion

This project presents an efficient underwater garbage detection system based on the YOLOv10n architecture. The proposed approach addresses the challenges of marine pollution by enabling accurate and real-time detection of underwater debris. The lightweight design of YOLOv10n reduces computational complexity while maintaining strong detection performance, making the system suitable for deployment on resource-constrained devices.

The developed system demonstrates the effectiveness of deep learning techniques in environmental monitoring applications. By combining efficient architecture design with real-time detection capability, the solution supports automated marine pollution monitoring. The system is scalable, adaptable to various underwater conditions, and capable of assisting cleanup operations. Overall, this work contributes to sustainable marine ecosystem management and highlights the potential of intelligent automation for protecting aquatic biodiversity.

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