

Under Water 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 global blue economy. The accumulation of underwater debris such as plastics, fishing nets, and industrial waste has significantly impacted marine biodiversity and environmental health. Effective detection and classification of such debris are essential for enabling timely intervention and supporting large-scale marine conservation efforts.

In this work, we propose an advanced underwater garbage detection system based on YOLOv10n, a state-of-the-art lightweight object detection model optimized for resource-constrained environments such as IoT devices and underwater robotic platforms. Unlike traditional object detection models that rely on computationally intensive backbones such as CSPDarknet, the proposed system leverages the efficient architecture of YOLOv10n to reduce model complexity while maintaining high detection accuracy.

The proposed model emphasizes low parameter count, reduced inference latency, and real-time processing capability, making it highly suitable for deployment on embedded systems. Experimental results demonstrate that the system achieves robust and precise detection of underwater debris under challenging conditions such as low visibility, color distortion, and dynamic backgrounds. Furthermore, the reduced memory footprint and computational requirements enable scalable deployment across multiple platforms, including Autonomous Underwater Vehicles (AUVs) and edge devices.

This research highlights the feasibility of integrating lightweight deep learning models into marine monitoring systems and provides a practical, cost-effective, and eco-friendly solution to combat marine pollution through intelligent automation.

Keywords

Underwater Garbage Detection, Marine Pollution, YOLOv10n, Object Detection, Deep Learning, Computer Vision, IoT, Edge Computing, Autonomous Underwater Vehicles (AUVs), Real-Time Detection, Lightweight Models, Environmental Monitoring

INTRODUCTION

Marine pollution has become one of the most critical environmental challenges of the 21st century, posing a significant threat to aquatic ecosystems, marine biodiversity, and human health. The rapid increase in plastic waste, abandoned fishing gear, and industrial discharge has resulted in the accumulation of large volumes of debris in oceans, rivers, and coastal regions. These pollutants not only disrupt marine habitats but also enter the food chain, leading to long-term ecological and economic consequences.

Traditional underwater monitoring techniques, including manual inspection and sonar-based detection systems, are limited in efficiency, scalability, and accuracy. Manual methods are labor-intensive, time-consuming, and prone to human error,

while sonar systems often lack the precision required for accurate classification of debris. Additionally, the underwater environment presents unique challenges such as poor visibility, light attenuation, scattering effects, and complex backgrounds, which further complicate detection tasks.

Recent advancements in computer vision and deep learning have revolutionized object detection by enabling automated and real-time analysis of visual data. Among these, the YOLO (You Only Look Once) family of models has gained widespread attention due to its ability to perform high-speed object detection with competitive accuracy. However, earlier YOLO models rely on computationally heavy architectures such as CSPDarknet, making them unsuitable for deployment on resource-constrained devices.

To overcome these limitations, this research proposes an efficient underwater garbage detection system using YOLOv10n, the nano variant of the YOLOv10 architecture. YOLOv10n is specifically designed to achieve a balance between accuracy and efficiency by reducing model parameters and optimizing computational operations. This makes it highly suitable for real-time applications on embedded and edge devices.

The primary objective of this work is to develop a robust, lightweight, and scalable system capable of detecting and classifying underwater debris in real time. By leveraging the advantages of YOLOv10n, the proposed system ensures reduced computational cost, faster inference speed, and improved adaptability to challenging underwater conditions. This contributes to the development of intelligent marine monitoring systems that support sustainable environmental management and conservation efforts.

LITERATURE SURVEY

The detection of underwater debris has been extensively studied, with various approaches proposed to address the inherent challenges of the marine environment. Early research primarily focused on traditional image processing techniques, including edge detection, thresholding, color segmentation, and feature-based methods. While these approaches were computationally efficient, they were highly sensitive to environmental variations such as illumination changes, turbidity, and noise, resulting in poor detection accuracy.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have significantly improved object detection capabilities. Region-based models such as R-CNN, Fast R-CNN, and Faster R-CNN introduced the concept of region proposal networks, achieving high detection accuracy. However, these models are computationally expensive and exhibit high latency, making them unsuitable for real-time underwater applications.

The introduction of single-stage detectors, particularly the YOLO (You Only Look Once) framework, marked a major breakthrough in real-time object detection. Models such as YOLOv3 and YOLOv4 improved detection accuracy while maintaining high processing speeds. YOLOv5 further enhanced performance through improved architecture design and ease of implementation. Despite these advancements, the reliance on complex backbones like CSPDarknet increases computational requirements, limiting their applicability in embedded systems.

To address these limitations, researchers have explored lightweight architectures such as MobileNet,

EfficientNet, and hybrid models combining YOLO with attention mechanisms. For instance, the YOLO-MES model integrates MobileNetV3 as a backbone and employs Efficient Channel Attention (ECA) to improve feature representation. While these approaches reduce model size and enhance performance, they often introduce additional architectural complexity and may still require optimization for real-world deployment.

Recent developments have focused on designing highly efficient object detection models with minimal computational overhead. The YOLOv10 architecture represents a significant advancement in this direction, offering improved efficiency, reduced latency, and enhanced feature extraction capabilities. The YOLOv10n variant, in particular, is optimized for low-resource environments, achieving competitive accuracy with a significantly smaller model size.

In addition to model development, several studies have emphasized the importance of data preprocessing techniques, including image enhancement, contrast adjustment, and data augmentation, to improve detection performance in underwater conditions. Transfer learning has also been widely adopted to address the challenge of limited labeled datasets.

Despite these advancements, challenges such as limited availability of high-quality underwater datasets, environmental variability, and real-time deployment constraints persist. The proposed system addresses these issues by leveraging the optimized architecture of YOLOv10n to achieve an effective balance between detection accuracy and computational efficiency, making it a practical solution for large-scale underwater garbage detection.

EXISTING SYSTEM

The current methods for detecting underwater debris primarily rely on manual surveillance, sonar imaging, and traditional computer vision techniques based on handcrafted features. These approaches are often time-consuming, labor-intensive, and prone to human error. Additionally, underwater environments introduce challenges such as low visibility, inconsistent lighting conditions, and complex backgrounds, which significantly reduce detection accuracy and reliability. To improve performance, deep learning-based object detection models such as **Faster R-CNN**, **SSD**, and **YOLO (You Only Look Once)** variants (YOLOv3, YOLOv4, YOLOv5) have been introduced. These models provide better accuracy and robustness compared to conventional techniques. However, they are computationally intensive, require large memory, and exhibit high inference latency, making them unsuitable for deployment on embedded or battery-

powered underwater devices like Autonomous Underwater Vehicles (AUVs), drones, and buoy-based systems.

Even relatively efficient models like YOLOv5 and YOLOv8 struggle to maintain an optimal balance between accuracy and computational efficiency in resource-constrained environments. To address this,

some research introduced modified architectures such as YOLO-MES, which incorporates lightweight backbones like MobileNet and attention mechanisms. While these improvements reduce model size and enhance feature extraction, they still require further optimization for real-world deployment in marine environments.

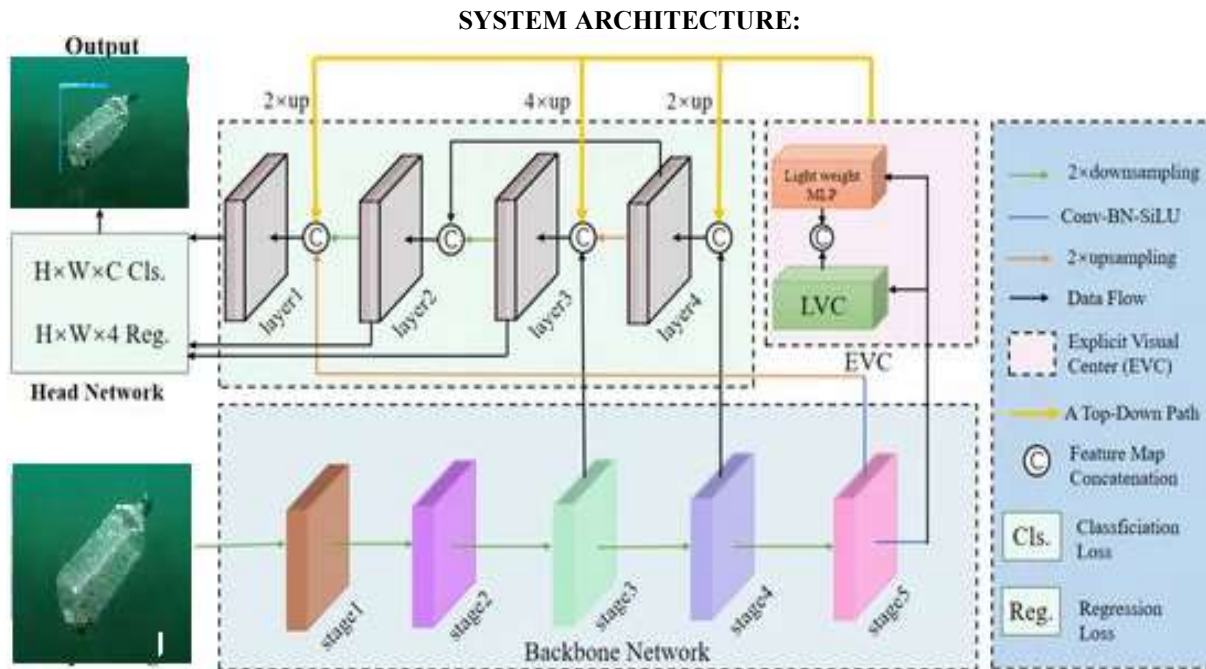


Fig - proposed model
MINIMUM SYSTEM REQUIREMENTS
HARDWARE REQUIREMENTS

- PROCESSOR : Pentium i3 Processor
- RAM : 4GB DD RAM
- HARD DISK : 450 GB

SOFTWARE REQUIREMENTS

- BACK END : PYTHON
- OPERATING SYSTEM : WINDOWS 10
- IDE ; Spyder3

PROPOSED SYSTEM

The proposed system enhances underwater garbage detection using YOLOv10n, an ultra-lightweight and efficient object detection model specifically designed for real-time applications on resource-constrained devices.

Unlike existing approaches such as YOLO-MES, which rely on MobileNet-based backbones and additional attention mechanisms, YOLOv10n integrates advanced architectural optimizations that

inherently improve computational efficiency. This eliminates the need for complex modifications while achieving high detection accuracy with significantly reduced memory and processing requirements.

YOLOv10n incorporates a streamlined backbone, an optimized feature pyramid network, and decoupled detection heads. These features enable efficient feature extraction and improved detection of small, overlapping, and cluttered objects—common challenges in underwater environments. The model is

also designed to handle adverse conditions such as murky water, low lighting, and motion blur with minimal pre-processing.

The system has been trained and evaluated on underwater garbage datasets, demonstrating an effective balance between speed, accuracy, and model size. Compared to existing solutions, the proposed approach offers:

- Faster inference suitable for real-time applications
- Lower computational and memory requirements
- Simplified architecture without additional attention modules
- High adaptability for deployment on edge devices

This makes the system ideal for integration with embedded platforms such as Raspberry Pi, NVIDIA Jetson, and underwater robotic systems, enabling scalable and energy-efficient marine monitoring.

EXISTING ALGORITHM: YOLO-MES

Algorithm Definition

The existing system utilizes **YOLO-MES (You Only Look Once with MobileNet and Efficient Channel Attention for Slim-neck)**, a modified version of the YOLO architecture tailored for underwater object detection.

YOLO-MES replaces the traditional CSPDarknet backbone with **MobileNetV3**, significantly reducing model size and improving computational efficiency. Additionally, it introduces the **MECAneck module**, which integrates MobileNet bottleneck layers with the **Efficient Channel Attention (ECA)** mechanism.

This design enhances the model's ability to capture cross-channel dependencies and improves feature representation, particularly for small and densely packed objects in underwater scenes. As a result, YOLO-MES achieves better accuracy than standard lightweight models while maintaining a relatively low parameter count.

However, the inclusion of attention modules and custom neck structures increases architectural complexity and may still limit deployment efficiency on highly constrained devices.

PROPOSED ALGORITHM: YOLOv10n

Algorithm Definition

The proposed system employs **YOLOv10n**, the nano variant of the YOLOv10 family, designed for high efficiency and real-time object detection on edge devices.

YOLOv10n introduces a redesigned backbone architecture, an improved feature pyramid network,

and decoupled detection heads. These enhancements enable better feature reuse, improved gradient flow, and more accurate object localization.

Despite its compact size and low computational requirements, YOLOv10n maintains competitive detection accuracy. It eliminates the need for additional attention mechanisms or complex architectural modifications, resulting in a simpler and more deployable model.

Key advantages of YOLOv10n include:

- Extremely lightweight architecture
- Reduced latency for real-time inference
- Efficient handling of small and overlapping objects
- Suitability for deployment on IoT and embedded systems

Overall, YOLOv10n provides an optimal balance between performance and efficiency, making it a highly effective solution for underwater garbage detection in real-world marine environments.

CONCLUSION

Marine pollution remains a pressing global challenge, demanding efficient and scalable solutions for monitoring and mitigation. In this project, an advanced underwater garbage detection system based on YOLOv10n has been successfully developed to address the limitations of traditional and existing deep learning approaches.

The proposed system demonstrates that lightweight object detection models can achieve high accuracy while significantly reducing computational complexity. By leveraging the optimized architecture of YOLOv10n, the system effectively detects and classifies underwater debris in real time, even under challenging environmental conditions such as low visibility, varying lighting, and background noise.

Compared to existing models like YOLO-MES and other YOLO variants, the proposed approach offers a better balance between speed, accuracy, and resource efficiency. Its low memory footprint and reduced inference latency make it highly suitable for deployment on embedded systems and IoT-based underwater platforms, including Autonomous Underwater Vehicles (AUVs) and edge devices.

Overall, this work highlights the feasibility of using advanced lightweight deep learning models for real-world marine monitoring applications. The system provides a scalable, cost-effective, and eco-friendly solution for underwater pollution detection, contributing to the protection of marine ecosystems and supporting sustainable development of the blue economy.

Future work can focus on expanding the dataset, improving detection under extreme underwater conditions, and integrating the system with autonomous robotic platforms for fully automated debris collection and monitoring.

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