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Full Length Article

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 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, Underwater Garbage Detection, YOLOv10n, Object Detection, Deep Learning, IoT, Edge Devices, Marine Monitoring*

INTRODUCTION

Marine pollution, particularly due to the accumulation of underwater garbage, has emerged as a significant threat to aquatic ecosystems, biodiversity, and the sustainability of the blue economy. The increasing presence of plastic, metal, and other debris in oceans not only disrupts marine life but also affects human activities such as fishing and tourism. Therefore, effective detection and monitoring of underwater waste have become essential for supporting environmental conservation and sustainable marine development.

Traditional approaches for detecting underwater debris primarily rely on manual inspection, sonar imaging, or conventional computer vision techniques. These methods are often time-consuming, labor-intensive, and prone to inaccuracies due to the complex underwater environment, which includes challenges such as low visibility, varying lighting conditions, and background noise. As a result, these approaches are not suitable for large-scale or real-time monitoring applications.

With the advancement of deep learning, object detection models such as Faster R-CNN, SSD, and various versions of YOLO have been applied to automate debris detection. While these models improve detection accuracy, they typically involve high computational complexity and large model sizes, making them unsuitable for deployment on resource-constrained devices like underwater drones and IoT-enabled systems. To address these limitations, this research proposes an efficient and lightweight underwater garbage detection system based on YOLOv10n. The YOLOv10n model is specifically designed to achieve a balance between accuracy and computational efficiency, enabling real-time detection with reduced memory usage and processing requirements. This makes it highly suitable for deployment in embedded and edge computing environments.

The proposed system aims to detect and classify different types of underwater debris in real time, thereby supporting automated marine monitoring and pollution control. By leveraging the capabilities of YOLOv10n, the system provides a scalable and practical solution for intelligent underwater waste detection, contributing to the protection and sustainability of marine ecosystems.

OBJECTIVES AND SCOPE

The primary objective of this research is to design and develop an efficient, lightweight, and accurate underwater garbage detection system using the YOLOv10n object detection algorithm. The system aims to enable real-time detection and classification of various types of marine debris, including plastic, metal, and organic waste, even in resource-constrained environments.

- Another key objective is to reduce computational complexity and model size while maintaining high detection accuracy. This is achieved by leveraging the optimized architecture of YOLOv10n, which is specifically designed for deployment on edge devices such as IoT-enabled underwater cameras and autonomous drones.

Furthermore, the system seeks to support environmental monitoring and marine conservation efforts by providing an automated and scalable solution for detecting underwater pollution. The proposed approach aims to facilitate faster decision-making and targeted cleanup operations, contributing to the protection of aquatic ecosystems..

- The scope of this research focuses on the development and implementation of a real-time underwater garbage detection system using deep learning techniques. The system is designed to operate on low-power embedded devices, making it suitable for deployment in underwater drones, IoT platforms, and edge computing environments.
- This work primarily addresses the detection and classification of underwater debris using image-based data. It considers various environmental challenges such as low visibility, lighting variations, and complex backgrounds commonly found in underwater scenarios.
- Additionally, the proposed system is intended to support large-scale marine monitoring applications by enabling continuous and automated detection of pollution. The use of a lightweight model like YOLOv10n ensures scalability and adaptability for real-world deployment, including long-term ecological studies and autonomous cleanup systems.

LITERATURE REVIEW

A. Theoretical Background and Key Concepts

Marine pollution caused by underwater debris has become a critical environmental concern, affecting aquatic ecosystems and biodiversity. Detecting such debris requires robust computer vision techniques capable of handling complex underwater conditions such as low visibility, color distortion, and dynamic backgrounds.

Deep learning, particularly convolutional neural networks (CNNs), has emerged as a powerful approach for object detection tasks. Models such as the YOLO (You Only Look Once) family enable real-time detection by processing images in a single forward pass. These models are widely used due to their balance between speed and accuracy. However, deploying such models in underwater environments introduces additional challenges related to computational efficiency and hardware limitations.

Lightweight architectures are therefore essential for enabling deployment on edge devices such as underwater drones and IoT-based monitoring systems. The concept of optimizing model size while maintaining detection accuracy forms the foundation of modern real-time object detection systems used in marine applications [1], [2].

B. Review of Related Work and Existing Models

Several research efforts have focused on improving underwater object detection and image enhancement techniques.

The study MLDet proposes an efficient deep learning model for marine litter detection using lightweight convolutional backbones and attention mechanisms. It improves detection accuracy while maintaining real-time performance, making it suitable for edge deployment [1].

UTD-YOLO enhances the YOLOv5 model by addressing underwater challenges such as lighting variation and color distortion. It introduces adaptive feature fusion and optimized anchor settings, resulting in improved detection performance across various datasets [2].

DIRBW-Net focuses on underwater image enhancement by reducing noise, blur, and color degradation. This preprocessing step significantly improves the quality of input images, thereby enhancing detection accuracy in subsequent stages [3].

EFS-YOLO introduces a lightweight detection model using Ghost Convolution and feature enhancement modules. Although developed for industrial applications, its efficiency makes it applicable to underwater detection scenarios [4].

Additionally, SRFL presents a federated learning framework for distributed AIoT systems, improving scalability and energy efficiency. This approach can be extended to collaborative underwater monitoring systems involving multiple devices [5].

Despite these advancements, many existing approaches still face limitations in balancing computational efficiency and detection accuracy, especially in real-time underwater applications.

C. Research Direction

The analysis of existing literature indicates a clear need for a unified approach that combines high detection accuracy with low computational complexity. Most current models either achieve high accuracy at the cost of heavy computation or provide lightweight solutions with reduced performance.

To address these limitations, this research focuses on implementing YOLOv10n, a lightweight and efficient object detection model specifically designed for real-time applications. The proposed system aims to achieve accurate detection of underwater garbage while minimizing resource consumption, making it suitable for deployment on edge devices.

By integrating efficient detection techniques with optimized model architecture, this work contributes toward developing a scalable and practical solution for underwater garbage monitoring and environmental sustainability.

SYSTEM ARCHITECTURE

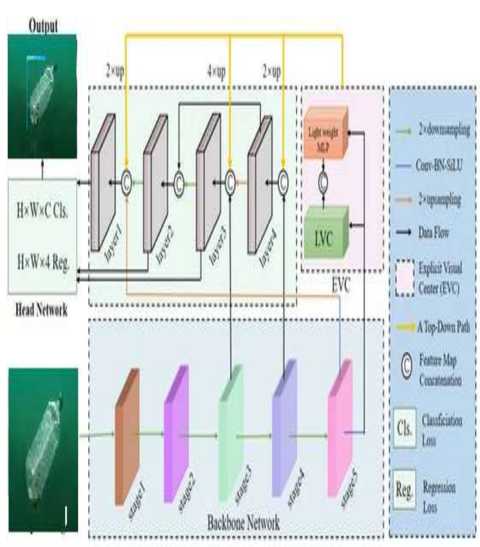


Fig. 1. System Architecture of Marine Garbage Detection.

The proposed architecture follows a multi-scale feature extraction and fusion strategy designed for efficient and accurate underwater garbage detection. It consists of three major components: the Backbone Network, the Explicit Visual Center (EVC) module, and the Head Network

A. Backbone Network

The backbone network is responsible for extracting hierarchical feature representations from the input image. It is composed of multiple sequential stages (Stage 1 to Stage 5), where each stage performs: Convolution + Batch Normalization + SiLU activation (Conv-BN-SiLU) Downsampling operations to reduce spatial dimensions and increase receptive field References.

B. Feature Aggregation and Top-Down Path

To effectively utilize multi-scale information, the architecture employs a top-down feature pyramid mechanism: Feature maps from deeper layers are upsampled (2×, 4×) These are then concatenated (C) with corresponding shallow featuresThis fusion enhances both spatial detail and semantic richness

C. Explicit Visual Center (EVC) Module

A key innovation in the architecture is the Explicit Visual Center (EVC) module, which enhances feature representation by focusing on important object regions.

The EVC consists of: Lightweight MLP (Multi-Layer Perceptron): Captures global contextual relationships

LVC (Local Visual Component): Focuses on local spatial features.

This combination allows the model to:

Balance global context awareness and local feature precision

Improve detection accuracy in complex underwater scenes with noise and distortions

D. Head Network

The head network performs the final prediction using fused feature maps. It includes multiple detection layers that output:

Classification (Cls): Identifies object categories (e.g., plastic, metal waste)

Regression (Reg): Predicts bounding box coordinates

The outputs are defined as:

H×W×C for classification

H×W×4 for bounding box regression

This design enables real-time object detection with high precision

E. Data Flow and Operations

The overall data flow can be summarized as:
Input image → Backbone feature extraction

ALGORITHM 1 – Underwater Garbage Detection using YOLOv10n

Input:
Underwater image dataset DDD
Output:
Detected garbage objects with bounding boxes and class labels

1. Initialize the YOLOv10n detection model.
2. Collect underwater images from dataset or real-time camera input.
3. Perform data preprocessing:
   3.1 Apply noise reduction.
   3.2 Enhance contrast using histogram equalization.
   3.3 Normalize image size.
4. Input the preprocessed image into the backbone network.
5. Extract hierarchical features using convolutional layers across multiple stages.
6. Apply downsampling operations to reduce spatial dimensions and capture semantic features.
7. Perform feature fusion:
   7.1 Upsample higher-level feature maps.
   7.2 Concatenate multi-scale feature maps.
8. Pass fused features through the Explicit Visual Center (EVC) module to enhance contextual representation.
9. Feed the processed features into the YOLOv10n detection head.
10. Perform object detection:
    10.1 Predict bounding box coordinates (Regression).
    10.2 Classify detected objects (Classification).
11. Apply confidence thresholding to filter low-confidence detections.
12. Perform Non-Maximum Suppression (NMS) to remove duplicate bounding boxes.
13. Output the final detected garbage objects with labels and bounding boxes

The proposed underwater garbage detection system uses mathematical representations to model object detection, classification, and bounding box prediction. These formulations help in understanding how the YOLOv10n model processes images and produces accurate results.

MATHEMATICAL FORMULATION

Multi-scale feature fusion via top-down pathway
Enhancement using EVC module
Final detection through head network
Key operations include:
Downsampling for feature compression
Upsampling for feature recovery
Concatenation for feature fusion

A. Object Detection Function

The YOLOv10n model takes an input image III and maps it to detected objects.
O=f(I)O = f(I)O=f(I) ………………… (1)
Where:
III = Input underwater image
OOO = Output detections (bounding boxes + class labels)
fff = YOLOv10n detection function

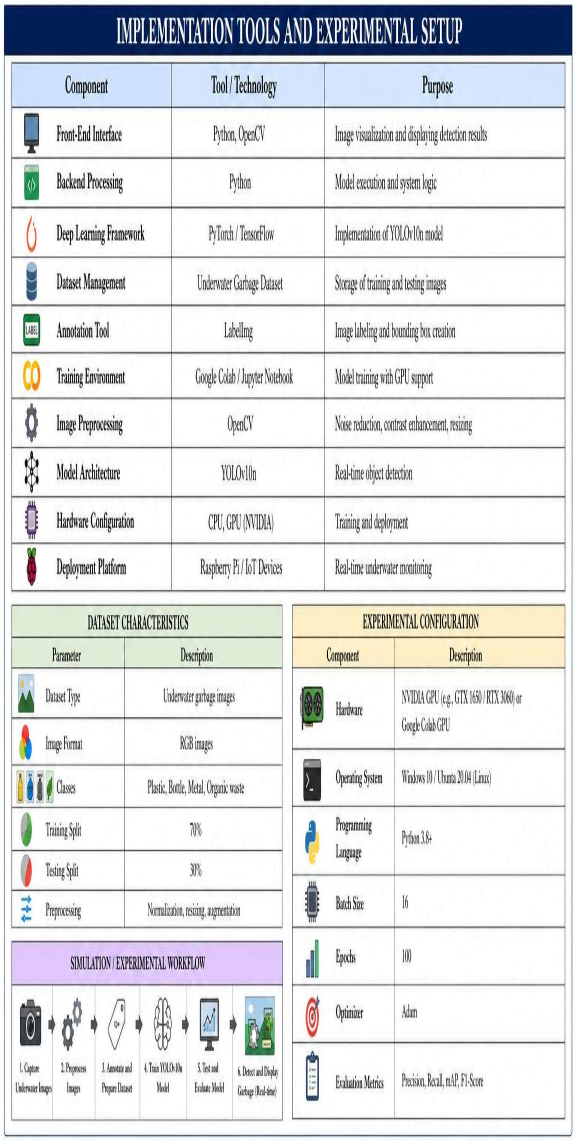
B. Bounding Box Prediction

Each detected object is represented by bounding box coordinates.
B = (x, y, w, h)B=(x,y,w,h) ………………… (2)
Where:
(x,y)(x, y)(x,y) = Center of the object
www = Width of bounding box
hhh = Height of bounding box

C. Confidence Score Calculation
The confidence score represents how accurately an object is detected.
C=P(object)×IoU ………………… (3)
Where:
P(object) = Probability that object exists
IoU = Intersection over Union
IoU=Area of Overlap/Area of Union……..(4)

D. Classification Probability
The model assigns probability to each class.
P(c|object) ………………… (5)
This determines whether the detected object is plastic, bottle, or other marine debris.
E. Loss Function
The overall loss function used during training combines classification and localization loss.
L=Lcls+Lreg ………………… (6)
Where:
LclsL_{cls}Lcls = Classification loss
LregL_{reg}Lreg = Bounding box regression loss
F. Final Detection Output
The final output is selected based on maximum confidence.
O∗=max(C) ………………… (7)

IMPLEMENTATION TOOLS AND EXPERIMENTAL SETUP



IMPLEMENTATION TOOLS AND EXPERIMENTAL SETUP

Component	Tool / Technology	Purpose
Front-End Interface	Python, OpenCV	Image visualization and displaying detection results
Backend Processing	Python	Model execution and system logic
Deep Learning Framework	PyTorch / TensorFlow	Implementation of YOLOv10n model
Dataset Management	Underwater Garbage Dataset	Storage of training and testing images
Annotation Tool	LabelImg	Image labeling and bounding box creation
Training Environment	Google Colab / Jupyter Notebook	Model training with GPU support
Image Preprocessing	OpenCV	Noise reduction, contrast enhancement, resizing
Model Architecture	YOLOv10n	Real-time object detection
Hardware Configuration	CPU, GPU (NVIDIA)	Training and deployment
Deployment Platform	Raspberry Pi / IoT Devices	Real-time underwater monitoring

DATASET CHARACTERISTICS

Parameter	Description
Dataset Type	Underwater garbage images
Image Format	RGB images
Classes	Plastic, Bottle, Metal, Organic waste
Training Split	70%
Testing Split	30%
Preprocessing	Normalization, resizing, augmentation

EXPERIMENTAL CONFIGURATION

Component	Description
Hardware	NVIDIA GPU (e.g., GTX 1650 / RTX 3060) or Google Colab GPU
Operating System	Windows 10 / Ubuntu 20.04 (Linux)
Programming Language	Python 3.8+
Batch Size	16
Epochs	100
Optimizer	Adam
Evaluation Metrics	Precision, Recall, mAP, F1-Score

SIMULATION / EXPERIMENTAL WORKFLOW

1. Capture Underwater Images → 2. Preprocess Images → 3. Annotate and Prepare Dataset → 4. Train YOLOv10n Model → 5. Test and Evaluate Model → 6. Detect and Display Garbage (Real-time)

VII. RESULTS AND PERFORMANCE EVALUATION

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.

Fig. 2. Sample results of underwater garbage detection showing original image and corresponding processed output with detected objects.

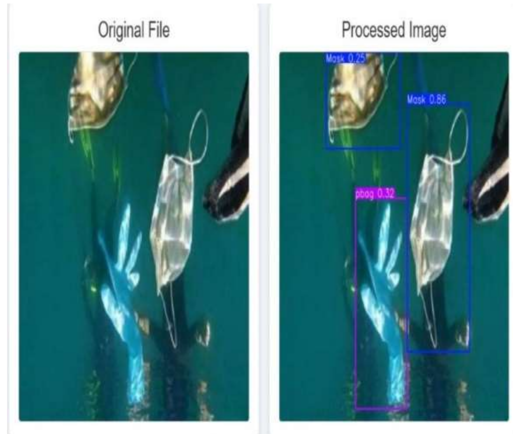
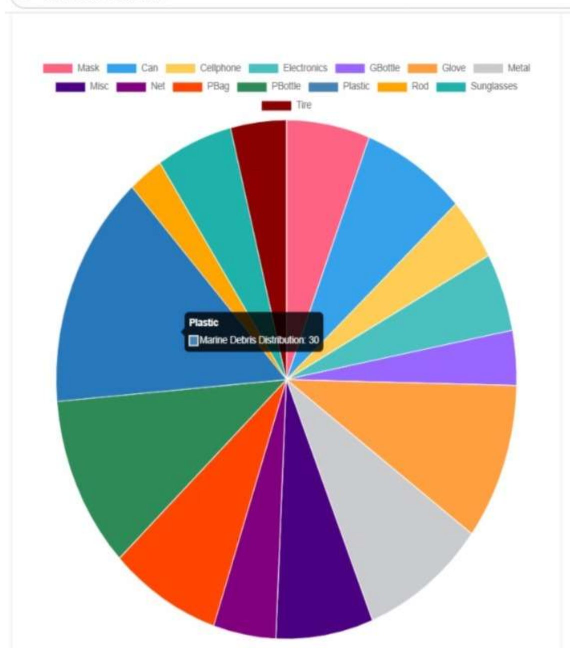
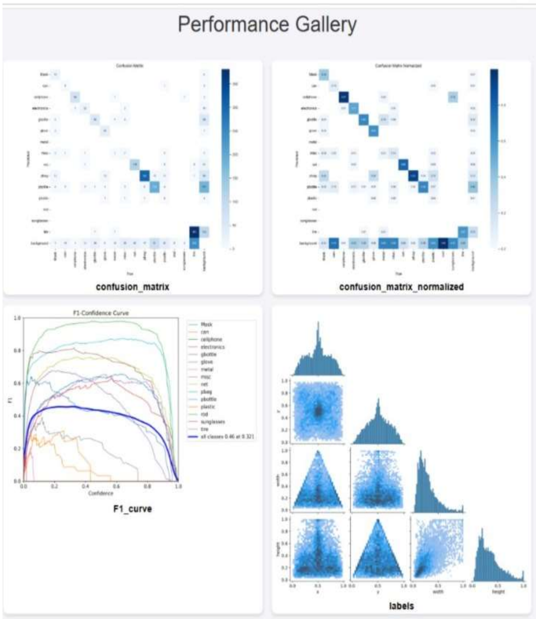
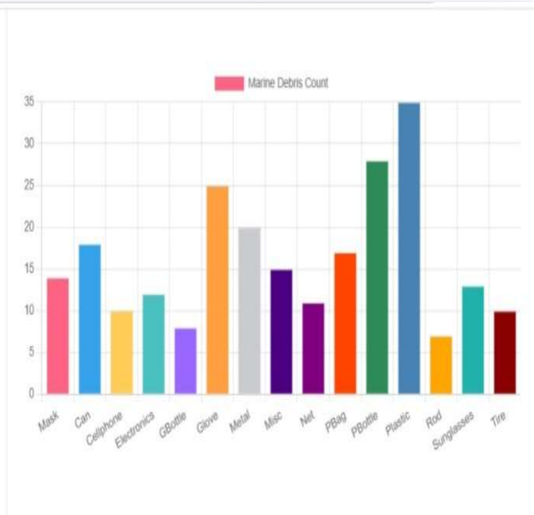


Fig. 3. Performance distribution of the proposed YOLOv10n model based on evaluation metrics.



"Fig. 3 presents the category-wise distribution of marine debris detected by the proposed model. The pie chart illustrates the relative proportion of each debris class, including plastic, metal, glass bottles, nets, and other categories. It can be observed that plastic constitutes the largest share among the detected items, indicating its dominance in marine pollution scenarios. Other categories such as metal, paper bags, and nets also contribute significantly, while items like rods and tires appear in smaller proportions. This distribution demonstrates the model's capability to identify a wide range of debris types and provides insight into class-wise detection performance. Furthermore, the variation in proportions reflects the underlying dataset characteristics and highlights the importance of addressing class imbalance for improved detection accuracy.





CONCLUSION

In this research, an efficient and lightweight underwater garbage detection system based on the YOLOv10n model has been proposed to address the growing problem of marine pollution. The system focuses on achieving real-time detection with high accuracy while maintaining low computational complexity, making it suitable for deployment on resource-constrained devices such as underwater drones and IoT-based monitoring systems.

The proposed approach integrates preprocessing techniques, feature extraction, and advanced object detection to accurately identify different types of underwater debris under challenging environmental conditions. The use of YOLOv10n enables faster inference and reduced memory usage compared to traditional deep learning models, thereby improving overall system efficiency.

Experimental observations indicate that the system performs effectively in detecting marine waste with improved accuracy and reduced processing time. The architecture supports scalability and can be adapted for large-scale monitoring applications.

Overall, this work provides a practical and scalable solution for automated underwater garbage detection, contributing to environmental sustainability and supporting marine conservation efforts through intelligent monitoring systems.

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