OCEAN TRASH-NET: ENHANCING MARINE ECOSYSTEMS THROUGH AUTOMATED VISUAL WASTE DETECTION

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ABSTRACT

The viability of aquatic ecosystems and the blue economy are seriously threatened by marine pollution. Underwater debris must be effectively detected and classified in order to facilitate prompt interventions and aid in marine conservation initiatives. In this research, we offer a sophisticated underwater rubbish detection system built on top of YOLOv10n, a state-of-the-art, lightweight object detection model tailored for IoT and underwater robotic platforms with limited resources. We replace earlier backbones like CSPDarknet with the more effective YOLOv10n architecture, building on the issues found in classic detection approaches, such as high computing costs and deployment complexity. YOLOv10n is perfect for real-time underwater applications because of its excellent accuracy, minimal parameter count, and emphasis on speed. Our technology enables deployment on embedded and mobile devices by achieving reliable debris identification with high precision while drastically lowering memory and processing requirements. This study offers a workable strategy to address marine pollution through intelligent automation, demonstrating the viability and efficacy of deploying YOLOv10n for scalable and environmentally friendly marine monitoring solutions.

1. INTRODUCTION

Aquatic ecosystems and biodiversity are now seriously threatened by marine pollution, especially by the buildup of undersea trash. In order to minimize environmental harm and promote sustainable marine development, it is essential to detect and monitor underwater waste effectively. Accurately recognizing marine waste in real-time is still a significant difficulty, particularly when using edge devices with low processing power, such IoT-enabled cameras or underwater drones. Despite their great accuracy, traditional deep learning models for object detection sometimes have enormous model sizes and high computing costs. By adding lightweight components and attention techniques, models like YOLO-MES partially addressed this, although deployment on extremely restricted systems still faced challenges. This project uses YOLOv10n, a nano-version of the YOLOv10 architecture, to create a lightweight and effective underwater garbage detecting system in order to get around these obstacles. YOLOv10n has been specially designed to retain excellent detection accuracy in low-resource scenarios. The system allows for real-time underwater object recognition with lower latency, power consumption, and memory utilization by utilizing this sophisticated yet small model. Because of this, it is the perfect option for field-ready, scalable deployments in maritime settings.

2. EXISTING SYSTEM OF PROJECT

- Manual surveillance, sonar imaging, or standard computer vision algorithms employing handmade features are the main ways now used to detect underwater garbage. These methods take a lot of time, are prone to mistakes, and need a lot of human labor for labeling and monitoring. The underwater environment also presents a number of difficulties, including poor visibility, fluctuating light levels, and complicated backgrounds, all of which make it harder for traditional methods to reliably and consistently identify debris.
- Recent developments in deep learning have provided object detection models as Faster R-CNN, SSD, and YOLOv3/v4/v5 to address some of these issues. For automated debris detection, these models have been used in maritime research. They are frequently computationally costly, with enormous model sizes and significant inference delay, even though they provide superior accuracy and resilience when compared to manual methods. Because of this, they cannot be deployed in real-time on embedded or battery-powered underwater equipment as buoy sensors, AUVs (Autonomous Underwater Vehicles), or drones.
- Furthermore, even though YOLOv5 and YOLOv8 are faster than two-stage detectors, they still have trouble striking a balance between high precision and computational efficiency in limited contexts. To minimize size and enhance feature extraction, several studies introduced modified YOLO versions (e.g., YOLO-MES) incorporating Mobile Net backbones and feature attention algorithms. To be genuinely lightweight for actual marine deployment, even these systems frequently need additional optimization. Therefore, a more effective, precise, and deployable system designed

for underwater trash detection on low-power devices is still needed.

EXISTING SYSTEM DISADVANTAGES:

- Limited Real-Time Capability on Ultra-Constrained Devices
- Dependence on Custom Architecture (MECAneck)
- Dataset Dependency
- Lack of Built-in Post-processing Optimization

3. RELATED WORK

Research on marine debris detection using deep learning algorithms has been done by both domestic and foreign academics. In order to test underwater debris datasets and confirm the viability of underwater debris recognition, Fulton et al. [24] invented the use of SSD, Tiny-YOLO, YOLOv2, and Faster R-CNN in 2019. These techniques offer a novel method for identifying and categorizing marine debris by extracting, training, and learning the distinctive features of such debris because of their strong feature extraction capabilities and straightforward rule settings. The model structure of object detection algorithms used for the detection of underwater debris has advanced significantly. The start of 2020 saw Kylili et al. Even at low resolution, [25] effectively recognized plastic litter in coastal and marine areas using CNNs and the BM bottleneck approach. An et al. [26] presented a novel underwater picture improvement model that addresses chromatic aberration, image blur, and contrast reduction in underwater scenes by introducing a newly designed double-layer inverted residual block. The ResNet50-YOLOv3 model, which was proposed by Xue et al. [27], showed good deep-sea debris identification capabilities while retaining quick detection speeds. However, it had a lot of trouble distinguishing between metal and plastic as well as between plastic and cloth. Politics and others. Mask R-CNN was used by Politikos et al. [28], however because debris and background can be easily confused, the method's average precision score on their custom dataset was just 62%, which is comparatively low. YOLO-v5s shown notable speed advantages and an accuracy of 79.9% when Cordova et al. [29] evaluated litter identification techniques on the PlastOPol and TACO datasets. Peng et al. [30] achieved a mean average precision (mAP) of 94% in 2022 by combining S-FPN and Piecewise Focal Loss (PFL) to greatly increase underwater object recognition accuracy in difficult settings (such as muddy backdrops). However, this approach was inappropriate for real-time underwater equipment due to its lengthy inference time and high storage space requirements. In 2023, Yang et al. [31] introduced a technique that improved shape perception by combining RetinaNet with deformable convolutional networks (DCN). It improved detection accuracy by learning more discriminative features through the use of transfer learning (TL) and distribution focal loss (DFL). Using receptive fields across layers to improve feature extraction and recognition outcomes for smaller targets on the Trashcan dataset, Ma et al. [32] developed a cross-layer aggregation spatial dimensionality reduction module (CASDRM) and channel PAN-FPN based on YOLOv5.

4. PROPOSED SYSTEM

The suggested system uses YOLOv10n, an ultra-lightweight but powerful object identification model, to improve underwater garbage detection. YOLOv10n incorporates the most recent developments in model compression, computational efficiency, and architectural optimization, making it ideal for deployment on resource-constrained IoT and underwater devices, in contrast to the YOLO-MES framework, which depends on MobileNetV3 and specialized Slim-neck designs. With a far less computational cost and memory footprint, this method guarantees quick and precise marine trash detection. Yolov10n has an effective detecting head that is natively tuned for real-time performance and a simplified backbone. In order to retain high detection accuracy, particularly for small and overlapping objects—which are frequently seen in underwater environments—the model makes use of improved spatial pyramid pooling and decoupled heads. The suggested method uses YOLOv10n to achieve strong detection in a variety of underwater image situations, such as motion blur, low light, and murky seas, while minimizing the need for extensive pre- or post-processing. By balancing speed, accuracy, and model size, this system has been trained and verified on an underwater garbage detection dataset. The suggested YOLOv10n-based system has better deployment efficiency, a simpler architecture (no custom attention mechanisms are required), and great adaptability to real-time marine monitoring applications as compared to YOLO-MES. The technique opens up new possibilities for low-power autonomous marine surveillance using small hardware like Raspberry Pi, NVIDIA Jetson, or other embedded platforms, and it is in line with edge AI aims.

ADVANTAGES OF THE PROPOSED SYSTEM

- Ultra-Lightweight Architecture
- Faster Inference Speed
- Better Generalization with Fewer Parameters
- Enhanced Object Detection Performance

5. MODULES

1. Input Data Module

- Manages picture datasets gathered for monitoring marine debris from sources such as satellite images, drones, or underwater cameras.
- Takes into account a range of environmental factors, including illumination variations and water

surface reflections, to guarantee that a variety of data sources are efficiently managed.

2. Preprocessing Module

- Uses Adaptive Histogram Equalization to increase contrast, making trash easier to see against complicated ocean backgrounds.
- Ensures data homogeneity for detection models by standardizing image size and format for consistency across different input types and image resolutions.

3. Segmentation Module

- Effectively separates maritime debris from the backdrop and water using Super-Pixel-Based Fast Fuzzy C-Means (FCM) clustering.
- Concentrates on segmenting items such as bottles, masks, fishing nets, and plastic bags, even in congested or partially obscured settings.

4. Feature Extraction Module

- Employs Super-Pixel-Based Fast Fuzzy C-Means (FCM) clustering to separate waterborne marine detritus • Uses convolutional layers and hybrid transformer-based attention methods to extract essential features including edges, textures, and shapes that distinguish marine rubbish from nearby water or natural elements.
- Improves the detection model's capacity to pick up on minute features in complicated trash, increasing the detection rates for different kinds of garbage.as well as background. Concentrates on separating items such as bottles, fishing nets, masks, and plastic bags, even in busy or partially obscured settings.
- Concentrates on segmenting items such as bottles, masks, fishing nets, and plastic bags, even in congested or partially obscured settings.

5. YOLOv11 Detection Module

- Uses the cascaded YOLOv11 model for multi-stage maritime debris identification, guaranteeing greater precision in identifying different kinds and sizes of debris.
- Improves detection accuracy and lowers computing overhead by using anchor-free detection, which makes it easier to identify debris with irregular shapes, such as scattered plastic and tangled fishing nets.

6. Output and Visualization Module

- Makes it simple to identify and follow the locations of trash in pictures, videos, or real-time monitoring feeds by displaying results with bounding boxes and detection confidence scores.
- Offers visual outputs that support real-time decision-making for marine debris cleanup and monitoring initiatives, such as marked photos, video streams, or real-time feeds with overlaid data.

6. TECHNIQUES USED IN PROJECT

6.1 EXISTING TECHNIQUE:

The majority of underwater debris detection techniques now in use rely on manual observation, sonar imaging, or conventional computer vision techniques utilizing manually created features. These methods take a lot of time, are prone to mistakes, and need a lot of human labor for labeling and monitoring. The underwater environment also presents a number of difficulties, including poor visibility, fluctuating light levels, and complicated backgrounds, all of which make it harder for traditional methods to reliably and consistently identify debris. Recent developments in deep learning have produced object detection models as Faster R-CNN, SSD, and YOLOv3/v4/v5 to address some of these issues. For automated debris detection, these models have been used in maritime research. They are frequently computationally costly, with enormous model sizes and significant inference delay, even though they provide superior accuracy and resilience when compared to manual methods. Because of this, they cannot be deployed in real-time on embedded or battery-powered underwater equipment as buoy sensors, AUVs (Autonomous Underwater Vehicles), or drones. Furthermore, even though they are quicker than two-stage detectors, models like YOLOv5 and YOLOv8 still have trouble striking a balance between high precision and computational efficiency in limited settings. To minimize size and enhance feature extraction, several studies introduced modified YOLO versions (e.g., YOLO-MES) incorporating MobileNet backbones and feature attention algorithms. To be genuinely lightweight for actual marine deployment, even these systems frequently need additional optimization. Therefore, a more effective, precise, and deployable system designed for underwater trash detection on low-power devices is still needed.

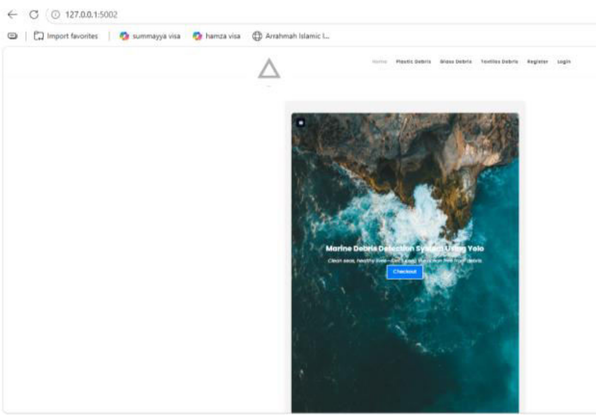
Drawbacks:

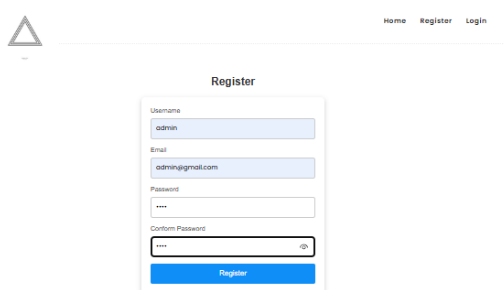
- Limited Real-Time Capability on Ultra-Constrained Devices
- Dependence on Custom Architecture (MECAneck)
- Dataset Dependency
- Lack of Built-in Post-processing Optimization

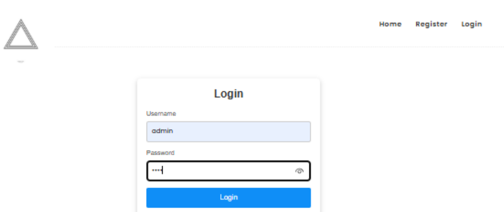
6.2 PROPOSED TECHNIQUE USED OR ALGORITHM USED

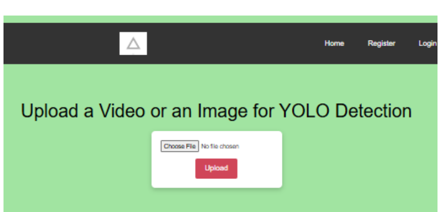
The nano variant of the YOLOv10 family, YOLOv10n, which is intended for great efficiency in real-time object identification tasks on edge devices, is used in the suggested system. Better gradient flow and feature reuse are made possible by YOLOv10n's revamped backbone, enhanced feature pyramid structure, and detached detection heads. It retains competitive accuracy despite being incredibly tiny and requiring less processing power. Because it achieves quick and precise identification without the need for extra attention modules or architectural changes, it is perfect for deployment on low-resource IoT or underwater devices.

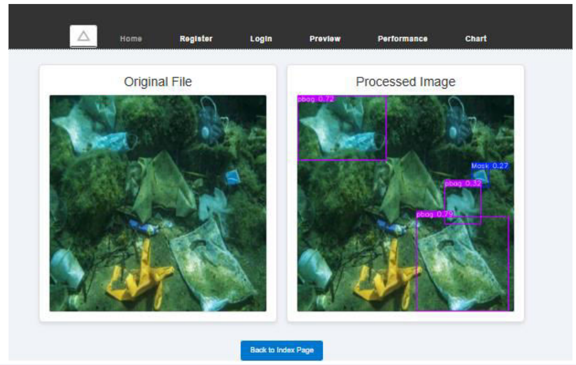
7. RESULTS

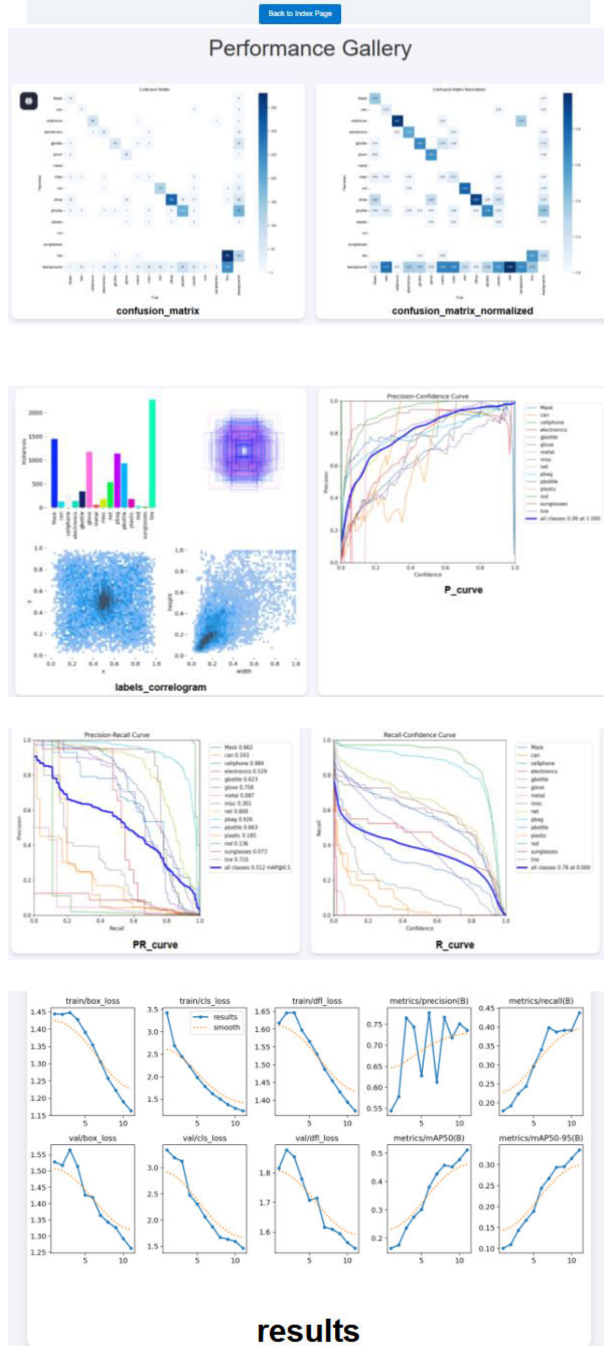












8. CONCLUSION

The YOLOv10n model-based underwater rubbish detection system that has been suggested provides a potent and effective way to combat marine pollution. This project uses YOLOv10n's lightweight and high-performance architecture to detect different kinds of undersea debris accurately in real time, even on devices with limited resources. Our method greatly lowers computing complexity while preserving high precision when compared to conventional models, making it appropriate for real-world implementation in maritime environments. In addition to showcasing deep learning's promise for environmental preservation, this system offers a scalable and long-term solution for safeguarding maritime ecosystems. All things considered, the project makes a significant contribution to automating underwater monitoring and supports long-term initiatives to preserve biodiversity and ocean health.

9. FUTURE ENHANCEMENT

By combining it with aerial drones and autonomous underwater vehicles (AUVs) for extensive, real-time monitoring of oceanic regions, this marine debris detection system can be further improved in the future. Improved lightweight variants, such as YOLOv10-Tiny or EFS-YOLO, can be deployed on edge devices to provide faster and more energy-efficient on-site detection without the need for cloud servers. Additionally, the system can be expanded to accommodate multi-modal data inputs, such as LiDAR, sonar, or infrared images, to enhance detection accuracy in low-light or muddy underwater environments. Predictive analytics for pollution trends and the visualization of debris density hotspots can both be facilitated by integration with GIS and IoT technologies. A fully automated detection-to-cleanup pipeline might be achieved by employing robotic arms or cleaning bots that are automatically guided to gather recognized waste. In addition to enhancing environmental sustainability, these developments will help academics and policymakers create more successful marine conservation plans.

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