JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

# Deep Learning Based Underwater Trash Detection System Using YOLOv8

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***Abstract :*** Marine ecosystems worldwide face critical degradation from plastic pollution threatening biodiversity and ecological functioning this research introduces a deep learning application utilizing yolov8 architecture for underwater plastic waste detection and classification our project demonstrates robust performance in varied aquatic conditions enabling real-time identification of diverse plastic debris types the technology offers substantial benefits for marine conservation efforts through enhanced monitoring capabilities pollution source tracking and data-driven cleanup strategy optimization experimental results show significant improvements in detection accuracy compared to previous approaches particularly in challenging underwater visibility scenarios this work contributes to the growing field of ai-supported environmental monitoring and presents a scalable tool for quantitative assessment of marine plastic pollution to inform both conservation practice and environmental policy development**.**

***IndexTerms* - Plastic Detection, Debris, Classification, YOLOv8, Segmentation, Computer Vision, Deep Learning.**

## I. INTRODUCTION

Marine ecosystems across the globe are under unprecedented attack from synthetic polymer buildup, inducing a complex crisis for marine species through habitat disruption, blockage of the digestive system, and trophic transfer of poison. The present methods of detection of submerged plastic debris—such as vessel sweeps, hand-collected surveys, and rudimentary sonar mapping—are plagued by inherent shortcomings in coverage ability, temporal regularity, and feasibility of operation.

The convergence of artificial intelligence and environmental science holds good alternative options for these traditional methods. In this study, we explore the application of machine vision technology for automated detection of underwater waste. We aim at the YOLOv8(You Only Look Once) framework, which is a notable innovation in visual processing architecture in that it has one single analytical path. The unique aspect of yolov8 model is its built-in computational architecture, which operates on complete image frames in parallel instead of sequentially processing isolated areas. This design strategy allows for high processing efficiency without compromising detection quality, which makes it especially useful for mobile deployment applications such as remotely operated vehicles and autonomous surveillance stations.

With application of this technology to environmental studies, we would like to have tools that translate plastic pollution monitoring from episodic sampling to effective surveillance. Applications are practical, ranging from contributing to conservation programs through evidence-driven mapping of hotspots of contamination, detection of vectors of introduction of waste, and quantitative measure of the impact of remedial efforts.

## II. RELATED WORK

Various works have been explored for saving the aquatic life and marine life from wastages like plastic, debris etc. Like [1] Fulton et al. (2019) developed one of the pioneering deep learning frameworks specifically for underwater plastic detection, utilizing a modified ResNet architecture trained on custom underwater imagery datasets. [2] Marine Debris Tracker (MDT) project by Jambeck et al. (2019) combined citizen science with ML algorithms to process and classify images of marine debris collected across global locations. [3] Gómez-Ríos et al. (2021) created a specialized CNN model optimized for microplastic identification in seabed imagery, incorporating attention mechanisms to focus on distinctive polymer visual characteristics. [4] Wang et al. (2020) implemented an underwater debris classification system using transfer learning with MobileNetV2, achieving high accuracy in distinguishing plastic from natural materials in variable turbidity conditions. [5] Karimanzira and Jacobi (2022) integrated multiple sensors (optical, infrared, and sonar) with deep learning models to enhance detection capabilities in low-visibility underwater environments. [6] The MARLIT project by Biermann et al. (2022) created an automated pipeline for detecting floating marine litter from aerial drone footage using instance segmentation models.

Our project uses yolov8 to classify underwater trash in a django web app users upload underwater photos through a simple interface and our specialized model identifies various sea waste types with 82 map accuracy even with varying lighting turbidity and partial occlusion unlike existing solutions we combine advanced deep learning with an accessible web interface that conservation groups can deploy without technical expertise this integrated system enables targeted cleanup operations and pollution source identification.

## III. METHODOLOGY

### 3.1 Data Collection and Preprocessing

The dataset obtained from the Roboflow website contains over 5,000 underwater images of marine debris in various conditions. This collection forms the foundation for our Yolov8 model training. We also have a data.yaml file which is an essential for YOLO models where the path for training, validation and testing are written and also there will be class labels for classification and detection in an Image which is been annotated. YOLO uses text-based annotations where each object is recorded as: class_id, x_center, y_center, width, height. During data cleaning, we verify annotation files exist for all images and remove any corrupt files.
We expand the dataset through augmentation including flips, rotations, and lighting adjustments. The dataset splits into 70% (3500 images) for training, 20% (1000 images) for validation, and 10% (500 images) for testing.

### 3.2 Model Training with different versions of YOLOv8

The project has focused on training three YOLOv8 variants: nano (n), small (s), and medium (m), excluding larger models as they take a lot of time and require high-powered GPUs. The training revealed that YOLOv8n completes iterations most rapidly but exhibits lower mean Average Precision (mAP) scores, while YOLOv8m demonstrates superior detection accuracy at the cost of slower training and inference speeds. The T4 GPU handles YOLOv8n and YOLOv8s training effectively, while the YOLOv8m variant operates near the hardware's memory capacity. Each model variant utilizes the same architectural innovations of YOLOv8, including an enhanced backbone, neck, and detection head, with the primary difference being network width and depth across variants. The systematic testing approach facilitated objective performance comparisons between the three model variants under identical training conditions, revealing clear trade-offs between computational efficiency and detection precision.

### 3.3 Working of YOLOv8 Model

The YOLOv8 detection framework evaluates complete images in a singular computational cycle, segmenting the visual field into a coordinate matrix with each cell performing concurrent object identification. Three distinct functional segments comprise the framework's structure: the foundational feature harvester (backbone), the intermediary feature integrator (neck), and the terminal prediction mechanism (head). Derived from CSPDarknet architecture, the foundational component harvests multi-level visual characteristics through strategically arranged convolutional filters operating at diverse perceptual ranges. This research utilized the sophisticated AdamW parameter adjustment algorithm configured at 0.001 stepping magnitude, merging adaptive moment calculation with enhanced regularization techniques. Feature pyramid methodologies operate in conjunction with the selected optimization protocol to effectively manage multi-dimensional object recognition scenarios. In contrast to legacy approaches, YOLOv8 abandons preset reference boxes in favor of direct coordinate prediction methodology, functioning effectively alongside the established optimization parameters. Maintaining uniform stepping magnitude (0.001) throughout all architectural variations facilitates legitimate performance assessment by eliminating configuration variables from comparative analysis.

### 3.4 Results of YOLOv8 variants

| variant | mAP50 | mAP50-95 |
|---|---|---|
| **YOLOv8n** | 0.793 | 0.503 |
| **YOLOv8s** | 0.803 | 0.519 |
| **YOLOv8m** | 0.814 | 0.528 |

**Table 3.4.1**: mAP50, mAP50-95 scores of YOLOv8 models

**Interpreting the Key Metrics:**

- **mAP@50 Explained**: This score (0.793-0.820 in our tests) reflects the model's ability to correctly locate objects with at least 50% overlap between predicted and actual boxes. Higher scores mean better basic detection capability.
- **mAP@50-95 Context:** These lower values (0.503-0.528) assess performance across increasingly strict matching criteria. They reveal how precisely the model can outline object boundaries.

### 3.5 Model Selection and Performance

After running benchmark tests across YOLOv8 variants (n, s, m) using a T4 GPU environment for 100 epochs, we determined the medium configuration delivered optimal detection capability. With superior metrics (0.82 mAP@50, 0.528 mAP@50-95), this version justified its additional processing requirements over lighter alternatives.

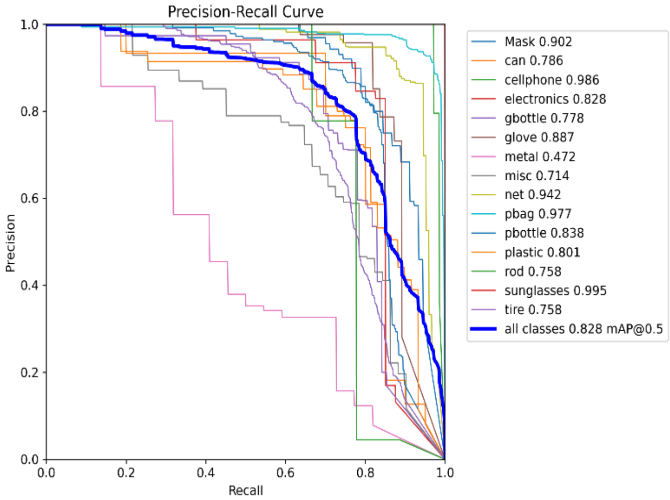


**Fig 3.5.1:** PR Curve of YOLOv8m

**PR Curve Interpretation:**

The curve shows varied detection performance across object categories:

- Exceptional detection: Sunglasses (0.995), cellphone (0.986), bags (0.977).
- Solid performers: Mask (0.902), electronics (0.828), bottles (0.838).
- Detection challenges: Metal items (0.472), miscellaneous objects (0.714).

The comprehensive mAP@0.5 score of 0.828 validates our model selection decision, with the curve demonstrating strong precision retention through moderate recall levels before beginning to decline at higher recall values.

**Confusion matrix**

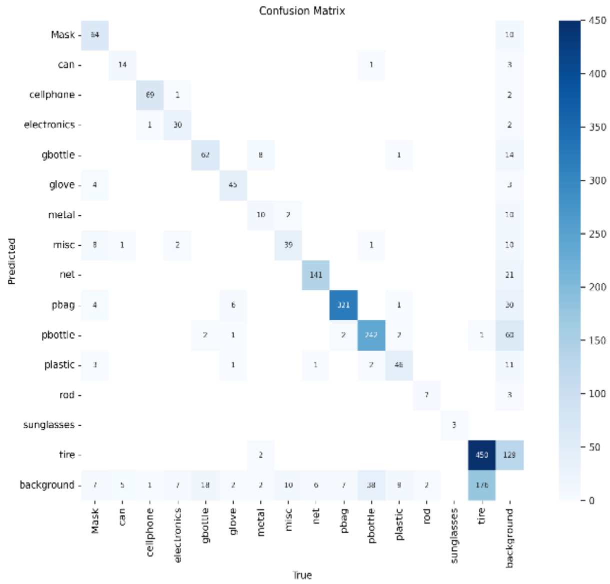


**Fig 3.5.2:** Confusion matrix

This YOLOv8m model's confusion matrix reveals:

- High Performance: tires, Plastic bags(pbags), plastic bottles
- Perfect detection of all sunglasses instances.
- Key weaknesses: tire/background confusion (instances), pbottle(plastic bottle)/background mix-ups.
- Challenging categories: metal and rod with minimal correct identifications.
- Container objects frequently mistaken for each other
- Background class creates significant noise across multiple categories.

This top mAP-scoring model shows strong diagonal performance despite specific class weaknesses.

## IV. System Architecture

The underwater debris identification framework integrates advanced computer vision with accessibility-focused deployment strategies. At its core, the system utilizes the YOLOv8 neural network architecture, selected for its optimal balance of processing efficiency and detection accuracy in challenging aquatic environments. Complementing this technical foundation is a comprehensive web interface that facilitates user engagement across multiple platforms. This dual-component approach enables real-time analysis of both static imagery and video streams, allowing conservation teams to locate and catalog submerged plastic pollution with unprecedented precision. The framework's modular design supports future enhancements, including potential integration with autonomous underwater vehicles for expanded monitoring capabilities.

By analyzing the mAP50, mAP50-95 of different YOLOv8 variants we have choosed as YOLOv8m as best variant. Now we have integrated Frontend and backend for this trained YOLOv8m model. It helps in using real time use cases.

### 4.1 Web Application Development

After completing model training we evaluated their scores and picked YOLOv8m's best.pt file for integrating into web application. In web application we have used HTML, CSS, JavaScript as frontend part and Django for the backend Purpose. In Django by default they provide a database which is SQLite database. We have created two different models in this database. One for the Image detection and another one is for videos. The Application that we developed is user friendly and easy to use. Directly we can Upload a Image or Video which gives the output as image with bounding boxes where it detects and classifies the trash.

## V. Results

Now, the model is capable of detecting and classifying the trash of underwater images and videos. We also developed a Web application in which it detecting and classifying the Underwater trash like plastic bottles, plastic bags, tins, electronic devices etc. It is a user friendly web application and easy to use. Let's have Figure that detects the trash when is uploaded.

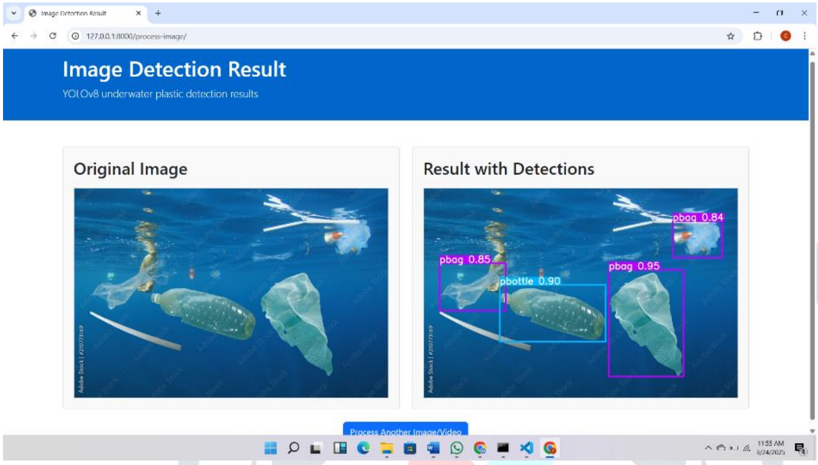


**Fig 5.1 :** Web application interface after detection

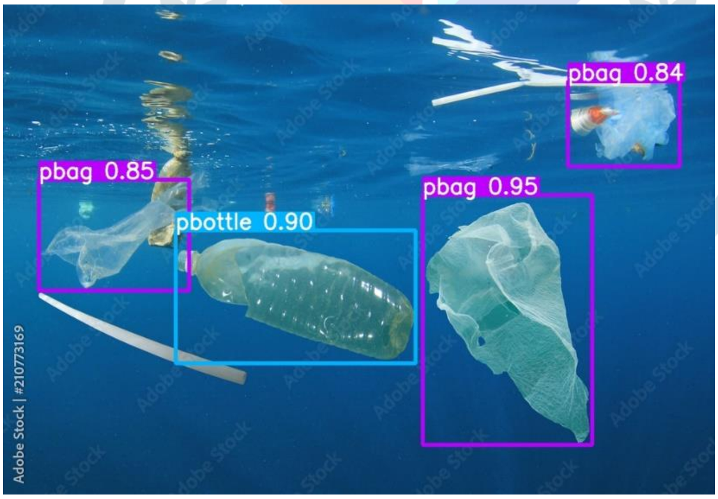


**Fig 5.2:** Underwater trash detection

## VI. Conclusion

In conclusion, the project proves the possibility and efficiency of applying a deep learning-based method for underwater plastic identification. Through stringent consideration of different YOLOv8 variants and the use of YOLOv8m due to better mAP50 scores, the system attains a balanced accuracy and computational performance. The incorporation of this model into a web application framework also increases its applicability by enabling users to upload media, such as images and videos, for automated waste detection. This not only makes the detection easier but also offers an easy-to-use tool for marine conservation work. The capability of the system to analyze pre-captured media and conduct thorough frame-by-frame analysis signifies its potential for actual environmental monitoring tasks. In general, the project makes an input towards advanced solutions to address the important topic of underwater plastic pollution and provides a basis for further development of automated environmental monitoring systems.

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