

Towards Sustainable Oceans: Deep Learning for Plastic Detection in Subaquatic Environment

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Abstract— Marine biodiversity and the health of the environment worldwide are seriously threatened by the fast buildup of plastic garbage in aquatic environments. The use of automated solutions is required since traditional techniques for identifying plastic waste under water are time-consuming and not scalable. Advanced sensor and computing capabilities on Autonomous Underwater Vehicles (AUVs) are making them essential instruments for detecting underwater garbage. Deep learning arose as a key component of these automated systems due to its exceptional performance in image identification tasks. While U-Net and DeepLab are excellent in segmenting plastic debris at the pixel level, models like YOLOv8m, YOLOv8n, YOLOv8s and SSD are being used in our work for real-time object identification.

These models use strong feature extraction and data augmentation strategies to tackle underwater obstacles, such as low visibility and changing surroundings. Metrics like Precision, Accuracy, F1-Score, and Recall are considered to assess performance and provide information on the correctness and dependability of the model. Real-time mapping, monitoring, and intervention in marine settings are ensured by integrating these technologies with AUVs. This study establishes the foundation for sustainable marine ecosystem management and highlights the abilities of deep learning to transform detection plastic waste in underwater.

Keywords— *marine pollution, underwater plastic detection, deep learning, YOLOv8, SSD, environmental monitoring.*

I. INTRODUCTION

The pressing global issue of ocean waste [1-3] has garnered increasing attention, and AI, mainly deep learning models, shown significant promise in addressing this challenge by automating marine debris classification and detection. Utilizing diverse datasets in conjunction with cutting-edge deep learning methods has shown encouraging outcomes in the recognition and categorization of distinct kinds of marine debris. The reviews [4-5] explore key advancements, methodologies, and datasets used in the classification and detection of ocean waste.

Particularly for identifying and categorizing marine trash from images are deep learning-based Convolutional Neural Networks (CNN) models ability; well-known models such as YOLO, Faster R-CNN, and U-Net provide reliable results. YOLO [6-9] is favored for real-time

detection, ideal for robotic waste collection, while Faster R-CNN offers high precision in detecting waste in images, and U-Net excels in pixel-level segmentation for detailed mapping of debris.

Despite these developments, problems like unbalanced datasets and environmental unpredictability still exist. It is challenging for models to generalize across conditions since marine debris can be found in a variety of situations, from clear coastal areas to murky deep-sea locations. Biased models can result from data imbalances, where some waste kinds are overrepresented, and models must be flexible and sensitive to changes in lighting and water clarity. For evaluating model accuracy, evaluation metrics such as Precision, Recall, and Intersection over Union (IoU) are essential, and efficiency as assessed by Frames Per Second (FPS) is given priority in real-time systems.

Using Adam and Adadelta as neural network optimizers, in Aral et. al. [10] classified Trashnet datasets using deep learning models Xception, DenseNet169, InceptionResnetV2, Densenet121 and MobileNet architectures. The improved Densenet-121 and Densenet-169 models produced test accuracy rates that were successful. The InceptionResNetV2 model was used to test the Adadelta and Adam optimizers across 100 epochs. This experiment resulted in a greater test accuracy for the Adam optimizer. The study restricts its exploration to standard deep learning architectures and does not include newer models. The optimizer comparison is limited to Adam and Adadelta, with no consideration for other key hyperparameters. The Trashnet dataset utilized may not accurately reflect real-world complications, limiting generalizability.

In the study, Pachaiyappan P et al.[11] proposed model effectiveness is validated using TrashCan dataset, which comprises a range of underwater scenes and objects, suggests using the YOLO (AIT-YOLOv7) network, an improved image technique, to identify items in underwater photographs. It utilizes updated U-Net, which aims on enlightening features through a convolutional channel, a updated swin transformer block for resolution augmentation, and spatial importance for color correction. As a result, the AIT-YOLOv7 network accurately recognizes and classifies the various types of objects in this dataset. According to experimental results, the suggested AIT-YOLOv7 net achieves mAP:0.5 with 81.4% for TrashCan dataset, which represents a rise of 16.39% over the methods SSD, YOLOv3, YOLOv4, and YOLOv7. Its focus on underwater conditions limits its applicability to other waste detection scenarios. The AIT-YOLOv7 model

may be computationally intensive, affecting real-time performance in some cases. Color correcting procedures may not be successful for all water types or pollution levels.

Fulton, M. et al. [12] considered the Trash-ICRA19 dataset for the trash detection data model, which includes three classes: plastics, ROV: all man-made objects, and biological material. Four models. The following were chosen: SSD with MobileNet v2, Faster RCNN-Inception v2, Tiny-YOLO, and YOLOv2. Faster RCNN with Inception v2 (mAP=81), Tiny-YOLO (mAP=31.6), YOLOv2 (mAP=47.9), and SSD combinedly MobileNet v2 (mAP=67.4). SSD has the fastest CPU inference speeds, but YOLOv2 provides a decent equilibrium of accuracy to speed. The Trash-ICRA19 dataset has a restricted class variation, which may hamper model efficiency in detecting different sorts of wastes. Faster RCNN, while accurate, has sluggish inference, rendering it unsuitable for real-time detection. The study did not investigate models suitable for more complicated situations, such as underwater or excessively congested sceneries.

Yuwei Cheng et al. [13] introduced FloW, dataset for detecting floating trash on surface of inland waters. The FloW has two sub-datasets: FloW-RI and FloW-Img and. The performance of certain traditional vision-based object detection techniques, such as n Cascade R-CNN, was evaluated on the FloW dataset. mmAP and FPS matrices were used to compare performance. It focuses solely on floating rubbish, excluding other types of waste such as submerged or urban trash. The dataset is new and tiny, which may influence model generalization. The study only examines traditional object detection algorithms, leaving out the possibility to test more recent deep learning models.

Khriss, A. et al.,[14] presented a comparative study of cutting-edge deep learning methods for detecting underwater objects, by aiming on marine garbage detection. The performance of 4 well-known object identification methods were evaluated, including SSD, Faster R-CNN, YOLOv8m, and YOLOv8, on two separate datasets: Deep Trash & TrashCAN. Performance metrics like Recall, mAP, and Precision were used to evaluate models and demonstrate YOLOv8m's superiority over others. It confines the study to the detection of marine debris, restricting its applicability to other contexts such as urban or inland waters. The performance of YOLOv8m is demonstrated on specific datasets, leaving its generalizability to other datasets untested. The study does not provide insights of computational demands for models to practical applications.

The considered models and dataset described under 2nd Section, key results were illustrated in 3rd Section, key inferences were presented under 4th Section, and the impact of models concluded in final 5th Section.

II. DATA AND METHODS

The approach is described in depth in this section, along with the deep learning models that were used. YOLOv8m, YOLOv8n, YOLOv8s, and SSD are the main subjects of the study because of their demonstrated effectiveness in object detection tasks in a variety of domains [15]. Capabilities in processing under real-time and great accuracy in identifying objects of different sizes and shapes are only two of the unique benefits that each

model has to offer. By utilizing these methods, the authors hope to thoroughly assess how well they locate and identify marine debris and other underwater objects, advancing environmental monitoring and intervention techniques in the process.

A. Model Architecture

The proposed system utilizes the YOLO (You Only Look Once) architecture for real-time object detection. This system employs a one-stage detection approach, where object classification and localization are simultaneously performed in a single forward pass over the network. This approach alleviates the requirement for post-processing steps and computationally expensive region proposal algorithms commonly found in traditional multi-stage pipelines. The YOLO model leverages a unified Convolutional Neural Network (CNN) architecture to directly forecast the bounding boxes and class probabilities from the full input image. This method results in faster inference times, making it suitable for real-time detection applications. The architecture is designed to handle several key tasks, including class prediction, object localization, and objectness scoring. The loss function used in the YOLO model incorporates these three factors, ensuring the optimization goal accounts for each of them.

The network is trained to minimize this combined loss, which results in an effective and efficient detection model. Fig. 1 depicts the overall architecture of the system. The model first extracts feature maps from the input image, further processed by fully connected layers to predict both the object class (via Softmax) and the bounding box coordinates (via a regressor). Fig. 2 presents the YOLOv8 architecture, which consists the CNN that extracts features from the input image is called the backbone. The unique CSPDarknet53 backbone used by YOLOv8 makes advantage of cross-stage partial contacts to enhance accuracy and transfer of information within layers. Neck, referred to feature extractor. The neck combines feature maps from numerous backbone stages in order to record data at multiple scales. The YOLOv8 Architecture uses a special C2f module in place of the conventional FPN (Feature Pyramid Network). It combines low-level spatial information and high-level semantic features to increase recognition accuracy of small objects. The HEAD is in charge of forecasting. Several detection modules are used by YOLOv8 for each grid cell in the feature map to forecast bounding boxes, objectness scores, and class probabilities. [16].

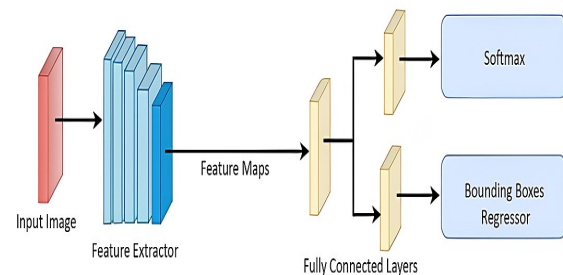


Fig. 1 One Stage Identifier [14]

In contrast to YOLO, the SSD (Single Shot Multibox Detector) architecture offers a novel method of object recognition that successfully strikes a balance between speed and accuracy.

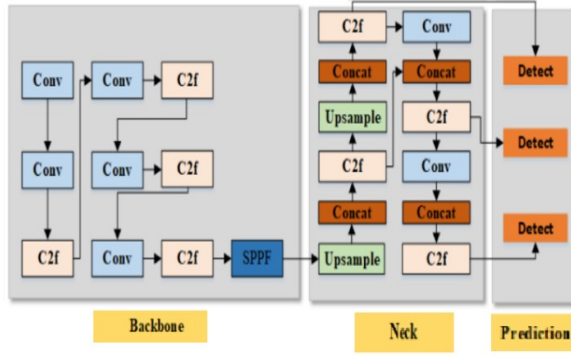


Fig. 2 Architecture: YOLOv8 [17]

SSD integrates object detection into a single neural network, similar to YOLO, but in contrast to traditional methods that rely on complex multi-stage pipelines. SSD retains high detection accuracy while achieving real-time inference speeds through a special technique. The model predicts class probabilities and bounding boxes across multiple network scales simultaneously, enabling it to effectively detect objects of varying sizes and shapes. This capability is enhanced by the use of multiple convolutional layers with different aspect ratios and sizes. For training, the SSD model employs a well-structured loss function that includes several components working together to ensure precise localization and classification.

B. Datasets

The TrashCAN dataset [18] was used for evaluate the models under consideration. The main training source was the TrashCAN dataset, which included 7212 annotated photos of marine life, ROVs, and underwater detritus. These photos, which were mostly taken from JAMSTEC: J-EDI dataset, which was maintained by Japan Agency of MEST, were painstakingly annotated using bitmaps, such as bounding boxes and segmentation. An example from the TrashCAN dataset is shown in Fig. 3.

To ensure complete compatibility with CUDA version-12.0, the experimental configuration make use of graphics card NVIDIA Tesla T4 and version 525.105.17 NVIDIA driver. The Tesla T4 is selected because of its powerful processing power and capacity to handle massive datasets, which are bolstered by its sizeable 15,360 MiB of GPU RAM. For training, Adam optimizer was used for batch size- 16 & with a learning rate - 0.001. In order to guarantee compliance with the selected architecture and preserve consistency among tests, input images standardized for resolution of 640×640.

C. Evaluation metrics

The two standard performance measures listed below were used to assess the four distinct networks utilized for the maritime trash detector[19-21]:

True-Positive, False-Positive, and False-Negative are represented by the letters TP, FP, and FN, respectively.

The chosen metrics offer a comprehensive picture of the model's detection accuracy, false alarm rates, and general efficacy in minimizing inaccurate or irrelevant data while gathering pertinent information. As the fundamental elements of the assessment system, Recall, Precision, F1 score, d Accuracy are important evaluation indicators [22-25].



Fig. 3 Dataset images: TrashCAN

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Mean Average Precision (mAP)} = \frac{1}{n} \sum_{i=1}^n AP_i$$

III. RESULTS

A comparison of models applied on TrashCAN dataset shown in Table 1. On dataset, YOLOv8m consistently performs effective than remaining models in every metric that is assessed. YOLOv8m achieves the highest precision (88%) , Accuracy(88.31%) and recall (88.71%) on the TrashCAN dataset. These findings demonstrate how YOLOv8m outperforms its predecessor YOLOv8n & YOLOv8s and other model such as SSD in detection of object tasks across considered dataset, demonstrating its resilience and effectiveness.

Table 1 Performance Outcomes

Model	Precision	Recall	F1-Score	Accuracy
YOLOv8n	0.8455	0.8510	0.8409	0.88515
YOLOv8m	0.8800	0.8871	0.8858	0.8831
YOLOv8s	0.8535	0.8601	0.8782	0.8596
SSD	0.8492	0.8350	0.8399	0.8360

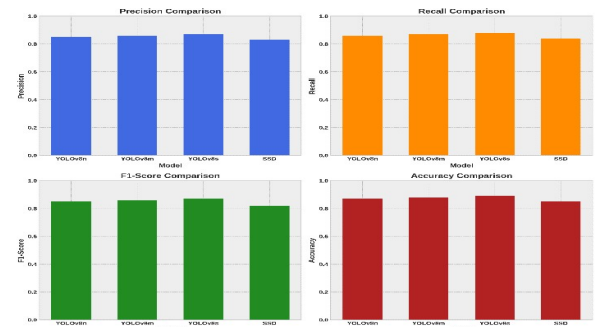


Fig. 4 Performance metrics comparison for YOLOv8m, YOLOv8n, YOLOv8s and SSD



Fig. 5 YOLOv8n Prediction

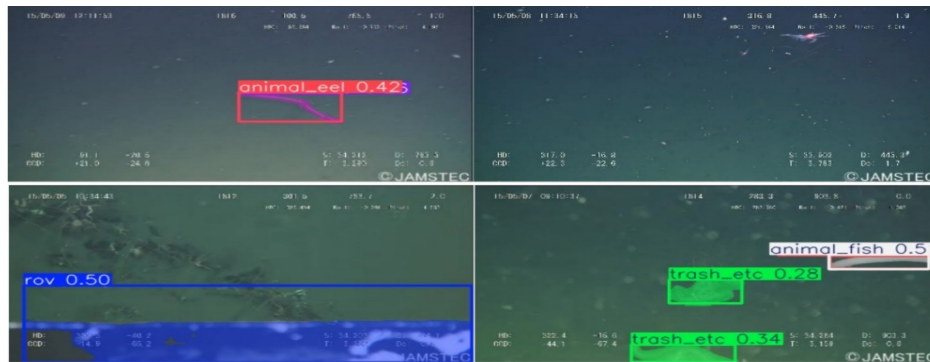


Fig. 6 YOLOv8m Prediction



Fig. 7 YOLOv8s Prediction

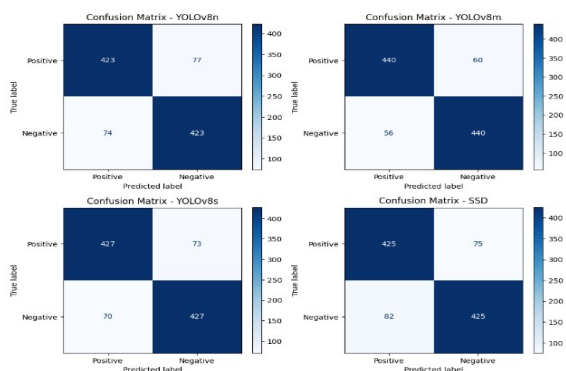


Fig. 8 Confusion Matrix for YOLOv8m, YOLOv8n, YOLOv8s and SSD

A thorough examination of the performance metrics for every item class in the TrashCAN datasets is observed. These findings confirm YOLOv8m's position as the top marine debris identification solution by highlighting its reliability and consistency over a wide range of object types. A thorough model comparison is provided in Table 1, where YOLOv8m is shown to be the best performer.

Notably, with a precision of 88.4% and a recall of 86.3%, YOLOv8m performs exceptionally well in the detection of plastic objects. Following closely behind, YOLOv8 produces outcomes that are competitive but fall short of YOLOv8s in the majority of criteria. In the meantime, YOLOv8n and YOLOv8s outperform SSD in terms of precision, recall, and mAP scores, despite having decent performance.

High precision and recall are still hard to achieve in the Shipwrecks class, which is a problem shared by all models.

These results demonstrate the remarkable efficacy of YOLOv8m in multi-class object identification tasks, showcasing its resilience and dependability in managing intricate detection problems.

Fig.4 offers a comprehensive examination of performance metrics of various models in the TrashCAN dataset utilizing YOLOv8m object detection model. The model exhibits strong overall performance. Differences in detecting accuracy are revealed by a closer examination of particular classes. The precision and recall scores of classes like "trash cup" and "trash bottle" are greater than those of classes like "animal crab" and "animal shells".

The model's efficacy in recognizing maritime debris and rest of items in the TrashCAN dataset is further highlighted by the mAP scores, which further highlight the model's capacity to precisely position objects across different IoU thresholds. Furthermore, YOLOv8m's performance in recognizing maritime trash and other items in the dataset is visually represented by Figure 6, which shows sample findings from the object detection procedure.

Fig. 5, Fig. 6 and Fig. 7 presents the predicted images by YOLOv8n, YOLOv8m and YOLOv8s respectively. Fig. 8 depicts the Confusion matrix of different selected models.

A. Discussion

The quantitative analysis highlighted the efficacy of several object identification models in identifying marine trash across multiple datasets and offered insightful information about how well they performed. Building on these results, it is imperative to investigate the wider ramifications and possible avenues for further study, with a focus on the difficulties presented by loud marine environments.

YOLOv8m consistently outperformed other models, such as SSD, when object detection models were compared on the TrashCAN datasets. This demonstrates YOLOv8m's resilience and efficiency in detecting maritime debris, enhancing its standing as a top option for environmental monitoring projects.

Differences in detection accuracy were found when the performance measures for distinct object classes within these datasets were examined more closely. Even while YOLOv8m performed well overall, it had trouble identifying uncommon things like "shipwrecks" and "animal crabs." This emphasizes the necessity of additional optimization to enhance detection skills for infrequent and uncommon debris pieces.

The difficulties of detecting marine trash in loud environments should be the main focus of future studies. These settings pose serious challenges to precise detection because of their crowded backgrounds and shifting situations. To increase adaptability and robustness of object identification models in demanding marine circumstances, promising approaches include utilizing data augmentation techniques, integrating sensor fusion, and incorporating domain-specific information.

Among the YOLOv8n, YOLOv8m, YOLOv8s, and SSD models, YOLOv8m is typically the best choice for the majority of object detection tasks, especially where accuracy and speed must be balanced. The quicker and smaller

YOLOv8m variation is intended for applications where real-time performance is crucial or when computational resources are scarce, like on edge devices. However, because it finds it difficult to detect smaller or more complex objects, its smaller size comes at the expense of slightly worse accuracy. The medium-sized model YOLOv8m provides a good balance between efficiency and performance, offering increased recall and precision without appreciably slowing down inference. For tasks requiring dependable detection across a range of object sizes and complexities, this makes it the ideal option.

SSD is a well-known object identification model that offers competitive accuracy when compared to YOLOv8 models, particularly for real-time applications. However, on the basis of accuracy and speed, SSD usually falls short of YOLOv8 models. SSD tends to be more computationally intensive than YOLOv8 models, despite being good at managing multi-scale object recognition by forecasting bounding boxes and class scores at various network layers. In the majority of situations, YOLOv8n and YOLOv8m beat SSD in terms of speed and accuracy thanks to their optimized designs and one-stage detection method. Therefore, YOLOv8m would be the better option than SSD and the smaller YOLOv8n variant for applications that require high accuracy and rapid inference.

IV. CONCLUSION

Based on the findings of this study, it is evident that deep learning techniques, particularly YOLOv8m, significantly improve the detection of marine debris in underwater environments. The comprehensive comparison of various object detection models, including YOLOv8 and SSD, reveals that YOLOv8m offers the best balance between accuracy, recall, and precision, making it the most reliable model for real-time plastic detection in marine ecosystems. The study highlights the challenges faced in detecting certain types of debris, particularly less common items like shipwrecks and animal crabs, underscoring the need for further model optimization to enhance performance across diverse object classes.

Despite the impressive results, the research also points out the ongoing challenges posed by noisy marine environments, where background clutter and changing conditions complicate accurate object detection. Future research could focus on improving the adaptability of these models by exploring data augmentation techniques, sensor fusion, and incorporating domain-specific knowledge to handle the dynamic nature of underwater environments more effectively. By addressing these challenges, deep learning models like YOLOv8m can play a crucial role in advancing real-time environmental monitoring and contributing to the sustainability of marine ecosystems.

In conclusion, the integration of advanced deep learning models in autonomous underwater vehicles (AUVs) provides a promising solution to the growing problem of marine plastic pollution. As these technologies continue to evolve, they hold the potential to revolutionize the way we monitor and mitigate environmental damage in our oceans, paving the way for more sustainable and efficient conservation efforts.

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