From Pixels to Plastic - Detecting, Tracking, and Counting Oceanic Plastic Pollution through Computer Vision

Mustapha N*

September 23, 2023

Abstract

Plastic pollution poses an alarming threat to marine ecosystems, necessitating innovative and efficient solutions for its monitoring and management. Building upon recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) [7], we have developed a cutting-edge, AI-driven model utilizing the YOLOv8 architecture[4]. This model not only excels in real-time detection of marine plastics but also integrates advanced tracking and counting capabilities. Tailored for compatibility with marine robotics and other low-resource applications, our approach offers a robust solution even in GPU-deprived environments setting it apart from previous efforts employing the R-CNN architecture[3]. Other recent studies have employed imaging technologies coupled with deep learning techniques, such as the deployment of bridge-mounted cameras on rivers in Jakarta and the use of Unmanned Aerial Systems (UAS) for marine litter mapping on beach-dune systems. Our model notably surpasses these methodologies in performance, achieving superior precision, recall, and overall efficiency metrics. Beyond its detection prowess, our model represents a paradigm shift in the computational efficiency of monitoring tools, poised to revolutionize the strategies to combat the plastic pollution menace in aquatic ecosystems.

Keywords:Plastic pollution in Oceans,Computer Vision,Object Detection,Object Tracking,Object counting

*https://www.linkedin.com/in/nadiera-mustapha-27230a180/

1 Introduction

The rapid urbanization and population growth has led to a surge in plastic consumption, with production reaching nearly 400 million tons per year[2]. Plastics, known for their non-biodegradable nature, pose a significant challenge to ecosystems, especially oceans[1] . The detrimental impacts on marine life are evident, with sea turtles facing ingestion and potential death, and other species being entangled in plastic debris [9]. Plastic pollution disrupts marine ecosystems, damages coral reefs and seafloor habitats, and interferes with the growth of plankton. Moreover, it burdens industries such as fishing, aquaculture, and tourism, and affects coastal communities and economies. The global reach of plastic pollution is extensive, polluting remote areas and causing biodiversity loss.This work introduces an artificial intelligence-based plastic detection model enriched with tracking and counting functionality to bolster global efforts in combatting the ramifications of plastic pollution.The model offers opportunities for early detection and continuous monitoring, targeted cleanup efforts, identification of pollution hotspots, and source identification for accountability. By harnessing the power of artificial intelligence, plastic pollution in our oceans can be proactively combated in ongoing efforts to protect marine ecosystems and biodiversity.

2 Methodology and Implementation

2.1 Dataset and Data Preparation:

The dataset, sourced from The Global Oceanographic Data Center (GODAC), featured images and videos from deep-sea locations like Lake Tahoe, San Francisco Bay, and Bodega Bay in California. Using Roboflow for image annotation, the dataset was split into three segments: 1900 images for training, 637 for testing, and 637 for validation. This 60/20/20 division ensured comprehensive learning, reliable optimization, and performance evaluation on new data.

2.2 Algorithms, Models, and Techniques:

The YOLO (You Only Look Once)[6] object detection system, renowned for its impressive blend of speed and accuracy, formed the cornerstone of our methodology .The YOLOv8 architecture, which shares a similar backbone with YOLOv5 ([10]) was specifically chosen, owing to its exceptional capacity for rapid and dependable object identification ([8]).

The YOLOv8 algorithm was fine-tuned on a dataset of oceanic plastic images and videos. To guarantee both model stability and efficiency, hyperparameters were tailored and key techniques implemented. A deliberate learning rate of 0.002 was chosen for gradual convergence, while a batch size of 16 struck a balance between computational efficiency and model stability. Training spanned over 250 epochs, employing early stopping as a safeguard, halting the process if validation improvement ceased for 50 consecutive epochs.

The AdamW optimizer[5] was used, complemented by weight decay. To fine-tune the learning rate, a cosine annealing schedule with a warm-up phase was employed, which expedited convergence and bolstered generalization. Furthermore, data augmentation techniques such as scaling, translation, rotation, shear, and flips, enriching the model's ability to generalize effectively was used.

Beyond object detection, the plastic detection model was further enhanced with tracking and counting capabilities through the integration of ByteTrack, a state-of-the-art tracking algorithm ([11]). Notably, ByteTrack demonstrated exceptional performance, achieving scores of 80.3 MOTA, 77.3 IDF1, and 63.1 HOTA on the MOT17 test set, securing its top position on the leader board among all trackers.

3 Results and Visuals

3.1 Object Detection Evaluation metrics and validation :

Precision (Box P), recall (Box R), mean Average Precision (mAP) at an IoU threshold of 0.50, and overall mAP scores were used as evaluation metrics to determine the models ability to accurately detect and localize images.results are as follows:

Table 1: Validation Results

Performance Metric	**Value**
Precision (Box P)	0.838
Recall (Box R)	0.687
mAP at IoU 0.50	0.756
Overall mAP	0.478

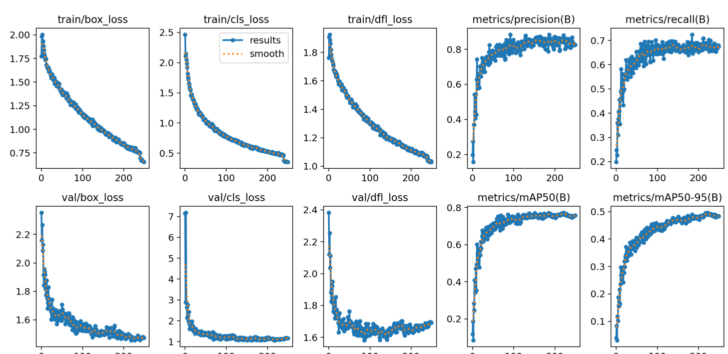
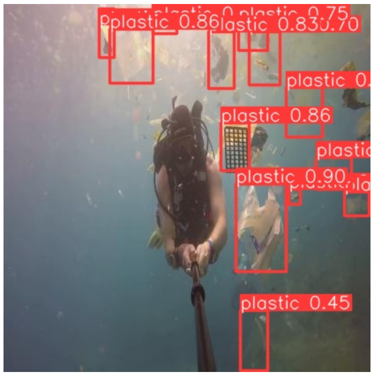
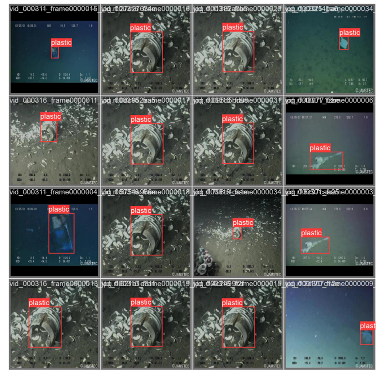


Figure 1: Evaluation Metrics



(a) Prediction on Test Image



(b) Predictions on Validation Images

Figure 2: Test and Validation Predictions

The above visualizations illustrate the model's performance on the validation dataset (see Figure 2b) and its predictions on the testing dataset (see Figure 2a).

3.2 Tracking and Counting Functionality

After integrating tracking and counting functionalities and running inference on the model it achieved an impressive inference speed of 3.5 milliseconds per image.

Figure 3 showcases the results obtained by running inference of the complete model on a video.

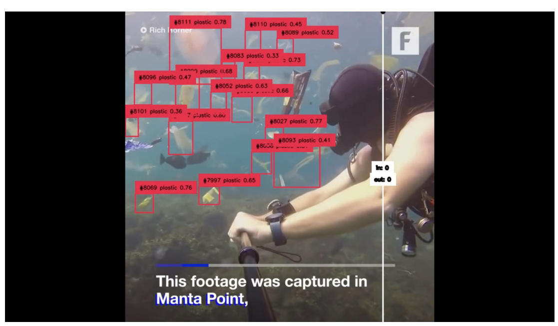


Figure 3: Video Inference Frame

4 Discussion

A precision (Box P) score of **0.838** (Figure 1.a) indicates a relatively low false positive rate, which demonstrates the model's capability to correctly identify and localize objects. A recall (Box R) score of **0.687** suggests that the model is effective in detecting a high proportion of actual objects within the images. An important observation during inference was the model's ability to distinguish between various objects categories, including coral/rocks, fish, and plastic. Notably, the model consistently identified plastic objects correctly.

By incorporating the BYTETracker algorithm, the plastic detection model demonstrates robust object tracking and counting functionalities. This integration empowers the model to accurately monitor the presence and movement of plastic objects across various visual data sources.From running inference the complete model has highlighted the seamless integration of advanced tracking and counting techniques. The fast inference speed allows the model to process and analyze images rapidly, enabling real-time plastic detection in the ocean. This capability is crucial for identifying and tracking plastic debris as it drifts or moves in the water, facilitating immediate response and intervention.

5 Conclusion

The resulting model can analyze videos, accurately detect plastic objects, track their movement, and even count the instances of plastic crossing a predefined boundary. Results indicate that the model achieved reasonable accuracy in detecting instances of plastic waste and shows the model's effectiveness in plastic detection and tracking in oceanic environments.This comprehensive solution enables effective monitoring and management of plastic pollution in aquatic environments. plastic detection model holds immense promise in addressing the pressing issue of plastic pollution in our oceans. By effectively detecting, tracking, and counting plastic objects in aquatic environments, this model enables proactive monitoring and management strategies.This integration paves the way for innovative and effective solutions to tackle this pressing global challenge.

6 Future Works

While our model has showcased promising capabilities in detecting marine plastics, we have identified several areas for potential improvement and further research:

- **Weather Conditions:** The model's performance can be affected by various weather conditions like fog, rain, or turbulent waters. Exploring robustness under these conditions will be a priority.
- **Dense Plastic Clusters:** Our current model excels in detecting dispersed plastic entities. However, detection in dense clusters poses a challenge. Optimizing the model for such scenarios will be crucial for comprehensive marine plastic detection.

These identified areas of enhancement will guide our next steps, ensuring a more resilient and universally adaptable model.

References

[1] Daniel Cressey. “The plastic ocean”. In: *Nature* 536.7616 (2016), pp. 263–265.

[2] PEPT Facts. “An analysis of European plastics production, demand and waste data”. In: *Plastics Europe* (2019).

[3] Muhammad Faisal et al. “Faster R-CNN algorithm for detection of plastic garbage in the ocean: a case for turtle preservation”. In: *Mathematical Problems in Engineering* 2022 (2022).

[4] G. Jocher, A. Chaurasia, and J. Qiu. *YOLO by Ultralytics*. Accessed: February 30, 2023. 2023. URL: `https://github.com/ultralytics/ultralytics`.

[5] Ilya Loshchilov and Frank Hutter. *Decoupled Weight Decay Regularization*. 2019. arXiv: `1711.05101 [cs.LG]`.

[6] Joseph Redmon et al. *You Only Look Once: Unified, Real-Time Object Detection*. 2016. arXiv: `1506.02640 [cs.CV]`.

[7] Mohsen Soori, Behrooz Arezoo, and Roza Dastres. “Artificial intelligence, machine learning and deep learning in advanced robotics, a review”. In: *Cognitive Robotics* 3 (2023), pp. 54–70. ISSN: 2667-2413. DOI: `https://doi.org/10.1016/j.cogr.2023.04.001`. URL: `https://www.sciencedirect.com/science/article/pii/S2667241323000113`.

[8] Juan Terven and Diana Cordova-Esparza. *A Comprehensive Review of YOLO: From YOLOv1 and Beyond*. 2023. arXiv: `2304.00501 [cs.CV]`.

[9] Colette Wabnitz and Wallace J Nichols. “Plastic pollution: An ocean emergency”. In: *Marine Turtle Newsletter* 129 (2010), p. 1.

[10] Sheng Xu et al. “An improved lightweight yolov5 model based on attention mechanism for face mask detection”. In: *International Conference on Artificial Neural Networks*. Springer. 2022, pp. 531–543.

[11] Yifu Zhang et al. *ByteTrack: Multi-Object Tracking by Associating Every Detection Box*. 2022. arXiv: `2110.06864 [cs.CV]`.