



YOLOv8 for Real-Time Microplastic Detection in Aquatic Environments

Sagurthi Kiran^{1*}, P Harikrishna²

Assistant Professor, CSE(AI&ML), CMR Technical Campus, Hyderabad, India¹

Associate Professor, CSE(AI&ML), CMR Technical Campus, Hyderabad, India²

*Corresponding Author

Abstract: Plastic waste is destroying marine ecosystems throughout the world and posing a threat to the life of animals and the health of the waters. This does research on a new deeplearning model named YOLOv8 to identify and classify underwater plastic trash. The system is highly functional in all sorts of water, and can detect different plastic waste in real time. The technology can be useful in the context of conserving the ocean by providing more accurate estimates of the amount of trash that exists, its origin, and the optimal clean-up strategies. Testing indicates that accuracy of the new method is far much superior to the previously used methods particularly when visibility of the water is low. The article contributes to the emerging research on AI in environmental monitoring, by offering a scaled instrument and measuring plastic pollution to direct conservation and policy-related actions.

Keywords: Locating plastic, gathering garbage, categorizing them, YOLOv8, computer vision, and deep learning.

1. INTRODUCTION

The world is witnessing a massive threat to marine environments in the accumulation of synthetic polymers. This poses a severe crisis to the marine life by interfering with the habitats, obstructing the digestive systems, and passing the poison to the food chain[1]. The existing methods of locating submerged plastic like fishing vessel sweeps, hand gathered survey, and simple sonar mapping have dire constraints. They are not extensive enough, they are not frequently used, and they are difficult to operate.

The combination of artificial intelligence with environmental science has superior alternatives than the prior procedures. This paper examines the machine vision in automatic identification of underwater waste. We dwell upon YOLOv8 (You Only Look Once) framework, a novel visual processing system and the unique analysis line. The design also has built-in mechanisms, allowing YOLOv8 to analyze entire image frames simultaneously, rather than pixel by pixel in small patches[3]. This enables it to operate with silk speed but still capable of detecting the things hence it is perfect to be utilized in mobile applications such as remotely operated vehicles and autonomous monitoring stations.[5].

Using this technology in the field of environmental research, we desire the tools which would transform the practice of tracking of plastic pollution into the continuous process. Conservation work could be assisted by these tools to map the hot spots of contamination, discover the location of the waste introduction, and quantify the impact of clean-up measures.

The major findings of this paper are

In this project, YOLOv8 is presented to detect microplastic in water with accuracy. The model is effective with microplastic pieces (small) under complicated water backgrounds.

It has the ability to sort out various kinds of micro plastic fibers and pellets and it works more effectively with bubbles and reflections. □ It is effective in detecting microplastic in water to aid in mitigating pollution.

2. RELATED WORKS

The individuals have experimented numerous methods of shielding underwater creatures against waste materials such as plastic and rubbish. In 2019, Fulton and group offered a deeplearning device which identifies plastic within pixel-based pictures in water. A ResNet design was adopted and trained on special underwater images. A similar application, the Marine Debris Tracker by Jambeck in the same year, sorted marine litter in images provided in the volunteer project, with machine learning. In 2021, Gómez -Rios et al constructed a CNN that was specifically aimed at detecting small pieces of plastic on the seabed; the CNN was able to focus attention on the shape and color of various plastics. In 2020, Wang and



co-authors applied the MobileNetV2 in conjunction with transfer learning to develop the system that can distinguish between plastic and natural material even in cases when the water is not transparent.

To improve the visibility of trash in water that is dark, Karimanzira and Jacobi, 2022, combined cameras, infrared and sonar sensors with a deep learning approach. MARLIT is an initiative in 2022 by Biermann, which deployed a floating litter detection automated system utilising drone camera footage and instance segmentation networks.

Our application applies yolov8 to detect underwater rubbish on a Django web app, where people post images of underwater trash on a pure interface, and our model finds various types of sea debris with 82 per cent accuracy, even at the time when the light obscure or partial cover of objects makes it difficult to view. We integrate aggressive deep learning with simple web interface that a user can use easily with no technical expertise. This system assists in scheduling of clean up work and locating areas of pollution.

3. METHODOLOGY

3.1 Proposed Work

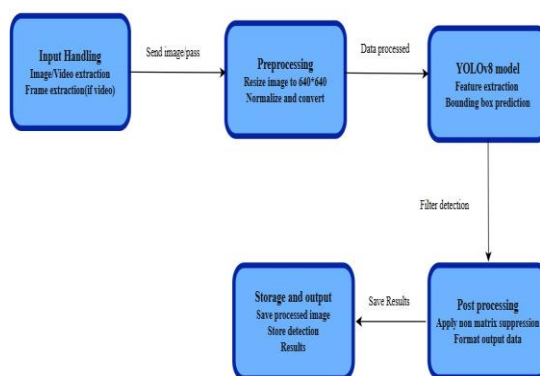


Fig 1. Architecture of the YOLOv8 model for microplastic detection under water

The figure presents the entire YOLOv8 architecture in locating microplastic in water. To start with we feed the model at first with an image. It then identifies features, makes predictions on the bounding boxes and classifies the objects. The end results are saved and the discovered images are shown after the post processing.

3.2 Dataset

The data that we have applied to work on this project is a set of publicly available data and images of underwater debris. The primary dataset that we used is the underwater detritus Dataset of Roboflow and we added additional images too enhance the generalization. Bounding boxes have been applied on the dataset to ensure that YOLOv8 learns. The data set is divided into Training set: 3,626 images, Validation set: 1,000 images, Test set: 501 images.

The database has a variety of detritus that must be identified and labelled. These types of wastes are Plastic Bottles, Glass Bottles, Plastic Bags, Electronic Gadgets, Fishing Nets, Gloves, and Masks.

All the images contain one or more of these objects and the annotations indicate the position of these objects. Such annotations enable the YOLOv8 to gain skills of identifying objects in an image.

3.3 Data collection and preprocessing

Roboflow has over 5,000 underwater images of sea debris in the dataset. Our training Yolov8 model is based on these pictures. There is also the data.yaml file which is required by YOLO models. It provides the model with directions to the training, validation, and test images, and gives the list of labels of objects in each image we have marked.

YOLO gives a description of every object in a picture using text files. The object id, the center of the object in X, the center in Y, the width and the height are put in a line of the file. As we process the data we make sure that all images have corresponding annotation files and AI drop broken files.



We increased the size of the dataset by doing modifications on the pictures such as reversing, rotating, and changing the lighting. The data was divided into 70 percent (3500 images) training, 20 percent (1000 images) validation, and 10 percent (500 images) testing.

3.4 Model Training With Different Versions of YOLOv8

Three small YOLOv8 models (nano-n), small (s), and medium (m)) were trained in the project. We did not achieve the larger models as they are time consuming and require high GPUs. YOLOv8n is the fastest and has lower mAP scores. YOLOv8m performs better in detection, however, it requires more time to train and run. n and s are well trained with T4 GPU, but almost all of its memory is utilized in m. Each of the models is based on the same YOLOv8 design a better backbone, neck, and head with the primary distinction being width and depth. The same procedure was followed in testing them and as such we were able to compare them equally and the trade offs between speed and accuracy.

3.5 Working of YOLOv8 Model

YOLOv8 is capable of object detection at a single pass. It divides the image into a grid and all the cells search simultaneously. The system consists of 3 components, the backbone, which gathers base features, the neck, which merges the base features, and the head, which makes final predictions. The backbone is supported by CSPDarknet. It applies numerous filters of varying sizes to extract information in the image. AdamW was employed in the study with a learning rate of 0.001. This is a combination of momentum and regularization to enhance training. This optimizer acts together with feature pyramid networks in recognizing objects at various sizes. In contrast to the previous models YOLOv8 does not utilise predefined anchors. Rather, it does direct prediction of object coordinates and is highly compatible with the selected optimizer. The similarity of the learning rate (0.001) of the model versions allows their comparison without introducing additional differences.

3.6 Results of YOLOv8 variants

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

Table 1: mAP50, mAP50-95 scores of YOLOv8 models

Interpreting the Key Metrics:

- **mAP@50 Explained:** The probability of this score (0.793-0.820 in our tests) is that the model can detect objects when the predicted box has the real box with an occupancy of at least 50%. The more the scores, the higher the basic detection.
- **mAP@50-95 Context:** These low values (0.503-0.528) test the goodness of the model when we adopt a set of matching rules that are more restrictive. They demonstrate the degree to which the edges of objects can be defined using the model.

3.7 Model Selection and Performance

We ran 100 rounds of training with YOLOv8 version n, s and m in 1 T4. The medium version was best in the object detection. Its scores (0.82 mAP-50 and 0.528 mAP-50-95) were superior and it was therefore worth the additional computation required in doing so over the smaller ones.

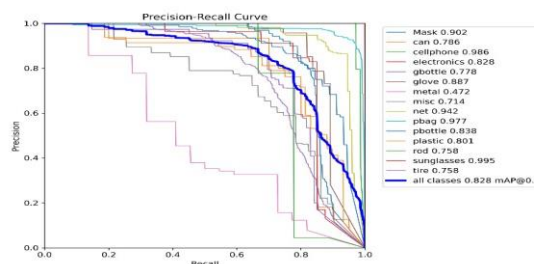


Fig 2: PR Curve of YOLOv8



PR Curve Interpretation:

The curve indicates the detection performance of our system with respect to the various categories of objects. It is the most effective on sunglasses (0.995), cellphones (0.986) and bags (0.977). It is also good with mask (0.902), electronics (0.828), and bottles (0.838). It does not cope with metallic objects (0.472) and miscellaneous objects (0.714). The total mAP of 0.828 and mAP of 0.5 of 0.828 indicate that we selected the appropriate model. At moderate recall, the curve remains very precise but at very high recall, this becomes less precise.

Confusion Matrix

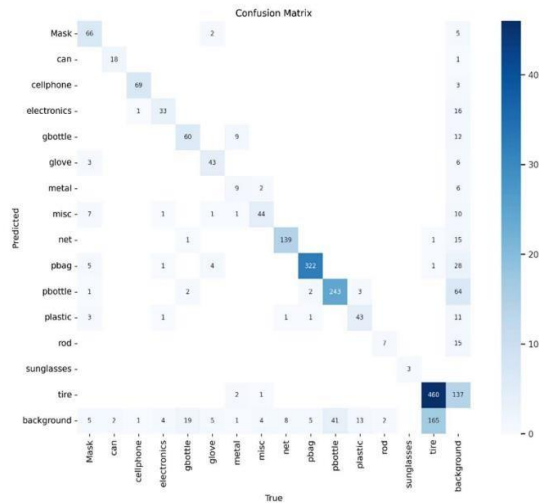


Fig 2: Confusion matrix

The confusion matrix of this YOLOv8m model demonstrates the excellent results in tire, plastic bags, plastic bottles, and all sunglasses are identified correctly. Its major weaknesses include misunderstanding between tire/ background components, and plastic bottle/ background. Metal and rod are tough classes having very low correct detections. Service containers are commonly confused with each other, and the background type bring much noise to a few categories. Despite these particular weaknesses, the overall score of the model is still high.

4. RESULTS AND DISCUSSION

The model is now able to identify and sort garbage in submerged images and videos. Another app that we created is a web app that identifies and categorizes underwater debris such as plastic bottles, plastic bags, cans, electronic, and other devices. Web application is simple to operate. The following is an illustration to depict the garbage when loading an image.

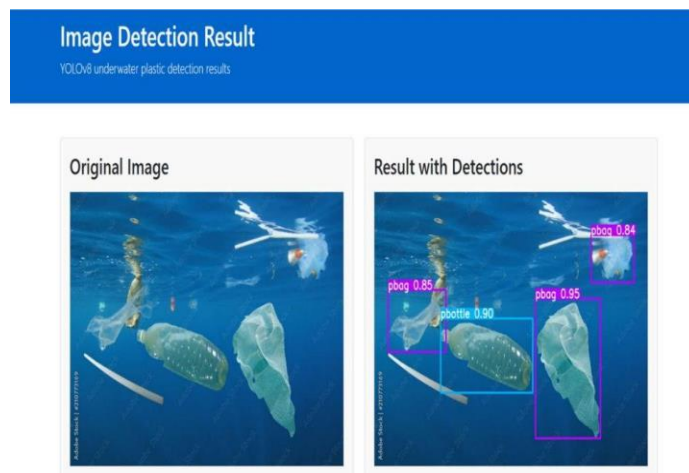


Fig 4.1: Web application interface after detection

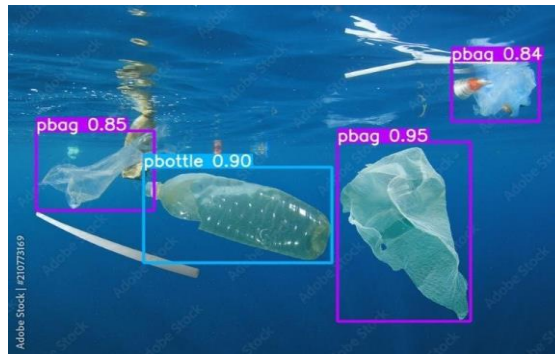


Fig 4.2: Underwater trash detection

5. CONCLUSION

To summarize, the project demonstrates that deep learning method can become an effective means of locating plastic at sea. The system was able to achieve good accuracy and speed by paying close attention to different YOLOv8 models comparing them and using the YOLOv8m with the highest mAP50 scores. It can also be useful when adding this model to a web application, which will enable candidates to add photos and videos to recognize waste automatically. This not only ensures ease of detection, but also gives some easy instrument of conservation of the seas. The fact that the system can scan the media captured in advance per frame indicates that it can be potentially used to monitor the real environment. On the whole, the project can contribute to the development of solutions to the critical problem of underwater plastic pollution and preconditions the further evolution of the automated monitoring systems.

6. FUTURE SCOPE

The present project is a trigger point towards the future project on automatic detecting of trash under water. Possible improvements are:

- Making the model functional on small gadgets such as autonomous underwater drones to be able to locate waste in real time.
- Adding variety to the data: The model should be added to work with different underwater environments.
- Opting to look at a continuous footage through live video rather than individual pictures.
- Collaborating with environmental organizations to apply this technology in massive marine clean up.

REFERENCES

- [1]. Agarwal S, Terrail JO, Jurie F (2018) Recent advances in object detection in the age of deep convolutional neural networks. arXiv preprint arXiv:1809.03193. <https://doi.org/10.48550/arXiv.1809.03193>.
- [2]. J. C. Hipolito, A. Sarraga Alon, R. V. Amorado, M. G. Z. Fernando and P. I. C. De Chavez, "Detection of Underwater Marine Plastic Debris Using an Augmented Low Sample Size Dataset for Machine Vision System: A Deep Transfer Learning Approach," 2021 IEEE 19th Student Conference on Research and Development (SCoReD), Kota Kinabalu, Malaysia, 2021, pp. 82-86, doi:10.1109/SCoReD53546.2021.9652703.
- [3]. R. Varghese and S. M., "YOLOv8: A Novel Object Detection Algorithm with Enhanced Performance and Robustness," 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS), Chennai, India, 2024, pp. 1-6, doi: 10.1109/ADICS58448.2024.10533619.
- [4]. W. Hao and N. Xiao, "Research on Underwater Object Detection Based on Improved YOLOv4," 2021 8th International Conference on Information, Cybernetics, and Computational Social Systems (ICSS), Beijing, China, 2021, pp. 166-171, doi: 10.1109/ICSS53909.2021.9722013.
- [5]. Han, Fenglei & Yao, Jingzheng & Zhu, Haitao & Wang, C.-H. (2020). Underwater Image Processing and Object Detection Based on Deep CNN Method. Journal of Sensors. doi:10.1155/2020/6707328.
- [6]. P. Adarsh, P. Rathi and M. Kumar, "YOLO V3- tiny: Object Detection and Recognition using one stage improved model," 2020 6th International Conference on Advanced Computing and Communication System (ICACCS), pp.687-694, 2020.
- [7]. "Waste Segregation using YOLO v8 based Object Detection and Robotics", International Journal of Emerging Technologies and Innovative Research (www.jetir.org), ISSN:2349-5162, Vol.11, Issue 4, page no.o591-o595, April-2024,.



- [8]. R. Yang, X. Lu, J. Huang, J. Zhou, J. Jiao, Y. Liu, F. Liu, B. Su, P. Gu, A multi-source data fusion decision-making method for disease and pest detection of grape foliage based on ShuffleNet V2, *Remote Sens (Basel)*. 13 (2021) 5102.
- [9]. K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, Las Vegas. (2016), pp. 770e778.
- [10]. S. Dong, P. Wang, K. Abbas, A survey on deep learning and its applications, *Comput Sci Rev* 40 (2021) 100379, <https://doi.org/10.1016/j.cosrev.2021.100379>.
- [11]. X. Xu, M. Zhao, P. Shi, R. Ren, X. He, X. Wei, H. Yang, Crack detection and comparison study based on faster R-CNN and Mask R-CNN, *Sensors* 22 (2022) 121.
- [12]. M. Shafiq, Z. Gu, Deep residual learning for image recognition: a survey, *Appl Sci* 12 (2022) 8972, <https://doi.org/10.3390/app12188972>.
- [13]. S. Dong, P. Wang, K. Abbas, A survey on deep learning and its applications, *Comput Sci Rev* 40 (2021) 100379.