Marine Plastic Debris Detection

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Abstract - *The health of oceans and marine ecosystems is seriously threatened by marine plastic trash. Every year, at least 14 million tonnes of plastic enter the ocean. At now, plastic waste dominates the marine litter population, accounting for 80% of all debris found in the ocean, ranging from surface waters to deep-sea sediments. Every continent has plastic beaches, with higher concentrations of plastic debris found close to well-known tourist attractions and densely populated places. Finding and keeping an eye on plastic debris in marine habitats is essential to creating mitigation plans that work and protecting aquatic ecosystem biodiversity.*

Keywords— *Yolov3, Yolov4, Yolov5, object detection, deep learning, transfer learning, and marine plastic detection*

1.INTRODUCTION

Marine plastic debris (MPD) is a major environmental problem with devastating impacts on marine life, beaches, tourism, and fishing. Detecting MPD is essential for effective monitoring and management, but traditional methods are time-consuming and labour-intensive. New technologies for automated MPD detection are being developed, including image processing, machine learning, and sensor-based technologies. Each technology has its own advantages and disadvantages, but all have the potential to revolutionize MPD detection. MPD detection technologies can be used for a variety of purposes, including monitoring pollution levels, tracking the movement of MPD, and assisting with cleanup efforts. By developing more accurate, robust, and scalable MPD detection technologies, we can reduce the impact of MPD on the marine environment.

1.1. PROBLEM STATEMENT

Plastic pollution poses an imminent threat to the marine environment, food safety , human health, eco-tourism, and contributes to climate change . Global plastic production has exceeded 500 million tons of plastic, and projections indicate that 30% of all produced plastic will end up discarded in the oceans. Researchers have documented a five-fold increase in plastic debris within the Central Pacific Gyre and have shown that plastic pieces now outnumber the native plankton 6:1 in terms of abundance . A significant amount of marine plastic (about 80%) originates from land-based sources : Most commonly in the form of food containers, such as plastic bags and bottles, and packaging materials. The other 20% stems from shipping vessel discharges and discarded commercial fishing gear . Studies have shown that removing plastic from the oceans will exponentially benefit the ecosystems. This includes the prevention of the movement of invasive species between regions, the prevention of its degradation into micro-plastics , and the decrease in emissions of greenhouse gases (thereby decelerating climate change)].

2. LITERATURE SURVEY

[11]The research paper by Hipolito et al. published in 2021 delves into the pressing issue of marine debris and proposes a solution using machine vision, specifically the YOLOv3 method, to detect underwater marine plastic waste. The authors effectively contextualize the environmental significance of the problem and advocate for technological advancements to mitigate its impact. The methodology is robust, employing a well-structured approach involving dataset preparation, image annotation, deep transfer learning algorithms, and data augmentation. The dataset utilized in this inquiry came from the Data Repository for the University of Minnesota (DRUM), specifically the Dataset of Underwater Trash. There are 8580 pictures in the collection, split into two categories: bio images (4290) and non-bio images (4290). The proponents chose a small sample size of 300 non-bio images. The chosen image dataset was used to construct training and validation sets. The training dataset featured 80% of the data, while the validation set only had 20% of the images. Results and discussions comprehensively present training, validation outcomes, and model evaluation using mean Average Precision (mAP). The study concludes by emphasizing the potential of machine vision in addressing marine plastic debris, highlighting an impressive mAP of 98.15% for model 19. Overall, the paper effectively communicates the gravity of the issue and demonstrates the efficacy of YOLOv3 in automated marine debris detection.

[10]An article by Nur Athirah Zailan and Anis Salwa Mohd Khairuddin published in 2021 effectively tackles the pressing issue of plastic debris pollution in riverine environments by proposing a YOLOv4-based algorithm for debris detection. It begins with a strong introduction,

highlighting the gravity of the problem and the necessity for efficient monitoring systems. The proposed debris detection system is trained on five object classes such as styrofoam, plastic bags, plastic bottle, aluminium can and plastic container. A total of 300 original images are augmented by adjusting the brightness level to imitate various environment conditions. Hence, a total of 900 images are used as training dataset. On the other hand, 30 test images for each class are used to test the effectiveness of the proposed detection model. The data processing section meticulously discusses image acquisition, dataset augmentation, and transfer learning using the MS-COCO dataset. The object detection methodology utilizing YOLOv4 is explained thoroughly, emphasizing the significance of spatial pyramid pooling and path aggregation network. The paper introduces and properly elucidates crucial performance evaluation metrics like mean average precision, precision, recall, and F1 score, offering a comprehensive analysis of the detection system's accuracy. The results and discussion section meticulously presents the outcomes, demonstrating the improvements achieved through transfer learning and data augmentation, further substantiated by comparison tables and graphs. The conclusion appropriately summarizes the study, emphasizing the advantages of YOLOv4 implementation and suggesting avenues for future enhancements. While an acknowledgment section recognizes the funding source, additional details regarding the dataset source, specifics of the YOLOv4 model architecture, and potential limitations could enhance the paper's depth and completeness.

[12]An article by Xue et al. published 2021 makes a significant contribution to the field of marine environmental studies by focusing on deep-sea debris classification using deep convolutional neural networks (CNNs). The authors successfully constructed the DDI dataset which is established based on the 9 deep-sea debris database obtained from the real deep sea by the Japan Agency for Marine-Earth Science and Technology (JAMSTEC) a crucial resource for training and validating machine learning models in this domain. The proposed Shuffle-Xception network model showed promising results, outperforming five other compared models, including LeNet, ResNetV2-34, ResNetV2-152, MobileNet, and Xception. Shuffle-Xception demonstrated the highest accuracy in classifying deep-sea debris categories, with an overall accuracy of 93.32%. The research is well-structured, providing a clear methodology and detailed experimental setups. The authors effectively interpret and present the experimental results, allowing for a comprehensive assessment of the proposed approach's effectiveness. In summary, this paper significantly advances the field by addressing a critical environmental concern and introducing a valuable dataset for future research. The proposed model, Shuffle-Xception, showcases strong potential and sets a solid foundation for further advancements in deep sea debris identification and environmental monitoring.

3. Methodology

The primary aim is to select best algorithm for the model building. On studying about features and implications of various we have chosen 2 models. And the Evaluation Metrics defined in different papers are also carefully studied and examined and consider it for the evaluation for our model.

3.1 Data Collection

The dataset was curated by collecting videos of marine plastic from the field in California (South Lake Tahoe, Bodega Bay, San Francisco Bay). The videos vary significantly in quality, depth, and visibility to better represent the harshness of marine environments. Collected various images of subsurface plastic debris.

3.2 Enhancements of Custom Dataset:

The following procedures were implemented for the deep learning models to detect marine plastic: a) Dataset Formatting The input data constituted of images and annotation labels for bounding boxes were converted into either a TFRecords (FasterRCNN and SSD), PyTorch (YOLOv5-S) or a Darknet format (YOLOv8) to process each respective model. The bounding boxes delimited each image's regions of interest based on 2D coordinates located in the respective annotation file. b) Image Pre-processing To ensure that learning occurs on the same image properties, auto orient was applied to strip images of their exchangeable Image file format (EXIF) data so that the models interpret images regardless of image format. Finally, the input images get resized and bounding boxes adjusted to 416x416 pixels. c) Data Augmentation To mitigate the effects of the model generalizing towards undesired features and to replicate underwater conditions such as variable illumination, occlusion, and color–the dataset was further enhanced by randomly changing the brightness and saturation of the images via PyTorch's builtin Transforms augmentation. These modified images were then added back into the dataset, effectively tripling the size of our dataset.

3.3 . Object Detection:

We used four state-of-the-art neural network architectures FasterRCNN with Inception v2, Single Shot Multibox Detector with MobileNet v2, YOLOv5- S and YOLOv4, downloaded from their respective repositories. The following software versions were used: Tensorflow1.5, PyTorch v1.8.1, Darknet, OpenCV version 3.2.0, and CUDA 11.2

1) Faster R-CNN:

The Faster R-CNN approach is employed in a real-time crime scene evidence processing system that can detect items in an interior setting. The proposed system employs the Region Proposal Network and the VGG-16 network for object detection. Seven Convolution layers with Max-pooling, one Flatten, and the SoftMax activation function comprise the following architecture. The first convolution layer has 32 filters, while the next six hidden layers include 100 filters, each measuring 3 x 3. Max-pooling is also performed at each layer on a 2 x 2 scale. The convolutional layers are then flattened and normalised using the SoftMax step. The activation function "ReLu" is used by all layers, and the output range ranges from 0 to infinity. The shear and stride values are both 1.

2) YOLOv5:

YOLOv5 (You Only Look Once) is now regarded the benchmark for object detection and face recognition. It has four versions: YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5xl. It is divided into three phases. The first step is the backbone network, which is a convolutional neural network that focuses on learning high-level features from input pictures. The neck is the second level of the network, and it is focused with learning characteristics at multiple scales in order to learn the same picture with varied sizes. In comparison to the backbone network, it has more layers. Finally, there is the head network, which is primarily responsible for identifying bounding boxes around objects and delivering final annotated pictures.

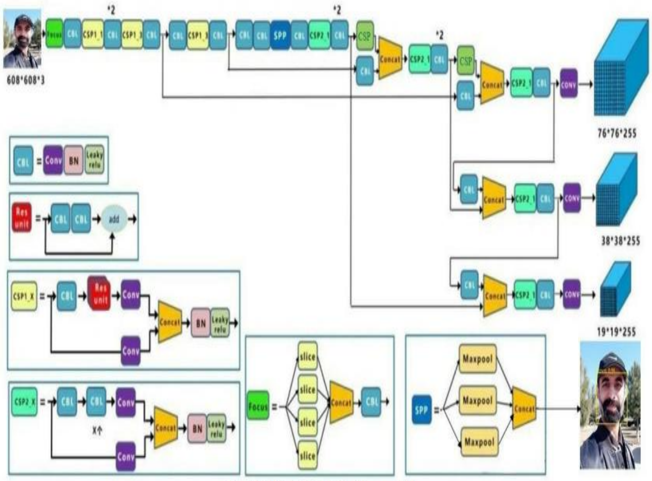

Fig. 3. YOLOv5s Network Architecture [19]

6) Simple YOLO

The You Only Look Once algorithm's primary goal is item recognition and categorization. The YOLO algorithm has four variations, each of which improves the model's performance. In comparison to RCNN, the YOLO algorithm employs a whole picture feature rather than a portion of the collected image. The YOLO method conducts bounding box and class prediction concurrently, which distinguishes it from other standard systems. Instead of a standard region proposal and classification, YOLO addresses the object detection problem as a regression problem. This allows YOLO to run more effectively in real-time while sacrificing some accuracy.

3.4 Evaluation Metrics

The models are evaluated using Precision, Accuracy Loss,etc

4. Results

MODEL	METRICS
YOLOV5-S	Mean Average Precision[MAP]= 0.851 F1 Score -0.89
YOLOV8	Precision- 0.82, F-score-0.86

5. CONCLUSION

This work's objective was to develop a deep learning vision model capable of consistently identifying and quantifying marine plastic near real-time. To attain this objective, a pair of general object detection models were constructed using two state-of-the-art deep learning models built for inference speed to measure which performed best. This study concludes that a marine plastic debris detection system based on the YOLOv5-S model would be fast, accurate, and robust enough to enable real-time marine plastic debris detection. This study shows that effective object detection models can be constructed using readily available, pre-enabled GPUs for reasonable costs. Furthermore, the dataset created for and utilized by this general detection model demonstrates that massive, highly curated datasets can be used in conjunction with samples relative to the domain of object detection and web scraping to produce promising results. This computer vision system enables multiple deployment methods to detect/monitor marine plastic and allows researchers to quantify marine plastic debris without physical removal.

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