Marine Waste Detection

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***Abstract*—Plastic pollution in the oceans poses a very significant threat to our marine ecosystems, biodiversity, human health, and countries economies. As this seems like a major concern to conserve and preserve our environment, we highlight the importance of marine life and address the efforts that should be made to reduce the plastic pollution in oceans.**

***Index Terms*—Plastic Pollution, Marine Debris, Deep Learning, Autonomous Underwater Vehicles (AUVs), Object Detection, Conservation, Evaluation Metrics**

I. Introduction

PLASTIC pollution has become a global challenge for many sectors, which include food safety, human health, marine life, and many more. Despite many efforts applied in this field, it still faces many problems, such as high cost, inaccurate assessment of plastic waste, labor work to solve such issues, and limitations to cover areas that are limited to rivers or lakes and do not cover large ocean bodies. Therefore, there is a need to have innovative solutions to address such issues globally.

A. Problem Statement

The major problem or the main cause includes the environmental harm to the water bodies in rivers, lakes, seas, and oceans. This is because currently more than 14 million metric tons of plastic are deposited in the ocean every year, causing the depletion of marine ecosystems. The current methods for monitoring marine plastic have high maintenance costs, higher building costs, and also require greater labor work. Moreover, the ocean is also polluted due to the rise of carbon dioxide in the environment, leading to the acidification of the water. So this brings in a solution to develop a machine learning model with computer vision to detect the plastic precisely and other marine debris throughout the entire water body.

B. Relevant Works

1) Current Actions and Technologies: Many initiatives are being taken in this direction to protect our environment. The Government of France has recently implemented the anti-waste law to aim to curb single-use plastic that ends up in freshwater. [1] It is noted that out of 14 million tons of plastic that end up in the ocean, 80% of the marine debris is found on the surface of the water or deep-sea sediments. [2] For this, many studies have been conducted, such as the remote sensing technique, which can be used to conduct aerial surveys on water bodies to detect floating plastic. [3] Research is made to analyze the underwater composition of plastic debris on the seafloor; this showcases the accumulation of plastic underwater. Many algorithms and the use of convolutional neural networks are used to quantify the issue. The SOTA for this is to deploy the autonomous underwater vehicles (AUVs), which are equipped with sensors and imaging systems to monitor marine plastic debris. They are capable of scanning large ocean beds. Many collaborative efforts are made by governments and NGOs to provide large datasets and databases for such technology that can detect plastic in the ocean. With the development of this ML model, the software aims to detect plastic in the ocean in order to collect those remains by the AUVs or by manual labor for small water bodies.

2) Brief Literature Survey: In recent studies, we have noticed that, using a combination of satellite imagery and oceanic modelling tools, we can analyse plastic trash in the North Atlantic Ocean. This analysis showcases the growing level of plastic pollution over time. This forces us to mitigate strategies to address issues for marine ecosystems. Furthermore, a report from the 2019 Ocean Conservancy states that there is an urgent need to manage the complex effects of plastic waste management on marine life, which also underlines the critical need to tackle the environmental threat that is aroused by plastic pollution and leads to the destruction of marine habitats. [4]

The challenges faced while doing the extensive analysis by Johnson et al, that come with doing marine debris monitoring projects. There was a lack of a standard evaluation process, the difficulty of keeping track of the analysed data, and restricted access to the distant regions. These things need to be solved quickly, and there should be advancements in technology as they are endangering marine life due to plastic pollution.

In the technological upgrade, Smith et al. played an important role in the advancement of improving marine debris detection and monitoring capabilities for growing plastic pollution. The study was focused on autonomous vehicles (AUVs) with cutting-edge imaging and sensor systems, with the help of (AUVs) the researchers can get good quality of data easily by covering areas of the ocean. The opportunity to improve the precision and efficiency of monitoring operation of plastic in oceans. [5]

Analytical deviation: Garcia-Hernandez et al, (2018) created a mathematical model for the forecasting of marine debris dispersion based on wind patterns and ocean currents. This work of Garcia served as the inspiration for the analytical deviation in our approach. Using this model as a base, our approach improves plastic detection accuracy by using advanced machine learning methods. [6]

Methods: For the detection of objects, we used a convolutional neural network (CNN) model based on the Quicker R-CNN framework proposed by Ren et al. (2015). Our approach optimize the performance for the detection of marine debris underwater by blending extra layers for feature extraction and classifying it.

Research Procedure: For the betterment of the spatial coverage and undertaking of marine debris monitoring, studies in the future may investigate the merging of satellite imaging with drone surveillance. Furthermore, advancements in machine learning algorithms, such as reinforcement learning, do have the capability to improve (AUV) navigation and technique in the identification of marine debris.

C. Our Contributions

In this study, we use deep learning and computer vision techniques to present a unique strategy to address the problems associated with monitoring marine plastic. Our method seeks to provide an accurate, dependable, and real-time system for measuring and identifying marine plastic waste across the whole water column. Our contribution consists of building on previous research and methods, diversifying datasets, introducing specific modifications, testing multiple object detection models, and assessing model performance with pertinent metrics.

D. Organization

The structure of this document is as follows. Section I gives a summary of our suggested methodology with its Introduction. The Proposed approach is covered in Section II.The algorithm of how the model is being trained is mentioned in the Section III. The remarks of the model are mentioned in Section IV. In Section V, The Graphical results are shown and in Section VI we have the Prediction result of the model. And at last we have the Appendix to briefly explain key terms in our project.

II. Proposed Approach

A. YOLO Model Configuration

YOLOv8, or (You Only Look Once, version 8, is a big step up in object detection and identification through the technology of deep learning. The essence of YOLOv8 is its efficiency and precision, and it strives to provide a unified solution for real-time object detection tasks, including the identification of marine waste.

Moreover, its unified architecture combines detection and classification in a single neural network. In contrast to the multi-stage and complex pipe methods in objection detection, YOLOv8 uses a single-shot, one-pass way for predicting the bounding boxes and class probabilities for all the objects in the input image. Besides, YOLOv8 is not only a means of simplicity in the model architecture but also offers quick inference speeds, which is useful in a dynamic marine environment where timely detection is a must.

Furthermore, YOLOv8 consists of different architectural advances and training techniques to enhance its detection accuracy. These include the employment of several advanced backbones, such as Darknet-53, which provide enough power for accurate object localization, recognition, and imaging. Furthermore, YOLOv8 maintains its accuracy by applying strategies like focal loss and anchor box clustering when identifying objects of different sizes and classes, including small fragments and broken marine waste.

The model is also designed to be efficient and can work well in various kinds of situations and systems, in spite of the number of computer resources available. The YOLOv8 model has a configurable architecture, which is one of its key strengths. It also allows the researchers to choose between various variants, like small, nano, and medium, depending on the specific needs of the application, whether it involves running the model on certain low-power devices for edge deployment or on high-performance servers for cloud-based inference. It is for this versatility that YOLOv8 is suitable for identifying marine wastes in a number of marine waste detection initiatives, be they situated along the coast or in open ocean environments.

On the other hand, transfer learning and data augmentation are the guiding principles in YOLOv8 that help in increasing its generalization power and robustness to variations in the environment. Lastly, using images from the large-scale object detection datasets, YOLOv8 will pre-train itself and fine-tune on the marine waste domain-specific datasets, making it well equipped to recognise and classify a wide range of marine waste, including plastic waste, fishing gear, and other pollutants.

B. Data Collection

We have collected a dataset of almost 3200 images from Japan Agency for Marine-Earth Science and Technology (JAMSTEC) for our project. Then we divided this dataset of Images into training, validating and testing data in the ratio of 60%, 20% and 20% respectively.

Then we create a text file corresponding to each image consisting of one or more lines, each line signifying an object in the image. Each line contains a class number for the object, the y-center and x-center coordinates of the bounding box and the height and width as well which is normalized from 0 to 1. This file is called as the label file for the image.We convert our image into a YAML file format because it's a prerequisite for employing YOLO.

C. Training the Model

The model was trained on a customized dataset with parameters modified for marine-specific accuracy and detection speed. Yolov8 uses Sigmoid for activation by default (we can change activation function by manually if we required).In YOLOv8, no pruning is done.Pruning is often achieved by dropping redundant weights, neurons, or layers of a deep network while attempting to retain a comparable test performance

III. ALGORITHMS

Algorithm used for detecting garbage using YOLO in pseudo-code format.

A. Algorithm for Data Prepossessing

Algorithm 1 Data Prepossessing for Garbage Detection

Require: Dataset D for test and train
Ensure: Pre-processed training and validation sets
for each image I in D **do**
  Resize I to the input size of the YOLO model
  Apply image augmentation techniques (e.g., rotation, flip)
  Annotate I with bounding boxes and class labels
end for
Split the dataset into training and validation sets =0

B. Algorithm for Training the YOLO Model

Algorithm 2 Training the YOLO Model

Require: Preprocessed training and validation data
Ensure: Trained model
Initialize YOLO model with pre-trained weights (if available)
Configure training parameters (e.g., learning rate, epochs)
while not converged **do**
  for each batch in training data **do**
    Forward pass
    Compute loss
    Backward pass and optimize
  end for
  Validate on validation set
  Adjust parameters if necessary
end while
Save the trained model =0

C. Algorithm for Detecting Garbage Using YOLO

Algorithm 3 Detecting Garbage in Sea Water Using Trained YOLO

Require: Trained YOLO model, test image or video frame
Ensure: Output with detections
Preprocess the image (resize, normalize)
Run the YOLO model to detect objects
for each detection in detections **do**
  Check confidence score
  if score above threshold **then**
    Classify object as garbage
    Draw bounding box and label on the image
  end if
end for
Display or save the output image =0

IV. REMARKS

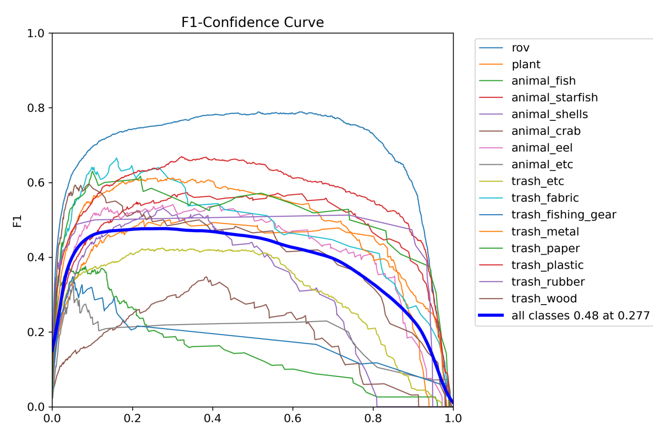
Although YOLOv8 model is one of the best in terms of object detection and localization but still every model has some limitations and problems which needs to be addressed. Here are some of the limitations of the YOLO model:

1) Because of its grid-based approach, YOLOv8 struggles with the problem of precisely locating small objects or objects with complex details. YOLO treats each grid cell equally, which leads to imbalanced class distributions which makes it perform poorer than other models.
2) YOLOv8 speed and real-time performance are one of the best when compared to other models, but this is at the expense of accuracy, especially for smaller objects or congested scenes. In comparison, some other models, one such being RCNN-based models focus on regional search mechanisms (like selective search in Fast R-CNN) which allows for accurate results. Also, here, the focus is more on accuracy rather than on speed.
3) Also, because of its fixed architectural-based design, it requires much more fine-tuning, which is not the case in RCNN because of its architectures like ResNet or EfficientNet, which allows quick adaptation to new domains or tasks.

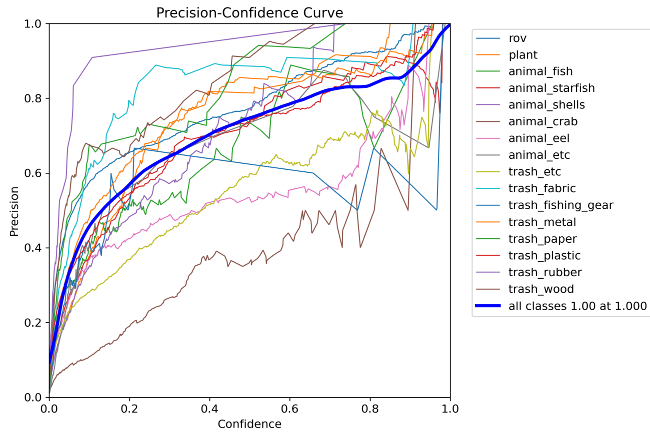
V. GRAPHICAL RESULTS

This Section shows the results of the YOLOv8 model. It has shown the different results which varies with all kind of marine debris including living animal too.

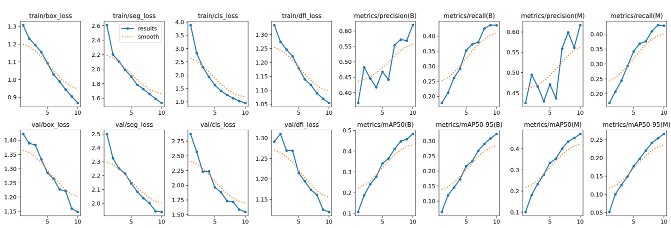
1) F1 score:



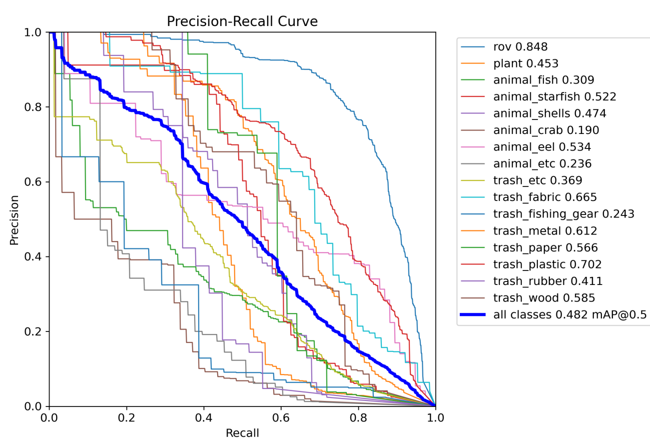
2) Precision:



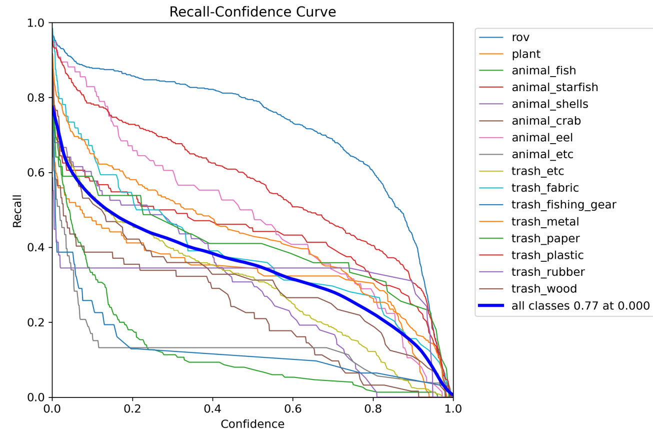
3) Result:



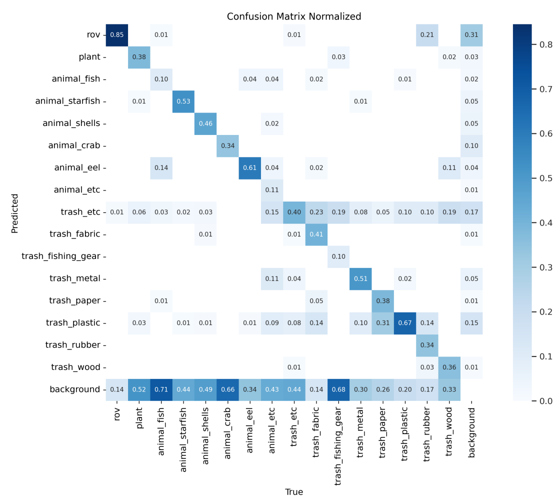
4) Precision Recall Trade-off:



5) Recall:



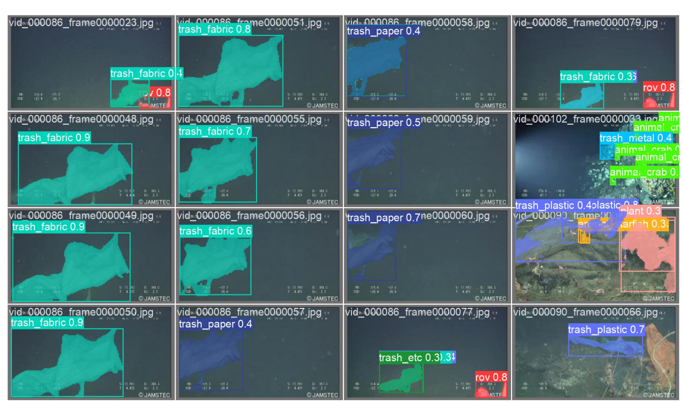
6) Confusion Matrix:



VI. Prediction Results

Now we will show the Output of prediction of the Trained Model on Validation Dataset

1) Batch 1:



2) Batch 2:

Fig. 6 gives the Confusion Matrix providing summary of classification performance, giving True Positives, False Positives, True Negatives and False Negatives. (Value in the Diagonals should be as high as possible and low otherwise).

Fig. 7 and Fig. 8 gives the predicted output for the validation dataset showing the predicted class and confidence score.

Appendix A
Key Terms

1) CNN Model: It is one form of deep studying model this is frequently used for image identification, category, and segmentation duties, it stands for convolutional neural network (CNN). Because CNNs can study complex styles instantly from uncooked pixel facts and report spatial hierarchies, they're very beneficial for interpreting visible statistics.
   Training of a CNN entails feeding categorised schooling information into the community and adjusting its parameters such as filter out weights and biases to minimize a loss function and optimize the model's overall performance. Once the version is trained, the CNN may be used to make predictions on new or unseen statistics by passing it through the network, which in turn go back us with the output possibilities of every magnificence.
2) AUVs : AUV stands for autonomous underwater vehicle. AUVs can be used as underwater vehicles to complete certain missions or tasks without the help of humans. AUVs can do their task on their own. They don't require human support because they are equipped with sensors, navigation systems, cameras and biological sensors for detecting marine life.
   The use of this automobile is mostly associated with oceanography, in which AUVs are used to collect information from ocean currents, study temperature gradients, and observe marine biodiversity, which provide us with important insights into oceanographic ecosystems. It is primarily used in environmental monitoring, in which AUVs are deployed to monitor and take readings of environmental parameters like water excellence, pollution degrees, and much more.
3) Object Detection:The object detection challenge includes finding and recognising things inside a picture or video frame. In evaluation to photograph type, which assigns a single label to the entire photograph, Object detection techniques locate and pick out many things of interest as well as the bounding boxes that belong to every one.
   It involves tactics like image preprocessing, characteristic extraction, object type, and put-up processing. This generation is generally utilised in self-sufficient automobiles, in our case, AUVs. It is broadly used in the medical area, surveillance, and safety.
4) Evaluation Metric: Evaluation metric is tool used to calculate the performance of machine learning model.this metric estimates how effectively a model works.
5) Deep Learning:Deep learning is a branch of machine learning that which uses artificial neural networks to learn from data. Deep learning models in particular, deep neural networks have shown accurate results. We have used its one of the concept mentioned above that is CNN.
6) F1 Score: F1 score is the harmonic mean of precision and recall. It indicated as to how much precise and accurate is our data.
7) Precision: Precision indicates how many of the predicted items are positively predicted. It is the ratio of True positives to the sum of True positives and False Positives.
8) Recall: Recall, on the other hand, indicates how many of the specific class items have been rightly predicted. It is the ratio of True Positives to the sum of True Positives and False Negatives
9) mAP :Mean average precision (mAP) is a metric commonly used to calculate the performance of object detection. It is commonly used in YOLO model. It calculates the precision-recall trade-off of the model.
10) IoU: Intersection over Union is calculated as the ratio of the region of overlap among the anticipated bounding container and the ground truth bounding container to the vicinity of union between them. IoU values variety from 0 to 1, wherein 0 suggests no overlap and 1 indicating ideal overlap. Higher IoU values imply higher agreement between the expected and floor reality bounding containers.

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