Seafloor Debris Detection using Integrated ResUNet and Yolov8 Model

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***Abstract*—Ocean pollution is a serious problem today. Many waste materials such as plastic, metal, and other debris are dumped into the ocean. These materials often sink and settle on the seafloor. This waste can harm marine animals and damage the ocean environment. Finding this debris manually using divers or underwater vehicles is difficult, costly, and time-consuming. Because of this, an automatic system is needed to detect debris in underwater images. This paper proposes a method for seafloor debris detection using deep learning techniques. In this paper, deep learning techniques are used for seafloor debris detection. First, underwater images are improved using Res U-Net to reduce blur and low visibility. Then YOLOv8 is used to detect and identify debris objects in the images. The system can automatically highlight the detected debris using bounding boxes, which makes it easier to see where the debris is present on the seafloor.The proposed model has got the of accuracy where 95% for image restoration and 86.6% for Debris Detection .This method helps in identifying underwater waste more quickly and accurately. It can also help researchers and environmental teams understand the level of pollution present in underwater areas.**

***Keywords*—Seafloor Debris Detection, Underwater Images, Deep Learning, Image Restoration, Object Detection, ResUNet, YOLOv8**

I. Introduction

The dumping of waste materials into the seas has become a major environmental concern of global concern because the wastes in oceans are growing in number of plastics, metals, fishing nets, glass and rubber. These wastes are also known as marine debris and are a major threat to marine environments, marine life, fishing and tourist activities [1]. Marine debris usually settles down on the bottom of the ocean and takes a long time to disappear because some of the materials such as plastics do not decompose easily and may cover vast regions of the ocean [2]. This issue is on the rise, which underscores the importance of the efficient marine debris monitoring and detection systems.

The marine debris is difficult to detect in the underwater setting because of the peculiarities of underwater imaging[5]. Low visibility, absorption of light, scattering, noise, and distortion of colors are among the factors that greatly reduce the quality of the image and thus hard to detect objects [6]. The outdated approaches of manual inspection or simple image processing algorithms are not efficient, time-consuming and cannot be effectively applied to observe large populations [20]. Thus, intelligent and automated methods are needed to enhance accuracy and efficiency in the detection.

As the field of artificial intelligence has evolved, scientists have begun to use deep learning in marine debris detection. Convolutional Neural Networks (CNN), Faster R-CNN, SSD and YOLO are the models that have proven to be effective in detecting objects by learning features through images automatically [4]. Specifically, models based on YOLO have been demonstrated to be effective in real-time detection, whereas other models have aimed at enhancing the accuracy and resilience in underwater complex conditions [7][. Also, underwater vehicles dataset and benchmark datasets have made it possible to train these models, enhancing their ability to identify different types of debris [3].

The primary Objectives of this paper include improvement of the underwater images quality through ResUnet architecture through minimizing image noises, blurs, and distortions in colors, and secondly, detection and classification of marine litter through the use of YOLOv8 object detection algorithm. Another purpose includes the enhancement of the performance of object detection and improving image restoration techniques in detecting marine litter.

Nevertheless, issues like poor datasets, the intricate underwater environment, and similarity of debris and natural objects remain [8]. To solve these problems, the current research suggested a deep learning-based system to identify seafloor debris, which incorporates image restoration and object detection. The proposed system will operate in the following sequence: First, underwater images will be processed through the ResUNet model to increase the quality of the image, and then the process of detecting debris will be used through the YOLOv8 model. The system is able to detect and track the location of debris objects with the help of bounding boxes, which allows efficient monitoring of marine pollution. Moreover, the suggested system is supposed to offer an effective and easy to use system in real world marine monitoring[3]. The system enables users to upload pictures of the underwater world, visualize the findings of the detection process, and analyze the environment conditions using deep learning models and the interactive interface[18]. This method does not only minimize manpower but also makes it possible to make quicker decisions in conserving the marines[12]. Researchers, environmental organizations and government agencies can use such automated systems to check the level of pollution, the amount of debris, and to arrange efficient cleanup processes [1].

The main objectives of this paper are as follows:

1) To enhance underwater images for improved visibility of underwater waste.
2) To develop a robust model for accurate detection and classification of underwater trash.
3) To evaluate the effectiveness of the proposed model and compare its performance with existing approaches.

This paper is organized into the following sections: Section II provides an overview of the literature survey for methods used in detecting marine debris. The methodology involved in the Paper process, involving image restoration with ResUNet and marine debris detection with YOLOv8, is provided in Section III. The results and outputs obtained from this experiment are presented in Section IV.

II. Literature Survey

Over the last few years, a number of scientists have been working on the identification of marine debris by underwater images and deep learning. The importance of marine debris detection has been realised because of the adverse effects it has on marine ecosystems and human activities. Zhao et al. [1] suggested a system that combines image restoration with detection methods, which enhance the detection performance in underwater conditions. Likewise, Fayaz et al. [2] designed an intelligent underwater object detection system to autonomous underwater vehicles and emphasized on the role of automated monitoring systems.

In deep learning, datasets are important in the training process. Duras et al. [3] proposed an underwater debris detection and segmentation dataset, which is helpful in enhancing model performance. The MARIDA dataset of marine pollution detection through satellite images was introduced by Kikaki et al. [9], allowing to monitor the pollution of the ocean on large scale. Such datasets can assist in creating powerful detection models.

A number of research works have devoted their attention to the implementation of deep learning models in detection of debris. The researchers of Sanchez-Ferrer et al. [5] performed experiments involving the use of object detection to identify marine debris. The YOLOTrashCan model suggested by Zhou et al. [7] enhances the performance of detection through feature fusion and attention mechanisms. Huang et al. [8] came up with a deep neural net-based system to detect debris in water in real-time. Xue et al. [10] used a model based on ResNet50 and YOLOv3, and it performed well to detect deep-sea debris.

One of the significant issues with underwater environments is image quality. Deluxni et al. [6] conducted a review of different image enhancement and restoration methods of underwater images. Li et al. [11] suggested an enhancement approach of underwater image by use of scene priors to enhance visibility. Berman et al. [12] proposed a haze-line based restoration method to reduce color distortion. Li et al. [13] used histogram equalization and wavelet transforms for enhancing underwater images. Yang et al. [14] presented a baseline dataset and assessment procedure of underwater image enhancement. Dehazing techniques that would enhance the clarity of images in harsh conditions were suggested by Peng et al. [15] and Zhang et al. [16].

Object detection methods based on deep learning have demonstrated high improvements over the conventional ones. Liu et al. [17] came up with a better model of YOLO-based detector of underwater in real-time. Sun et al. [18] implemented transfer learning methods in detecting underwater trash and enhancing the accuracy as the data available is small. The results of Mandal et al. [19] showed that deep learning and computer vision methods are effective in detecting marine debris. Duarte et al. [20] overviewed different methods of deep learning in underwater image segmentation and classification.

Despite a number of methods suggested, there are still a number of difficulties. These are low quality of the image, lack of datasets, and distinguishing between the debris and natural objects. Thus, it is believed that a combination of image restoration and object detection methods can be a reasonable solution to enhance marine debris detection. In this paper, the proposed system combats these challenges by incorporating both image enhancement with ResUNet and debris detection with YOLOv8.

III. Proposed Methodology

In order to detect seafloor debris effectively and accurately, the proposed system will make use of two deep learning models, i.e., ResUNet and YOLOv8. Image restoration is used with the ResUNet model to improve the quality of underwater images by eliminating noise, blur and distorting color. The enhanced images are subsequently fed into the YOLOv8 model, which is efficient and accurate in detecting debris objects. The joint work of these two models promotes the overall system performance and makes the detection of the system to be a reliable one in a complicated underwater environment.

A. Image Restoration using ResUNet

The most common issues in underwater photos are the blurring, noise, low contrast, and color distortion since light is absorbed and scattered while passing through water. These problems may complicate the object detection process because objects become blurred and distorted, making it hard to detect any possible debris. Therefore, for successful object recognition, image restoration should be performed.

The proposed solution is based on ResUNet neural network to increase image quality. This model is based on U-Net architecture, which is widely used for image restoration and segmentation. ResUNet introduces the concept of residual learning for better and efficient functioning. Thus, U-Net consists of two parts – the encoder to detect image characteristics and the decoder to construct an enhanced image.

When training the proposed model, the European Underwater Image Degradation and Restoration (EUVP) dataset will be utilized. However, the raw data of the underwater scene

TABLE I
COMPARISON OF PREVIOUS METHODS

Reference	Methodology Used	Dataset Used	Performance Metrics
[1]	Deep learning-based object detection network	Real underwater images from Koh Tao, Thailand	mAP 91.2%
[2]	Object detection model with underwater image restoration	Deep-sea debris image datasets	mAP 94.35%
[3]	Faster R-CNN, YOLO-v6	Shallow-water marine debris dataset	mAP 91.2%
[4]	YOLOv7-based instance segmentation network	Satellite remote sensing images	F1-score 77%
[5]	Mask R-CNN	Marine debris image datasets	mAP 86%
[6]	Underwater image enhancement using deep learning models	Not applicable	mAP 68.9%
[7]	YOLO-v11	Underwater marine debris datasets	mAP 65.01%
[8]	DSDebrisNet	Deep-sea underwater image datasets	Detection accuracy 73.4%
[9]	U-Net, Random Forest	MARIDA dataset (Sentinel-2 images)	mAP 65%
[10]	ResNet50-YOLOv3 hybrid network	Custom AUV underwater datasets	mAP 71%

should not be considered degraded since it provides high-quality images without artifacts. Thus, the dataset should be artificially degraded using different algorithms like adding noise, blurring, and reducing image contrast.

The degraded images should be used as inputs during training. On the other hand, ground truths will consist of original images, which are supposed to be restored successfully after training.

After successful image processing, degraded images will be transformed into high-quality images with sharp edges and high contrast. Thus, the detection and bounding will become much simpler because of increased image clarity.

Therefore, the images obtained after restoration will be transferred to a YOLOv8-based detector and classifier for debris identification.

B. Debris Detection Using YOLOv8

The next step in the system is debris detection after the underwater images are improved using the Res U- model. The restored images are used as input for the object detection model in this stage. The goal of YOLOv8 model is to detect seafloor debris in this work. YOLO stands for "You Look Once." It is a learning based object detection model that can detect objects in images quickly and accurately. It divides the image into regions and checks each region to see if a debris object is present. In this methodology the YOLOv8 model is trained to detect debris such as plastic waste, metal objects, fishing nets and other marine trash. The TrashCan dataset is used for training and testing the debris detection model.

This dataset contains underwater images with different debris objects collected from underwater environments. During training the YOLOv8 model learns the features which include shapes, edges, textures and debris object patterns. By learning these features the YOLOv8 model becomes able to identify debris objects when they appear in complex underwater backgrounds. When the YOLOv8 model detects debris in an image it draws a bounding box around the detected debris object. Along with the bounding box the YOLOv8 model also provides a class label that indicates the type of debris detected. The YOLOv8 model is suitable for this pipeline because it performs object detection in a step. This makes the detection process faster compared to traditional object detection methods. Faster detection is useful when the system is used for time underwater monitoring. After detection the performance of the YOLOv8 model is evaluated using evaluation metrics such as Precision, Recall and Mean Average Precision. The system can automatically Locate debris, in underwater images which can help researchers and environmental organizations monitor marine pollution and support ocean cleaning efforts using the YOLOv8 model.

The fig 1 is the flowchart which shows the general workflow of the proposed seafloor debris detection system. The process starts with collecting data and concludes with detecting debris in underwater conditions in real time. This paper uses two datasets: the EUVP dataset and the TrashCan dataset. The EUVP data is composed of images of high quality underwater, the main use of this data is to train the image restoration model. The TrashCan dataset consists of images different types of debris like plastic, metal and discarded fishing nets.

The images obtained are first preprocessed, cleaning and resizing them to achieve uniformity and compatibility with deep learning models. The EUVP data is also artificially corrupted to induce noise and blur in order to simulate real underwater conditions with the help of computer vision technique. The degraded images are subsequently provided to the ResUNet architecture image restoration model to train. ResUNet model is trained to sharpen underwater images, boosting visual clarity, diminishing noise, and blurry images.

After restoration, the enhanced images are used for further processing. TrashCan dataset is annotated and labeled with the objects of the rubbish in the images. The trained YOLOv8 object detection model is then trained on this labeled dataset. The trained YOLOv8 model finds debris in the restored images and creates bounding boxes around the detected objects.

Precision, recall, and mean Average Precision (mAP) are used to assess the model performance. Lastly, the system is

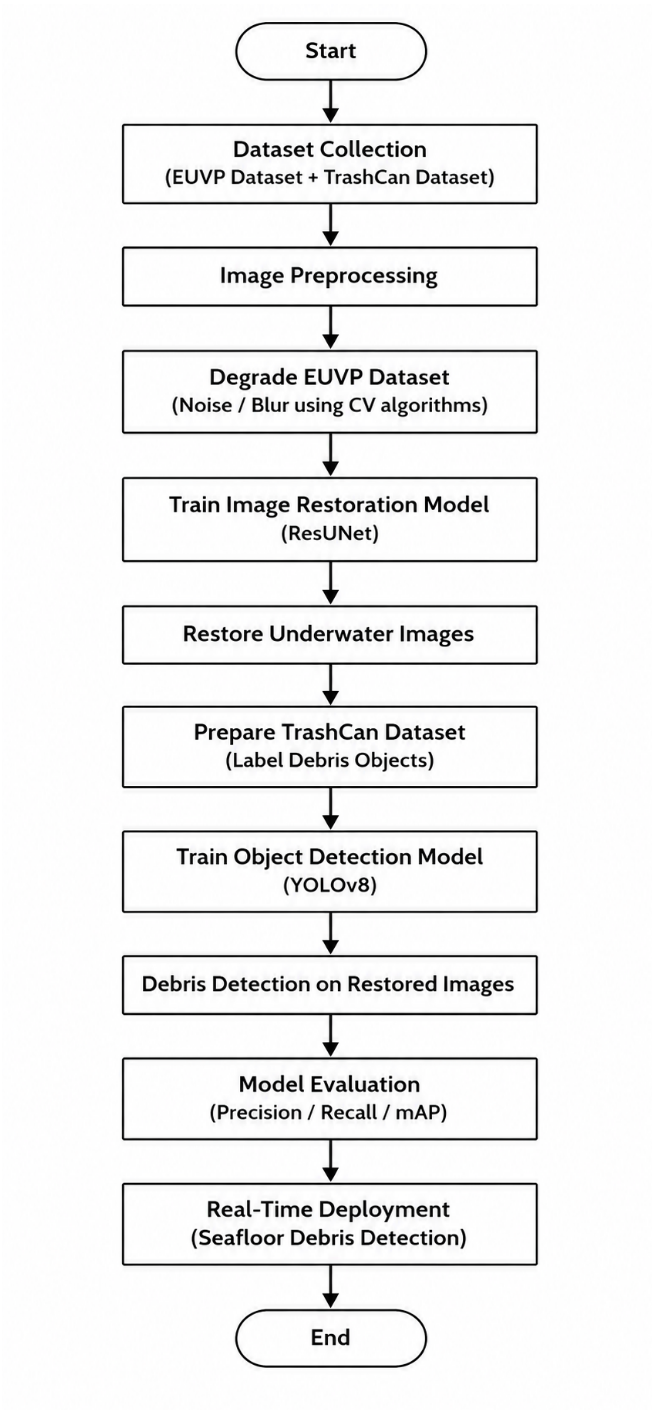


Fig. 1. Proposed architecture of Seafloor Debris Detection system

implemented as a real-time seafloor debris detector to effectively monitor pollution in the sea and assist in conservation of the environment.

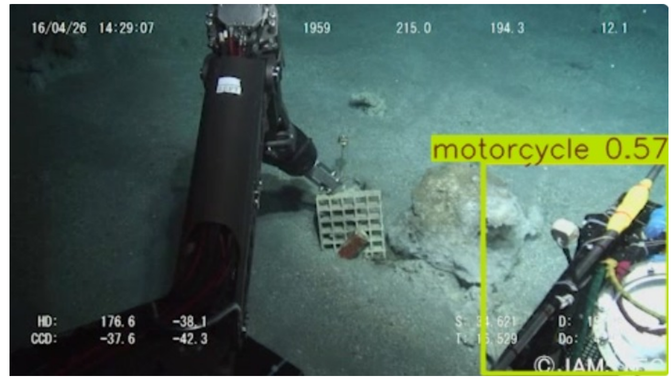


Fig. 2. Detection of Motorcycle Debris with Confidence Score using YOLOv8 [21]

Figure 2 depicts an application of the underwater detection of debris in the proposed system. The picture is a real seafloor captured by an underwater camera or robot and is slightly less visible owing to environmental parameters such as low lighting conditions and scattering.

As can be seen, YOLOv8 identifies an item that is classified as a motorcycle with a probability of 0.57. As one can see, the model detects a sufficiently large item despite a rather busy underwater background.

In this case, the natural items are sand and stones along with artificial debris. It should be noted that the separation of natural and artificial objects may pose some difficulties. Despite this, the method works effectively in identifying debris.

Thus, the proposed technique successfully detected underwater debris in the real seafloor setting.

IV. RESULTS AND DISCUSSIONS

Results and discussions provide details on the datasets employed, with specific mention of the EUVP dataset for image restoration purposes and the TrashCan dataset for identifying marine debris. A comparison table is also given to compare our model's performance against that of previous studies. This analysis focuses on several critical performance measures, namely precision, recall, and mAP. To prove that our model can detect seafloor debris with bounding boxes, example output images are also presented.

A. DataSet Description

B. Comparision of Previous Methods

The table 3 below provides a comparative paper among some existing methodologies for the detection of marine debris. Researchers have utilized different deep learning algorithms along with image processing techniques with the help of different datasets like under water images, satellite images, etc. Performance of the methodologies is based on the metrics like mAP, F1-Score, and detection accuracy. By

TABLE II
EUVP DATASET SPECIFICATIONS[22]

Specification	Details
Dataset Name	EUVP
Domain	Underwater Image Enhancement
Data Type	Image dataset (paired and unpaired)
Total Images	20,000+ images

TABLE III
TRASHCAN DATASET SPECIFICATIONS [21]

Specification	Details
Dataset Name	TrashCan Dataset
Domain	Underwater Object Detection
Dataset Source	Underwater images containing marine debris
Data Type	Image dataset (object detection)
Total Images	2,500 – 10,000+ images
Number of Classes	6 – 10 categories

looking at the comparative analysis, it can be noticed that the methodology which uses deep learning outperforms traditional methodologies.

C. Outputs

The proposed approach was examined using images of the sea floor collected by the TrashCan dataset in order to test the system's ability to detect sea debris. This system combines image restoration via ResUNet with object detection through YOLOv8.

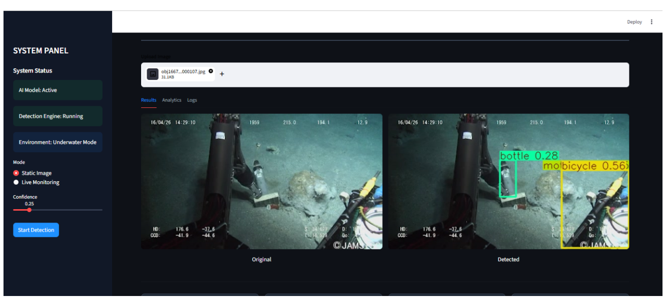


Fig. 3. User Interface Showing Original and YOLOv8 Detected Output

Fig 3 depicts the implementation details of the marine debris detection system design. The left-hand side presents a screenshot of the system panel that provides information regarding the status of the AI model as well as the operation mode. Based on this information, it can be observed that the AI model is active while the detection engine is operating in the underwater mode. Also, the user can input an image through the GUI and initiate the detection process. As for the right-hand side, it presents the original image and detected output. In particular, the original image presents an underwater image with the presence of debris on the seafloor. Meanwhile, the detected output presents the detected objects based on YOLOv8 model.According to the detected results, the following items were detected by the system, including the detection of a bottle and a motorcycle-like item. Additionally, each object is accompanied by labels and confidence scores.

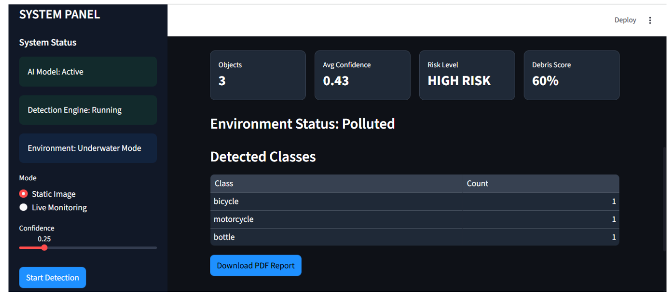
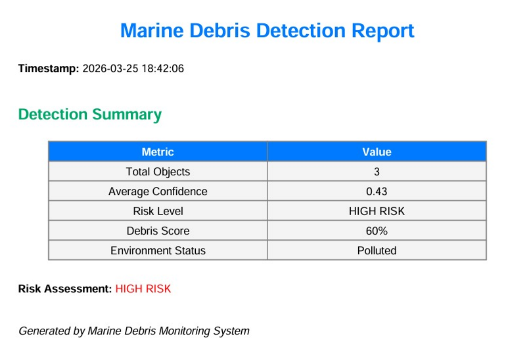


Fig. 4. UI Showing Detection Results, Risk Level, and Debris Statistics

Figure 4 presents the final output from the developed system via the user interface. The system's panel presents the status of the AI model showing that the AI model is active while the detection engine is operating under underwater mode. In the results section, further details are presented on the detected objects. It reveals that a total of 3 objects are identified with an average score of 0.43. As per the detection results, the system determines the environment as polluted and categorizes it as highly risky with a debris score of 60%. Moreover, it can be seen that the detected classes, alongside their count, are presented. For instance, the objects include 'bicycle', 'motorcycle' and 'bottle'. It is clear from the above output that the system does not just detect the objects but also provides information on important factors such as environment condition and level of risk associated with them.


Marine Debris Detection Report

Timestamp: 2026-03-25 18:42:06

Detection Summary

Metric	Value
Total Objects	3
Average Confidence	0.43
Risk Level	HIGH RISK
Debris Score	60%
Environment Status	Polluted

Risk Assessment: HIGH RISK

Generated by Marine Debris Monitoring System

Fig. 5. Generated Marine Debris Detection Report Showing Summary Metrics

Figure 5 represents the auto-generated report of the marine debris detection system. It describes the results of the detection process in an organized manner. Important details such as total object detection, average confidence score, risk level, debris score, and environmental state are provided in the report. As per the findings of the detection process, 3 debris objects were found having an average confidence score of 0.43. This implies that the environmental state is polluted and has a high-risk level. Moreover, a debris score of 60In this way, the generated report clearly describes the results of the marine debris detection process in an easy-to-understand manner.

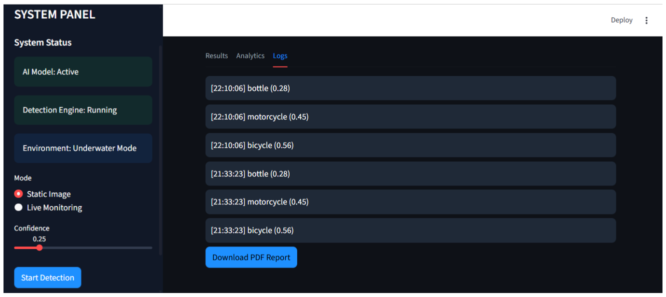


Fig. 6. Detection Logs Displaying Detected Objects with Confidence Scores

In Figure 6, the logging data generated by the seafloor debris detection system can be seen via the user interface. At the top left corner, the panel indicates that currently, the detection process is active. This means that the AI model is activated, the detection engine is functioning, and the system is in underwater mode. Furthermore, users have the freedom to select between static image analysis and live monitoring. They can also change the threshold confidence of detection.

At the top right corner, the logs section displays real-time outputs generated by the YOLOv8 model. Every record includes the timestamp, the type of object detected, and its corresponding confidence value. For example, there are detections for different types of objects that can constitute debris, such as bottles, motorcycles, bicycles, among others. In conclusion, logging provides an easy-to-understand history of all detection activities and helps monitor the performance of the system.

TABLE IV
PERFORMANCE METRICS COMPARISON

Model	Accuracy	Precision	Recall	F1-Score
ResUNet	95%	94%	95%	94.5%
YOLOv8	79%	70%	65%	67%

The evaluation of the proposed method is done based on commonly used metrics such as Accuracy, Precision, Recall, and F1-Score (Table 1V) .All the mentioned metrics are used to assess the efficiency of both image restoration and object detection models.

i. **ResUNet Model:** The image enhancement model ResUNet achieved 95% accuracy, 94% precision, 95% recall, and 94.5% F1-Score. The results indicate that the model is highly effective in reducing noise, blur, and color distortion. The high recall value shows that important image features are preserved during restoration.
ii. **YOLOv8 Object Detection Model:** The YOLOv8 model achieved 79% accuracy, 70% precision, 65% recall, and 67% F1-Score. The detection performance is moderate due to low visibility, complex backgrounds, and limited dataset size. The lower recall indicates that some debris objects are not detected.

The results indicate that the image enhancement model (ResUNet) improves the performance of the object detection model (YOLOv8).

V. CONCLUSION AND FUTURE SCOPE

The system suggested is an efficient solution to detecting seafloor debris regarding deep learning techniques. It is an image restoration and object detection combination that enhances accuracy in underwater conditions. ResUNet has been used to improve the quality of the image by eliminating noise, blur, and color distortion. The YOLOv8 model is able to detect debris objects like plastics, metals and fishing nets. This integration enhances the performance of detection as opposed to the traditional approach. The system also has a user friendly interface and automated report generation feature. It minimizes human input and helps in effective surveillance of marine pollution giving an accuracy of 86.6% in debris detection and 95% in image restoration. In general, the system helps to protect the environment by allowing detecting and analyzing the underwater debris more effectively.

The system can also be enhanced to accommodate real time stream of underwater video.

i. Real-time deployment can be achieved by integration with autonomous underwater vehicles.
ii. It is possible to improve the system with more visualization and detailed report analytics.
iii. The detection of marine species and coral health and debris can be incorporated in future work.

On the whole, it is possible to develop the system into an ocean monitoring and environmental management system.

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