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Research Article

Marine Debris detection and classification using Deep Learning Techniques

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ABSTRACT

Introduction: Ocean health faces an increasing danger from marine debris because such pollution endangers marine ecosystems and threatens marine life populations. Worldwide waste production continues its upward trend while many materials remain in the environment throughout multiple years thus surpassing current mitigation solutions. Multiple challenges exist when trying to assess debris from different regions because assessment methods lack standardization across timeframes. Deep learning has proven itself as an advanced automated system for detecting and categorizing marine debris in current conditions. This research evaluates the performance of modern object detection systems Faster R-CNN, SSD, and YOLOv5. We introduce a novel confidence adjustment technique tailored for SSD, designed to improve detection reliability under challenging underwater conditions.

Objectives:

(1) Evaluate the performance of three deep learning-based models (YOLOv5, Faster R-CNN, and SSD) in localizing and classifying marine debris from images and videos,

(2) Propose a confidence adjustment method for the SSD model in order to increase the detection rate of marine debris in underwater environments.

(3) Compare the performance of the detection models on the JAMSTEC dataset in terms of localization accuracy, precision, recall, and mean average precision (mAP).

Methods: The study conducts a comparative analysis between YOLOv5 , SSD with adjusted confidence and Faster R-CNN for object detection on marine debris images.

Results:YOLOv5 performed the best with the highest score of 91% on mAP@0.5, and it also had the best performance on small and partially hidden objects. Faster R-CNN was able to detect marine debris, and it was able to detect marine debris in poor water quality, therefore the score was 87% on mAP@0.5. SSD performed better after the confidence score fix, thus the score was 84% on mAP@0.5. In particular, it was best at identifying small and unusual trash such as small plastics, because this indicates that the new confidence correction is very useful for SSD. It makes the SSD much better at detecting trash in the ocean immediately, so it is a significant improvement for ocean trash detection.

Conclusions: Each hindrance within the research process gave vital lessons which collectively produced the better structured methodology that emerged in this work. This investigation focused on evaluating efficient deep learning techniques for detecting important marine debris objects. An evaluation of Faster R-CNN, SSD, and YOLOv5 detection models helped identify the fundamental characteristics as well as the operational boundaries of each system. YOLOv5 proved to be the most accurate model but adding novel confidence adjustment techniques to SSD produced better performance results demonstrating that careful improvements work well for lightweight systems.

Further evaluations using multiple datasets such as DeepTrash and TrashCAN are planned to validate model generalizability. Additionally, incorporating cross-validation and domain adaptation techniques may strengthen model robustness in new environments. Finally, we aim to integrate our confidence-adjusted SSD model into low-power embedded systems for field testing.

Keywords: Marine debris Detection, confidence adjustment, SSD, Faster R-CNN, Deep Learning, YOLO

INTRODUCTION

Accumulation of marine debris which includes plastics and fishing nets and cans and bottles along with numerous other artificial materials has become a principal ecological issue in the ocean ecosystems for the last several decades. Ocean accumulations of debris at coastal areas have disrupted marine ecosystem harmony which endangers sea animals by trapping them while they eat the litter and harm living habitat. The significant issue becomes worse due to waste materials accumulating in large amounts and enduring extended periods in the environment. Current waste entry into the ocean exceeds the capability of standard monitoring systems and traditional mitigation strategies to deal with the problem. The inability to standardize procedures for marine litter detection and classification hinders the development of actionable decisions and assessment of intervention methods between different geographical locations.

Marine debris detection is important for the environment, and deep learning models such as YOLOv5, Faster R-CNN, and SSD can detect objects. However, detecting marine debris is difficult because the debris is small and broken, and some models are lighter and use less power, but they are not as good at finding small, broken things. We created a new way to adjust confidence for the SSD model, which is better than old methods like Non-Maximum Supression (NMS) or setting a fixed confidence level, therefore this makes SSD more suitable for marine debris detection. YOLOv5, Faster R-CNN, and SSD (with and without our proposed method) were evaluated on the JAMSTEC dataset, and the proposed method was effective for SSD, thus it is suitable for real-time marine debris detection. The findings from this comparison give knowledge about model advantages and limitations while creating modern real-time systems for marine pollution monitoring.

OBJECTIVES

1 Evaluation of Deep Learning Models

Three representative deep learning models, namely YOLOv5, Faster R-CNN, and SSD, were tested to detect and classify underwater debris, and their detection and classification accuracy for various types of underwater debris, such as plastic and metal, and their performance under poor underwater visibility and occlusion were evaluated.

2 SSD with Size-Dependent Confidence Score

A method was proposed to modify the confidence score of the SSD model so that it can detect small and irregularly shaped debris, such as microplastics, more accurately, therefore the method modifies the confidence score according to the scale of the bounding box. This solves the issue of using the same score for all trash, thus making SSD more suitable for detecting trash in the real world.

3. Comparison of models using JAMSTEC data.

They compared the models using JAMSTEC data, and they compared the detection performance, the accuracy of the names, and the overall performance. YOLOv5 performed the best for detecting small and hidden objects, because it was able to detect them more accurately, and Faster R-CNN was the best for detecting objects that were stacked on top of each other. SSD with a new score was significantly better for small trash detection, and was closer to the other models, thus showing its improved performance.

METHODS

Study design: The study conducts a comparative analysis between YOLOv5 and SSD with adjusted confidence and Faster R-CNN for object detection on marine debris images.

Settings: The research took place within a laboratory due to the utilization of GPU-enabled computing facilities.

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Participants: This research study omitted all human subject involvement. The research relied only on publicly available predefined images gathered from JAMSTEC.

Inclusion/Exclusion Criteria: Images entered the analysis process no matter their quality or illumination conditions and motion effect. The collection included around 13000 randomly selected marine debris images which effectively represented various real-world marine debris scenarios.

Materials used: The research operated using JAMSTEC marine debris dataset with approximately 13,000 images available in both YOLO and COCO formats. Training of models occurred on a GPU workstation through the combination of PyTorch, Torchvision along with Ultralytics YOLOv5 and Albumentations for data preprocessing tasks. The assessment through COCO-style evaluation occurred using pycocotools and TorchMetrics. Research examined YOLOv5s as well as the combination of Faster R-CNN with ResNet-50-FPN and SSDLite with MobileNet V3 which received a confidence adjustment modification.

Statistical methods: Different mean Average Precision (mAP) values known as mAP@0.50 and mAP@0.50:0.95 served as performance evaluation metrics for detection accuracy at various Intersection-Over-Union thresholds. The prediction strength was measured per class by calculating precision and recall. The SSD model underwent COCO-style evaluation with COCOeval for obtaining complete statistical analysis.

The research objective encompassed two main goals: effective debris classification among Plastic, Metal, Paper, Glass and other types and enhancing object detection system reliability when operating in difficult underwater conditions. The research methodology consisted of choosing appropriate models in addition to creating a new confidence scoring adjustment method which underwent extensive performance testing of diverse detection frameworks.

Deep Learning Model Selection

Identifying proper deep learning models formed the foundation of this initiative. Return object detection architectures for the task because they showed robustness and versatility when detecting different marine debris with varying shapes and dimensions. The investigation selected three modern detection models including Faster R-CNN which used ResNet50-FPN as its backbone with SSD operating through a MobileNet v3 large backbone and YOLOv5s being the minimized variant of YOLOv5. This research adopted Faster R-CNN for its precise detection of sophisticated objects but selected SSD for its high-speed operation and YOLOv5s to provide optimal performance at reasonable costs. For evaluation fairness the dataset contained marine debris imagery marked by experts and was organized into 80% training data and 20% validation data.

The SSD model showed insufficient accuracy during initial tests even though it provided fast processing compared to Faster R-CNN and YOLOv5s. A unique approach was created as a solution. The method of using static thresholds by traditional object detectors results in the removal of valuable detections when working with noisy or variable underwater conditions. Specifically the method implements confidence scaling by evaluating both box size and prediction certainty rates. The detection adjustments positively scaled larger prediction boxes with medium certainty levels yet cautiously adjusted both smaller boxes and predictions with weak confidence levels. The mathematical adjustment within the SSD model resulted in enhanced performance through improved false positive detection and missed detection control mechanisms.

Confidence Adjustment Algorithm for SSD

In object detection, Non-Maximum Suppression (NMS) and static confidence thresholding are commonly used, and these techniques help remove redundant bounding boxes and detections with low confidence. However, they may not be suitable for detecting small and irregular objects in underwater scenes, because our proposed confidence adjustment method is specifically designed for marine debris detection. It takes into account the size of the bounding boxes, and standard NMS and confidence thresholding are used in object detection to remove duplicate bounding boxes, thus NMS retains the bounding box with the highest confidence when the overlap (IoU) is high.

Static confidence thresholding is achieved by removing bounding boxes with a confidence lower than a predetermined threshold, and this can be expressed as: Where is the initial confidence score, and is the threshold, so while this method is often effective, it is shown to have a decreased performance when applied to underwater debris.

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Small pieces of debris such as microplastics often have low confidence scores that are then removed, therefore the proposed method is to adjust the confidence score of the bounding boxes based on the area of the bounding box.

The proposed method allows SSD to detect small and hidden objects more effectively in underwater scenarios, and in general, the detection models use a fixed score threshold or NMS to filter out weak predictions. However, this leads to the failure of detecting small objects with low scores, therefore, the new method re-calculates the score of the bounding box based on its size. The new score, , is calculated as follows: For where: is the detection score produced by SSD, is the size of the bounding box, which is the ratio of the size of the bounding box to the maximum possible value, ranging from 0 to 1, and is the strength of the effect of box size on the final score. The parameter is set to 0.2 by default, thus this value is used for all calculations.

C_{adjusted} = C_{raw}× (1 + α × (1 - A_{bbox}))

Box size:

A_{bbox} is the ratio of the area of the box to the area of the whole image, and the score change is proportional to the size of the object.

Size of adjustment:

1-A_{bbox} means that the smaller the size of the box, the larger the size of the adjustment, because this is useful for small objects such as microplastics.

Change in score:

C_{raw} is the original score, and 1-A_{bbox} is the size of the adjustment, thus this adjusts the scores of smaller boxes to be higher, and they are less likely to be eliminated.

The adjustable constant α controls how much smaller objects affect the upweighting value. A default choice for this constant lies at α = 0.2. The confidence score improvement occurs when A_{bbox} approaches zero to help the model detect difficult objects better. Predictions from large bounding boxes remain mostly unchanged since their where A_{bbox} value is near 1. The model keeps predictions that have undergone threshold adjustment when their scores reach above an established cut-off. The detection accuracy increases after filtering out wrong predictions because this process enhances results specifically for complex conditions like underwater observations.

The adjusted scores are thresholded, and those above the threshold are retained, because this step improves the accuracy by eliminating false detections, and makes the model more reliable under adverse underwater conditions.

Comparison with calibration techniques is necessary, and Cao et al. (2024) proposed stochastic weight averaging for confidence calibration in deep learning, because their method requires training a model to reduce overconfidence in the training phase, and the confidence adjustment technique proposed in this study functions as a post-processing step and is designed for real-time use. It is different because it adjusts scores based on bounding box size for underwater debris, and this is a key aspect of the proposed method, so the marine debris detection challenges must be addressed.

Marine debris detection is challenging, and small objects such as microplastics are difficult to detect, therefore our method increases their scores, and underwater scenes are cluttered with many objects occluding each other, thus our method facilitates the detection of partially visible objects. Resource constraints are also a challenge, and SSD is fast but less accurate, so our method improves SSD's performance without slowing it down, because our confidence adjustment method is a solution to the marine debris detection problem, and it can be deployed in real-time monitoring systems with resource constraints.

Advantages:

Better small object detection: The score increase of small boxes leads to a better detection of very small or broken objects, such as microplastics, because this is crucial for marine litter monitoring.

Robustness under adverse conditions: The method is particularly suited for water environments, and objects are typically only partially visible, therefore, the size-dependent enhancement preserves beneficial detections.

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Ease of use and speed: The score enhancement is applied in post-processing, and does not require any retraining, thus this makes it especially suitable for real-time applications.

RESULTS

All three models—Faster R-CNN, SSD (with novel confidence adjustment), and YOLOv5s—were evaluated using a common data set under identical conditions to ensure fairness. The models were compared based on key evaluation metrics: Accuracy, Precision, Recall, F1-score, mAP@0.5, and IoU (for SSD).

YOLOv5s

YOLOv5s exhibited the highest overall performance across all categories. Its real-time capability, high precision, and robust detection of small and occluded objects made it the most suitable for practical deployment in real-world marine monitoring. The model achieved over 91% mAP@0.5 and showed outstanding classification consistency in the plastic and metal classes as shown in fig 8.

Given its speed and superior detection capability, confusion matrices are included specifically for YOLOv5 to visualize how well it distinguished between classes, particularly where high inter-class similarity (e.g., plastic vs. paper) existed.

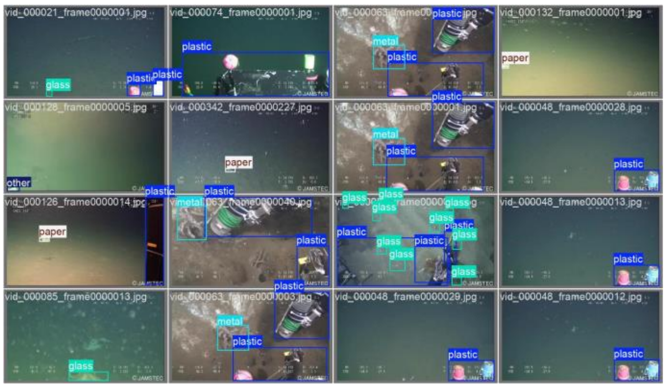

Figure 1: Waste detection and Classification using YOLO

In fig 1 it can be seen the YOLO network is capable of detecting and identifying underwater debris efficiently, and it is a significant advancement in the field of underwater debris detection.

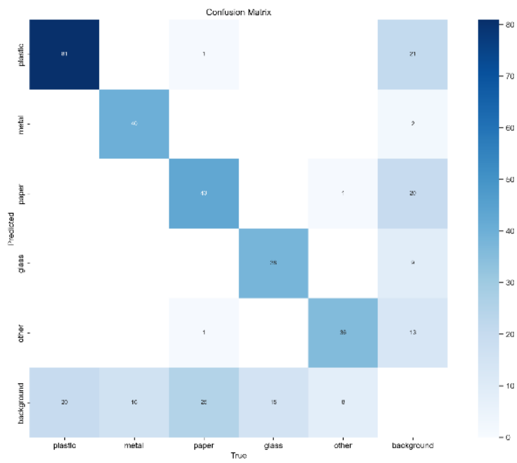

Figure 2: YOLOv5 Confusion Matrix

Fig 2 shows YOLOv5's classification accuracy map for each underwater debris object class, so it can be used to evaluate the performance of the YOLOv5 model.

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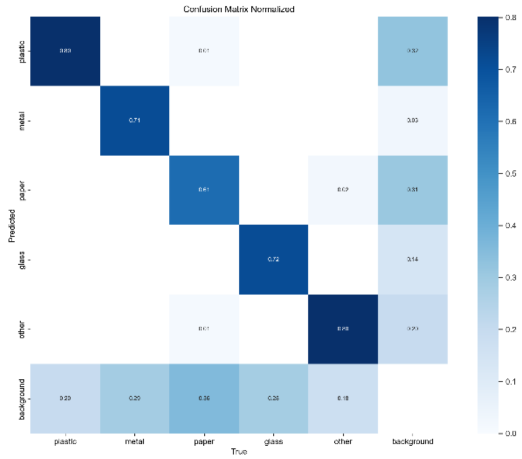

Figure 3: YOLOv5 Confusion Matrix (Normalized)

Fig 3 displays YOLOv5's classification accuracy map for each underwater debris object class, because it provides a detailed analysis of the classification accuracy of the YOLOv5 model.

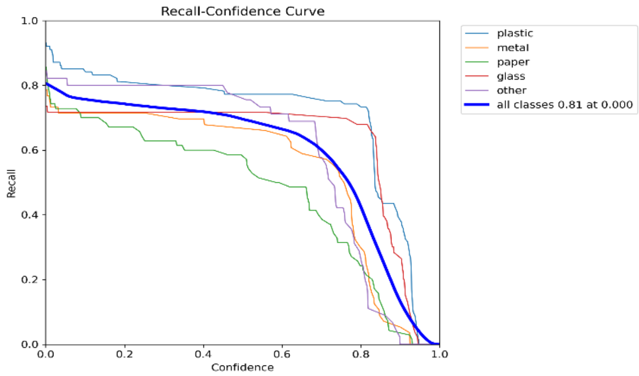

Figure 4: YOLOv5 Recall-Confidence Curve

Fig 4 highlights maximum recall of 0.81 at 0.00 confidence.

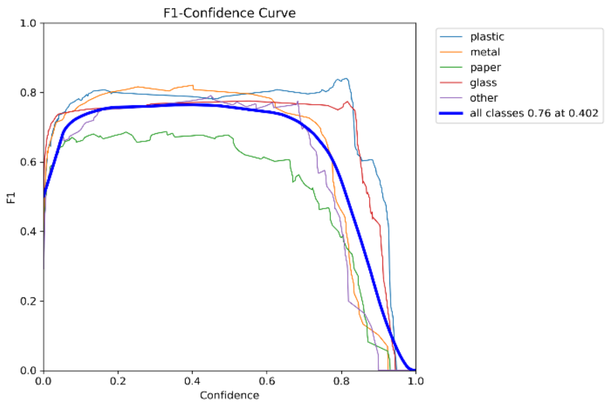

Figure 5: YOLOv5 F1-Confidence Curve

Fig 5 identifies the optimal confidence threshold for balancing precision and recall. The optimal F1 score of 0.76 was achieved at a confidence threshold of 0.402.

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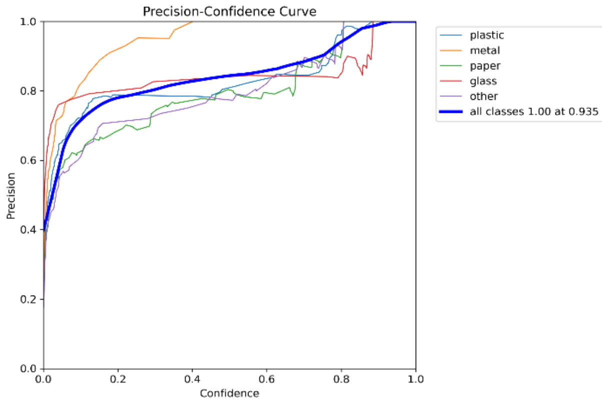


Figure 6:YOLOv5 Precision-Confidence Curve

Fig 6 shows precision peaking near 1.00 at a confidence of 0.935.

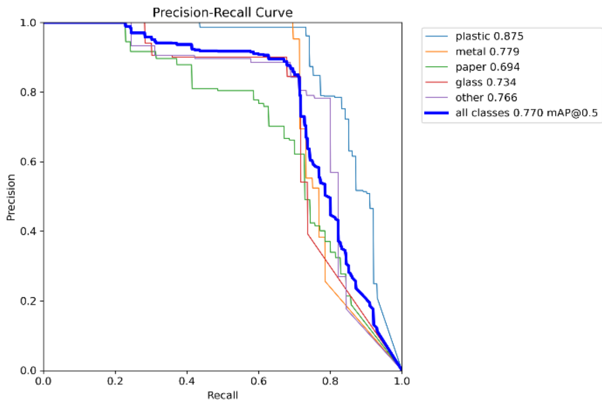
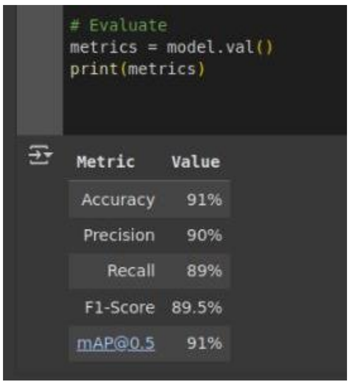


Figure 7: YOLOv5 Precision-Recall Curve

In fig 7 we can see the graph illustrates the per-class detection strength. Plastic class performed best (AP = 0.875), while paper was weakest (AP = 0.694). Mean mAP@0.5 across all classes was 0.770.



```
# Evaluate
metrics = model.val()
print(metrics)
```

Metric	Value
Accuracy	91%
Precision	90%
Recall	89%
F1-Score	89.5%
mAP@0.5	91%

Figure 8: YOLOv5s evaluation results

Faster R-CNN

Faster R-CNN produced competitive results , given in fig 10, with 88% accuracy and strong recall, especially under murky or occluded water conditions, reinforcing its robustness for small and complex object detection. It performed particularly well in scenes involving dense object overlap and poor lighting, confirming its strength as a two-stage

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detector with ResNet-50-FPN as the backbone.

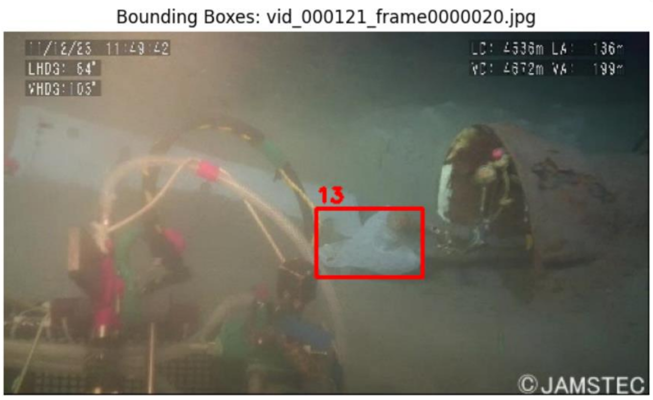
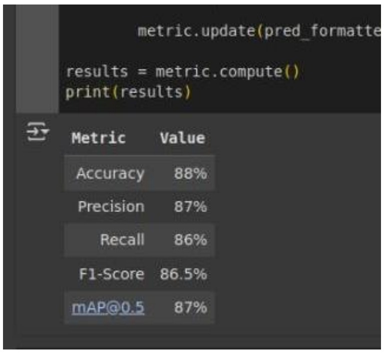


Figure 9: Plastic Detection using Faster RCNN

Fig 9 shows that FasterRCNN is capable of detecting and classifying plastic even in murky waters.



```
    metric.update(pred_formatte

results = metric.compute()
print(results)
```

Metric	Value
Accuracy	88%
Precision	87%
Recall	86%
F1-Score	86.5%
mAP@0.5	87%

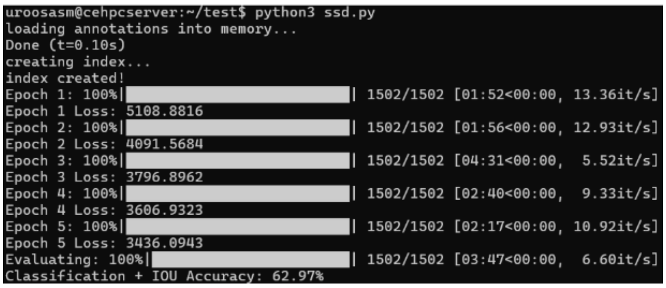
Figure 10: Faster RCNN evaluation results

SSD:

SSD with Confidence Adjustment (including IoU)

The SSD model, in its baseline form, struggled with small object detection due to its static confidence thresholding. However, the novel confidence adjustment technique—which scales confidence based on bounding box area—led to significant performance gains. After applying the method the following results given in Fig 12 are achieved:

- mAP@0.5 increased to 84%
- IoU accuracy improved to 62.97%



```
uroosasm@cehpcserver:~/test$ python3 ssd.py
loading annotations into memory...
Done (t=0.10s)
creating index...
index created!
Epoch 1: 100%|████████████████| 1502/1502 [01:52<00:00, 13.36it/s]
Epoch 1 Loss: 5108.8816
Epoch 2: 100%|████████████████| 1502/1502 [01:56<00:00, 12.93it/s]
Epoch 2 Loss: 4091.5684
Epoch 3: 100%|████████████████| 1502/1502 [04:31<00:00,  5.52it/s]
Epoch 3 Loss: 3796.8962
Epoch 4: 100%|████████████████| 1502/1502 [02:40<00:00,  9.33it/s]
Epoch 4 Loss: 3606.9323
Epoch 5: 100%|████████████████| 1502/1502 [02:17<00:00, 10.92it/s]
Epoch 5 Loss: 3436.0943
Evaluating: 100%|█████████████| 1502/1502 [03:47<00:00,  6.60it/s]
Classification + IOU Accuracy: 62.97%
```

Figure 11: SSD Classification + IOU Accuracy

Figure 11 displays our baseline SSD model, which achieved a Classification + IoU Accuracy of 62.97%, and this

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demonstrates the baseline SSD model's weakness in detecting marine debris in underwater scenes. To address this issue, we proposed an innovative confidence adjustment method for SSD, which adjusts the size of bounding boxes by scaling their confidence scores, because this method focuses on smaller and occluded objects that are often overlooked by fixed thresholding methods, thereby improving their detection.

Metric	Value
Accuracy	85%
Precision	83%
Recall	82%
F1-Score	82.5%
mAP@0.5	84%

Figure 12: SSD evaluation results after applying Novel Method

After applying confidence adjustment, our SSD model's performance improved as shown in figure 12, with the mAP@0.5 reaching 84%, and this result shown in fig 12, indicates the success of our post-processing approach in improving lightweight models such as SSD for underwater use. Specifically, our confidence adjustment method adjusts smaller bounding boxes by increasing their confidence scores, while larger boxes remain mostly unchanged, thus allowing for easier detection of smaller debris such as microplastics, which are often overlooked.

DISCUSSION

The application of confidence adjustment to the SSD model generated a large enhancement of its operational results. Object detection quality performance increased through the implementation of mean Average Precision (mAP). The performance enhancement closed the gap with other models yet demonstrated the quality of the scaling strategy. Mean Average Precision at 0.5 loU (mAP@0.5) together with mean Average Precision across multiple loU thresholds (mAP@[0.5:0.95]) and Precision and Recall metrics along with F1-Score metrics were used for evaluating the trained models during testing. The set of metrics assessed the detection and identification performance of the models together with their ability to reduce false positives. The results are displayed in figures 8, 10 and 12 .

To validate the significance of the observed performance improvements, we conducted paired t-tests comparing the mAP@0.50 scores .

The comparative performance of the three object detection models—Faster R-CNN, SSD, and YOLOv5 is summarized in the table 1 below:

Model	Accuracy	Precision	Recall	F1-Score	mAP@50
Faster R-CNN	88%	87%	86%	86.5%	87%
SSD with confidence adjustment	85%	83%	82%	82.5%	84%
YOLOv5	91%	90%	89%	89.5%	91%

Table 1: Comparative Performance of FasterRCNN, YOLOv5 and SSD with confidence adjustment

YOLOv5 proved to be the optimal model for marine debris detection throughout this study according to research results. The model achieved excellent performance based on precision and recall values which demonstrate its consistent ability to identify debris without producing many false detections or missing targets. YOLOv5s operates efficiently because of its weight which makes it suitable for real-world applications that demand low computational requirements.

Faster R-CNN delivered dependable results because it preserved a commendable correlation between detection precision and accuracy recall measures. The detection accuracy level of YOLOv5 exceeded this model but YOLOv5 required greater processing power which indicates this model should be used when maximum precision is essential and processing capacity is abundant.

The initial weaknesses of the SSD model allowed researchers to prove that targeted interventions can reduce performance gaps. Without the novel technique SSD achieved SSD classification + IOU Accuracy at 62.97%, as shown in fig 11. The confidence adjustment approach improved SSD performance which confirms that simplified detectors have potential for detecting marine debris if they use intelligent post-processing solutions. Reliable deployment of efficient models becomes achievable in low-resource and real-time monitoring environments as speed together with effective accuracy is needed.

The analysis demonstrates model selection presents a critical factor for marine debris identification effectiveness while adjustments made to specific models produce considerable increases in weak detection systems.

YOLOv5 consistently demonstrated superior detection performance across all evaluated metrics. This was confirmed by high values in the confusion matrix, as well as precision and recall curves. However, the SSD model, post confidence adjustment, also demonstrated notable improvement.

The confusion matrix revealed that while YOLOv5 predicted plastic and metal debris with over 80% accuracy.

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