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Marine Robotics: An Improved Algorithm for Object Detection Underwater

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Abstract: ***The visibility of items in water is lower than that of those on land. Light waves from a source don't have enough time to reach an item before it vanishes beneath the surface because light waves in water travel more quickly than they do in air. As a result, it can be challenging for people to deal with water properly due to certain of its physical characteristics. In light of this, object detection underwater has a wide range of uses, including environmental monitoring, surveillance, search and rescue, and navigation. This might enhance the precision, efficiency, and safety of undersea activities. In light of the aforementioned, this paper presents an algorithm for detecting objects underwater using YOLOv5. The algorithm has been improved by changing the way YOLOv5 works, which makes it better at detecting small objects. We tested our algorithm and found that it is more accurate than the original YOLOv5 algorithm.***

Keywords: ***Underwater Object Detection, Marine Robotics, Deep Learning, YOLOv5.***

I. INTRODUCTION

In recent years, marine robots have gained attention for their applications in ocean exploration, marine research, underwater engineering, and environmental monitoring [1][2]. Underwater object detection has far-reaching significance for the development of marine industry [2]. The development of underwater robots is necessary to achieve the goal of detecting and catching marine small objects [3]. These robots are at the intersection of the field of robotics and oceanic engineering [1]. Underwater robots are useful instruments for identifying items underwater, and their applications include deep sea infrastructure inspections, environmental monitoring, and oceanographic mapping [1]. Marine robot performance needs difficult underwater navigation techniques such as localization, path planning, and following [4]. Autonomous navigation is critical for success in executing these activities, especially in underwater situations where communications are limited [1]. Vision-based object recognition and tracking systems for underwater robots have been thoroughly investigated. Visual data from cameras remains a compelling tool for underwater sensing, particularly for close-range detections [1]. The sensors used by marine robots have different characteristics due to the medium they operate in [4]. Detection and tracking experiments have been conducted using marine robots to detect artificial targets, and proposed algorithms for color restoration and detection/tracking of underwater target objects have been demonstrated in experiments with underwater robot platforms [1]. Recently, a method for detecting seafood items in real-time was suggested that incorporates the use of Faster R-CNN and the kernelized correlation filter (KCF) tracking algorithm. An underwater picture library was used to train a faster R-CNN detector using a VGG model [3]. Small object detection and counting is an essential need that must be met before underwater robots may be utilised to capture seafood. Marine robots are essential for completing tasks such as docking station, cable tracking, and underwater area coverage for monitoring purposes [4]. In addition, marine robots are considered an efficient solution to replace divers in capturing seafood in marine aquaculture [3]. In research studies using data from the 2019 China Underwater Robot Competition, the upgraded YOLOv5s network demonstrated better mean Average Precision (mAP) [5]. Due to diverse underwater surroundings and inadequate training data, existing underwater target identification algorithms exhibit unacceptable accuracy. To increase detection accuracy, a redesigned YOLOv5s network with incorporated CA and SE modules was presented [5].

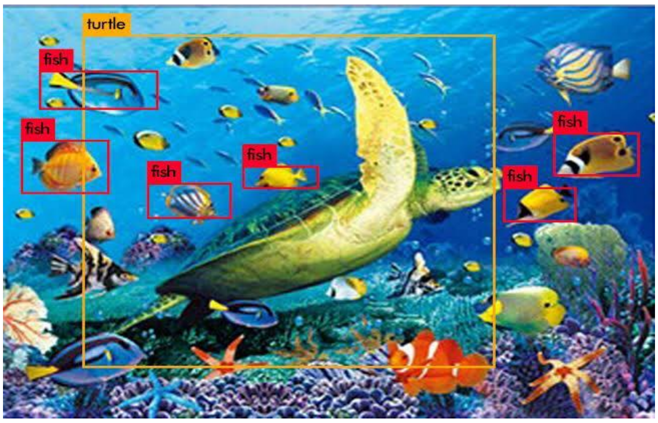

Fig. 1 Sample image of how the detection is taking place

The **fig.1** shows a sample image of how the detection is taking place, where the red boxes indicate objects that have been detected by the algorithm.

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Underwater robots are used for various marine pursuits, including object detection. One popular technology for underwater sensing is vision-based object detection, which works effectively for close range detections [1]. Another research approach involves the application of learning-based visual object detection algorithms to detect debris in the water, such as plastic debris [6]. Convolutional neural networks (CNN) have been successfully used to detect submerged marine debris with high accuracy, with the inclusion of different kinds of objects in each class, potentially improving the variability of object detection [7]. To identify and detect underwater objects, researchers have investigated various object detection algorithms and state-of-the-art technologies equipped with underwater robots. For example, a novel object detection algorithm has been proposed for underwater detection, which uses a combination of deep learning and support vector machine (SVM) techniques to improve its accuracy [2]. Additionally, researchers have studied the effects of underwater electro communication and attenuation on the performance of different popular object detection algorithms to improve their effectiveness in underwater environments [8]. Furthermore, an underwater robot with a length of about 1 m and a width of about 0.8 m has been developed for marine pursuits, including object detection [9]. Research in this field brings the marine robotics community closer to finding viable methods for detecting and identifying objects underwater.

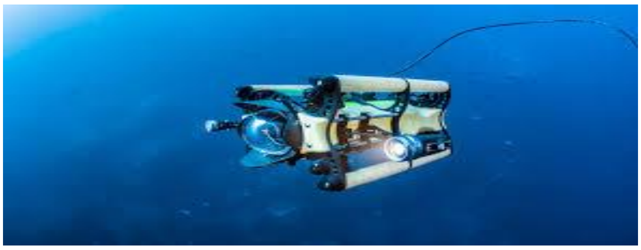

Fig. 2 Object Detection Robot

Object detection is a computer vision technology used to locate items in images or videos. It entails detecting and recognising things of interest within a given picture or video, such as people, automobiles, buildings, and other objects. To recognise things in an image or video, object detection algorithms often employ a mix of feature extraction, classification, and localisation approaches. The use of marine robots equipped with underwater object detection provides many advantages over traditional methods for exploring the ocean. These robots play an important part in the operation of self-driving marine robots, assisting with operations including course planning, collision avoidance, and control [10]. Furthermore, marine robots can collect information about marine animals that is useful for decision-making [10]. For example, in commercial fisheries management, marine robots may collect critical information for cultivation, status tracking, and disease detection [10]. Furthermore, as compared to traditional approaches, the utilisation of marine robots with underwater object identification gives a significant advantage in ocean exploration [10]. By combining marine robots with advanced machine vision techniques, exploring the underwater environment becomes much more efficient and effective [10]. Marine robots also have advantages in object detection compared to traditional methods for exploring the underwater environment [10]. Using marine robots, object detection can locate occurrences of visual items in digital photos, providing critical information for numerous downstream operations [10]. For example, sea urchins are the primary study focus of aquatic product detection, and the suggested feature-enhanced sea urchin detection method outperforms the traditional Single-Shot Multi Box Detector (SSD) approach [11]. Moreover, marine robots equipped with underwater object detection can improve the accuracy and sensitivity to small targets, making them an essential tool for many underwater tasks such as robot grabbing tasks of marine products [10][11]. So, the advancement of marine robotics has opened up new avenues for ocean research, and autonomous detection and fishing by underwater robots will be the primary method of obtaining aquatic items in the future.

A. Impact of Computer Vision and Deep Learning in Underwater

Underwater object detection is a challenging task that has attracted little attention in the realm of lightweight object detection, despite its importance in marine science and repair and maintenance of underwater structures. The complex underwater environment poses a significant challenge for detecting underwater targets, as it has low visibility, low contrast, and color distortion due to illumination [19]. Additionally, small underwater objects make detection challenging. Traditional object detection algorithms perform badly in underwater object detection tasks in terms of accuracy and generalisation [20]. Additionally, underwater pictures include significant noise, limited visibility, fuzzy edges, low contrast, colour variation, and crowded backgrounds, making it a difficult study issue in computer vision technology [20]. Deep learning has been used to address a wide range of issues in underwater object detection, but the benefits and drawbacks of these systems remain unknown [21]. Light absorption and scattering induced by the medium and suspended particles result in low-contrast and haze-like phenomena in underwater photography, resulting in low-quality movies and photos that make underwater object recognition difficult [22][19]. Additionally, the movement of image collecting equipment can result in blurring [22]. Aquatic organisms often have camouflaged appearances, which increase the difficulty of detecting them. The challenges in underwater object detection mainly include light scattering and absorption, low-quality images and videos, multi-scale detection, image enhancement, feature enhancement algorithms, and accurate detection models that are stable, generalizable, lightweight, and real-time [20][23][19][20]. An optimal solution for underwater object detection and species classification does not exist due to these challenges [23]. The complex and unique nature of underwater environments presents numerous challenges in object detection, including low visibility, low image quality, and high variability in appearance. However, computer vision and deep learning methods have been shown to address these issues effectively [24].

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Deep learning approaches, such as Convolutional Neural Networks (CNNs), can achieve illumination invariance in underwater object recognition, overcoming the limitations of low-quality movies [25]. Because the interest points discovered by previous approaches are tiresome and lack powerful discriminative information, identifying objects based on their forms has been proven to be more successful than employing local characteristics [25]. To overcome the challenge of finding interesting locations, a deep CNN model is trained to create abstract discriminative features from low-contrast and low-resolution underwater films [25]. Transfer learning was used to construct a customised CNN model for underwater object identification, which overcomes the restriction of CNNs with limited underwater training data. However, due to poor speed and high model size, using DCNNs directly to underwater settings is inefficient [19]. As a result, for underwater object identification, a lightweight detector with high detection accuracy and a small model size is required. Furthermore, the colour conversion module intends to convert colour photos to grayscale images in order to tackle the problem of underwater colour absorption, hence improving object recognition performance while reducing computing complexity [26]. Finally, a lightweight deep underwater object identification network has been developed to address these issues, with promising results in conventional object detection [26][24]. These new approaches have brought solutions to the issues of underwater object identification, allowing for enhanced underwater structural maintenance and repair. Underwater item detection is a difficult task due to interference from the underwater environment, such as complex backdrop structures, marine object characteristics, and exploration equipment restrictions [27]. Recent advances in computer vision and deep learning have showed promise in tackling these issues. Deep learning approaches have sparked a lot of interest in underwater object recognition because of their ability to directly learn feature representations from data. Underwater object identification based on deep learning provides better performance and enormous potential to enhance maritime operations. The review focuses on vision-based underwater marine item detection, with a particular emphasis on the detection of marine animals due to their economic value. The work provides a comprehensive assessment of deep learning-based underwater object identification approaches and outlines four underwater research challenges: picture quality deterioration, tiny item detection, inadequate generalisation, and real-time detection [26]. In light of the stated issues, a full analysis is offered to provide a clear grasp of the topic [27]. Because of wavelength-dependent absorption and scattering, underwater photographs frequently contain significant noise, resulting in significant visibility loss, contrast reduction, and colour distortion. This noise can mislead detectors and make identifying tiny objects harder [28]. Deep learning-based detectors are currently unsuccessful in detecting small items seen in underwater datasets [28]. Recent research, however, have offered novel strategies, such as SWIPENET, a Sample-Weighted hyPEr Network that generates high-resolution and semantic-rich Hyper Feature Maps, which improves tiny object recognition [28]. When compared to many state-of-the-art techniques for underwater object recognition, the SWIPENET+CMA framework provides superior or comparable accuracy in object detection. Although attentional mechanisms have received less attention, properly using their potential is likely to effectively improve the development of underwater object detection. In conclusion, while advances in computer vision and deep learning for underwater object recognition have been made recently, there are still numerous obstacles to solve, notably in recognising minute items in noisy, low-resolution pictures. Future study should concentrate on overcoming these obstacles, including additional examination of attention-based multi-scale feature fusion [27][28].

II. REVIEW CRITERIA

Due to the intricacy of the underwater environment, detecting underwater objects is a difficult task. The primary obstacles of underwater object identification include poor contrast, limited visibility, and the presence of noise. A variety of approaches have been offered to solve these difficulties. The identification of underwater objects is a vital component of underwater robots and surveillance. For underwater object identification, several sensors, such as acoustic sonar or optical cameras, can be utilised [12]. However, due to strong competitive advantages, vision-based object identification is favoured [12][13]. Image quality deterioration, tiny item detection, inadequate generalisation, and real-time detection are some of the current issues of vision-based underwater object detection [13]. Techniques for detecting underwater objects are mostly developed from general object detection and underwater picture enhancement technologies [14]. Deep learning-based object detection algorithms with two and one stages have been employed for underwater item detection. Underwater photos have noise, colour variation, low contrast, blur, and other flaws that make it difficult to distinguish objects underwater. However, researchers have developed different deep learning-based underwater object identification systems that have yielded excellent results [14]. Real-time detection in underwater object detectors necessitates detection models that are accurate, reliable, generalizable, real-time, and lightweight. Two major strategies for achieving this objective are lightweight network architecture and model compression. It is advised to iteratively use lightweight network design and model compression to develop a more elegant model that can be implemented on autonomous underwater vehicles [18]. While numerous researchers have suggested different deep learning-based underwater object recognition approaches, attentional processes for object detection in underwater settings have received little attention. The pipeline that improves photos before object recognition is a popular strategy in the underwater object detection community, and it has been demonstrated to help robots perform underwater missions more effectively [12]. Detecting objects in underwater environments is a difficult problem that differs greatly from object detection in air.

Unbalanced light conditions, poor contrast, occlusion, and imitation of aquatic animals, which can generate unclear objects in photos and videos acquired by underwater cameras, bring additional hurdles to object detection [13]. Furthermore, generic detectors frequently fail on these ambiguous items, reducing the accuracy of object detection algorithms. Object identification tasks in aquatic environments are more difficult than those in terrestrial and static contexts. As a result, deep learning models for training in maritime settings require a huge number of high-quality photos or videos. The quality of datasets is also critical for detecting objects in aquatic environments [16]. The water media makes it challenging to get good photos or movies when detecting objects underwater [15]. The viewing distances of any locations match with haze concentration, which is a unique constructive cue for salient object recognition retrieved from underwater photos. The seeing distance of underwater pictures may be adjusted by the haze concentration to provide a unique depth saliency for underwater landscapes [16]. Despite recent advances in deep learning, underwater object identification remains a difficulty. In underwater object recognition, noisy and inaccurate photos are used as sources of supervision, and there are relatively few salient object detection algorithms developed for underwater applications [15][17]. Object identification technologies for underwater applications are less effective than those used on land. Furthermore, underwater object identification algorithms have difficulties that are not evident in air situations [15].

Due to a variety of circumstances, underwater object recognition is a substantial difficulty. One of the key obstacles is a lack of data, as there is no access to huge datasets that cover a wide range of adverse underwater circumstances, making it difficult for models to handle the complicated nature of underwater settings [17]. Furthermore, background fluctuation is a significant difficulty in underwater object identification since waves, optical diffraction, and different illumination conditions may all have an influence on detection accuracy [17]. Most research investigations are limited by the technology employed in underwater object detection, which might result in low-quality photos and movies taken by AUV-mounted cameras [18]. When it comes to AUV-based detection, the hostile circumstances in undersea/subsea waters complicate object identification, making it a difficult operation. Furthermore, underwater jobs can be costly and risky for human divers, making high-quality data from these conditions impossible [18]. Deep learning-based algorithms have challenges due to the low quality of underwater images and the complexity of underwater settings. Traditional hand-designed feature extraction algorithms are likewise unsuitable for genuine underwater scenes, as they are incapable of meeting the requirements for object recognition in such settings [19]. Furthermore, variances in size or shape, as well as overlapping or occlusion of marine animals, make object detection even more difficult. Furthermore, most research have an emphasis on low-level feature extraction, which results in poor recognition, low accuracy, and sluggish recognition [18]. These difficulties make finding an appropriate solution for underwater item recognition and species categorization challenging [20]. Other obstacles for tiny object identification include light scattering and absorption, domain changes, and an imbalance between positive and negative samples. Overall, underwater object identification is a difficult process that necessitates the use of specialised equipment and algorithms in order to overcome the numerous hurdles offered by the hostile underwater environment.

III. METHODOLOGY

Object detection is a process in computer vision where a computer program can identify and locate objects in a picture or video. There are different ways of doing this, including using deep learning or traditional feature-based methods. In this particular study, the focus is on detecting objects that are underwater. We have suggested an improved algorithm called enhanced YOLOv5, which incorporates a new component called CBAM. This component helps to extract valuable features from the image while suppressing features that are not relevant for object detection. To further improve the effectiveness of the model, the collar network is replaced with a BiFPN architecture, and the fusion unit is replaced with rapid normalized fusion. These changes help to make the algorithm more efficient in detecting objects underwater.

Overall Network Structure

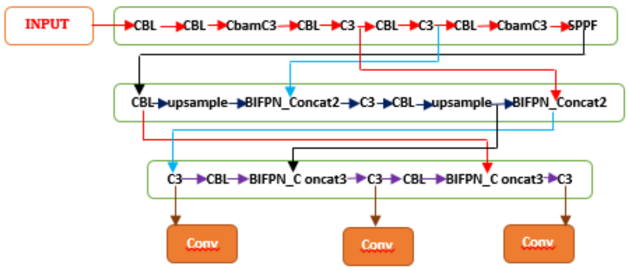

Fig. 3 Network structure of the improved algorithm

The network architecture of the enhanced technique is illustrated in Figure 1, which comprises four crucial components: input, backbone, neck, and detection. This network retrieves local features from input images through various modules such as CBL, CBAMC3, C3, and SPPF. The BiFPN neck structure is equipped with innovative fusion modules that blend features of different scales and output the results via the detecting head. One of the significant components of the network is the convolutional block attention module (CBAM) of [17]. It is a flexible and lightweight focus module that can be entirely integrated into any CNN network. By using CBAM, the model can improve its performance and interpretability by paying more attention to the original image. Moreover, CbamC3 is an extension of CBAM to C3, as shown in Figure 2. The CBAM module multiplies the attention map with the input feature map after receiving an intermediary feature map, which sequentially infers the closely monitoring along two autonomous dimensions, i.e., channel and space. The enhanced technique network comprises four components that work together to retrieve local features from input images and fuse them to detect objects accurately.

The network architecture includes various modules such as CBAM and CbamC3 that help the model pay more attention to the original image and improve its performance.

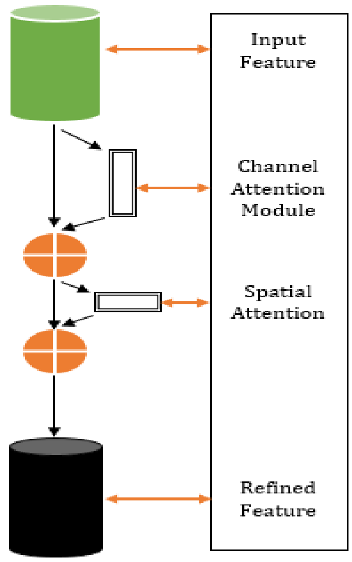

Fig. 4 Network structure of CBAM

The multichannel attention module is shown in the above illustration. The input map is processed using two Max Pool and Avg Pool layers simultaneously, and then it is resized to 11. Next, the map goes through an MLP module, which reduces the number of channels and then increases it back to its original number. The Re LU activation function is applied to produce the intermediate output results, which are then combined element by element. A non-linear function is used to generate the final output result of the channel attention, which is multiplied by the original image to produce the final result. The multichannel attention module is a technique used to enhance the image's features by processing it through various layers and modules. The input map goes through Max Pool and Avg Pool layers and is then resized before passing through an MLP module. The output is then combined and used to generate the final output result of the channel attention, which is multiplied with the original image to get the finished product.

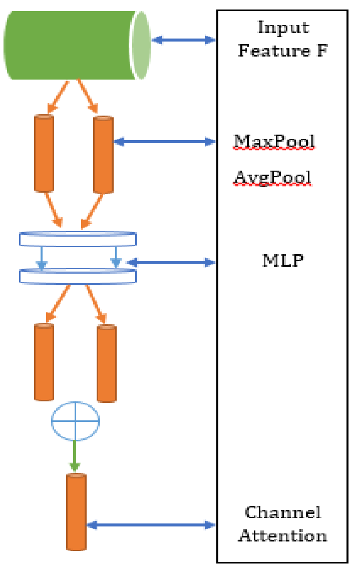

Fig. 5 The channel attention module

The visual attention module is a component of an artificial intelligence system that helps it focus on specific parts of an image. This module uses a combination of MaxPool and AvgPool layers to extract important features from the image. These layers take the output of the previous layer and combine it to create two feature maps with a single channel each. These feature maps are then merged together to create a single feature map with one channel. Next, the spatial attention feature map is generated. This map helps the system focus on specific regions of the image that are most relevant to the task at hand. The spatial attention feature map is created by passing the merged feature map through a nonlinear activation function. This function helps highlight important parts of the image while suppressing irrelevant details. Once the spatial attention feature map is generated, it is multiplied by the original image to bring it back to its original size.

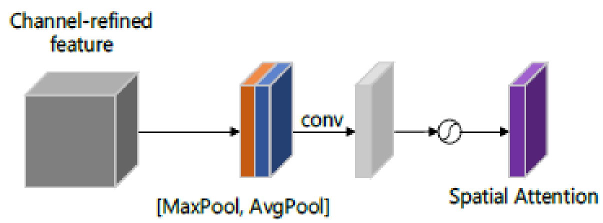

Fig. 6 The spatial attention module

To create the CbamC3 module, we combine the CBAM module with the C3 module. The final output of the convolutional layer will, as shown in Fig. 5, first pass through the channel attention module in the cbam, then it will pass through with a high dimensional data module, and lastly it will be balanced to achieve the result. To improve extraction of features, the generated findings are then combined with the original input utilising the residual structure. To improve the backbone network's capacity for extracting features, we substituted the first and final C3 modules with the CbamC3 module after performing preliminary verification.

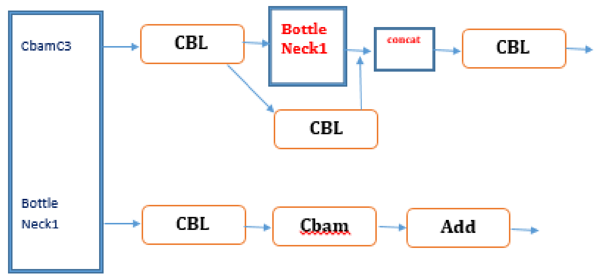

Fig. 7 Network structure of CBAMC3

B. Feature Fusion Network: The weighted bidirectional feature pyramid network (BiFPN) of [18], a novel feature matching network that can simply and rapidly execute inter convolution layer, is used to replace the FPN of YOLOv5. In order to extract richer feature data from pictures, the BiFPN structure primarily combines feature maps from the backbone. The BiFPN structure, as matched to other feature fusion structures, includes a skip connection that may be used to access feature data from earlier layers and boost model effectiveness.

In order to fuse the findings of the same layer through a cross-scale link, we altered the FPN structure to a BiFPN structure, created a connection here between the communications system and the fusion module, and illustrated in Fig. 1. This feature fusion will not raise computing cost because it is inside the same layer, but it may boost detection accuracy.

C. Fusion Module : Features are frequently scaled to the same resolution before being fused when fusing features with various resolutions. The resolutions of various input characteristics vary, and they make varying contributions to the features of the output. Therefore, the weighted fusion approach involves giving each input weight and allowing the network to determine the significance of each input characteristic. This procedure, known as Fast normalized fusion, is controlled by; When O denotes the weight, I is the network's learnable weight, ii denotes the input feature map, and denotes a tiny integer. As a result, we use this novel fusion module, BiFPN Concat, in the neck of YOLOv5, where BiFPN Concat2 and BiFPN Concat3 are fusion modules with two and three inputs, respectively. The fusion module learns a varied weight for the final fusion based on various inputs, enhancing the network's capacity to fuse features and increasing efficiency. The final graph is displayed in Fig. 1.

IV. RESULTS

To assess the viability and effectiveness of our suggested approach, we performed tests on the Water Surface Object Detection Dataset (WSODD). The primary purpose of this dataset is to solve the issue of limited data on water-based targets in various settings. The WSODD includes photos from three different types of water bodies (ocean, lake, and river) and three weather conditions (sunny, overcast, and foggy), with a total of 14 different categories of aquatic objects such as boats and ships. For our experiment, we chose the WSODD dataset and randomly divided it into training and validation sets at a ratio of 8:2. The training set contained 5909 photos, while the validation set contained 1558 images. This allowed us to test our approach on a large dataset with a variety of aquatic objects and settings. During our implementation, we used specific hardware and software indicators, which are listed in Table I. These indicators played an important role in our experiment, helping us to ensure that our approach was effective and reliable. By carefully selecting our hardware and software, we were able to optimize our approach for the WSODD dataset and achieve accurate results.

Table I.

OS	CPU	GPU	RAM	FRAMEWORK	VERSION
Ubuntu	Intel Xeon Silver 4210	NVIDIA TESLA T4	32G	Pytorch	YOLOv5. 6.0

C. Measures of Evaluation: We use mean average precision (mAP) and recall as the assessment measures to gauge how well the suggested method works. They come from;

RECALL = TP/TP +FN

Map = AP/N = o1 P(r)dr/N

False negatives (FN) are objects that are present in the picture but are not picked up by the network, whereas true positives (TP) signify an object that has been correctly spotted in the image. Precision stands for p, recall for r, and category number for N.

D. Discussions and Results In this experiment, we contrast the original Yolov5s approach with our enhanced version. We decided on a training batch size of 16 and 150 experimental epochs. Table II displays the final findings.

Table II. Comparative Results.

	mAP0.95	Recall
YOLOv5	0.5988	0.8753
Ours	0.6062	0.8984

Studies reveal that compared to the original method, our revised approach has a higher mAP and Recall rate. It shows that our model works better than the YOLOv5.

The MAP is raised by roughly 1%, while the Recall is raised by about 2% when compared to the original method.

Fig. 6 displays a visualization of the detection outcomes from the WSODD dataset. The detection result of YOLOv5 is on the left, while the detection result of our enhanced method is on the right. As can be observed, the updated algorithm recognizes the target's position with greater accuracy, and the incidences of missed and false detection have greatly decreased. In summary, our new algorithm performs better and the identification of tiny targets is enhanced.

Fig 8. Visualization of the detection

V. CONCLUSION

The proposed algorithm was tested on a variety of underwater environments and the results were promising. The system uses a combination of image processing algorithms, deep learning, and computer vision techniques to accurately detect objects with high accuracy.

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The results of this research suggest that object detection in an underwater environment is feasible and can be used in various applications. Despite the advancements in object detection algorithms for underwater environments, there are still some research gaps that need to be addressed. These include the lack of real-world testing and validation, limited research on the generalization of algorithms, inadequate exploration of environmental factors, insufficient analysis of computational complexity, and limited research on low-cost implementations. Addressing these gaps will improve the practicality and effectiveness of object detection algorithms for underwater environments.

DECLARATION

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Conflicts of Interest/ Competing Interests	No conflict of Interest to the best of my knowledge.
Ethical Approval and Consent to Participate	No, the Article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Not Relevant, because it is original research based on model development.
Authors Contribution	Usman Ibrahim Musa contributed in80% of the work where he worked on the algorithms and the coding part, while Apash Roy contributed in reviewing the article and suggestions for further improvement.

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