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Investigating the Accuracy of Object Detection in Underwater Images: A Comprehensive Review

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***Abstract*— Developing an effective underwater object detection method is crucial for both the conservation and utilization of marine life. However, the complexity and unpredictability of underwater environments introduce numerous challenges into the field of underwater object detection. The exploration and monitoring of underwater environments present unique challenges due to factors such as poor visibility, Color distortion, and varying lighting conditions. There have been numerous automatic techniques devised to tackle these challenges. Deep learning algorithms like Faster R-CNN, YOLO, SSD and machine learning algorithms which include SVM, RF, K-NN, Naive Bayes etc., which can be implemented over a large number of underwater images to detect objects or marine organisms present within them. For preprocessing the images, several Image processing techniques have been developed like Color correction, Contrast enhancement, Noise reduction etc. to optimize the detection process. This research paper discusses many object detection approaches in underwater images that have been proposed by researchers in recent years and challenges that are being encountered. In this study, we examined the performance of various deep learning algorithms used by various researchers in their paper in the context of underwater object detection.**

***Index Terms*— Underwater object detection, Deep Learning, Machine Learning, Image Processing Techniques.**

I. INTRODUCTION

The vast and mysterious world under the ocean's surface has endless secrets, from biodiversity-rich marine life to forgotten shipwrecks with a fascinating history. Understanding these mysteries requires the capacity to detect and identify objects hidden in the ocean's depths. Identification of objects in underwater images, accomplished via the combined efforts of image processing and Deep learning techniques, is a powerful tool for discovering the secrets hidden under the waves. This survey article takes a broad look at the approaches, technology, and applications related to identification of underwater objects or organisms in underwater images. The detection of objects in underwater images is of paramount importance in various domains, including marine biology, environmental monitoring, and underwater robotics. In this context, this paper presents a comprehensive exploration of object detection techniques specifically tailored for underwater imagery, aiming to address the complexities associated with this unique domain. For this purpose, we require a real-world data set containing underwater images. Underwater environments, with their inherent challenges such as poor visibility, varying light conditions, and image distortions, pose significant obstacles to effective object detection. So preprocessing is the first step to do

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to increase the quality of images for detection of objects in images easily. Image processing techniques play a crucial role by enhancing the quality of underwater images. They correct colors distorted by the water, improve contrast, reduce noise, and generally make these images more usable for analysis. Sometimes there might be a chance of getting error like underfitting if there are not enough images in the dataset. So, to avoid this type of errors Data Augmentation is one of the way. Data augmentation is a method that involves generating additional images by applying various transformations to existing images, serves as a vital role in improving the robustness of object detection models. Through augmenting dataset with variations in lighting, angles, and environmental conditions, the models become more adaptive to the dynamic underwater environment. Common software tools for image processing in underwater applications include Opencv in Python, MATLAB etc. One of the most important Step in the detection process is selecting the perfect algorithm which gives high accuracy and better performance. The choice of algorithm is not one-size-fits-all. Researchers continually seek to enhance object detection performance, adapting to the unique challenges of underwater conditions. Sometimes, they may choose a different algorithm over a previous one because it offers advantages in terms of speed, precision, or the ability to handle specific underwater challenges. There are many Machine learning algorithms like Random Forest, Support Vector Machine, Naïve Bayes, K-NN and Deep learning algorithms like CNN, R-CNN, Faster R-CNN, SSD, YOLO versions are available. According to studies, Deep Learning algorithms outperform Machine Learning algorithms in terms of performance, accuracy, and speed. So, it's better to use Deep learning Algorithms. The field of object detection in underwater imagery is marked by the continuous evolution of algorithms, each designed to tackle the unique challenges posed by this environment. Understanding the performance of these algorithms is crucial in selecting the right tool for the job. We delve into the key algorithms that have been prominently used, examining their accuracy and processing speed. YOLO is renowned for its real-time detection capabilities. It offers impressive speed and can process images quickly. However, its accuracy may be slightly lower compared to algorithms with multi-stage approaches like Faster R-CNN. Single Shot MultiBox Detector is another algorithm designed for real-time object detection. It offers a balance between accuracy and speed. While it may not be as accurate as Faster R-CNN, its faster processing makes it suitable for applications where real-time detection is critical. Region-based Convolutional Neural Network is a widely recognized algorithm known for its accuracy in object detection. By combining a region proposal network with a convolutional neural network (CNN), it excels in precise object localization. While it delivers exceptional accuracy, it may not be the fastest option due to its multi-stage architecture. During the training process, a critical aspect is how the input dataset is divided. The dataset is commonly divided into three subsets: the training set, the validation set, and the testing set. The training set is employed to teach the algorithm. The validation set aids with fine-tuning the algorithm's parameters and checking for overfitting. The testing set is used to assess the performance of the algorithm on unseen data, ensuring that it generalizes well to real-world situations. Proper dataset division is essential for developing robust and accurate object detection models. In the field of algorithm training, popular software tools include Tensor Flow, PyTorch, and Keras. These platforms provide the infrastructure for training and fine-tuning deep learning models on underwater image datasets. Furthermore, we have to evaluate these object detection systems using a variety of metrics, including accuracy, precision, recall, F1-Score, Intersection over Union (IoU), Mean Squared Error (MSE), and frame processing time. These metrics help us assess how accurately and efficiently these systems identify underwater objects, crucial for a wide range of applications. Draw a table showing different algorithms and their accuracy's and f1 score.

II. LITERATURE

Akshita Saini and Mantosh Biwas [1] ,2019 have discussed about detecting objects in underwater images by applying adaptive thresholding. Underwater photos are generally ruined due to sunlight dispersion and absorption. Hence, before detecting objects in underwater images, the images should be enhanced. As a result, they suggested a method for quickly detecting objects in underwater photos, in which they improved the images by boosting the contrast and segmented them while extracting boundaries. Image segmentation is done by using adaptive thresholding with Sobel operator. They have taken real underwater images datasets and calculated the efficiency of their proposed method based on two important parameters. The first is the Peak signal-to-noise ratio (PSNR), which is used to compare the compression quality of the source picture with the output image. If the PSNR value is high, it means the image quality is enhanced. Second parameter is Structural Similarity Index (SSIM) is applied to measure the similarity between two images and it's range lies between -1 to 1. It indicates 1 if two images are same. Finally, they concluded that images should have high PSNR and SSIM values to be clearly visible and distinguish. They compared their results with other methods like Canny operator, Prewitt Operator etc. And the comparison results have shown that their proposed method is very effective and can detect objects easily. They utilized the MATLAB 2016 toolbox with a 1.70 GHz CPU core.

Hai Huang et al [2] ,2019 in this paper researchers featured Faster R-CNN Method for Detecting and Recognizing Marine Organisms Using Data Augmentation Faster R-CNN is a supervised algorithm. So, it requires labelled image dataset for processing which is challenging to get especially for Marine Organisms. They have taken 1800 labelled images but they are insufficient to train Faster R-CNN model. So, in order to enhance the amount of photographs in the collection, researchers used three data augmentation approaches appropriate for underwater marine creatures. The three data augmentation methods are Simulate marine turbulence, Simulate different shooting angles, Simulate uneven illumination. Underwater images are blur and have less clarity due to the optical property of water and light scattering. So to restore the images they used Simulate marine turbulence in which firstly they calculated turbulence coefficient k for the dataset and applied Weiner Filter with different coefficients K and then they applied inverse Weiner filter to decrease the level of turbulence in images. They have taken four values as K= {0.0005,0.001,0.0015,0.002}. Marine creatures like sea cucumber, sea urchins and scallops always sticks to sea floor. As a result, their photographs are taken from top angle. Therefore, they performed Affine transform and Perspective Transform to increase number of images in dataset. Illumination is the key factor in detecting and recognizing objects in marine organisms. The seafloor is less illuminated for image capturing. Therefore, different uneven illuminations are present in underwater images. To achieve even illumination in underwater images they performed Simulate uneven illumination in which they used spatial filtering operation. By these augmentation processes number of images in input dataset increased to train the Faster R-CNN model. They performed algorithm individually on the three dataset images obtained from three Data augmentation processes. Later they fused all the images and trained the model. From all the processes they got highest average accuracy from fused dataset only which is 59.93%. And also they compared their results with previous data augmentation processes but it was proved that their method gave better results.

MD Moniruzzaman et al [3] ,2019, explored the use of faster R-CNN-based Deep Learning for detecting seagrass from underwater digital photos. In recent times, advanced computer techniques have become really good at finding objects in pictures. But when it comes to finding seagrass in underwater photos, things get tricky. The main reason is that there haven't been enough pictures to teach the computer what seagrass looks like underwater. Plus, underwater photos have their unique challenges, like low visibility and similar-looking plants. To solve this problem, the researchers made a special collection of 2,699 underwater pictures, all showing a type of seagrass called Halophila ovalis. The training process involved splitting the input dataset into a training set and a testing set. The training set contained 2,160 images, while the testing set contained 539 images and named it as ECUHO-1, enabling the model to learn and validate its performance. The lab images were further divided into a separate dataset, ECUHO-2, for training, and evaluation. Data preprocessing is a crucial component of the algorithm. The collected underwater images, obtained from both real-life and laboratory environments, underwent resizing to ensure consistent input dimensions for the neural network. Techniques for data augmentation, such as random horizontal flips were applied to diversify the training dataset and enhance network generalization. As we know that Deep learning algorithms require labelled data for that purpose the researchers used expert annotation and labelled the images with a Python-based graphical image annotation tool called LabelImg. These annotations serves as ground truth for training and evaluation. They used a computer program called Faster R-CNN along with a smart network known as Inception V2 to teach the computer how to spot seagrass in these images. They found that the computer program was pretty good at it. In a test, it got mAP(mean average precision) value as 0.3464 for images taken in a lab and 0.261 for images taken in real underwater conditions, which is quite good. Seagrass is essential for marine life, so being able to find and monitor it accurately is a big deal. Before, people used older, less efficient methods to do this, but now deep learning is stepping in to help. The researchers suggested that, in the future, they could make the computer program even better by giving it more clear pictures and possibly using some clever techniques to create fake images for training. In a nutshell, this study shows that modern technology can help us find seagrass in underwater photos, which is crucial for understanding and protecting marine ecosystems.

Avinash Mahavarkar et al [4], 2020, authors examined the use of Underwater Object Detection using Tensorflow. The authors tackle underwater object detection, highlighting the complexities associated with dissolved RGB constituents in deep water. Their approach employs TensorFlow and the Faster R-CNN algorithm to ensure optimal accuracy. They emphasize the necessity of precise machine learning algorithms trained on datasets, splitting images into 80% training and 20% testing. The authors revealed the limitations of traditional techniques like Haar classifiers, SVM, and HOG for underwater scenarios. It underscores the significance of edge detection, feature matching, and custom-designed algorithms for object detection, with background subtraction further enhancing accuracy. The paper employs machine learning, specifically the TensorFlow framework, to address these challenges. The Faster R-CNN algorithm is chosen for development, demonstrating the significance of this Deep learning technique. Here the authors setup of an underwater tank with a camera system, and suspended some objects like Toothbrush, Clock, Bottle, Cup, etc in the tank and took the pictures of those objects. They used those images as dataset. And finally they got 0.2s as test time, 97.65% as training accuracy by using Faster R-CNN algorithm. They compared their results with other algorithms also but it was proved that Faster R-CNN is the best of all the algorithms. The primary software highlighted is TensorFlow, particularly TensorFlow 1.14, which plays a central role in this project. They also discuss the utilization of different models within TensorFlow, including Fast R-CNN, YOLO, and other pre-trained models.

Hao Wang and Nanfeng Xiao [5], 2023, Underwater Object Detection Method based on Improved Faster RCNN was described. In the realm of marine biology and environmental science, the conservation and effective utilization of marine organisms have been a subject of growing interest due to their rich biodiversity. However, the examination and continuous keeping track of marine habitats, especially seafloor, are laden with challenges rooted in the complexities of underwater environments. These include factors such as low light, high pressure, and extreme temperatures, which lead to photos of aquatic life that are hazy and indistinct, as well as noise and image distortion problems. Traditional manual exploration methods, being time-consuming and costly, possess inherent limitations. Hence, the need for undersea object detection and monitoring that is steady, dependable, and rapid in such harsh underwater settings is becoming increasingly necessary. In order to tackle these issues, in this paper the researchers enhanced the Faster RCNN algorithm for the detection of specific marine organisms, including holothurian, echinus, scallop, starfish, and waterweeds. The improvements were manifold, beginning with the substitution of Res2Net101 network was used with the VGG16 structure in the initial feature extraction module. This change bolsters the network's capability to capture intricate features within the underwater domain. To overcome the imbalance between positive and negative samples within bounding boxes, the Online Hard Example Mining (OHEM) technique is proposed. Further optimization is achieved through the introduction of the Generalized Intersection Over Union (GIOU) and Soft Non-Maximum Suppression (Soft-NMS) techniques, refining the bounding box regression mechanism. Moreover, a multi-scale developing approach is employed to enhance the model's robustness, particularly critical in the face of varying object sizes and environmental conditions. A number of elimination tests were carried out on the improved Faster RCNN model showcases significant improvements, including a 3.3% increase in mean Average Precision (mAP@0.5), reaching 71.7%, compared to the original model, a 2.5% rise in the F1-score, and an overall boost in accuracy, highlighting the practical effectiveness of the algorithm in the underwater object detection and marine organism conservation and research in complex underwater environments.

Pengfei Shi et al [6], in 2021, researchers examined the use of Underwater Biological Detection Algorithm Based on Improved Faster-RCNN. Researchers discussed an advanced underwater biological algorithm for detection, which builds upon Faster-RCNN model and addresses the challenges associated with underwater image analysis. Underwater organisms play a vital role in the ecological environment, but their accurate detection is often hindered by issues like low-quality imaging, varying shapes and sizes of organisms, and overlapping or occlusion. The authors propose several key improvements to enhance detection accuracy. They incorporate ResNet as a feature extraction network and introduce BiFPN (Bidirectional Feature Pyramid Network) to improve feature extraction and multi-scale feature fusion. Moreover, they replaced traditional IoU with EIoU (Effective IoU) to refine bounding boxes and utilize K-means++ clustering for better anchor box generation. The results demonstrate remarkable enhancements in detection accuracy, with the proposed algorithm achieving an 8.26% increase in mean Average Precision (mAP) compared to the traditional Faster-RCNN. The performance tests reveal that these enhancements have minimal impact on the model's operating efficiency. Furthermore, a comparison with the YOLOv4 model underscores the superiority of the proposed algorithm, which exhibits a 17.58% higher mAP and significant gains in detection accuracy across various underwater organisms. In conclusion, the study introduces an efficient algorithm for underwater biological detection, presenting promising prospects for ecological research and environmental monitoring within underwater ecosystems. Future research should focus on optimizing the algorithm's speed to meet real-time detection requirements.

Nurcahyani Wulandari et al [7] ,2022, have studied about Comparison of Deep Learning Approaches for Detecting Underwater Objects. This study investigates underwater object detection using various deep learning models, along with Faster-RCNN, SSD, RetinaNet, YOLOv3, and YOLOv4, and evaluates their performance on the RUIE dataset. Notably, Faster-RCNN achieved a mean Average Precision (mAP) of 58.88% and detected objects in approximately 1.42 seconds. SSD yielded an mAP of 36.97% with a detection time of about 0.81 seconds. In contrast, RetinaNet exhibited a robust mAP of 81.72% but operated relatively slower at 2.23 seconds. YOLOv3 delivered an mAP of 83.07% and impressive detection speed at just 0.50 seconds. Lastly, YOLOv4, with mAP of 83.70%, was slightly slower at 0.65 seconds. Python was the primary programming language for model development, and the experiments were conducted on a PC equipped with an Intel i7-10510U CPU, 16 GB of RAM, and an NVIDIA GeForce MX230 graphics card. This study comparison reveals that YOLOv3 is the most promising model, as it balances a high mAP of 83.07% with an impressively fast detection time of just 0.50 seconds. This research assists in choosing the most suitable deep learning model for detecting undersea objects by balancing accuracy and efficiency.

Fenglei Han et al [8], 2020, researchers featured Deep CNN Method for Underwater Image Processing and Object Detection. The paper emphasizes the growing importance of undersea autonomous operation for deep-sea exploration and the use of lucrative resources. It underscores the pivotal role of intelligent computer vision in this context, where the challenging high-pressure deep-sea environment necessitates autonomous systems. The core challenges of underwater exploration pertain to the quality of image data captured, particularly weak illumination, low-quality imagery, and noise. In the realm of image preprocessing, the paper underscores the crucial role of enhancing image quality as a fundamental step in underwater object detection. It introduces a novel approach that combines the Max-RGB and Gray-Scale methods, effectively addressing the color distortion arising from water absorption. Furthermore, the paper introduces a Convolutional Neural Network (CNN) method that proves vital for enhancing weakly illuminated underwater images, essentially serving as a machine learning solution to this problem. Moving on to object detection, the paper elaborates on the architecture of a deep CNN network designed for this purpose. It highlights the importance of two distinct schemes that improve the YOLO V3-based object detection system, resulting in enhanced accuracy and real-time performance, especially in underwater environments where traditional methods often fall short. The research then delves into the experiments conducted to evaluate various object detection methods, including Fast RCNN, Faster RCNN, YOLO V3, and the proposed methods. Findings suggest that the proposed Scheme 2 exhibits superior accuracy and real-time detection capabilities, positioning it as solution for identification of underwater objects. In conclusion, the paper underscores the efficiency of the proposed methods identification of underwater objects, particularly for identifying marine organisms. While these techniques offer promise, the authors acknowledge the need for more diverse underwater datasets to further enhance system performance and accuracy in varying underwater conditions.

Jayaraj Velusamy et al [9] ,2019, researchers examined the use of object detection in underwater images using Faster Region based convolutional neural network. The presented research focuses on a vision-based approach for detecting underwater objects, specifically those placed within underground pipelines and marine life such as fish. The technique relies on a Faster R-CNN to automatically recognize these objects. This detection process is enhanced through color compensation and image enhancement techniques, enabling more accurate identification of submerged objects. The application of Faster Region-Based CNNs allows for real-time pixel classification in underwater images, aiding in the identification of various objects within the observed scenes. Geometric reasoning is employed to reduce false detections and enhance overall accuracy. The preprocessing stages encompass image acquisition, gray-scale conversion, filtering, and histogram equalization. Gray-scale conversion is crucial for transforming the input RGB images into a standardized 0 to 255 pixel range, while filtering helps enhance the quality of the images. Histogram equalization, on the other hand, is used to improve image contrast. Morphological operations such as Otsu thresholding, erosion, and dilation further refine the preprocessing steps, contributing to better object detection and classification. The classification process involves a Faster Region-Based CNN that employs selective search to extract region proposals, subsequently used for object classification. The CNN serves as a feature extractor, and the extracted features are input into an SVM for object presence prediction. Additionally, offset values for bounding box precision enhancement are predicted. The results of this research indicate an impressive 90% accuracy rate for the classification process, demonstrating the effectiveness of the proposed method. Future work can further enhance accuracy and detection performance, addressing variations in underwater conditions and camera angles to achieve even better results. In summary, this study introduces an efficient vision-based approach using CNNs and preprocessing techniques to detect objects underwater, showing promise for applications in underground pipelines and marine environments. The achieved 90% accuracy rate highlights the potential of this method for various underwater scenarios and encourages further research in this field.

Here the Fig. 1. is a pie chart drawn to show the type of software used by the authors for their respective purposes. Most of the authors about 71% used python language. Python language can be written and run in many softwares like IDLE, Google Colab, Pytorch, Tensorflow etc. As the authors didn't mentioned any particular software they used to run those python codes we have taken it as python as a Software tool. The remaining 29 % of the authors used Matlab as their software.

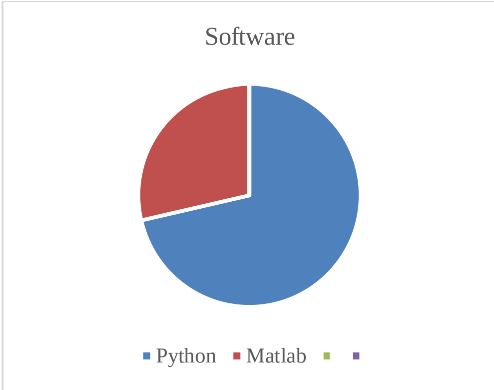


Fig. 1. Pie chart depiction of software used to train the network.

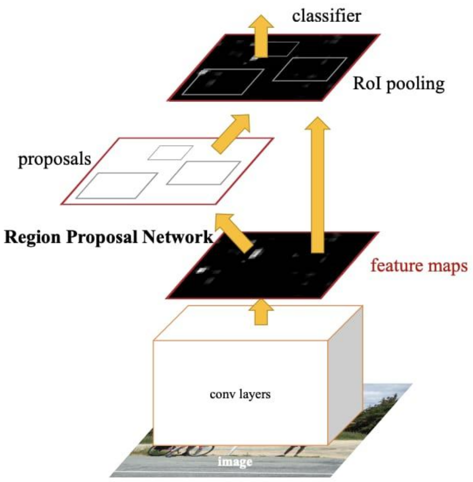
TABLE I. REPRESENTS THE DATASETS AND SOFTWARE USED BY RESEARCHERS IN DIFFERENT PAPERS

Ref No.	No. of images in the Underwater dataset	Software
[1]	Not mentioned in the paper	MATLAB
[2]	1800 labelled images	Not mentioned in the paper
[3]	2,699 underwater images of Halophila ovalis	Python
[4]	COCO Dataset	Python
[5]	3500 images	Python
[6]	5543 images	Python
[7]	1,800 labelled images	Python
[8]	18000 images	Not mentioned in the paper
[9]	Not mentioned in the paper	MATLAB

III. LITERATURE CLASSIFICATION

After analysing various studies on the object detection in underwater images using various deep learning techniques, we have found that utilizing Faster Region Based Convolutional Neural Network (Faster R-CNN), which is generally used for image recognition and pixel data manipulation, can be highly advantageous in this realm. Among the array of object detection techniques available, Faster R-CNN emerges as a robust choice in the realm of deep learning-based object detection. This model, employing a two-stage design, brings together a region proposal network (RPN) with a Fast R-CNN detector, resulting in a powerful combination of advantages. This architecture enables the model to learn intricate visual features and patterns within images, making it highly suited for complex object detection tasks. Additionally, it excels in precise object localization, a critical aspect in scenarios that demand accurate bounding box predictions, such as in medical imaging or robotics applications. Notably, Faster R-CNN exhibits modularity and adaptability, allowing it to be employed in various domains, rendering it a versatile solution for object detection tasks. Its consistent demonstration of state-of-the-art performance in object detection competitions underscores its effectiveness. Underwater object detection poses specific challenges, including limited visibility, image distortions, and complex underwater backgrounds. Faster R-CNN's attributes extend seamlessly to this domain. The model's capacity to capture and learn from diverse visual patterns positions it as a compelling choice for underwater object detection, where precision, adaptability, and high performance are paramount. This literature classification underscores the significance of Faster R-CNN in object detection and, in particular, its applicability to underwater object detection. Currently we are working on the project called identification of underwater objects using Faster R-CNN Algorithm. Further we will compare the performance of our model with other models also.

After studying various Object Detection Techniques, we came to know that Faster R-CNN is an effective method. Because of it's speed and accuracy. Though it gives less accuracy when compared to YOLO method but it's speed is more. So we have selected Faster R-CNN algorithm to implement our project after studying various algorithms.



[10] Fig.2. A typical Faster R-CNN Network

IV. CONCLUSION

Our survey paper has provided an insightful overview of the object detection landscape, emphasizing the significance of Faster R-CNN as a versatile and high-performance model. This research showcases the model's adaptability and accuracy, making it a promising solution for both general and specialized domains, including underwater object detection. As the demand for robust object detection systems continues to rise across various sectors, Faster R-CNN stands as a pivotal player in the ever-evolving field of computer vision. The future scope of this type of projects involves enhancing

Faster R-CNN's performance in challenging environments, such as improving object detection in underwater scenes. Integration with emerging technologies like 3D object detection and multi-modal sensing will expand its capabilities. Collaborations with marine research and autonomous underwater vehicle (AUV) projects could lead to valuable applications in marine exploration and environmental monitoring. This paper serves as a valuable resource, guiding researchers and practitioners towards deeper exploration and advancements in object detection methodologies.

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