International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

An Integrated Multi-Stage Framework for Underwater Image Enhancement and Marine Object Detection Using CLAHE-Based Contrast Optimization and Faster R-CNN

Batti Tulasi Dasu
Department of Information Technology
Mahatma Gandhi Institute of Technology
Gandipet,Hyderabad -500075, India

Ejjagiri Sahithi
Department of Information Technology
Mahatma Gandhi Institute of Technology
Gandipet, Hyderabad-500075, India

Mungi Adithya Vardhan Reddy
Department of Information Technology
Mahatma Gandhi Institute of Technology
Gandipet, Hyderabad-500075, India

***Abstract* - The water environment poses challenges to image acquisition because of the poor visibility of the image due to the absorption of light and the scattering and color distortion effects. The challenges in underwater imaging result in images that are difficult to process and analyze because they have low contrast, high noise, and color degradation. The proposed solution offers a and image processing techniques deep learning technique to design a multi-step process for improving underwater images and detecting objects. The proposed solution utilizes the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique for image improvement, the Faster R-CNN used as the Convolutional Neural Network model based on regions for detecting object,**

offering real-time object recognition. The proposed solution has achieved significant improvements in both image visibility and detection accuracy and these are critical in underwater robotic operations and marine exploration

***Index Terms* - Underwater image enhancement, underwater imaging, color distortion correction, Contrast Limited Adaptive Histogram Equalization (CLAHE), object detection, Faster R-CNN, convolutional neural networks (CNN), marine exploration, underwater robotics.**

1.INTRODUCTION

The latest improvements in underwater imaging and vision systems play an important role in enhancing underwater exploration, surveillance, and robotics today, as affirmed in literature [1]. Oceans and underwater environments are complex and dynamic, with visibility greatly affected by absorption, scattering, and distortion of light and colors.As such, images acquired under these conditions are prone to low contrast, noise, and color changes, making their analysis and interpretation extremely challenging. Considering an environmental and scientific viewpoint, there is an imperative need for an effective system of improving and analyzing underwater images, as well as detecting objects in water, for example, biodiversity, navigation, and resource exploration, as discussed in literature [3],[4]. A system which can perform effectively in deteriorating underwater environments helps in reducing dependency on observing them manually and increases the reliability of automated underwater tasks [5], [6]. Also, common methods for picture improvement techniques, such Retinex and histogram equalization theory-based correction, and those using fusion, increase noise in the image and cannot generalize well over various underwater environments [7].

This renders these approaches unfit for large-scale and real-time use in underwater environments, as conditions change rapidly. Although recent studies using DL techniques for underwater image enhancement and object detection have recorded significant improvements in the quality of underwater images and object identification accuracy, they are still confronted with problems of high computational and data requirements, as well as the need for real-time performance, as discussed in [8].

In addition, underwater object detection algorithms are largely affected by the nature of the images being used, as any form of degradation in image contrast and overall color quality significantly reduces theirability, particularly in the identification of tiny

things in the scene, as covered in [9].

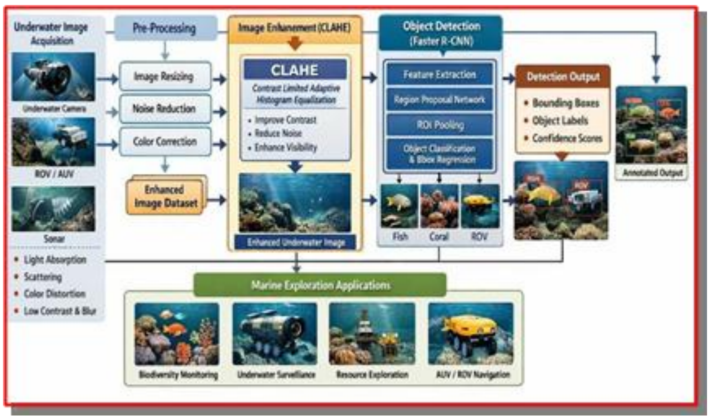


Fig. 1: A Multi-Stage System for Enhancing Underwater Images and Detecting Objects for Marine Exploration

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

Table I:Test Dataset for UIE and Object Detection

Author & year	Limitations/Issues	Existing method	Proposed Approach	Dataset Utilization	Techniques Applied	Tools Used	Validation Metrics	Future Directions
Cong et al., 2024	Requires large labeled dataset and high computational power	Traditional Image processing methods	Comprehensive deep-learning based UIE methods	UIEB and other public datasets	CNN,GNN-based enhancement	Python, PyTorch	PSNR, SSIM	Lightweight real-time enhancement.
Liao & Peng, 2024	Poor handling of complex underwater lighting	Physical model-based enhancement	Multi-task fusion enhancement	Real-world underwater images	Color correction and image fusion	MATLAB,python	Visual quality Improvement	Adaptive enhancement models
Zhang et al., 2024	Loss of fine details after enhancement	Basic CNN enhancem models	Multiscale encoder–decoder network	UIEB Dataset	Deep feature extraction	PyTorch	CCF ,FDUM	Better integra with Detection.
Li et al., 2022	Low detection accuracy on degraded images	Basic YOLO-based detection	Image enhancement with YOLOv5S	Marine biological dataset	CLAHE + YOLOv5S	Python, OpenCV	Precision,Recall P	Real-time underwater Detection.
Ji et al., 2023	Separate enhancement and detection pipelines	Independent enhancem models	Joint enhancement object detection	Underwater dataset	o Super-resolution detection	TensorFlow, Python	Detection Accura	Unified end-to-end systems

The diagram explains a step-by-step process that starts with capturing underwater images and then improves their quality through pre-processing and CLAHE enhancement to make them clearer and more visible. After enhancement, the images are analyzed using the Faster R-CNN model to detect underwater objects accurately, helping in marine activities such as biodiversity study, surveillance, resource search, and autonomous vehicle navigation.

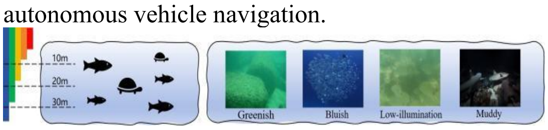


Fig. 2: Various color distortions in underwater

In continuation of these challenges (Ref. Fig. 1), this research proposes.A multi-phase underwater photo enhancement and object detection framework that combines efficient image processing techniques with deep learning–based detection models. The proposed approach employs Contrast Limited Adaptive Histogram Equalization (CLAHE) for enhancing image contrast and visibility, followed by Faster R-CNN for accurate underwater object detection. By enhancing quality of image before detection, the proposed system ensures that the performance of object detection performance remains consistent in various underwater conditions.

The major contribution of this research can be summarized as follows:

- A unified multi-stage approach that works together with underwater object detection and image enhancement to improve visibility in underwater environments.
- Application of CLAHE as an effective and computationally efficient contrast enhancement technique suitable for real-time underwater imaging.
- Utilization of Faster R-CNN for accurate detection of underwater objects, improving detection reliability in low-contrast and color-distorted images.
- Demonstration of improved image visibility and detection accuracy, making the proposed system suitable for underwater robotics, marine exploration, and surveillance applications.

II. LITERATURE REVIEW

Underwater image enhancement (UIE) has been extensively researched to counter the effects of underwater optical properties. Cong et al. [1] classified UIE techniques into non-deep learning-based and deep learning-based techniques, pointing out that non-deep learning-based techniques are based on assumptions and lack robustness in complex underwater environments. Although deep learning-based techniques show better enhancement quality, they are data and computationally expensive.

The proposed methods have balanced enhancement but may not work well in extreme underwater environments. GAN-based methods and transformer models have further enhanced the performance of UIE; however, they have high computational complexity [6], [7]. Underwater object detection has also been a focus of research. Yang et al. [8] introduced the application of AUVs and ROVs in underwater surveillance, and they stated that the quality of images is an important factor that influences the accuracy of object identification. Li et al.[9] reviewed the methods of underwater object detection and reached a conclusion that image enhancement can enhance the reliability of object detection .Object detection systems may not function well in low-visibility environments due to the background noise makes it hard to identify the object boundaries clearly [16].The study emphasizes that refining foreground regions and integrating preprocessing with detection improves localization accuracy and robustness under visually degraded environments[16] .The extraction of features at different scales improves the capacity of the object detection system to identify small and partially hidden objects in low-visibility environments.

TABLE I summarizes test dataset for image enhancement in various underwater conditions of existing models.

III. PROPOSED METHODOLOGY

In this section, the working of proposed system for underwater image enhancement and marine image detection is explained in detail. Underwater images usually suffer from poor visibility and distortions due to challenging environmental conditions. The proposed system incorporates image preprocessing, contrast enhancement, and object detection using a deep learning technique to resolve these problems and performance.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

Fig. 2: Proposed System for Image Enhancement.

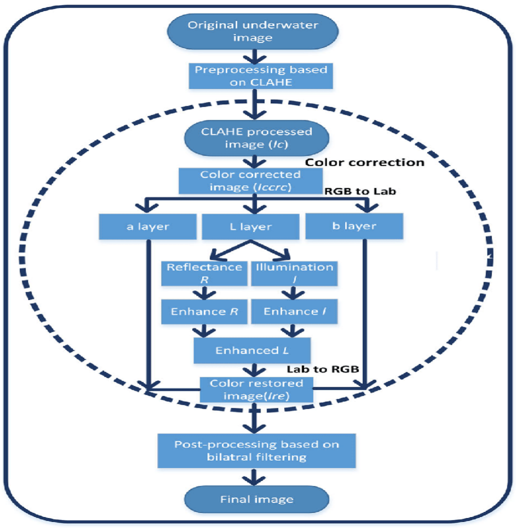


Table 2 Acronyms used in proposed system

Term / Symbol	Description
Image Preprocessing & Enhancement	
I_raw	Raw underwater input image
WB	White Balancing for color correction
I_wb	White-balanced image output
CLAHE	Contrast Limited Adaptive Histogram Equalization
I_enh	Image with improved contrast
I_final	Final enhanced image used for detection
Detection Components	
CNN	Convolutional Neural Network for feature extraction
Faster R-CNN	Regio-based CNN
RPN	Region proposal Network for candidate object regions
F	Feature map extracted from input image
ri(x,y,w,h,s)	Proposed region with position,size,object score
(x,y)	Bounding box centre coordinates
W,h	The bounding box's height an d width
c	Detection confidence score
θ	Confidence threshold for valid detections
NMS	Non-Maximu Suppression for removing overlapping detections
IoUth	Intersection-over-union threshold
Datasets & Tools	
UIEB	Underwater Image Enhancement Benchmark Dataset
OpenCV	Image processing library
Numpy	Numerical computation library
TensorFlow/PyTorch	Deep learning frameworks
Performance Metrics (Detection & Enhancement)	
FDUM	Feature Detail Underwater Measure -evaluates preservation of fine image details.
CCF	Color Contrast factor -measures contrast improvement in underwater pictures
PSNR	Peak Signal-to-Noise Ratio for Picture Quality evaluation
SSIM	Structural Similarity Index Measure
Precision	Ratio of correct detections among predicted objects
Recall	Ability to detect all relevant objects
F1-Score	Combined measure of precision and recall
mAP	Mean Average Precision and recall
IoU	Intersection over Union measuring bounding box accuracy

Fig. 2 shows the workflow of the system. To start with the system receives the input images and then the images are preprocessed and enhanced using CLAHE. After images are enhanced then sent to the Faster R-CNN model for object identification. At last, system evaluates the detection results and produces the output. Fig. 3 represents the detailed architecture of the image enhancement and detection framework.

A. Image Preprocessing and Enhancement

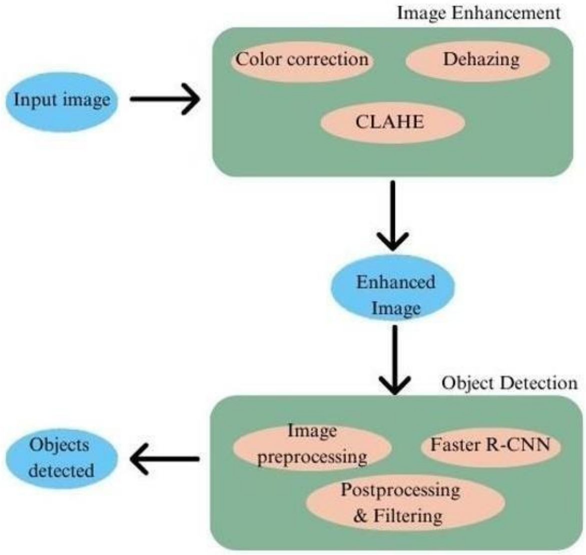
Underwater images are suffered by several issues such as distortion of color, low contrast, noise, and haze. These problems occur mainly due to absorption and scattering of light in water. To handle these issues, the proposed system follows a multi-stage image enhancement process.

1) Color Correction using White Balancing

The first step in preprocessing is color correction using white balancing. The raw underwater image IrawI_{raFw}Iraw is processed to normalize its color

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

Fig. 3: Proposed method architecture



channels and reduce the dominant blue-green color cast commonly found in underwater scenes:

$$Iwb=WB(Iraw)$$

Here, W B represents the white balancing operation, which supports in restoring natural and realistic color tones in the image.

1) Contrast Enhancement using CLAHE

After color correction, image is enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE). This framework increases the local contrast and overall

visibility of the picture:

$$I\_enh=CLAHE(Iwb)$$

To do this, CLAHE divides the image into small parts and applies histogram equalization to each one separately. It also limits amplification of excessive contrast, which helps to reduce noise. The final image obtained after enhancing is:

$$I\_final = f(I\_enh)$$

where f represents the enhancement function. This preprocessing and enhancement phase increases the quality and clarity of images, which can be used for accurate object identification.

B. Faster R-CNN for Object Detection

Once the image is enhanced, it is passed to the object identification module that works on the Faster R-CNN deep learning model.

1) Feature Extraction

The enhanced image *I_final* is initially processed by a convolutional neural network to extract important visual features:

$$F=CNN(I\_final)$$

where F represents the high-level feature map obtained from the image.

2) Region Proposal Network (RPN)

The extracted features are then sent to the Region Proposal Network (RPN), which locates the regions that are potential in the image that may contain objects:

$$R= \{r1, r2, ..., rn\}$$

Each proposed region is denoted as:

$$ri=(x,y,w,h,s)$$

where (x,y) represent the location, width and height are represented by w,h, and s is the objectness score.

3)Classification and Bounding Box Prediction

The regions that are proposed classified into different object groups, and their bounding boxes are:

$$B= \{b1, b2, ..., bn\}$$

$$bi=(x,y,w,h,c)$$

where c is the confidence score for each detected object. Only detections with confidence above a predefined threshold θ are considered valid:

$$bi \in D \Leftrightarrow ci \geq \theta$$

This step ensures that only reliable detections such as fishes and underwater structures are retained.

C. Detection Confidence and Filtering Mechanism

To improve detection accuracy, Non-Maximum Suppression (NMS) is used to remove overlapping and redundant bounding boxes:

$$D\_final=NMS(B,IoUth)$$

where IoUthIoU_{th}IoUth is the intersection-over-union threshold.
After this filtering process, the system produces the final output consisting of enhanced images with accurately detected and labeled underwater objects.

EXPERIMENTAL SETUP AND EVALUATION

The proposed enhancement of images in underwater and detection of objects was implemented using the Python programming language in a suitable deep learning environment. For experimentation on the suggested approach, a computer with an Intel Core processor, 8-16 GB RAM, and optional NVIDIA GPU support was considered. For efficient image processing and object detection in underwater images, open-source libraries like OpenCV,

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

NumPy, TensorFlow/PyTorch, and Faster R-CNN were considered. Jupyter Notebook and Visual Studio Code were considered for the implementation of the suggested underwater image processing approach.A. Performance Analysis

For the experiment, publicly available datasets were considered for underwater images, specifically UIEB (Underwater Image Enhancement Benchmark) dataset. The datasets provide images acquired in a natural environment with varied illumination and visual conditions such as distortion of color, contrast and visibility issues for underwater images. The datasets were divided into training, validation, and testing in the ratio 80-10-10 for unbaised testing. The images were preprocessed using white balancing and CLAHE followed by object detection using the Faster R-CNN.

A. PERFORMANCE ANALYSIS

Performance of the proposed image enhancement and detecting objects in underwater are used to improve quality of images and detecting objects with accuracy. The effectiveness of CLAHE to improve the degraded images and further to improve the effectiveness of the Faster R-CNN detection.

Performance of the image enhancement was assessed using regular quality measurement such as Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), and contrast improvement. Results from the analysis demonstrated that CLAHE significantly improved the underwater images in regard to the visualization of the images, contrast brightness, and. Color distortions and haze have been reduced, making the features of the images identifiable compared to the raw underwater images. This is supported by the improvement in PSNR and SSIM values.
For Object Identification Analysis, metrics such as F1-Score, Precision, Recall, Mean Average Precision (mAP), and Intersection over Union (IoU) were considered. In addition, it was recognized that with Faster R-CNN, detection accuracy was more prevalent when the images were enhanced rather than the original images. During the enhancement stage, it was realized that the visibility of the features was greatly enhanced, leading to better detection of objects such as fish, corals, among other underwater objects. The greater values of mAP and IoU were also recognized, coupled with a significant reduction in incorrect identification.

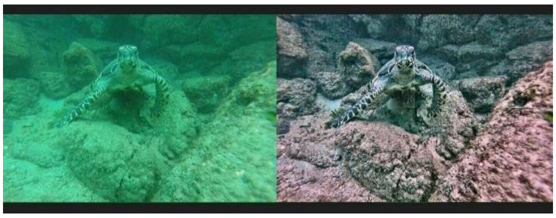


Fig 4 – original and enhanced image

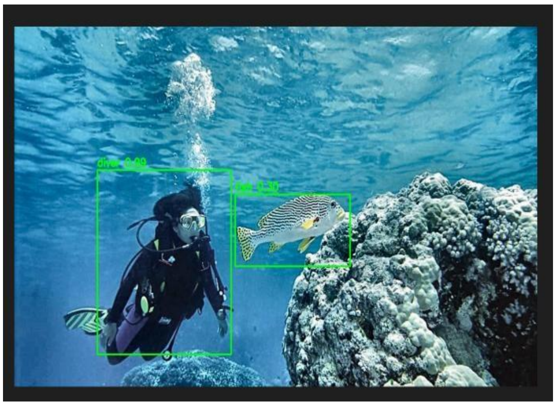


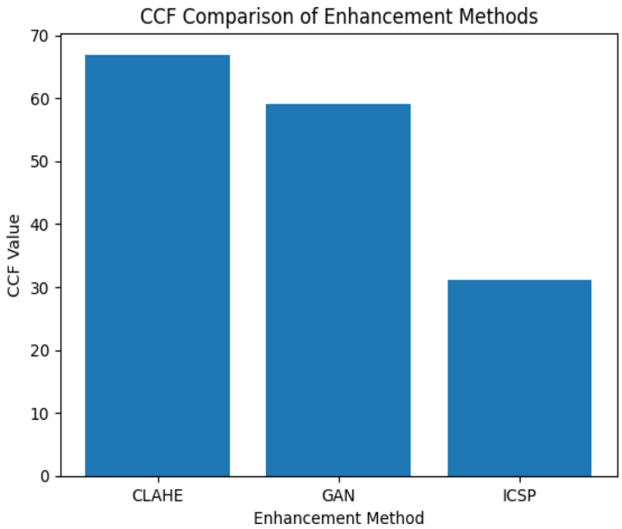
Fig 5– object detection of enhanced image

Fig 6- object detection of enhanced image

TABLE II : Enhancement Performance comparison of existing models vs proposed

MODEL	FDUM	CCF
CLAHE	7.44	63.91
GAN	9.66	59.06
ICSP	2.95	31.11

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026



The performance of CLAHE, GAN, and ICSP was evaluated using both quantitative metrics and visual analysis. The comparison shows that each method improves underwater image quality in a different way. CLAHE demonstrated the strongest performance in terms of color contrast, achieving the highest CCF value. This indicates that CLAHE is highly effective in enhancing visibility and correcting low-contrast regions commonly found in underwater images. The enhanced images produced by CLAHE appeared clearer and more suitable for subsequent object detection tasks. GAN-based enhancement achieved the highest FDUM value, indicating better recovery of fine image details. The GAN-enhanced images appeared smoother and visually more natural compared to other methods. However, the contrast improvement achieved by GAN was slightly lower than that of CLAHE. While GAN excels in preserving textures and details, its higher computational complexity makes it less practical for lightweight or real-time underwater applications. The performance of ICSP was relatively lower in terms of FDUM and CCF. Although it was able to provide some contrast to the image, it was not as effective as CLAHE and GAN in terms of improving the details of the image. The images processed by ICSP were darker and less informative.

IV. CONCLUSION AND FUTURE SCOPE

The suggested DL model for image enhancement and object identification works effectively. First, underwater images are selected and processed to address the challenges of low visibility, low contrast, and color changes resulting from water conditions. Image enhancement techniques, including white balancing and CLAHE, are applied to increase the quality of the image.

Once image has been improved, a Faster R-CNN model, which has been trained on the COCO dataset, is applied to perform object detection, creating bounding boxes and detected objects with labels. Enhanced image results in a higher accuracy of object detection compared to the actual underwater image.

The suggested approach has a modular structure, including image loading, enhancement, detection, and saving, making it easy to scale up or change the models. Image comparison of the original, enhanced, and detected images can be applied in the evaluation and presentation of results. The suggested approach can be used to improve object detection in underwater areas, including marine life, underwater explorations, and autonomous vehicles.

In addition, in remote-operated vehicles (ROVs), the enhancement of image quality in autonomous underwater vehicles (AUVs) will lead to correct navigation, obstacle detection, and environment mapping, among other uses, as indicated in the results, showing the appropriateness of the CLAHE method.

Future research can be directed to developing hybrid enhancement techniques that can combine the conventional methods, such as the CLAHE method, with deep learning-based methods, among other directions. Integrating the enhancement module with the existing underwater object detection and segmentation systems can be carried out to determine the impact of the enhancement module on these systems, among other directions. Expanding the system to support real-time processing of underwater video streams and implementing it in AUVs or ROVs can increase the real-time use of the system in real-world scenarios.

REFERENCES

1. Xiaofeng Cong, Yu Zhao, Jie Gui, Junming Hou and Dacheng Tao "A Comprehensive Survey on Underwater Image Enhancement Based on Deep Learning", Volume3,2024 https://doi.org/10.48550/arXiv.2405.19684

2. Kaibo Liao and Xi Peng "Underwater image enhancement using multi-task fusion" 2024 https://doi.org/10.1371/journal.pone.0299110

3. Dehuan Zhang, Jingchun Zhou, ChunLe Guo, Weishi Zhang, Chongyi Li "Synergistic Multiscale Detail Refinement via Intrinsic Supervision for Underwater Image Enhancement",Volume4,2024 https://doi.org/10.48550/arXiv.2308.11932

4. Liu, B.; Yang, Y.; Zhao, M.; Hu, M. A Novel Lightweight Model for Underwater Image Enhancement.Sensors2024,24,3070. https://doi.org/10.3390/s24103070

5. Xiuwen Bi, Pengfei Wang, Wei Guo, Fusheng Zha and Lining Sun "RGB/Event signal fusion framework for multi-degraded underwater image enhancement", Volume11–2024 https://doi.org/10.3389/fmars.2024.1366815

6. Yang, J.; Huang, H.; Lin, F.; Gao, X.; Jin, J.; Zhang, B. Underwater Image Enhancement Fusion Method Guided by Salient Region Detection. J. Mar. Sci. Eng. 2024, 12, 1383. https://doi.org/10.3390/jmse12081383

7. Shijian Zheng, Rujing Wang, Shitao Zheng, Liusan Wang and Zhigui Liu "A learnable full-frequency transformer dual generative adversarial network for underwater image enhancement", Volume 11 - 2024 | https://doi.org/10.3389/fmars.2024.1321549

8. Sen Lin, Yuanjie Sun and Ning Ye "Underwater image restoration via attenuated incident optical model and background segmentation", Volume 11 - 2024 | https://doi.org/10.3389/fmars.2024.1457190

9. Gong, T.; Zhang, M.; Zhou, Y.; Bai, H. "Underwater Image

Enhancement Based on Color Feature Fusion."Electronics2023,12,4999.https://doi.org/10.3390/electronics12244999

10. Er, M.J.; Chen, J.; Zhang, Y.; Gao, W. "Research Challenges, Recent Advances, and Popular Datasets in Deep Learning-Based Underwater Marine Object Detection: A Review." Sensors 2023, 23, 1990. https://doi.org/10.3390/s23041990

11. Ji, X.; Liu, G.-P.; Cai, C.-T. "Collaborative Framework for Underwater Object Detection via Joint Image Enhancement and Super-Resolution." J. Mar. Sci. Eng. 2023,11,1733. https://doi.org/10.3390/jmse11091733

12. Li, P.; Fan, Y.; Cai, Z.; Lyu, Z.; Ren, W. "Detection Method of Marine Biological Objects Based on Image Enhancement and Improved YOLOv5S." J. Mar. Sci. Eng. 2022,10,1503. https://doi.org/10.3390/jmse10101503

13. Hu, K.; Weng, C.; Zhang, Y.; Jin, J.; Xia, Q. "An Overview of Underwater Vision Enhancement: From Traditional Methods to Recent Deep Learning." J. Mar. Sci. Eng.2022,10,241. https://doi.org/10.3390/jmse10020241

14. Liu, Z.; Zhuang, Y.; Jia, P.; Wu, C.; Xu, H.; Liu, Z. "A Novel Underwater Image Enhancement Algorithm and an Improved Underwater Biological Detection Pipeline." J. Mar. Sci. Eng. 2022,10,1204. https://doi.org/10.3390/jmse10091204

15. Zhang, X.; Fang, X.; Pan, M.; Yuan, L.; Zhang, Y.; Yuan, M.; Lv, S.; Yu, H. A "Marine Organism Detection Framework Based on the Joint Optimization of Image Enhancement and ObjectDetection."Sensors 2021,21,7205.
https://doi.org/10.3390/s21217205

16. B. T. Dasu, M. V. Reddy, K. V. Kumar, P. Chithaluru, N. Ahmed, and D. S. Abd Elminaam, "A self-attention driven multi-scale object detection framework for adverse weather in smart cities," *Scientific Reports*, vol. 16, p. 1992, 2026, doi: 10.1038/s41598-025-31660-4.