Underwater Image Enhancement

A report submitted for the Research Project(7th Semester)

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Abstract

There are numerous difficult aspects of picture improvement, including low-light image enhancement, dehazing, deraining, denoising, and many more. The improvement of underwater images is one of these difficult fields. Underwater image enhancement is a key field of research because it can improve the clarity and quality of underwater image capture. It has several uses, including search and rescue missions, scientific investigation, underwater archaeology, and marine life inspection. Low contrast, light dispersion, low light, and prolonged haziness are just a few of the difficulties this enhancement typefaces, all of which lead to poorer image quality. Recently, several attempts to improve such photos have been proposed by researchers from all over the world, some of which use deep learning techniques while others use more conventional methods. Given all the flaws, our primary contribution will be the creation of a learning-based model to improve underwater image quality and maintain the intrinsic details of the photographs. To demonstrate the effectiveness of our approach, the simulations and experimental findings will also be contrasted to benchmark modern techniques.

Keywords: *Image Enhancement, Underwater Image Enhancement, Deep Learning.*

1 Introduction

Scattering, absorption, and backscattering are common phenomena that degrade underwater photographs and can cause low contrast, color casts, and blurring. This can make extracting important information from the photos challenging, restricting their usage in various fields. The creation of innovative, effective methods for enhancing underwater photos is the main objective of this research. This project will be particularly challenging in terms of developing and putting into practice new underwater picture-enhancing algorithms that consider the underwater environment's unique difficulties.

In this research, we will assess a Deep Learning algorithm against diverse underwater photographs taken in the actual world. The experimental validation will be carried out by using a variety of actual underwater photographs from diverse sources.

1.1 Image Enhancement

Image enhancement is the process used to improve the quality of images. It aims to enhance and produce more valuable images by reducing noise, increasing contrast, and adding detail. This improves visibility, recognizes objects, and finds hidden information. In various applications, such as underwater imaging, medical imaging, and photography, image enhancement is routinely employed to create better-looking and more valuable images.
There are many kinds of image enhancements are there. Such as-
Contrast Enhancement: Makes differences in brightness or color more noticeable, improving image clarity. There are many kinds of contrast enhancement available.Un-sharp masking, contrast limited adaptive histogram equalization (CLAHE), adaptive histogram equalization, etc.
Noise Reduction: Reduces unwanted changes in pixel values, making the image smoother. Noise can caused by different factors such as sensor noise, transmission noise, etc. A few techniques are there to remove noise, like Spatial filtering and frequency domain filtering.
Sharpness Enhancement: Emphasizes edges and fine details, making objects stand out. There are many kinds of Sharpness Enhancement techniques available. Like Unsharp masking, High-pass filtering, and Deconvolution.
Brightness and Color Adjustment: Adjusts overall light, dark, and color balance for better viewing. There are different ways to adjust the brightness and color of an image, such as Using a histogram, curves, sliders, etc.

1.2 Underwater Image Enhancement

Underwater image enhancement is a set of techniques and processes to improve the quality and visibility of underwater images. Water naturally scatters and absorbs light, resulting in diminished contrast, color distortion, and blurriness in underwater photographs. Underwater image enhancement aims to improve the clarity and quality of pictures taken in watery environments.

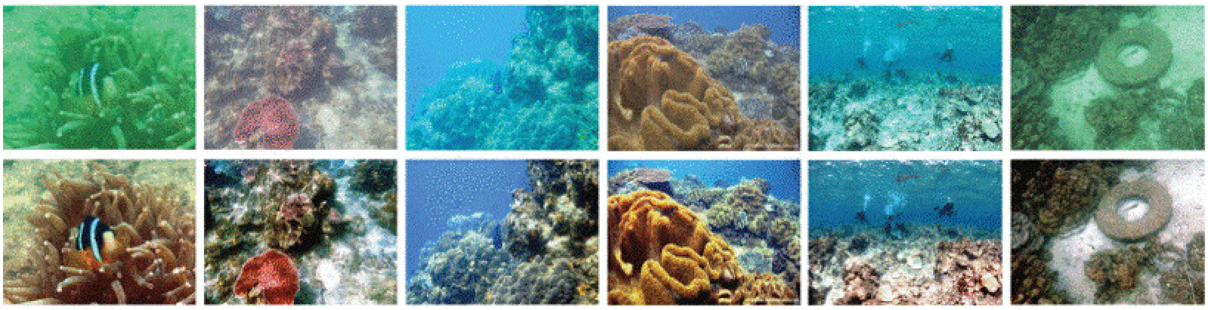


Figure 1: Underwater Image Enhancement

1.3 Application Areas of Underwater Image Enhancement

The significance of underwater image enhancement across various domains is enormous. A few application areas are-

1. **Marine Biology and Ecology**
2. **Underwater Archaeology**
3. **Oceanography and Environmental Monitoring**
4. **Underwater Exploration**
5. **Underwater Robotics and Autonomous Vehicles**
6. **Underwater Infrastructure Inspection**
7. **Underwater Search and Rescue Operations, etc.**

2 Research Problem

2.1 Dataset Collection Difficulties

One of the most significant challenges is acquiring a dataset of underwater images. Access to underwater environments, especially deep-sea, can be challenging and expensive. Underwater conditions vary significantly based on water type (saltwater, freshwater), depth, and location (ocean, lake, river). Collecting images that cover this wide range of conditions can be logistically complex. The equipment required for underwater photography, such as waterproof cameras and submersibles, can be expensive. Maintaining and operating these equipment in harsh underwater environments can pose technical and financial challenges.

2.2 Color Imbalance

Water absorbs the light. This makes colors less vibrant and the image less clear. So, underwater photos often look blue or green. Sometimes, the water absorbs colors differently, causing color distortion in the image. Fixing this is tricky and needs advanced techniques.

2.3 Low Light

In deeper underwater, there's less sunlight. This makes the images dark, with poor contrast and lots of noise, making it hard to see details. To brighten things up, divers often use unique underwater lights. However, handling these lights in different underwater situations can be tricky and require special skills. Due to limited light in the underwater environment, the noise increased in the underwater images

2.4 Diverse Underwater Conditions

Different underwater environments present unique challenges that require specific techniques to handle the situations.

2.5 Underwater Equipment Limitations

Underwater Equipment must be needed to be waterproof and capable of handling underwater pressure. Because of this, there are huge limitations in underwater equipment. And for these factors, the price of the underwater equipment is very high.

2.6 Scattering and Absorption

Water scatters and absorbs light. It causes image degradation and color distortion.

3 Research Objectives

1. to investigate cutting-edge underwater picture-enhancing methods.
2. To create a model that can efficiently improve and address the issue of color inequities and poor contrast.
3. Simulated results to demonstrate the effectiveness of our suggested model.

4 Research Questions

1. How can sight be made better in dim lighting?
2. Can underwater image enhancement techniques leverage deep learning?
3. Can underwater photographs be improved using CNN techniques?

5 Literature Review

Li, Chongyi, et al. [1] proposes a new underwater image enhancement technique, Water-Net, trained on the UIEB dataset. Regarding visual and picture quality metrics, The Water-Net operates at a cutting-edge level. The UIEB dataset is useful for developing and testing underwater image enhancement techniques. Modern underwater picture enhancement techniques can considerably improve the visual quality of underwater photographs. However, there is still room for improvement in image quality metrics.

Wheres Liu, Peng, et al. [2] evaluated the Deep Residual Framework approach on the UW-IQA dataset and contrasted it with other cutting-edge techniques. The results showed that the suggested technique delivered the best results in terms of visual quality and picture quality parameters. Images of the ocean can be effectively enhanced using the deep residual framework. The underwater image enhancement procedure performs better thanks to the residual learning module's potential to learn the residual between underwater and clear photos. Modern visual and image quality metrics can produce performance using the suggested technique.

Zhou et al. [3] suggest a multi-feature prior fusion (MFPF) based underwater image enhancement technique. This is accomplished by extracting and combining various underwater photo feature priors, such as global contrast, local contrast, saturation, and exposure. The technique also comprises gamma correction spatial linear adjustment. These methods address underwater image color cast, exposure, low contrast, and detail loss. To provide high-quality enhancements without the use of complicated underwater optical imaging models, several feature priors from a single input image are integrated as the main innovation. The paper uses a qualitative evaluation to compare the suggested MFPF method to 12 existing techniques, including model-free and model-based methods. Using representative underwater photographs that have been degraded from different datasets, the assessment entails visually evaluating the enhancement results. According to the results, the MFPF approach improves both subjective and objective enhancement effects by successfully harmonizing contrast and color while preserving the inherent qualities of the image. However, it points out that the method disregards the connection between scene depth and degradation, allowing room for potential advancements in subsequent studies. In the abstract, no precise quantitative accuracy measurements are given.

Table 1: LR Table

Paper name	Author	Publisher	Year	Type	Method	Paired or Unpaired
Deep Underwater Image Enhancement [4]	Saeed Anwar, Chongyi Li, Fatih Porikli	arXiv	2018	DL	Convolutional Neural Network (CNN)	Paired
Underwater image enhancement: A comprehensive review, recent trends, challenges and applications [5]	Smitha Raveendran, Mukesh D. Patil, Gajanan K. Birajdar	Springer	2021	Traditional	Polarization-Difference Imaging (PDI)	Paired
Fast Underwater Image Enhancement - GAN with Enhanced Underwater Visual Perception Dataset [6]	Md Jahidul Islam, Youya Xia, Junaed Sattar	IEEE	2020	DL	CNN, GAN	Both Paired and Unpaired
A deep CNN method for underwater image enhancement [7]	Yang Wang, Jing Zhang, Yang Cao, Zengfu Wang	IEEE	2017	DL	CNN	Paired

Table 1: (continued)

Paper name	Author	Publisher	Year	Type	Method	Paired or Unpaired
Underwater Image Enhancement via Minimal Color Loss and Locally Adaptive Contrast Enhancement [8]	Chongyi Li, Xiaojie Guo, Chunle Guo, Xin Liang, Chuan Wang	IEEE	2022	UIE	MLLE	Paired
Underwater Image Enhancement With Hyper-Laplacian Reflectance Priors [9]	Peixian Zhuang, Xinfeng Zhang, Shuyuan Yang, Yanlong Cao, Zhenzhen Zhang, and Jiawan Zhang	IEEE	2022		Hyper-Laplacian Reflectance Priors	Paired
Underwater image enhancement method via multi-feature prior fusion [3]	Jingchun Zhou, Dehuan Zhang, Weishi Zhang	Springer	2022	ML	Multi-Feature Prior Fusion (MFPF)	Paired
Underwater Image Enhancement Quality Evaluation: Benchmark Dataset and Objective Metric [10]	Qiuping Jiang, Yuese Gu, Chongyi Li, Runmin Cong, Feng Shao	IEEE	2022	Traditional	deep neural network	Paired

Table 1: (continued)

Paper name	Author	Publisher	Year	Type	Method	Paired or Unpaired
Underwater Image Enhancement by Attenuated Color Channel Correction and Detail Preserved Contrast Enhancement [8]	Weidong Zhang, Yudong Wang, Chongyi Li	IEEE	2022	Traditional	ACCC, DPCE	Paired
Underwater Image Enhancement Method via Multi-Interval Subhistogram Perspective Equalization [11]	Jingchun Zhou, Lei Pang, Dehuan Zhang, Weishi Zhang	IEEE	2022	Traditional	Multi-interval sub histogram perspective equalization (UMSHE)	Paired
Underwater image enhancement method with light scattering characteristics [3]	Jingchun Zhou, Xiaojing Wei, Jinyu Shi, Weishen Chu, Weishi Zhang	Science-Direct	2022	Traditional	Light scattering characteristics (LSC)	Paired

Table 1: (continued)

Paper name	Author	Publisher	Year	Type	Method	Paired or Unpaired
Underwater Image Enhancement via Medium Transmission-Guided Multi-Color Space Embedding [12]	Chongyi Li, Saeed Anwar, Junhui Hou, Runmin Cong, Chunle Guo, Wenqi Ren	IEEE	2021	DL	Ucolor	Paired
Twin Adversarial Contrastive Learning for Underwater Image Enhancement and Beyond [13]	Risheng Liu, Zhiying Jiang, Shuzhou Yang, Xin Fan	IEEE	2022	DL	Twin adversarial contrastive learning	Unpaired
Underwater Image Enhancement Using a Multiscale Dense Generative Adversarial Network [14]	Yecai Guo, Hanyu Li, Peixian Zhuang	IEEE	2019	DL	Multiscale dense generative adversarial network (MDG-GAN)	Paired

Table 1: (continued)

Paper name	Author	Publisher	Year	Type	Method	Paired or Unpaired
Target Oriented Perceptual Adversarial Fusion Network for Underwater Image Enhancement [15]	Zhiying Jiang, Zhuoxiao Li, Shuzhou Yang, Xin Fan, Risheng Liu	IEEE	2022	DL	Target Oriented Perceptual Adversarial Fusion Network (TOPAL)	Paired
An Underwater Image Enhancement Benchmark Dataset and Beyond [1]	Chongyi Li, Chunle Guo, Wenqi Ren, Runmin Cong, Junhui Hou, Sam Kwong, Dacheng Tao	IEEE	2019	DL	Water-Net	Paired
Underwater image enhancement with global–local networks and compressed-histogram equalization [16]	Xueyang Fu, Xiangyong Cao	Science-Direct	2020	DL	Global–local networks and compressed-histogram equalization for underwater image enhancement	Paired
UW-GAN: Single-Image Depth Estimation and Image Enhancement for Underwater Images [17]	Praful Hambarde, Subrahmanyam Murala, Abhinav Dhall	IEEE	2021	DL	UW-GAN	Paired

Table 1: (continued)

Paper name	Author	Publisher	Year	Type	Method	Paired or Unpaired
LAFFNet: A Lightweight Adaptive Feature Fusion Network for Underwater Image Enhancement [18]	Hao-Hsiang Yang, Kuan-Chih Huang, Wei-Ting Chen	IEEE	2021	DL	Lightweight Adaptive Feature Fusion Network	Paired
Perceptual Underwater Image Enhancement With Deep Learning and Physical Priors [19]	Long Chen, Zheheng Jiang, Lei Tong, Zhihua Liu, Aite Zhao, Qianni Zhang, Junyu Dong, Huiyu Zhou	IEEE	2020	DL	Perceptual Underwater Image Enhancement	Paired
UGIF-Net: An Efficient Fully Guided Information Flow Network for Underwater Image Enhancement [20]	Jingchun Zhou, Boshen Li, Dehuan Zhang, Jieyu Yuan, Weishi Zhang, Zhanchuan Cai, Jinyu Shi	IEEE	2023	DL	UGIF-Net	Paired

Table 1: (continued)

Paper name	Author	Publisher	Year	Type	Method	Paired or Unpaired
Underwater Image Enhancement With a Deep Residual Framework [2]	Peng Liu, Guoyu Wang, Hao Qi, Chufeng Zhang, Haiyong Zheng, Zhibin Yu	IEEE	2019	DL	Deep Residual Framework	Paired
Underwater Image Enhancement based on Deep Learning and Image Formation Model [21]	Xuelei Chen, Pin Zhang, Lingwei Quan, Chao Yi, Cunyue Lu	arxiv	2021	DL	Deep Learning and Image Formation Model	Paired
Benchmarking Underwater Image Enhancement and Restoration, and Beyond [22]	Guojia Hou, Xin Zhao, Zhenkuan Pan, Huan Yang, Lu Tan, Jingming Li	IEEE	2020	DL	GAN	Paired

Table 1: (continued)

Paper name	Author	Publisher	Year	Type	Method	Paired or Unpaired
Underwater Image Enhancement Based on Global and Local Equalization of Histogram and Dual-Image Multi-Scale Fusion [23]	Linfeng Bai, Weidong Zhang, Xipeng Pan, Chenping Zhao	IEEE	2020	Traditional	Dual-image multi-scale fusion.	Paired
An Effectual Underwater Image Enhancement using Deep Learning Algorithm [24]	G. Ramkumar, Anitha. G, Suresh Kumar M, M. Ayyadurai, Senthilkumar C	IEEE	2021	DL	UNET-UIE	Paired
An Experimental-Based Review of Image Enhancement and Image Restoration Methods for Underwater Imaging [25]	Yan Wang, Wei Song, Giancarlo Fortino, Li-Zhe Qi, Wenqiang Zhang, Antonio Liotta	IEEE	2019	Experimental based review	IFM-free methods: Color correction, Contrast enhancement, Dehazing, Sharpening. IFM-based methods: Dark channel prior (DCP), Non-local means (NLM), Deep learning-based methods.	Both Paired and Unpaired

Table 1: (continued)

Paper name	Author	Publisher	Year	Type	Method	Paired or Unpaired
Underwater image enhancement based on DCP and depth transmission map [26]	Haifeng Yu, Xinbin Li, Qian Lou, Chengbo Lei, Zhixin Liu	Springer	2020	Traditional	Double transmission map, Homomorphic filtering, Dual-image wavelet fusion	Paired
Underwater image enhancement using an edge-preserving filtering Retinex algorithm [27]	Peixian Zhuang, Xinghao Ding	springer	2020	Traditional	Retinex model with gradient-domain guided image filtering (GGF).	Paired
Learning-based approach to underwater image dehazing using CycleGAN [28]	Shima Ramesh Maniyath, K Vijayakumar, Laxman Singh, Sudhir Kumar Sharma, Tunde Olabiyisi	springer	2021	ML	CycleGAN	Paired

6 Methodology

6.1 Basic Image Processing Tecniques

Fundamental procedures that change digital images to improve their quality, extract valuable information, or get them ready for future analysis are known as basic image processing techniques. There are numerous methods for processing images, including gamma correction, picture segmentation, image restoration, etc. Gamma correction is used to control the overall brightness of images. It is also used with photos that are found to be either bleached out or too dark. The following are some fundamental methods for image processing:
Image Grayscale Conversion: Converting an image to grayscale involves averaging or applying weighted combinations to the color channels of the original color image. Images in grayscale minimize computing complexity and streamline processing.
Histogram Equalization: Histogram equalization involves rearranging the intensity levels in an image's histogram to improve contrast. Dark and light areas may become easier to identify as a result.
Image filtration: Apply filters (like Gaussian or median) to minimize noise and blur the image (smoothing).
Sharpening: Use filters like the Laplacian or high-pass filters to enhance edges and minute details.
Image Thresholding: By adjusting a threshold value, a grayscale image can be transformed into a binary image. Pixels are assigned a color depending on whether they are above or below the threshold.
Edge Detection: Edge detection methods, such as the Sobel, Canny, or Prewitt edge detectors, are used to find edges and boundaries inside a picture. Edges frequently represent important characteristics in an image. Use morphological procedures to change the appearance and organization of objects in an image. Examples of these operations include dilatation and erosion. These are frequently employed for activities like object identification and noise reduction.
Image Rotation and Scaling: Rotate or resize an image to the appropriate angle. Using this, photos can be resized or aligned.
Image cropping: Cut off any unneeded areas of an image to concentrate on a certain area of interest. Apply filters or other methods to an image to reduce noise.

Image Compression: Use techniques like JPEG or PNG compression to lower the file size of photographs while maintaining an acceptable level of quality.

These fundamental image processing methods provide the foundation for increasingly difficult image analysis and computer vision jobs.

6.2 CNN Models

Convolutional neural networks (CNNs) have excelled at several image-improving tasks. The goal of image enhancement is to raise the standard of an image by making it more aesthetically pleasing, easier to understand, or more suitable for a given application. Because CNNs are skilled at learning intricate patterns and characteristics from huge datasets, they can be used for image-enhancing applications.

The following are some typical picture-enhancing jobs that utilize CNNs:
Image denoising: A crucial aspect of image enhancement is eliminating noise from images. CNNs can be trained to recognize the features of noise and reduce it effectively while keeping crucial visual details. This has been accomplished using a variety of designs, including U-Net, Deep Residual Networks, and even straightforward autoencoders.
Image deblurring: CNNs can be used to improve blurry photographs. The network gains the ability to restore minute features lost to blur and enhance the image's overall sharpness. CNNs can be used to remedy both defocus and motion blur.
Image super-resolution: Super-resolution tries to enlarge and improve the spatial resolution of an image. CNNs excel at this task in particular. Models like ESRGAN and SRCNN have been utilized for super-resolution tasks.
Image Contrast Enhancement: Increasing contrast can improve an image's details and visual attractiveness. CNNs may be used to manipulate contrast by learning to change pixel intensities.

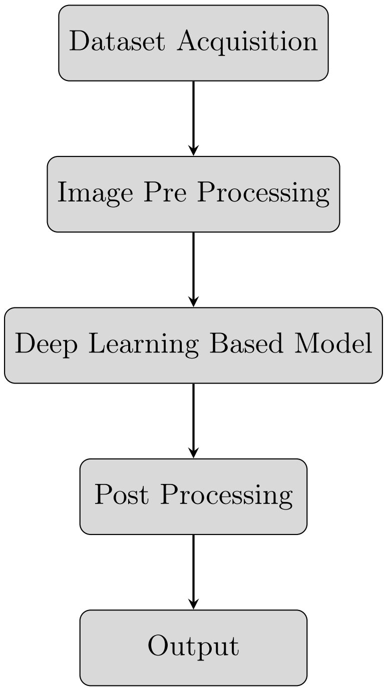
Using CNNs, one may adapt the creative style of one image to another, creating aesthetically pleasing and artistic images, even if this is not exactly a task related to image improvement. The effectiveness of CNNs in image enhancement tasks can also be increased using transfer learning and generative adversarial networks (GANs).

7 Proposed Approach

7.1 Approach

Start by gathering underwater photos. Then, pre-process the images by cleaning up the images, fixing colors, and aligning them. Then, enhance the image quality using the Deep Learning Model to make the pictures look better. Then, Fine-tune the enhanced photos if needed (post-processing). Finally, the output will be clearer and more colorful underwater images for science, research, or other uses.

7.2 Flow Chart



8 Expected Contributions

8.1 Improved Underwater Imaging

The underwater image quality will improve as a result of this research. For marine biologists, underwater explorers, and businesses like robotics and inspections, this is significant since it improves their ability to see and comprehend what is occurring below the surface.

8.2 User-Friendly Algorithm

The goal of this research is to create a user-friendly deep-learning method that will make underwater image enhancement easier. Users of all backgrounds will be able to easily enhance the quality of their underwater visuals thanks to this breakthrough.

8.3 Commercial Opportunities

This endeavor will benefit underwater photography. For companies that use underwater imagery, this may completely alter the playing field. Consider how great-looking underwater images can be created by tourism and entertainment businesses so that more people will be attracted to their offerings.
Overall, This underwater image enhancement project will improve underwater image quality. This project will also help to improve the deep learning models and computer vision techniques for underwater image improvement, so it will also advance the field of computer science engineering.

9 Timeline

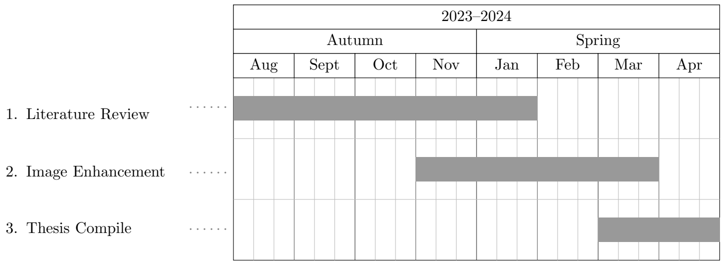


Figure 2: Road Map

10 Conclusion

Enhancing underwater images is difficult for a variety of reasons. The caliber of underwater photos can now be improved thanks to considerable advancements made in recent years and various ways.

There are two varieties of underwater image enhancement. The other is based on deep learning techniques, whereas the first is based on traditional image-processing methods. Deep learning-based algorithms are a potent new tool for underwater image enhancement. Traditional image-processing techniques include color correction, contrast enhancement, and noise reduction. For underwater image improvement, some difficulties must be overcome. The fact that current techniques were created for certain underwater settings is one of the difficulties. As a result, not all underwater photos can be captured effectively using a single technique. Another difficulty is that deep learning-based approaches need a lot of training data, which is very hard to gather.

References

[1] Chongyi Li, Chunle Guo, Wenqi Ren, Runmin Cong, Junhui Hou, Sam Kwong, and Dacheng Tao. An underwater image enhancement benchmark dataset and beyond. *IEEE Transactions on Image Processing*, 29:4376–4389, 2019.

[2] Peng Liu, Guoyu Wang, Hao Qi, Chufeng Zhang, Haiyong Zheng, and Zhibin Yu. Underwater image enhancement with a deep residual framework. *IEEE Access*, 7:94614–94629, 2019.

[3] Jingchun Zhou, Dehuan Zhang, and Weishi Zhang. Underwater image enhancement method via multi-feature prior fusion. *Applied Intelligence*, 52(14):16435–16457, 2022.

[4] Saeed Anwar, Chongyi Li, and Fatih Porikli. Deep underwater image enhancement. *arXiv preprint arXiv:1807.03528*, 2018.

[5] Smitha Raveendran, Mukesh D Patil, and Gajanan K Birajdar. Underwater image enhancement: a comprehensive review, recent trends, challenges and applications. *Artificial Intelligence Review*, 54:5413–5467, 2021.

[6] Md Jahidul Islam, Youya Xia, and Junaed Sattar. Fast underwater image enhancement for improved visual perception. *IEEE Robotics and Automation Letters*, 5(2):3227–3234, 2020.

[7] Yang Wang, Jing Zhang, Yang Cao, and Zengfu Wang. A deep cnn method for underwater image enhancement. In *2017 IEEE international conference on image processing (ICIP)*, pages 1382–1386. IEEE, 2017.

[8] Weidong Zhang, Peixian Zhuang, Hai-Han Sun, Guohou Li, Sam Kwong, and Chongyi Li. Underwater image enhancement via minimal color loss and locally adaptive contrast enhancement. *IEEE Transactions on Image Processing*, 31:3997–4010, 2022.

[9] Peixian Zhuang, Jiamin Wu, Fatih Porikli, and Chongyi Li. Underwater image enhancement with hyper-laplacian reflectance priors. *IEEE Transactions on Image Processing*, 31:5442–5455, 2022.

[10] Qiuping Jiang, Yuese Gu, Chongyi Li, Runmin Cong, and Feng Shao. Underwater image enhancement quality evaluation: Benchmark dataset and objective metric. *IEEE Transactions on Circuits and Systems for Video Technology*, 32(9):5959–5974, 2022.

[11] Jingchun Zhou, Lei Pang, Dehuan Zhang, and Weishi Zhang. Underwater image enhancement method via multi-interval subhistogram perspective equalization. *IEEE Journal of Oceanic Engineering*, 2023.

[12] Chongyi Li, Saeed Anwar, Junhui Hou, Runmin Cong, Chunle Guo, and Wenqi Ren. Underwater image enhancement via medium transmission-guided multi-color space embedding. *IEEE Transactions on Image Processing*, 30:4985–5000, 2021.

[13] Risheng Liu, Zhiying Jiang, Shuzhou Yang, and Xin Fan. Twin adversarial contrastive learning for underwater image enhancement and beyond. *IEEE Transactions on Image Processing*, 31:4922–4936, 2022.

[14] Yecai Guo, Hanyu Li, and Peixian Zhuang. Underwater image enhancement using a multiscale dense generative adversarial network. *IEEE Journal of Oceanic Engineering*, 45(3):862–870, 2019.

[15] Zhiying Jiang, Zhuoxiao Li, Shuzhou Yang, Xin Fan, and Risheng Liu. Target oriented perceptual adversarial fusion network for underwater image enhancement. *IEEE Transactions on Circuits and Systems for Video Technology*, 32(10):6584–6598, 2022.

[16] Xueyang Fu and Xiangyong Cao. Underwater image enhancement with global–local networks and compressed-histogram equalization. *Signal Processing: Image Communication*, 86:115892, 2020.

[17] Praful Hambarde, Subrahmanyam Murala, and Abhinav Dhall. Uw-gan: Single-image depth estimation and image enhancement for underwater images. *IEEE Transactions on Instrumentation and Measurement*, 70:1–12, 2021.

[18] Hao-Hsiang Yang, Kuan-Chih Huang, and Wei-Ting Chen. Laffnet: A lightweight adaptive feature fusion network for underwater image enhancement. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, pages 685–692. IEEE, 2021.

[19] Long Chen, Zheheng Jiang, Lei Tong, Zhihua Liu, Aite Zhao, Qianni Zhang, Junyu Dong, and Huiyu Zhou. Perceptual underwater image enhancement with deep learning and physical priors. *IEEE Transactions on Circuits and Systems for Video Technology*, 31(8):3078–3092, 2020.

[20] Jingchun Zhou, Boshen Li, Dehuan Zhang, Jieyu Yuan, Weishi Zhang, Zhanchuan Cai, and Jinyu Shi. Ugif-net: An efficient fully guided information flow network for underwater image enhancement. *IEEE Transactions on Geoscience and Remote Sensing*, 2023.

[21] Xuelei Chen, Pin Zhang, Lingwei Quan, Chao Yi, and Cunyue Lu. Underwater image enhancement based on deep learning and image formation model. *arXiv preprint arXiv:2101.00991*, 2021.

[22] Guojia Hou, Xin Zhao, Zhenkuan Pan, Huan Yang, Lu Tan, and Jingming Li. Benchmarking underwater image enhancement and restoration, and beyond. *IEEE Access*, 8:122078–122091, 2020.

[23] Linfeng Bai, Weidong Zhang, Xipeng Pan, and Chenping Zhao. Underwater image enhancement based on global and local equalization of histogram and dual-image multi-scale fusion. *IEEE Access*, 8:128973–128990, 2020.

[24] G Ramkumar, M Ayyadurai, C Senthilkumar, et al. An effectual underwater image enhancement using deep learning algorithm. In *2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)*, pages 1507–1511. IEEE, 2021.

[25] Yan Wang, Wei Song, Giancarlo Fortino, Li-Zhe Qi, Wenqiang Zhang, and Antonio Liotta. An experimental-based review of image enhancement and image restoration methods for underwater imaging. *IEEE access*, 7:140233–140251, 2019.

[26] Haifeng Yu, Xinbin Li, Qian Lou, Chengbo Lei, and Zhixin Liu. Underwater image enhancement based on dcp and depth transmission map. *Multimedia Tools and Applications*, 79:20373–20390, 2020.

[27] Peixian Zhuang and Xinghao Ding. Underwater image enhancement using an edge-preserving filtering retinex algorithm. *Multimedia Tools and Applications*, 79:17257–17277, 2020.

[28] Shima Ramesh Maniyath, K Vijayakumar, Laxman Singh, Sudhir Kumar Sharma, and Tunde Olabiyisi. Learning-based approach to underwater image dehazing using cyclegan. *Arabian Journal of Geosciences*, 14(18):1908, 2021.