(Online) ISSN 2712-0554
Original Research

Heritage and Sustainable Development
Vol. 7, No. 2, 2022, pp.1017-1030
https://doi.org/10.37868/hsd.v7i2.1596

Underwater image enhancement using multiple processing techniques based on DCP, CLAHE, CNNs, and U-Net

Ameen A. Noor[1*], Nur Intan Raihana Ruhaiyem[2]
[1] Department of Computer Science, Mustansiriyah University, Baghdad, Iraq
[2] School of Computer Science, Universiti Sains Malaysia, Penang, Malaysia

* Corresponding Author Email: a.ameen63@uomustansiriyah.edu.iq

Received Jun. 26, 2025
Revised Aug. 28, 2025
Accepted Sep. 5, 2025
Online Oct. 1, 2025

Abstract

In the last decade, interest in the underwater world has increased due to the abundance of resources and abundant species of aquatic organisms and their reliance on them as a source of food or energy. It was necessary to prepare the necessary conditions to make what is underwater visible naturally, which is difficult to achieve due to the loss of color in the blue and red channels, in addition to darkness, fog, refraction, and dispersion. All of these things require us to do our best to make what is underwater easy to control and monitor. For this reason, work was done to develop a fusion algorithm for many techniques, starting with removing fog, improving luminance, reducing noise and preserving edges, then obtaining fine details, then multi-level analysis to enhance lighting, then building the trained model to extract image features and improve them for vision, highlighting final details and improving sharpness, then performing the accurate evaluation process using quality measurement standards between the original and final images, Which led to obtaining good results for the proposed method compared to modern algorithms in terms of results with the standard quality criteria used (PSNR, SSIM, RMSE, VIF).

Keywords: Underwater world, Underwater visible naturally, Improving luminance, Enhancing lighting, Extracting image features, Improving sharpness

1. Introduction

We can say that the underwater world is a very large world, containing many aquatic organisms such as fish, microorganisms, worms, and algae, along with coral, numerous pipelines for transporting and extracting oil, and a wealth of resources in the oceans. Regulating this domain presents a significant challenge for the global community, encompassing scientists and researchers specializing in underwater imagery. They encounter numerous obstacles, including insufficient clarity and subpar quality resulting from light refraction, dispersion, and diffusion, as well as the presence of microorganisms in the water and the variations between deep and shallow regions, all of which adversely affect image quality and precision [1].

When reviewing recent research, it was found that various techniques were used to process the image and solve problems related to improving it and making it of high quality. Through research, it was found that there are three mechanisms used for processing, the first of which depends on physical processing (traditional) to treat problems of light scattering, refraction, blurring, and noise reduction, which, in turn, is not sufficient for complete processing. The second category encompasses techniques and algorithms pertaining to artificial intelligence, leading to the creation of various algorithms. These include those that aid in selecting, identifying, and evaluating alternatives to determine optimal values. Additionally, learning algorithms, such as the CNN algorithm and its advancements, are utilized to improve image contrast and sharpness [2]. The third category integrates the preceding two types, involving processing and contemporary techniques [3-4]. This study summarizes sophisticated techniques for enhancing underwater photos.

1. Proposing an algorithm that integrates classical methods, such as filters for noise reduction while maintaining image structure, with advanced techniques, including artificial intelligence algorithms utilizing Convolutional Neural Networks (CNN) and U-Net, to extract and analyze significant features.

2. Train the model from its inception on the chosen dataset (LSUI) until it surpasses numerous others by yielding results deemed satisfactory after assessment with established quality metrics such as PSNR and SSIM [5].

2. Research method

After extensive study and review of the modern mechanisms used in the field of enhancing underwater images and the ratios used in them, the following figure shows us the ratios and their use.

Figure 1. The percentage of techniques used to enhance underwater images

This section will showcase research on picture enhancement that utilizes prior approaches and generative adversarial networks.

Liu et al [6] introduced a light field (LF) image reduction technique based on view synthesis via a Generative Adversarial Network (GAN). The technique transmits solely random sub-images (SAIs) and reconstructs the remainder on the decoding end. Disparity estimation and unsampled SAI estimation using a GAN model improve the reconstruction quality and enhance generative precision. A loss function based on perceptual quality guarantees the retention of texture. Experimental findings indicate that the technology surpasses alternative compression strategies in both conventional measures and perceptual quality.

Luo et al [7] introduced an algorithm for underwater picture restoration that prioritizes improvements in contrast, white balance, and histochrome identification. This approach leads to a reduction in color shifts by refining RGB channel value models, achieving an average PSNR of 12 dB. Awan et al. [8] presented a project that utilized the UWNET network, employing the Discrete Wavelet Transform (DWT) and Inverse Discrete Wavelet Transform (IDWT) to restore images through feature extraction, correct color discrepancies by compensating for the attenuation of blue and red color channels, and enhancing color and contrast through color adaptation transformation. The results demonstrated improvements in peak signal-to-noise ratio (PSNR) and root mean square error (RMSE), utilizing EUVP and LSUI datasets.

Baccouch et al. [9] used the ACDC database to test how well U-Net and CNN could separate medical images, specifically cardiac magnetic resonance imaging (MRI). High-precision results were obtained with the U-Net technique, with an average DSC index of 97.9% and an average Hausdorff distance of 5.318 mm. This technique excels in image segmentation thanks to its ability to train quickly and to have no direct connection between its layers, thus achieving results that are close to reality.

Menon et al. [10] relied on the method of combining the two mechanisms, convolutional neural networks (CNN) and generative adversarial networks (GAN), to combine the improvement properties of these two techniques for image processing. Standard quality criteria (SSIM) and (PSNR) were used on AVB-type data to obtain clear quality in fluctuating lighting conditions.

Tang et al. [11] address severely degraded images captured in poorly lit areas or areas with shallow water. Researchers used the neural architecture search (NAS) technique by developing a U-NET model for image enhancement. Additionally, it incorporates a search space that encompasses operators such as transformers, alongside selectable multi-head units.

The research by Benaida et al [12] examines a novel approach to image enhancement by integrating the Convolutional Neural Network (CNN) algorithm with the Single Scale Retanx (SSR) algorithm. A two-input neural network achieves this by using original images and SSR-enhanced images as inputs, combining their outputs with CNN blocks to extract optimal features. We utilized the databases (UIAP, IOVP), and the experiments showed significant image enhancements, surpassing the lighting ratio of alternative methodologies.

The study by Devecioglu et al [13] focused on the restoration of underwater image quality by addressing issues of color distortion, reflection, scattering, and limited visibility. We developed a paradigm that includes two equally functioning networks: the Apprentice Recreator (AR) and the Master Recreator (MR) network. The first enhances the image, while the second assesses its quality. We designated the comprehensive model as Co-Operational Recreator Networks (CoR-NETs). We achieved optimal performance by utilizing the LSUI database.

Li et al. [14] proposed to build a technique (CFD-Net) based on differential feature decomposition (Contrastive Feature Disentanglement) and use a multi-stream mechanism (Multistream Decomposition Architecture) consisting of three decoders to separate the features reflecting the degradation and important details to enhance images and reduce noise and work on integrating differential learning (Hierarchical Contrastive Learning) to enhance features for the quality of work.

Yang et al. [15] proposed a method to improve depth images in two stages of processing. The first stage is done on the color space (RGB) based on the characteristics of the weakness of color gradations in water by using the color correction technique to eliminate color deviation due to water absorption. The second stage uses the Golden Jackal algorithm to improve the image contrast by improving the intensity of the gray color and the distribution of the histogram. After studying the previous research, some weaknesses were revealed, as shown in Table 1.

Table 1. Weaknesses of the aforementioned studies

Method	**Issues**	**Weaknesses**
Light Field(LF)Image Compression, GAN, Performance Evaluation (Liu et al.)	Reliance on Random SAI Selection, Complexity of GANs, Perceptual Quality	Trade-off between quality and efficiency, Generalization Capability, Sensitivity to Random SAI Selection:
White Balance Correction, Histochrome Identification (Luo et al.)	Low Value in PSNR, Color Distortion Complexity, Limited Scope of Evaluation	Limited Quality Metrics, Computational Complexity

Method	Issues	Weaknesses
UWNET, DWT, IDWT, Color Compensation (Awan et al.)	Complexity of DWT/IDWT, Color Loss Compensation	Computational Overhead, Sensitivity to Dataset Bias, Visual Artifacts
U-Net, CNN, ACDC (Baccouch et al.)	Difficulty of training, longer training time	Need for tagged data, a balance between accuracy and speed of execution
CNN, GAN, AVB Dataset (Menon et al.)	Training difficulty, implementation time	Increased computational complexity
NAS, U-Net, Transformers(Tang et al)	Loss of detail, NAS complexity	Lack of data, reliance on search space
SSR, Two-Input Neural Network, CNN (Benaida et al.)	Loss of detail, neural network complexity	Processing time, need to adjust the model design
CoR-NETs, AR, MR (Devecioglu et al.)	Color distortion, scattering, and reflection Model complexity	Reliance on specific quality standards, challenges in image processing

3. The proposed approach

To address the complexities of processing underwater photographs and the related obstacles, a mechanism was presented that combines modern processing techniques with conventional image modification methods to attain optimal visual quality, as follows:

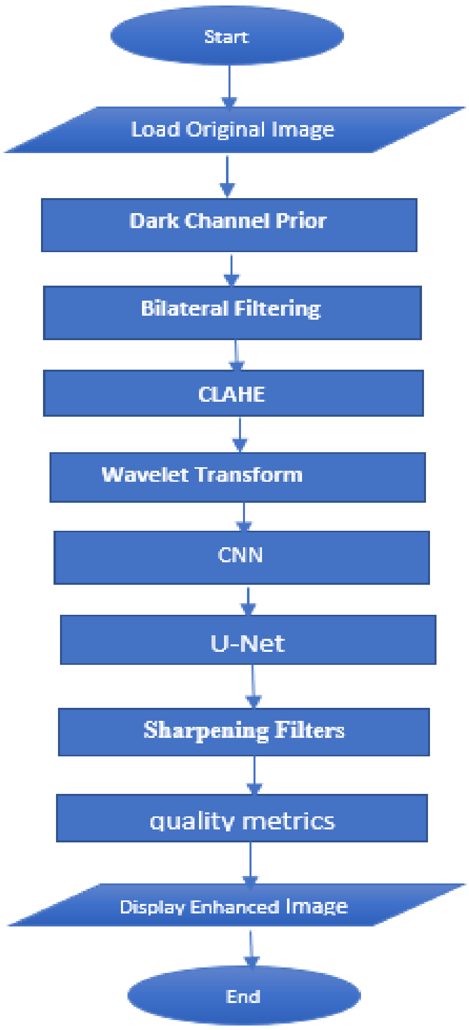

Figure 2. Flow chart of the system

3.1. Dark channel prior

The diminished contrast of the underwater image resembles the indistinct image produced on foggy days. Consequently, we can employ underwater picture enhancement through haze removal to achieve the minimal value of the image's dark channel, as demonstrated in the following equation [16]:

$$I_p^{dark}(i) = min(min\, I_p^c(z)) \quad (1)$$

Which, $I^{dark}{}_p$(i) denotes the ith dark pixel corresponding to the sixth superpixel, and $_c$ is the channel of r,g,b, and z∈ M_i . The transmission image is estimated as follows by using the dark image based on super-pixel DCP.

3.2. Bilateral filtering

A bilateral filter is defined as a weighted average of adjacent pixels. Equation 2 [17] illustrates how smoothing utilizes the difference in value between neighboring pixels to maintain edges.

$$BF[I]p = \frac{1}{Wp}\sum_{q\epsilon s} G\sigma\varsigma(\| p - q \|)G\sigma r(|Ip - Iq|)Iq \quad (2)$$

3.3. Contrast-limited adaptive histogram equalization (CLAHE)

To enhance brightness and contrast following the fog removal phase, the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique was employed, facilitating the acquisition of a superior underwater image [18].

3.4. Wavelet transform

Wavelet analysis plays a crucial role in partitioning image data into two cohesive categories: details and approximations, which represent directional information. The low-frequency (approximation) and high-frequency (detail) parts of the image are separated by using high-pass and low-pass filters to make this happen [8].

3.5. Convolutional neural networks (CNNS)

This method possesses an intuitive and uncomplicated structure, facilitating simplicity and rapid implementation in comparison to other deep learning algorithms. It possesses the capability to extract characteristics from underwater photographs, as well as to process various types of images to enhance their quality effectively [4, 12].

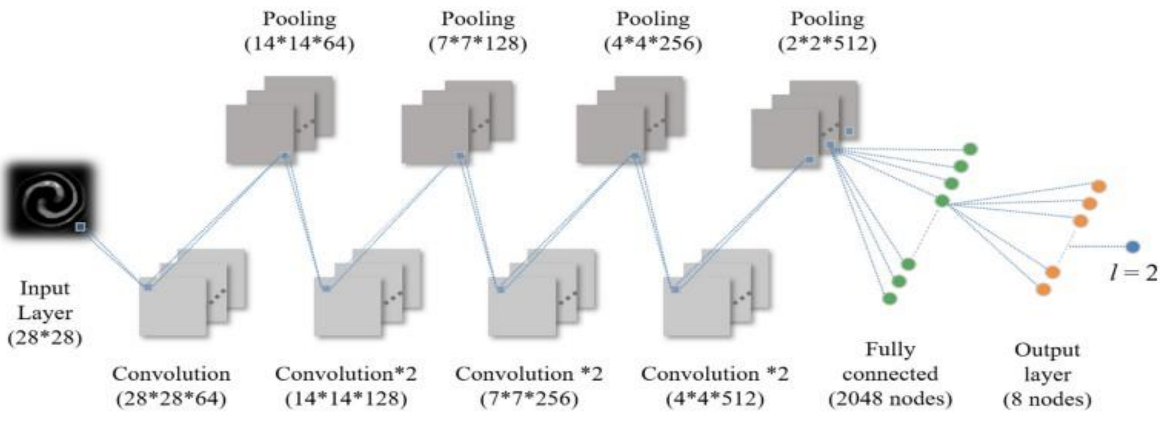

Figure 3. The diagram of the CNN model architecture [4]

3.6. U-Net model

The U-Net model is employed to retain characteristics from being diminished during convolution and aggregation. In all three processes, features are first reduced, encrypted, and slowed down. The sample is then increased by moving features from the encryption layer to the decryption layer, and so on, with each encryption layer corresponding to its own decryption layer. This model offers advantages such as training capability, speed, and accuracy when utilizing data sets [19].

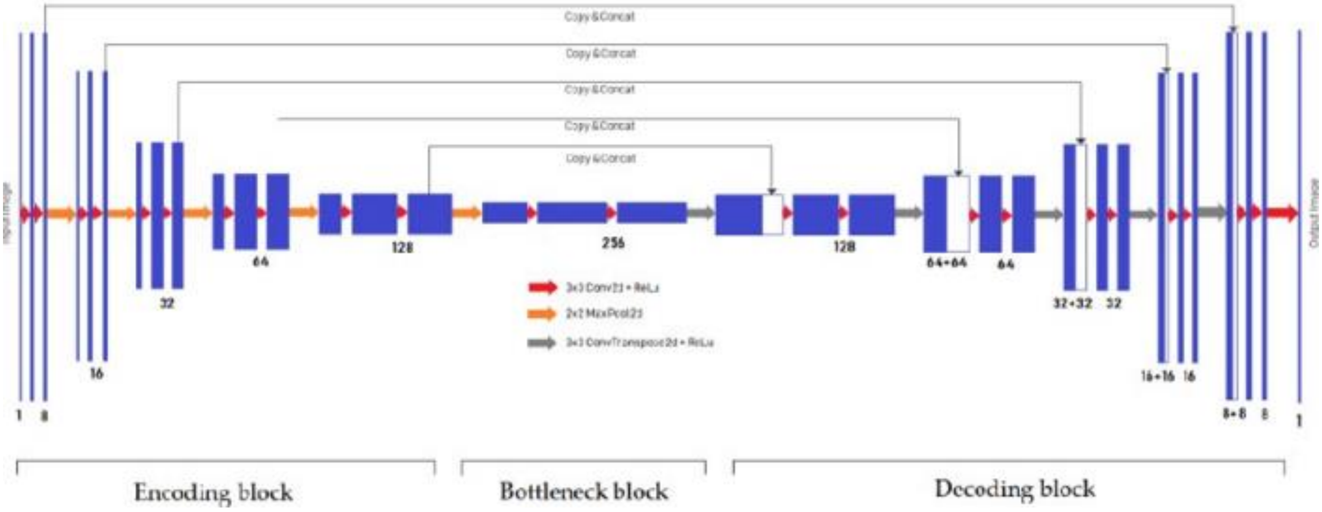

Figure 4. Architecture of U-Net segmentation model [18]

3.7. Sharpening filters

This type of filter helps to smooth noise without distorting details, in addition to enhancing edges without amplifying noise [20].

$$\int_{S} = f + \lambda f_{\mathrm{h}} \tag{3}$$

$$H_s\,(m,n) = {}^{\delta}(m,n) + \lambda h_h\,(m,n) \tag{4}$$

4. Results and discussion

This chapter will present a comprehensive account of all experiments performed on the data set, in relation to its surroundings, along with an analysis of the results collected.

4.1. LSUI dataset

The underwater dataset (LSUI) was utilized to train the networks on the original reference images, which contain noise and a total of 890 images, categorized into three types: the training set, comprising 700 images; the validation set, consisting of 100 images; and the test set, containing 90 images.

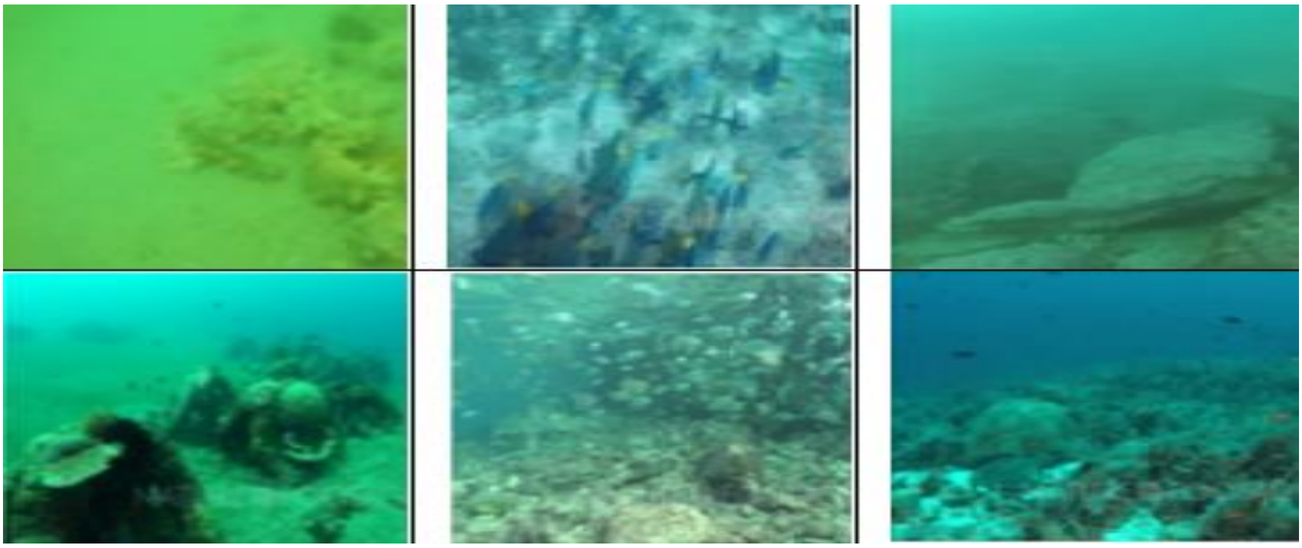

Figure 5. A set of original images to be tested on

4.2. Experimental environment

A diverse array of sophisticated approaches, including CNN, U-NET, and CLAHE, was employed to provide precise and beneficial outcomes. These were amalgamated with conventional processing techniques employed before and during deployment, such as Dark Channel before, Bilateral Filtering, Wavelet Transform, and Sharpening Filter. The execution took place in the following environment. Environment: CPU: Core i7 13620H, Storage: 512 GB SSD NVMe, RAM: 16 GB DDR5 5200 MHz, GPU: NVIDIA RTX 4050 6 GB.

4.3. Evaluation

Many experiments were conducted using many algorithms, techniques, and efforts; this mechanism was reached as a complement to expressing the results of the objective evaluation.

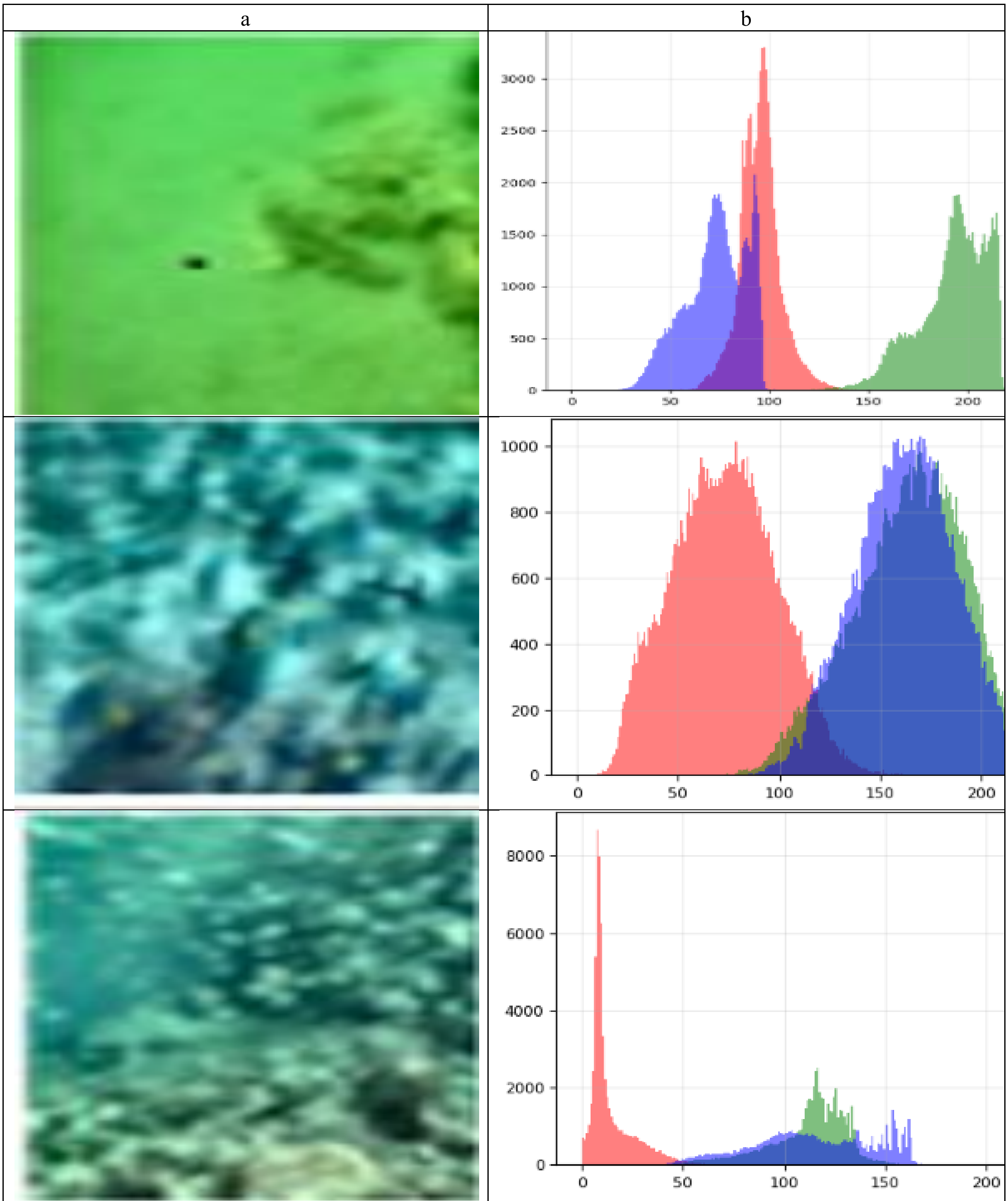

Figure 6. Shows the original images (a) with the pixel density (b) for each

a	b
Figure 6. continues…	

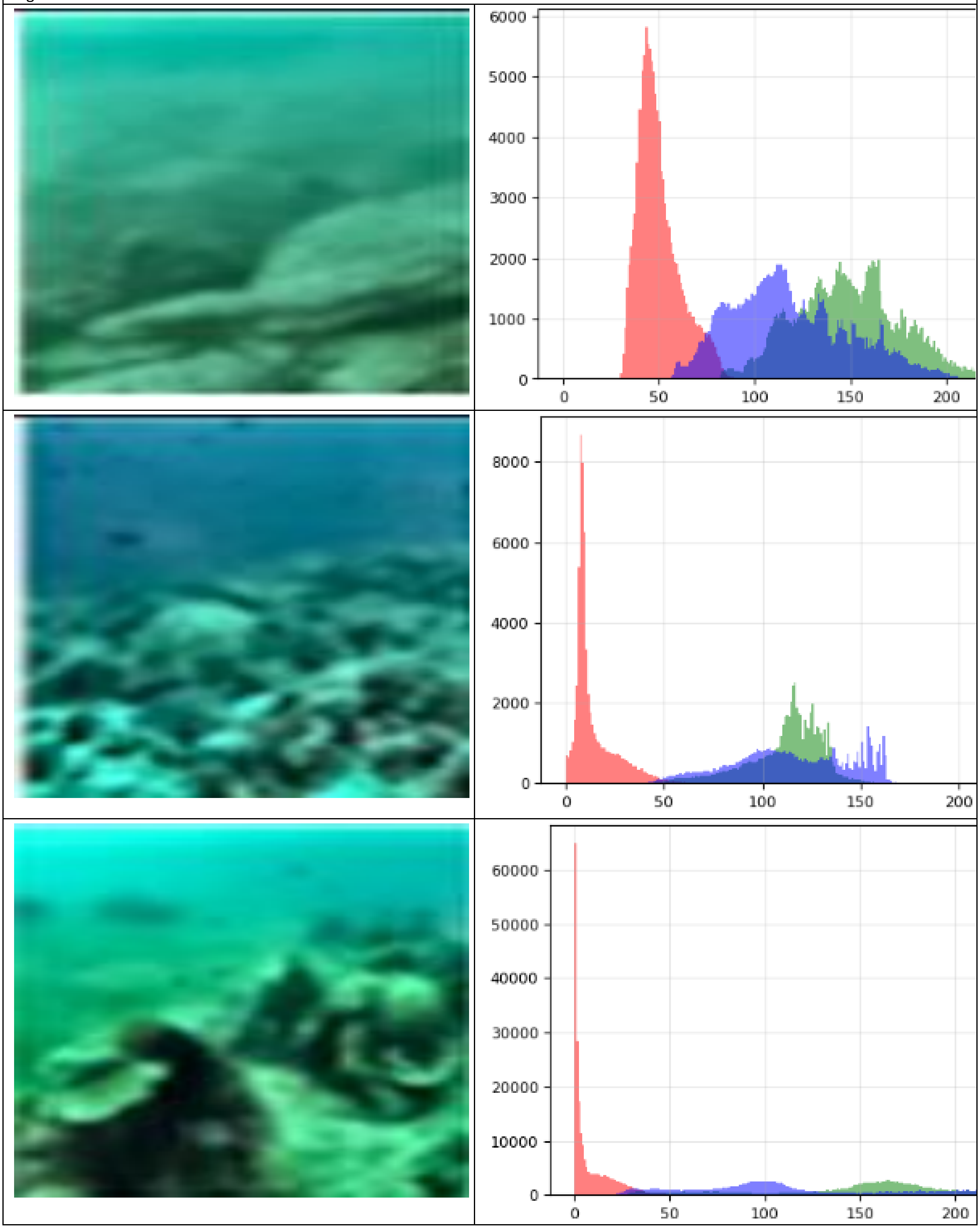

Figure 6. Shows the original images (a) with the pixel density (b)for each

4.3.1. Subjective evaluation

This paper is conducted by submitting the original images from the database (LSUI) to a variety of algorithms and mechanisms. The process involves a series of steps that begin with the darkening step to get rid of fog, then move on to the smoothing, clarification, wave transformation, CNN algorithm, U-Net, and sharpening filter steps. These steps help make the noise smoother and the enhancement of edges, resulting in a clear and accurate colored image. The following table illustrates the final result.

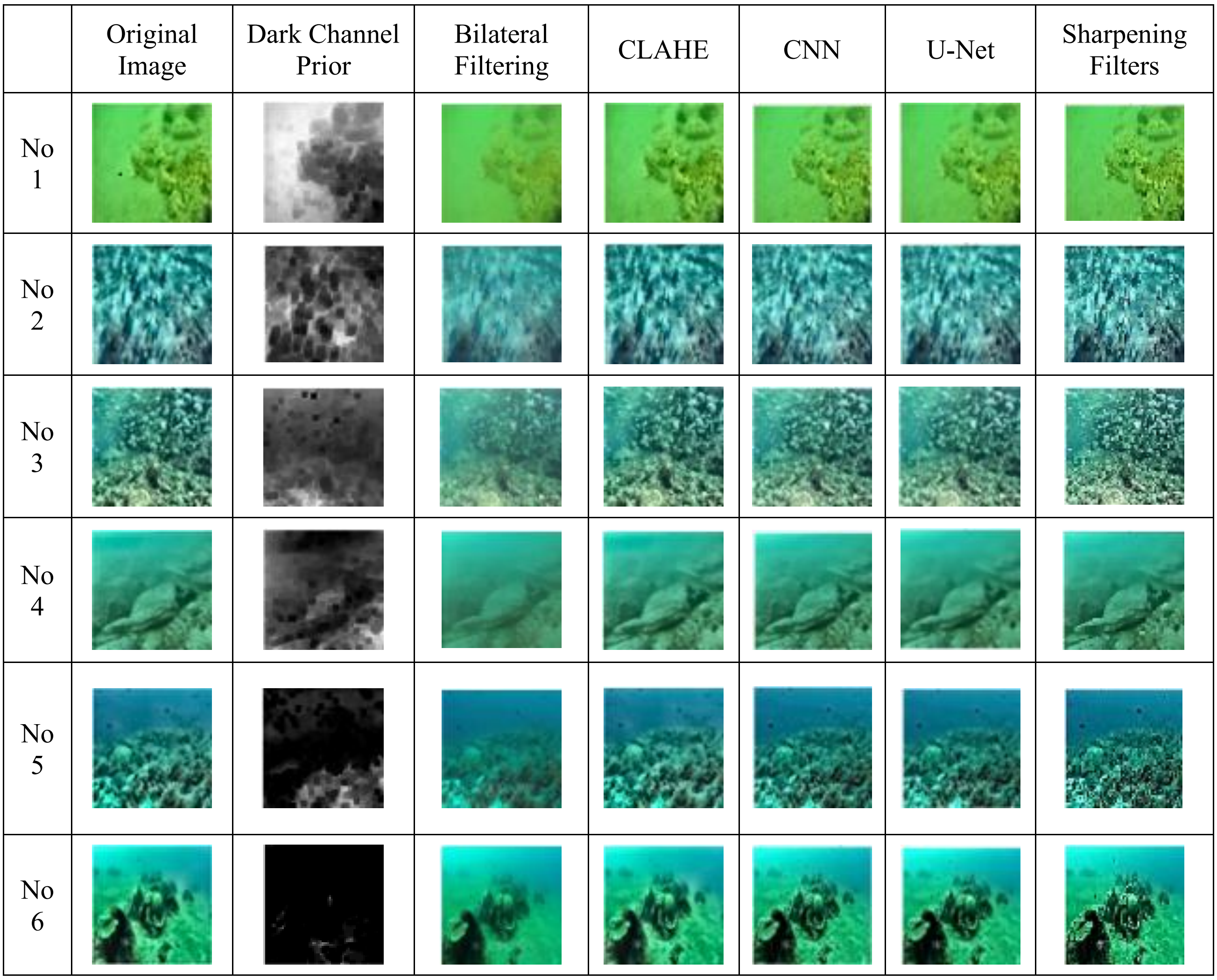

Figure 7. Analysis of images

Figure 7 represeints analysis of images starting from the original image through the detailed sequence: previous dark channel, then bilateral filtering, then CLAHE, then CNN algorithm, then U-Net, then Sharpening Filters. It has proven its worth in this sequential order to obtain high accuracy.

4.3.2. Objective evaluation

In order to guarantee that the image has reached a higher quality, the standard criteria for the final image quality in comparison to the original image were used. PSNR, SSIM, MSE, RMSE, and VIF were among the options, as illustrated in the following equations that incorporate the vocabulary of the aforementioned criteria:

$$PSNR = 10.log_{10}\left[\frac{M * N * 225^2}{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(P(i.j) - C(i,j))^2}\right] \qquad (5)$$

Where M is the digital image's width and N is its height. The plain image's pixel value is P (I, j), and the encoded image's pixel value is C (I, j) [21].

$$SSIM(x,y) = \frac{(2u_x u_y + c_1)(2\sigma_{xy} + c_2)}{(u_x^2 + u_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (6)$$

Where μ_x The mean of x in the pixel sample, μ_y The mean y of the pixel sample, σ_x^2 the variance of x,

σ_y^2 the variance of y, σ_{xy} the covariance of x and y, $c_1 = (k_1 L)^2$, $C_2 = (k_2 L)^2$

Two variables are used to stabilize the division with a weak denominator. L represents the dynamic range of the pixel values. $k_1 = 0.01\ and\ k_2 = 0.03\ by\ default$ [22].

Mean Squared Error (MSE) between two images, such as g(n,m) and $\hat{g}(n, m)$is defined as

$$MSE = \frac{1}{MN}\sum_{N=0}^{M} \cdot \sum_{m=1}^{N}[\hat{g}(n,m) - g(n,m)]^{\ 2} \qquad (7)$$

Let us suppose that $\theta^{\wedge}$ bean estimator with respect to a given estimated parameter θ, the Root Mean Square Error is actually the square root of the Mean Square Error as [20].

$$RMSE(\theta^{\wedge}) = \sqrt{MSE(\theta^{\wedge})} \qquad (8)$$

The mutual information (C, E) is calculated to estimate the quantity of reference image information, while I (C, F) is computed to calculate distorted image information. N represents the number of local blocks in the image band. The definition of the final VIF index is based on the previously mentioned model [23].

$$VIF = \frac{\sum_{j=subbands} I(c^{N_j}:F^{N_j}|s^{N_j})}{\sum_{j=subbands} I(c^{N_j}:E^{N_j}|s^{N_j})} \qquad (19)$$

The following table shows us some standard quality criteria between the original image and the final image.

Table 2. Standard quality criteria

No.	PSNR	MSE	SSIM	RMSE	VIF
1	30.28	219.41	0.9050	14.81	0.4812
2	28.05	752.10	0.6740	27.53	0.3479
3	28.17	1087.69	0.6638	32.98	0.3325
4	30.39	208.72	0.8223	14.45	0.4891
5	28.30	671.52	0.7551	25.91	0.3870
6	28.94	446.59	0.7749	21.13	0.4221

The results presented in the preceding table were obtained by employing a standard set of quality criteria. We compared the results obtained in the following table to a set of previous studies that utilized deep learning in image processing.

Table 3. Comparison of underwater image enhancement techniques with recent studies

Study	Techniques Used	PSNR (dB)	SSIM	Main advantages	Limitations
Luo et al. [7]	GAN +Disparity Estimation	14.9593	0.6027	Significant improvement in color and contrast, Integrated color balance	Red channel processing may be limited, +Relying on contrast enhancement alone
Awan et al. [8]	Contrast Enhancement+ White Balance Adjustment	19.89	0.55	DWT and IDWT+ Efficient color correction	Needs real-time performance improvement+ Performance in perceptual indicators is not consistent compared to other methods.
Menon et al. [10]	CNN, GAN, AVB Dataset	20.67	**0.9558**	Innovative hybrid approach + Improved visual and metric quality	Limited effect in dark areas+ Complexity of training+ Limitations in detail restoration

Study	Techniques Used	PSNR (dB)	SSIM	Main advantages	Limitations
Tang et al. [11]	NAS, U-Net, Transformers	26.13	0.8608	Automatic neural network design+ Expanded search space+ Adaptability	Computational complexity+ Data dependence
Benaida et al. [12]	SSR, Two-Input Neural Network, CNN	23.50	0.92	Effective integration of traditional and modern techniques+ Outstanding performance	Model complexity+ Limitations on generalization:+ Further improvement is required
Devecioglu et al [13]	CoR-NETs, AR, MR	24.54	-	Superior performance+ Innovative design	Limited reliance on real data+ Generalizability+ Reliance on numerical criteria
Sun et al [24]	Conditional Diffusion Model +Semi-Supervised Learning+Ghost-UNet	25.71	0.89	Lightweight model for faster +Exceptional underwater image enhancement	Performance depends on high-quality training data + Further validation needed in real-world underwater scenarios
Proposed Research (2025)	DCP +Bilateral Filtering +CLAHE +Wavelet Transform +CNN+U-NET +Sharpening Filters	**30.28**	0.9050	Logical sequential processing +Combination of multiple techniques+ Deep learning integration (CNN & U-Net)+	Computational complexity+ Possible detail loss

5. Conclusions

This sequential algorithm applies a series of image processing and enhancement techniques in a specific order. It begins with the Dark Channel Prior (DCP) filter, which removes fog and improves image clarity. Next, bilateral filtering is used for noise reduction while preserving edges. To further enhance contrast and extract fine details, the CLAHE (Contrast Limited Adaptive Histogram Equalization) technique is applied, making the image more uniform and visually balanced.

Following this, the Wavelet Transform is used for multi-level analysis to enhance luminance and highlight important features. The processed image is then passed through a CNN-based pre-trained model to improve overall image quality by learning relevant features. After feature extraction, the U-Net architecture—with its encoder-decoder structure—is used to refine details, enhance visual features, and maintain realistic colors.

Finally, sharpening filters are applied to enhance edge definition and overall image sharpness.

As shown in Table 2, implementing this algorithm in Python and evaluating it with various image quality metrics demonstrated its effectiveness. The model achieved PSNR values above 30, RMSE values below 32, and SSIM values close to 1, outperforming other deep learning models. Future work will focus on improving the model by increasing the number of training cycles, adding more layers, and expanding the dataset, while also considering computational efficiency and processing time.

Acknowledgements

The authors would like to express their gratitude to Mustansiriyah University, Baghdad, Iraq (https://uomustansiriyah.edu.iq/), and to USM University for their assistance with this research work.

Author contribution

Amin and Intan contributed to the study conception and design. Data collection and interpretation were performed by Amin and Intan. The first draft of the manuscript was written by Amin. All authors read and approved the final manuscript.

References

[1] P. Tang, L. Li, Y. Xue, M. Lv, Z. Jia, and H. Ma, "Real-World Underwater Image Enhancement Based on Attention U-Net," *Journal of Marine Science and Engineering*, vol. 11, no. 3, p. 662, 2023. [Online]. Available: https://www.doi.org/10.3390/jmse11030662

[2] Z. H. Ali, A. A. Noor, and M. A. Jassim, "VIKOR Algorithm Based on Cuckoo Search for Multi-document Text Summarization," in *Proc. Int. Conf. Applied Computing to Support Industry: Innovation and Technology*, Cham, 2019, pp. 57–67. [Online]. Available: https://www.doi.org/10.1007/978-3-030-30760-6_6

[3] S. Zaidi, P. Singh, and P. Guha, "Designing a U-Net Architecture for Underwater Image Enhancement," in *2024 National Conference on Communications (NCC)*, 2024, pp. 1–6. [Online]. Available: https://www.doi.org/10.1109/NCC57218.2024.10004101

[4] A. Noor and N. I. Ruhaiyem, "Underwater image processing based on CNN applications: A review," in *Proc. Cognitive Models and Artificial Intelligence Conf.*, 2024, pp. 75–84.

[5] F. H. Abbood, "Color Image Segmentation by EFCM Clustering (using Mahalanobis distance)," *Journal Of AL-Turath University College*, no. 12, 2012.

[6] D. Liu, X. Huang, W. Zhan, L. Ai, X. Zheng, and S. Cheng, "View synthesis-based light field image compression using a generative adversarial network," *Information Sciences*, vol. 545, pp. 118–131, 2021. [Online]. Available: https://www.doi.org/10.1016/j.ins.2020.08.046

[7] W. Luo, S. Duan, and J. Zheng, "Underwater image restoration and enhancement based on a fusion algorithm with color balance, contrast optimization, and histogram stretching," *IEEE Access*, vol. 9, pp. 31792–31804, 2021. [Online]. Available: https://www.doi.org/10.1109/ACCESS.2021.3053303

[8] H. S. A. Awan and M. T. Mahmood, "Underwater Image Restoration through Color Correction and UW-Net," *Electronics*, vol. 13, no. 1, p. 199, 2024. [Online]. Available: https://www.doi.org/10.3390/electronics13010199

[9] W. Baccouch, S. Oueslati, B. Solaiman, and S. Labidi, "A comparative study of CNN and U-Net performance for automatic segmentation of medical images: application to cardiac MRI," *Procedia Computer Science*, vol. 219, pp. 1089–1096, 2023. [Online]. Available: https://www.doi.org/10.1016/j.procs.2023.02.147

[10] A. Menon and R. Aarthi, "A Hybrid Approach for Underwater Image Enhancement using CNN and GAN," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 6, 2023.

[11] Y. Tang, T. Iwaguchi, H. Kawasaki, R. Sagawa, and R. Furukawa, "AutoEnhancer: Transformer on U-Net architecture search for underwater image enhancement," in *Proc. Asian Conf. Computer Vision*, 2022, pp. 1403–1420.

[12] O. Benaida, A. Loukil, and A. A. Pacha, "New underwater image enhancement technique using single scale retinex and CNN fusion," *South Florida Journal of Development*, vol. 5, no. 9, pp. e4429, 2024.

[13] O. C. Devecioglu, S. Kiranyaz, T. Ince, and M. Gabbouj, "Blind Underwater Image Restoration using Co-Operational Regressor Networks," *arXiv preprint arXiv:2412.03995*, 2024. [Online]. Available: https://arxiv.org/abs/2412.03995

[14] F. Li, W. Li, J. Zheng, L. Wang, and Y. Xi, "Contrastive Feature Disentanglement via Physical Priors for Underwater Image Enhancement," *Remote Sensing*, vol. 17, no. 5, p. 759, 2025. [Online]. Available: https://www.doi.org/10.3390/rs17050759

[15] J. Yang and J. Wang, "Underwater image enhancement method based on golden jackal optimization," *Optics Communications*, vol. 552, p. 130064, 2024. [Online]. Available: https://www.doi.org/10.1016/j.optcom.2023.130064

[16] H. Chen, H. He, and X. Feng, "Underwater Image Enhancement Method Based On Color Correction and Dark Channel Prior," in *Journal of Physics: Conference Series*, vol. 2066, no. 1, p. 012050, Nov. 2021. [Online]. Available: https://www.doi.org/10.1088/1742-6596/2066/1/012050

[17] S. Paris, P. Kornprobst, J. Tumblin, and F. Durand, "Bilateral filtering: Theory and applications," *Foundations and Trends® in Computer Graphics and Vision*, vol. 4, no. 1, pp. 1–73, 2009. [Online]. Available: https://www.doi.org/10.1561/0600000009

[18] M. Zheng and W. Luo, "Underwater image enhancement using improved CNN based defogging," *Electronics*, vol. 11, no. 1, p. 150, 2022. [Online]. Available: https://www.doi.org/10.3390/electronics11010150

[19] T. Shynu, S. S. Rajest, and R. Regin, "A Convolutional Neural Network with a U-Net for Brain Tumor Segmentation and Classification," *Central Asian Journal of Medical and Natural Science*, vol. 4, no. 6, pp. 1326–1343, 2023.

[20] Y. Wang, "Image filtering: noise removal, sharpening, deblurring," in *EE 3414 Multimedia Communication Systems*, Polytechnic University, 2006.

[21] O. C. Devecioglu, S. Kiranyaz, T. Ince, and M. Gabbouj, "Blind Underwater Image Restoration," 2024.

[22] U. Sara, M. Akter, and M. S. Uddin, "Image quality assessment through FSIM, SSIM, MSE and PSNR—a comparative study," *Journal of Computer and Communications*, vol. 7, no. 3, pp. 8–18, 2019. [Online]. Available: https://www.doi.org/10.4236/jcc.2019.73002

[23] H. Yan, P. Zhao, Z. Du, Y. Xu, and P. Liu, "Frequency division denoising algorithm based on VIF adaptive 2D-VMD ultrasound image," *PLOS One*, vol. 16, no. 3, p. e0248146, 2021. [Online]. Available: https://www.doi.org/10.1371/journal.pone.0248146

[24] L. Sun, W. Li, and Y. Xu, "Ghost-UNet: Lightweight model for underwater image enhancement," *Engineering Applications of Artificial Intelligence*, vol. 133, p. 108585, 2024. [Online]. Available: https://www.doi.org/10.1016/j.engappai.2024.108585