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Hybrid Approach for Enhancing Underwater Image Based on Deep Learning Techniques

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ABSTRACT

Underwater image enhancement addresses issues like reduced visibility, color loss, and haziness caused by light absorption and scattering in aquatic environments, impacting marine biology and underwater robotics. To make underwater pictures more accurate again, they have to be fixed using special, high-tech methods because they are exposed to harsh conditions like color dispersion, blurriness, the spread of impurities, light refraction, and the presence of shallow areas. All of these factors have prompted the discovery of mechanisms capable of enhancing this type of image. Machine learning and deep learning approaches have emerged in addition to the traditional methods of improving photos. The techniques used contributed greatly to improving this type of images and making them appear more clearly. By reviewing previous studies, we are able to combine classical and modern mechanisms, starting with the huge database available (LSUI) to use it as a database to go through the rest of the stages, such as super-resolution and using filters to remove noise, passing through the color correction stage for its superior quality. The next step is to use the deep learning algorithm. This process results in high-resolution and high-quality results for images after displaying them on standard quality standards and criteria.

1. INTRODUCTION

As a result of the challenges facing underwater images and their importance, it has become a very important research field due to the exposure of light to many harsh conditions such as dispersion, absorption, poor color accuracy and their disappearance at depth levels, in addition to blurriness, all of which affect the green, blue, and even red colors. These problems arise because sunlight and light level weakens underwater due to absorption at different levels depending on the strength of the color, so that red is absorbed easily and quickly first, followed by green, and finally blue, which is the main reason for giving the oceans and seas their blue color. Therefore, low contrast is a general problem in the process of taking pictures underwater, which makes it difficult to monitor and obtain the necessary data for biology, archaeology, and underwater robotics [1, 2].

To solve these problems, many mechanisms have been developed that aim to improve this type of images, and many traditional methods have been used, such as determining contrast and improving image contrast, in addition to the histogram equation, which leads to adjusting and improving the image [3]. More modern techniques such as Retinex-based color correction have helped restore natural colors by simulating human color vision, which addresses color loss under water [4]. Some algorithms have also been adapted, such as the (DCP) Dark channel Prior mechanism, which is used to remove the haze that causes light scattering, to eliminate blur and improve the image [5].

Deep learning algorithms such as generative adversarial networks (GANs) and convolutional neural networks (CNNs) have recently been shown to be extremely effective at enhancing underwater images [6, 7]. These algorithms are capable of managing a huge amount of data used to learn the characteristics and patterns of underwater images, as they have the ability to adjust the contrast, colors, and automatic sharpness of images [7]. The combination of standard methods such as super-resolution with deep learning mechanisms has led to great success in obtaining better image quality and its applications underwater [8]. These processes are integrated into the application and are innovative and lead to improving images and overcoming the consequences and basic challenges due to the environment and its difficulty underwater. This is also contributed to by the quality of the cameras and devices used to take the images [9].

The work at hand is done through the use of a set of classical and modern techniques such as the haze removal filter (DCP), the Retinex technology used for color correction, and the super-resolution technology in addition to the (CNN) algorithm. This method of combining these mechanisms has proven the ability to improve images and their clarity through vision and through image quality standards (PSNR, SSIM).

2. RELATED WORK

Figure 1 illustrates the distribution of various techniques used in underwater image enhancement. This distribution was designed based on extensive research on previous studies in underwater image processing. The figure highlights a strong emphasis on techniques such as Dark Channel Prior (DCP), Convolutional Neural Networks (CNNs), Retinex, Super-Resolution, Generative Adversarial Networks (GANs), and noise reduction.

DCP occupies the largest portion, as shown in the figure, underscoring its crucial role in noise reduction for underwater images. Additionally, CNNs and Retinex each account for 20% of the distribution, emphasizing their significance in feature extraction and color correction. Other methods, such as GANs and Super-Resolution, are also employed to enhance underwater image quality.

To address the numerous challenges associated with underwater imaging, researchers have implemented various techniques, including applying different filters for image processing and utilizing deep learning algorithms. In this section, we will explore some of these methods that have been adopted by previous researchers to improve underwater image clarity, particularly in cases where image quality is poor.

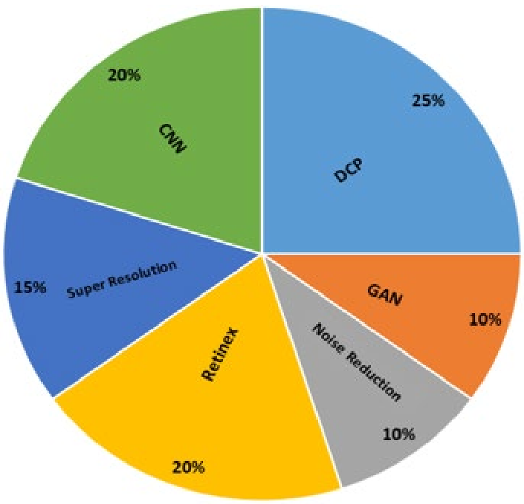

Figure 1. Techniques for underwater image enhancement: DCP, CNN, Retinex, and GANs

Color correction technology is an important step in improving underwater photos [4]. The preponderance of blue and green tones caused by light absorption underwater necessitates procedures to restore the images original hues. Modern color restoration approaches, including algorithms like white balance adjustment and deep learning-based methods, have proven useful in restoring realistic colors in underwater scenes by correcting light absorption and scattering effects.

The UW-NET model [10] is designed to capture underwater images using Discrete Wavelet Transform (DWT) and Inverse Discrete Wavelet Transform (IDWT) for client identification. The process begins with color correction for the red and blue channels, followed by color-adaptive adjustment with contrast enhancement. The study demonstrates that the model excels in key evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR) and Root Mean Square Error (RMSE). Additionally, the model is further optimized to achieve real-time performance and effectively address various underwater imaging challenges.

The Global-Local Image Perceptual Score (GLIPS) is an innovative approach for evaluating the quality of images generated by intelligent algorithms [11]. This method aligns more closely with human perception compared to conventional evaluation metrics. GLIPS assesses local similarity using Transformer-based attention mechanisms and global similarity through Maximum Mean Discrepancy (MMD). To enhance the interpretability of results, the study also presents the Interpolative Binning Scale (IBS).

A hybrid approach is poposed [12] for underwater image enhancement that does not rely on channel assumptions. Instead, it utilizes adaptive color correction and Retinex transition map estimation to improve image quality. By avoiding uneven channel stretching and ensuring global color balance, the method enhances underwater images effectively. Experimental results indicate that the proposed approach outperforms both reference-based and non-reference-based evaluation methods.

Underwater images enhancement using the R-UNIQUE model integrates neural network-based Retinex deconvolution and adaptive color correction with the HUT network to enhance contrast and reduce blur [13]. By adapting to various marine environments, the model aims to overcome the limitations of traditional techniques. Despite its success, the study suggests further exploration of self-supervised training methods and improvements in real-time performance for more efficient underwater imaging.

A novel method [14] has been proposed to tackle motion blur and noise that arise from low-frame-rate video capture. This approach capitalizes on Deep Internal Learning to achieve true Temporal Super-Resolution (TSR), thereby enabling the reconstruction of high-quality footage. Without relying on external datasets or pre-training, the method enhances temporal resolution by extracting training examples from spatiotemporal regions within the same video, alternating between spatial and temporal dimensions. The model outperforms conventional techniques trained on external datasets, particularly in dynamic and complex scenarios.

Lightweight and efficient networks, FEAN, is designed to enhance underwater super-resolution (SR) images using Frequency-Enhanced Attention Modules (FEAMs) [15]. To address color distortion and low contrast, the network extracts features through multiple frequency pathways. By combining high- and low-frequency data, the model effectively improves details and color adjustment, achieving superior performance with lower computational complexity than conventional methods. While the model demonstrates strong results, particularly on the USR-248 dataset, challenges remain due to the diversity of aquatic environments and the limited availability of training data.

Multitasking scheduling approaches aimed at enhancing system throughput while reducing context switching costs [16]. The proposed strategy is a hybrid of Round Robin and Shortest Remaining Time First (SRTF), combining the advantages of both scheduling algorithms. In this approach, the quantum time update is determined based on the slice bit and the remaining time of the packet, optimizing task execution efficiency.

The method that integrates a Generative Adversarial Network (GAN) with a Convolutional Neural Network (CNN) enhanced image quality and address optical distortions caused by light in underwater environments [17]. By leveraging the strengths of both architectures, the GAN generator produces additional synthesized images, which in turn expand the training dataset, improving the model’s ability to restore and enhance underwater images.

Table 1 summarizes the main issues and limitations of existing underwater image enhancement methods, including uneven color correction, high computational complexity, limited real-time performance, insufficient data generalization ability, and poor adaptability to dynamic scenes.

Table 1. Limitations and challenges in existing underwater image enhancement methods

Method	Issues	Weaknesses
Modern Color Correction Techniques [4]	Mostly on conventional correction methods, such as white balance, which can have trouble handling complicated situations	Performance is impacted uneven color distributions or extremely fluctuating illumination
UW-Net Model [10]	Focuses on red and blue channel repairs separately, which could cause an imbalance in the whole.	Improving real-time performance is necessary to satisfy the demands of real-world applications
GLIPS Metric [11]	The emphasis is on human perception compatibility, however the computationally intensive computations increase execution time	Adapting to different aquatic habitats or irregular visual patterns might be difficult
Adaptive Correction Method [12]	Depends on global color balancing, which may overlook small local nuances	Limited flexibility in dealing with settings with uneven lighting distribution
R-UNIQUE Model [13]	Uses dense neural networks, resulting in slow operating performance.	Real-time performance has limitations, self-supervised training approaches are required to improve efficiency
True Temporal Super-Resolution [14]	Relies entirely on data from the same video, rendering it inappropriate for handling highly different datasets.	In dynamic scenarios with rapid motion, performance may degrade
FEAN Network [15]	A lack of different data and difficulty with varying aquatic settings make it difficult to generalize.	In unstudied context, performance is limited, and training data is in short supply
GAN+ CNN [17]	Model complexity / Determining a delicate balance of generator and discriminator	Poor dark area processing and detail recovery

3. THE PROPOSED APPROACH

After extensive study and review of previous research, the results it has reached, the mechanisms and techniques that are used by them, we decide to work by collecting some mechanisms that have proven their worth in presenting the work in the best possible way, as shown in Figure 2.

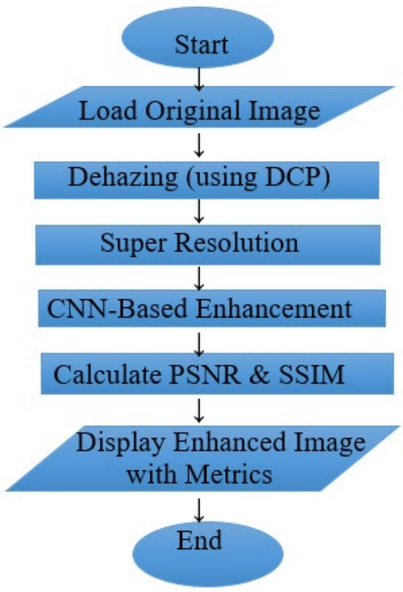

Figure 2. Flow chart of the system

3.1 LSUI dataset

The LSUI underwater image dataset consists of 4279 natural images exposed to various types of noise obtained from the Internet and collected using popular search engines such as Google, Bing, and Yahoo. They are RGB images in this dataset, where 3500 images are used for training, 500 images are used for validation, and the remaining 279 are for testing purpose.

3.2 Dehazing filters

Particles and particles suspended under water cause haze, so we need to use dehazing filters to help make the image appear clearer and to be easy to use with the rest of the mechanisms used. For example, we used Dark Channel Prior (DCP), which is useful for dealing with underwater images [18].

$$I(x) = J(x)\tau(x) + A(1 - \tau(x)) \quad (1)$$

The coefficients used in this equation are $I(x)$ representing the original image, x representing the pixels, and the image restored by removing the haze is $J(x)$. The value of the luminance intensity is A, and the coefficient representing the transmittance is $t(x)$. The unknowns A and $t(x)$, which are the two main keys to obtaining a good image $J(x)$, are estimated in DCP algorithms.

3.3 Color correction

A color correction and detail enhancement filter are implemented to resolve the issues Low contrast and color variation in underwater images. It uses an improved non-local noise removal algorithm to remove noise from the underwater image as well as to process the image color, The method depends on uniform lighting and gray world assumptions, as in the following equation in space $I\alpha\beta$ and with color coordinatesRGB $f_j(m,n)$ in space $LMS(L_i(m,n))$ as follows: [19].

$$L_i(m,n) = D_{i,j} * f_j(m,n) \quad (2)$$

where the $D_{i,j}$ transformation matrix obtained as product of the transformation matrix $D_{i,j} = T\chi YZ\ i,j.Tlms\ i,j$ and according to Eq. (2) and computing the logarithm

$$\log L_i^*(m,n) = log \frac{L_j(m,n)}{\overline{L_i}} \quad (3)$$

By applying the logarithm quotient rule and multiplying by the $T_{pca,i\,j}$ matrix, we obtain:

$$T_{pca,i\,j}\, log\, L_i^*(m,n) = T_{pca,i\,j}\, log\, L_i\,(m,n) - T_{pca,i\,j}\,\log \overline{L_\iota} \quad (4)$$

Thus we get the required expression for the equation:

$$l_{l\alpha\beta,i}^*(m,n) = l_{l\alpha\beta,i}(m,n) - \bar{l}_{l\alpha\beta,i} \quad (5)$$

3.4 Super resolution

The process aims to convert low-resolution images into high-resolution images by enlarging and enhancing the image using a convolutional network (convolution neural network) by entering the low-resolution image as a bicubic interpolation layer to the original image size, as shown in Figure 3. the data using the convolutional layer and adding details to improve image quality and reduce noise to improve performance metrics [20].

3.5 Convolution neural network

Convolution the fundamental structural elements of CNN architecture are pooling and fully connected layers. The pooling layer and several convolution layers are repeated., in addition to the possibility of repeating the number of cycles and changing the number of filters to the number that achieves the purpose of using them, and one or more fully connected layers are added. Forward propagation is the process of transforming the input data into output using these layers, Figure 4 illustrates the architecture of the CNN algorithm and it also depends on the training cases that the programmer specifies to infer an increase in the accuracy of the images used [20].

By using images from different environments, whether shallow or deep, we used layers with a number of (9-15) layers for the purpose of improvement and revealing fine details, and the filters were from 128 to 256 to 512 to explore more complex features, and after cycles that reached 1000 cycles and a number of (4279) images, As for time, the obstacles were that the more the number of cycles, the number of filters, or the number of images increased, we would face the need for a longer time for implementation, especially at the beginning of implementation. However, in other and natural repetition cases, the time is normal for the algorithm used. To give an example of this, we take cycle number 797 out of 1000 cycles. The model took about 253 milliseconds for each step. At the end of this cycle, the value of the loss on the training data was equal to 0.00078154, and the value of the loss function on the validation data was 0.0017. This indicates that the model was working well and achieving the desired accuracy.

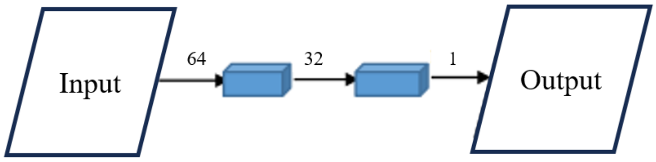

Figure 3. Super resolution architecture

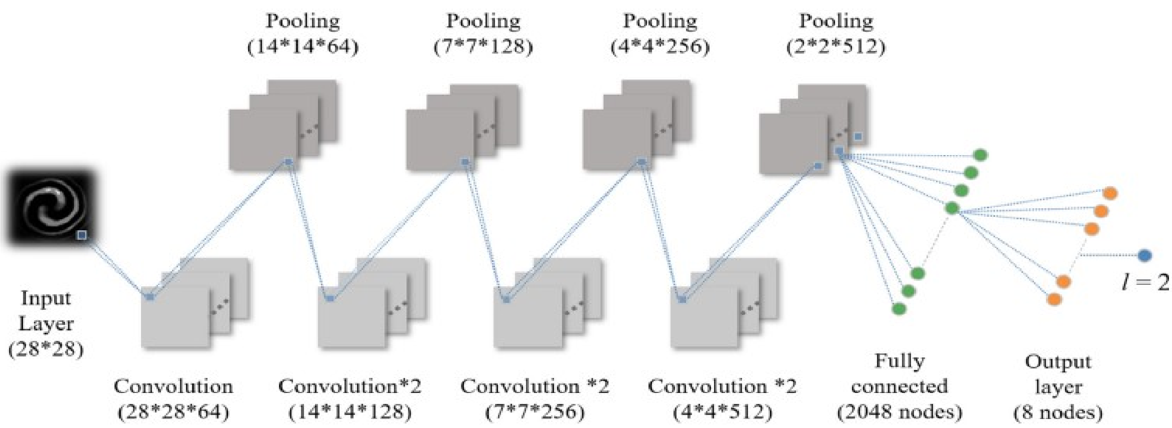

Figure 4. Overview of CNN [21]

The algorithm below illustrates the suggested approach for the underwater image enhancement system. The suggested approach uses a combination of a number of techniques that contribute to improving the work and showing it in the best condition, which consists of five parts: the first and second stages are pre-processing, the third stage is based on super-resolution, the fourth stage uses the CNN algorithm, and the fifth is the quality metrics stage. The image is improved in the first section with a haze filter as a pre-processing step using Dark Gen Prior. In the second part, the Retinex algorithm is used, while in the third stage, the super-resolution technique is extracted, and the fourth stage is the CNN algorithm in the training, testing, and validation stages. Two hidden layers, the input layer, and the output layer make up the CNN algorithm's four layers. To improve contrast, the median filter eliminates noise and the histogram equation from the photos. The basic concept behind the proposed system is to obtain high-quality images and then go through the final stage, which is calculating the commonly used quality metrics, which are BSNR and SSIM, to know the accuracy and quality of the obtained images.

Algorithm 1. Application of mechanisms used for improvement
Input: Input Underwater Images from (LSUI) dataset Output: Image Processor Result 1. Apply Dark Channel Prior for Dehazing 2. Apply Retinex Algorithm for Color Correction 3. Using Super Resolution Technique 4. Apply CNN from Deep Learning Enhancement 5. Calculate Image Quality metrics (PSNR, SSIM)

4. RESULTS AND ANALYSIS

From the LSUI database (Figure 5), the following models are used to enter them into the application phase within the proposed algorithm.

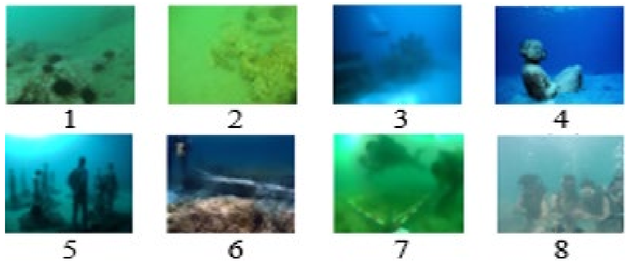

Figure 5. A few instances sampled from the LSUI set; the LSUI images are of size 256 × 256

Quality assessment

Peak signal to noise ratio (PSNR) is among the most often used tests in the imaging field enhancement or processing to obtain the standard quality between the initial picture and the final one. It also indicates the changes in pixel values between them. The equation below explains the formula used

$$PSNR = 10.log_{10}\left[\frac{M * N * 225^2}{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(P(i.j) - C(i,j))^2}\right] \quad (6)$$

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) [22, 23].

SSIM (Structural similarity index)

A method for forecasting the perceived quality of digital photos, as well as other kinds of digital images and videos, is the structural similarity index, or SSIM. It can also be used to gauge how similar two photos are to one another. The following equation represents this fully referenced measure [24].

$$SSIM(x,y) = \frac{(2u_x u_y + c_1)(2\sigma_{xy} + c_2)}{(u\frac{2}{x} + u\frac{2}{y} + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (7)$$

where u_x The mean of x in the pixel sample, u_y. The mean y of the pixel sample, σ_x^2 the variance of x, σ_y^2 the variance of y, $2\sigma_{xy}$ the covariance of x and y,

$$c_1 = (k_1 L)^2 \,, C_2 = (k_2 L)^2 \quad (8)$$

Two variables are used to stabilize the division with a weak denominator. L represents the dynamic range of the pixel values.

$$k_1 = 0.01 \; and \; k_2 = 0.03 \; by \; default$$

According to the algorithm and the corresponding flowchart, the image undergoes testing after passing through several stages using the Python programming language in the Google Colab environment. The process begins with the noise removal stage, followed by the color correction stage. Next, the image proceeds to the accuracy evaluation stage, and finally, the training and testing stage is conducted using the CNN algorithm.

After completing the programming processes and obtaining what is shown in Figure 6, from the processes of transforming the image from one state to another, and through the naked eye, we can differentiate between the images in terms of clarity and accuracy before we carry out the processes of measuring the image quality in the next stage.

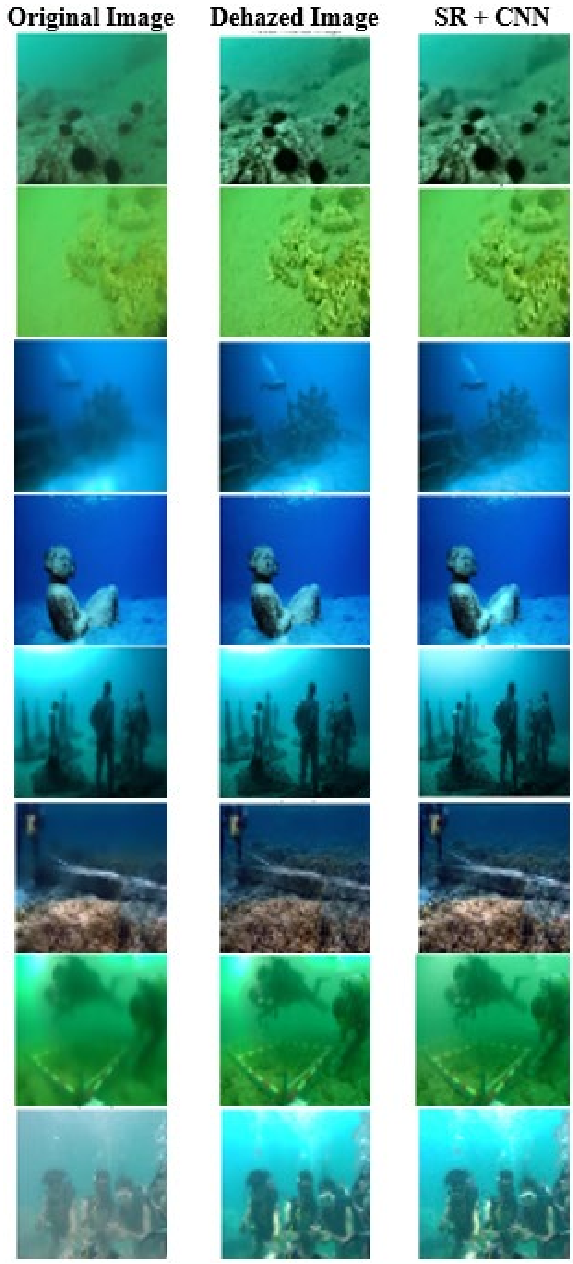

Figure 6. Output result of dehazed image and SRCNN image

Two important criteria are used to measure the quality of the resulting image through the application of the algorithm in two stages after the fog removal stage and the second stage after implementing the super-resolution stage and applying the deep learning algorithm. The results are as follows.

Table 2 shows us the values obtained after the beginning of the next trend between the original image and after implementing the Hyzink technique and the next stage after implementing the Deep Learning techniques, which are considered acceptable and good results according to the final measurements.

Figure 7 shows the graph of the values obtained for the quality criteria (PSNR and SSIM).

Table 2. Performance comparisons on our work Dehazed and SRCNN technique

Frame	Tanique	PSNR	SSIM
1	Dehazed	33.90	0.8560
	SRCNN	33.96	0.9011
2	Dehazed	38.98	0.8819
	SRCNN	39.10	0.9543
3	Dehazed	33.50	0.8519
	SRCNN	33.60	0.9325
4	Dehazed	37.00	0.9051
	SRCNN	37.08	0.9052
5	Dehazed	39.00	0.7997
	SRCNN	39.10	0.8998
6	Dehazed	34.21	0.8725
	SRCNN	34.22	0.7935
7	Dehazed	34.20	0.8167
	SRCNN	34.26	0.9031
8	Dehazed	41.70	0.9105
	SRCNN	41.78	0.9011

After implementing the current study and obtaining the results included in the previous table of international quality standards and comparing them with some previous studies that adopted the subject of improving underwater images, the measurements appeared as in Table 3.

It is clear to us from the previous table and in comparison, with previous studies that the combined technique we used has proven its worth through the values obtained.

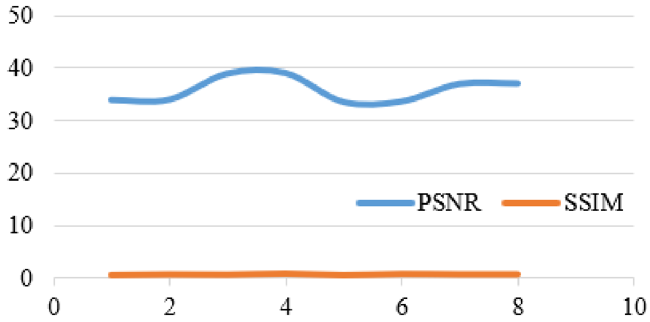

Figure 7. Plot of PSNR-SSIM values

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

Ref.	Techniques Used	PSNR (dB)	SSIM	Advantages	Limitations
[4]	CNN+ Dense fusion	23.026	0.879	•Strong performance across various image types. •Lightweight and fast training network.	• Complex database setup. • Limited capacity for large-scale applications.
[10]	DWT+IDWT+ U-Net+coler correction	19.89	0.55	•Improved color accuracy. •Effective overall performance.	•Perceptual performance requires further fine-tuning.
[11]	Transformers-based attention mechanisms+MMD + IBS +	>32	>0.7	•Enhanced precision and reliable performance. •Improved interpretability.	•High computational complexity. •Requires high-quality training data.
[12]	Retinex Transition Map+ Color Correction+ White Balance	19.31	0.79	•Does not rely on prior assumptions. •Reduces distortions and enhances overall image quality.	•Implementation complexity. •Requires careful adjustment to prevent color correction errors.
[13]	HUT + color correction+Neural network-based Retinex decomposition	26.090	0.914	•Effectively handles blur and color distortion. •Adaptable to various underwater image formats.	•Lacks real-time processing capability. •Limited reference data may restrict training effectiveness.
[14]	TSR +CNN + Recurrence of Space-Time Patches	34.33	0.96	•Eliminates motion aliasing and motion blur. •Utilizes self-supervision and deep internal learning.	•Computationally intensive. •Performance may vary in low-recurrence scenarios.
[15]	FEAN+FEAM + Gaussian Filter+ Convolution Layers	26.188	0.694	•Corrects color distortion effectively. •Efficiently integrates low- and high-frequency data.	•High model complexity. •Potentially large computational cost.
Proposed Research	Dehazing + Color Correction + Super Resolution + CNN	33.60-41.78	0.79-0.91	•Combines multiple methods to achieve superior image quality.	•Slightly higher computational cost, but manageable.

5. CONCLUSIONS

The research aims to provide a mechanism to improve underwater images clearly and accurately using a haze removal filter by applying a pre-dark generation filter, then performing a color correction process using Retinex technology, then going through the super-resolution stage to prepare and improve the image after the correction stage, and then going through the final stage, which is the deep learning algorithm CNN. The results showed, through the use of international standard quality criteria to measure PSNR and SSIM image quality, that the algorithm used has proven its efficiency, and it is possible to develop the work in the future using advanced mechanisms or a combination of them to obtain better results.

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