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Enhanced Underwater Fish Image Processing by Noise Elimination, Saturation Adjustment, and Edge Sharpening Technique

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Abstract

Analyzing underwater images and improving their quality is a difficult task for researchers. Processing underwater images is extremely difficult because of the low contrast, noise, and blurriness brought on by light scattering and absorption. Since the longer wavelengths of sunshine are unable to get deep into the water due to salinity and an abundance of dissolved pollutants, underwater image becomes a crucial research topic, but the photos appear blurry, noisy, and faded. By combining bilateral filtering for decreased noise, saturation improvement for color restoration, and Laplacian sharpening for clarity, this study suggests a novel method for improving underwater image quality. The datasets FishImg and Fish4Knowledge were used to test the approach. With an estimated Peak Signal-to-Noise Ratio (PSNR) of 45.38 dB, Structural Similarity Index (SSIM) of 0.9888, and Mean Squared Error (MSE) of 1.88, the empirical findings show a notable improvement in image quality over current methods. The method improves clarity while maintaining structural integrity, which makes underwater photos better suited for aquatic research, marine object detection, and environmental monitoring. All things considered, the suggested framework offers a workable and efficient way to enhance underwater image quality in actual applications.

Key Words: Underwater Image Analysis, Bilateral Filtering, PSNR, SSIM, MSE.

1 Introduction

Digital image processing is widely used in industrial production, video monitoring, intelligent transportation, and remote sensing due to the quick development of computer vision. It is essential in many areas, spanning daily life and the military [1]. However, faults are frequently caused by unforeseen events while collecting images, particularly in low-light conditions, such as indoors, at night, or in overcast environments. In these conditions, color distortions and turbulence from weak subsurface reflections significantly degrade image quality [2]. As a result of extra procedures, including conversion, storage, and transmission, the quality of these low-light images is further reduced. Low-light conditions, which are characterized as environments with illumination outside the usual level, are present in any photograph captured in insufficient lighting [3].

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Conventional investigations in marine environments depend on divers, who must contend with weather, water quality, and professional skills in addition to the possibility of causing disruptions to marine life and other hazards. Because of human limits, time constraints, and fieldwork expenses, it might be difficult to observe animals in the wild, even though it is necessary for ecological research [4]. A limited field of vision, depth restrictions, and complicated functioning are some of the drawbacks of underwater visualization systems, which employ optical cameras or approaches like polarization, stereo/panoramic, and spectral imaging [5].

Underwater vision is greatly impacted by light absorption and scattering, which are dependent on the intrinsic optical characteristics of water [6]. These phenomena make processing aquatic images extremely difficult since they reduce contrast, introduce blur, and lessen overall visibility, all of which degrade image clarity. Forward scattering blurs picture features, whereas retrograde scattering creates a veil effect that reduces luminance [7]. Additionally, while increasing depth results in wavelength-dependent color loss, synthetic light increases scattering and produces pronounced bright patches. In order for enhanced the clarity of images, augmentation or restoration techniques are required because these inherent disruptions further reduce image quality [8].

Underwater recognizing targets has grown in significance for naval defense and the marine industry as ocean surveillance techniques improve; still, low contrast, visual disturbance, and general image deterioration make reliable detection challenging [9].

With hues vanishing in order of wavelength, red at 3m, orange at 5m, yellow at 10m, and green and purple at further depths, underwater images become darker as depth rises and light levels decrease [10]. Image augmentation methods are necessary for better target detection since underwater fish images tend to suffer from distortion, low contrast, poor resolution, and color variations as a result of technical limitations of the environment [11].

This paper introduces an innovative framework for enhancing underwater images that combines Laplacian sharpening for edge clarity, bilateral filtering for noise reduction, and saturation correction for color restoration in an integrated process. The technique greatly increases PSNR, SSIM, and MSE while maintaining structural features, making images more useful for ecological surveillance, evaluation of behavior, and fish detection. The method is replicable, expandable, and relevant to actual underwater vision systems; it has been tested on publicly accessible datasets. Visual systems are hampered by insufficient saturation and fuzzy images caused by weak shadows, noise, and color distortion in low brightness [12]. Image processing and visual data mining concepts are advanced by image enhancement approaches that increase visibility, robustness, and dependability [13].

2 Literature Reveiw

Double-Stage Gaussian Filter (DSGF) is applied to RGB components, subsequent to contrast-limited adaptive histogram equalization and median filtering; the results are combined using Principal Component Analysis (PCA) and post-processed with color contrast modification. This DSGF and fusion-based method is suggested to improve underwater photographs [14]. An adaptive Look-Up-Table (LUT), an edge preserving filter, and improved color correction are employed in an underwater picture improvement technique to handle diminished visibility and color distortions brought on by suspended dust. The method outperforms current techniques by improving luminance through the use of CLAHE, sharpening, gamma correction, and chrominance adjustments [15]. These techniques mainly rely on global rectification or fusion mechanisms, which can result in over-enhancement or loss of edge sharpness, particularly in areas with little detail.

To reduce distortion and increase the clarity of images, a suggested image enhancement technique combines bilateral filtering with histogram equalization. A PSNR of 0.71 is achieved by enhanced histogram equalization, which improves broad contrast without going overboard, while bilateral filtering performs exceptionally well in complex datasets [16]. This study proposes an approach for enhancing underwater images that combines bilateral filtering, adaptive color enhancement, probabilistic tonal operator, and an altered multi-scale fractional order-based operator. The technique reduces noise, eliminates color cast, improves contrast, sharpens edges and

dark details, and avoids overexposure. Results from experiments show that they perform better or on par with current techniques [17].

Speckle noise impairs the clarity of images in sonar, which can be employed for tracking fish habitats and detecting underwater objects. Bilateral and directed filters are two efficient spatial filtering procedures used in this article to reduce noise. MSE, PSNR, and SSIM are used to evaluate image quality, and the results demonstrate better de-speckling efficiency [18]. Visibility issues arise in low-light underwater photography, particularly at very deep depths. Using regional contrast knowledge, this research suggests a dehazing paradigm that tackles halo antiques, scale consistency, and oversaturation. The Ocean Dark dataset is presented, showing better improvement over current techniques [19].

Despite obstacles like reflecting light and darkness, underwater image processing is essential for marine security. Using Wiener filtering, sharpening, and contrast stretching, this work suggests an improvement strategy that outperforms current methods [20]. Light absorption and dispersion cause blurred and color aberrations in underwater optical images. This study suggests a technique for sharpening images that improves color correction and combustion expulsion while effectively maintaining hue, saturation, and clarity through the use of a corresponding broad variation model, red-blue dark channel prior (RBDCP), and detail hoisting [21]. Because of reflected light and dispersion, underwater optical images have low contrast and chromatic distortion. To achieve higher image quality across a variety of underwater situations, this work suggests a fusion-based enrichment strategy that uses red channel correction, gray world assumption, CLAHE, adaptive unsharp masking, and Gaussian pyramid fusion [22]. The integrated problems of edge blurring, color fading, and texture loss, particularly in poor lighting or deep-water conditions, are not addressed in the majority of works.

The main methods of several underwater image-enhancing techniques, such as filtering, histogram equalization, fusion, and dehazing, are compiled in Table 1. Additionally, it compares the efficacy of each approach using performance indicators like entropy, SSIM, and PSNR.

3 Methodology

Because of how light propagates out and how it weakens at higher levels, pictures of fish taken underwater often have noise, color loss, and blurriness. These problems make it hard to see important details like texture, color, and edges, which makes it hard to identify fish. To fix this, our method includes an extensive enhancement process that is specially designed for images of fish underwater. The dataset is first made better by using a bilateral filter to get rid of noise while keeping important edges. Because lowering noise can blur the edges, sharpening methods are used to make the edges clearer and help fish be seen better. In addition, saturation augmentation is used to revive brightness and enhance identification in low-light circumstances because underwater photography exhibits severe color fading. Fig. 1 illustrates the three-stage preprocessing pipeline: bilateral filtering, saturation boosting, and Laplacian sharpening applied to input fish images to obtain enhanced outputs.

In contrast to earlier approaches like DSGF [14] or adaptive LUT techniques [15], which mainly concentrate on either minimizing noise or color correction, our method sequentially and synergistically blends these processes. It uses tailored saturation adjustment depending on underwater luminescence qualities and, in a unique way, prioritizes boundary conservation during denoising. Results from integration strategy and parameter tuning on two different underwater datasets show that our method is more successful and robust than current methods in terms of PSNR, SSIM, and MSE.

3.1 Datasets Overview

Fish4Knowledge and FishImg, two publicly accessible datasets, were used to assess the described algorithm. The fluctuating and crowded backgrounds, changing foreground objects, motion blur, shadows, camera flicker, and other environmental variables in both datasets pose significant obstacles for fish tracking and detection.

Because of these intricacies, they are ideal for evaluating the algorithm's resilience and efficacy in practical settings.

Table 1: Summary of underwater image enhancement techniques

Ref.	Methodology	Key Features	Metrics	Results
[14]	DSGF and fusion	DSGF, CLAHE, PCA fusion, contrast correction	SSIM, AMBE	Improved contrast and clarity
[15]	Color correction and adaptive LUT	LAB color space correction, CLAHE, LUT, Laplacian filter	Visibility, contrast	Reduced color cast, sharper edges
[16]	Histogram Equalization and bilateral filtering	Contrast enhancement, noise reduction	PSNR (0.71-0.95)	Balanced brightness and noise reduction
[17]	Multi-scale fractional order and bilateral filtering	Edge enhancement, dehazing	Contrast improvement	Clearer underwater details
[18]	Sonar image despeckling	Bilateral and guided filtering	MSE, PSNR, SSIM	Reduced speckle noise
[19]	Low-light image dehazing	Local contrast-based dehazing	Visibility	Enhance low-light visibility
[20]	Wiener filter deblurring	RGB separation, sharpening, contrast stretching	Sharpness, contrast	Improved image clarity
[21]	Image sharpening with RBDCP	Structural decomposition, detail lifting	Hue balance	Enhanced colors and textures
[22]	Color correction and unsharp masking	CLAHE, Gaussian pyramid fusion	Contrast enhancement	Better contrast and generalization

**AMBE = Absolute Mean Brightness Error*

A publicly accessible standard database for classifying varieties of fish in aquatic situations is the Fish4Knowledge dataset. There are 27,370 annotated photos of 23 distinct fish species in it. The collection of images is a carefully selected subset of the broader Fish4Knowledge project, which followed over 1 billion fish and processed over 90,000 hours of underwater footage. It contains photos of various resolutions. The Taiwan Power Company, Taiwan Institute of Oceanography, and Kenting National Park collected the data [23]. With a download size of 2.76 KB, the FishImg dataset is freely accessible on Kaggle and is still the original source. There are precisely 18,000 fish photos in the data set, plus ground-based truth files. The material was divided into 1260 validation dataset photos, 2700 test data images, and 5040 training images after the TensorFlow ground truth files were eliminated. A training set (7290 photos), test set (900 images), and validation set (810 images) were created for PyTorch [24].

3.2 Image Enhancement

A non-linear filter with edge preservation and noise reduction capabilities is called a bilateral filter. This filter preserves the image's integrity by eliminating the noise material without causing excessive blurring. The fundamental idea of driving a bilateral filter is that two pixels are adjacent to one another based on their similar photometric ranges as well as their presence in areas adjacent to them. Using a bilateral filter has some benefits over the identical filter since it preserves the edges by utilizing intensity variances. It determines the local

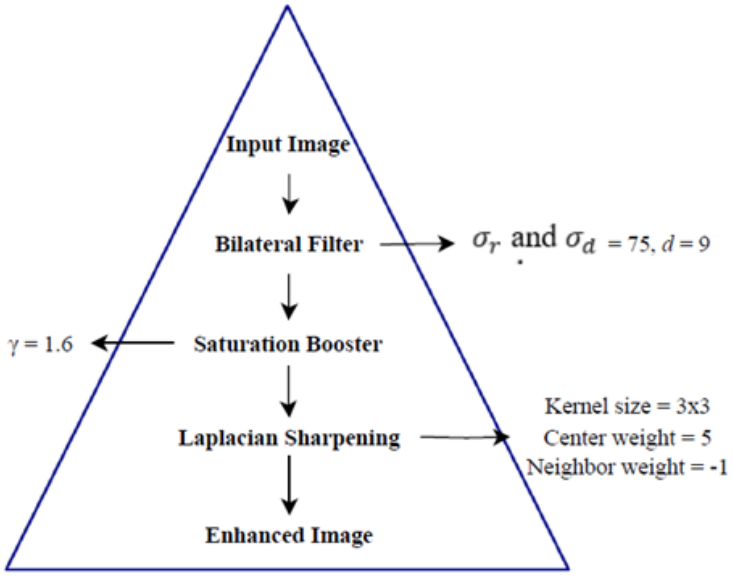

Figure 1: Three-stage pipeline flow of the proposed method

neighborhood's weighted sum of pixels. A weighted average is utilized to replace the pixel value for each nearby pixel. The output of a bilateral filter for an arbitrary pixel x can be formulated using (1) as:

$$I_x(x = p) = \frac{1}{W_p} \sum_{q \in S} g_s(\|p - q\|)\, f_r(I_p - I_q)\, I_q \tag{1}$$

It is a normalized weighted average where p and q are the pixel coordinates, S represents the spatial neighborhood of $I_x(x)$, g_s is a spatial Gaussian that reduces the influence of distant pixels, f_r is a range Gaussian that lessens the impact of pixels q when their spectral amounts deviate from the amplitude of the pixel p, I_p [25]. W_p is the normalization factor, which can be computed using (2) as:

$$W_p = \sum_{q \in S} g_s(\|p - q\|)\, f_r(I_p - I_q) \tag{2}$$

Here, g_s is the spatial kernel for softening coordinate disparities, and f_r is the range kernel for smoothing intensity differences. Let (k, l) be the neighboring pixel coordinate and consider a pixel with coordinates (i, j) that needs to be denoised using the bilateral filter [16]. The weight to be assigned to the pixel (k, l) to denoise a pixel at (i, j) is calculated using (3) as:

$$w(i, j, k, l) = \exp\left(- \frac{(i - k)^2 + (j - l)^2}{2\sigma_d^2} - \frac{\|I(i, j) - I(k, l)\|^2}{2\sigma_r^2} \right) \tag{3}$$

Here σ_r and σ_d are the smoothing parameters, $I(i, j)$ and $I(k, l)$ are the pixel intensities. The two parameters that regulate the bilateral filter's behavior are σ_r and σ_d. The bilateral filter's amplitude region behavior is specified by σ_r, and its spatial domain behavior is specified by σ_d. Important characteristics in the image may become over-smoothed as σ_r and σ_d rise. As a result, setting the control parameters' starting values needs careful consideration. While σ_d values do not change significantly with noise variation, σ_r values do. However, it is challenging to determine σ_r and σ_d for each image to obtain high-quality images. The values of σ_r and σ_d have a major impact on a bilateral filter's performance. Because of the enormous complexity and number of images, it is time-consuming and challenging to manipulate these variables for various groups of images [26].

Bilateral filtering is a strong and efficient image processing technique that significantly reduces distortion in addition to protecting the image's edge data. The algorithm that follows describes the sequential processing steps that improve fish images before they are detected and classified.

1. Employ a bilateral filter with the following settings for the denoised image: diameter = 9, $\sigma_r = 75$, and $\sigma_d = 75$.
2. Convert the denoised image to the HSV color space.
3. Multiply the saturation layer by 1.6 to obtain the HSV-enhanced image.
4. Revert the HSV-enhanced image to the saturated BGR color space.
5. Apply the Laplacian sharpening filter using a kernel.
6. Return the sharpened image as the improved output image.

Because the water medium influences light absorption, underwater photographs usually seem blue or green. Correcting the color discrepancies is a top concern to obtain a high visibility underwater image [27]. Color distortion in underwater photographs is frequently brought on by different lighting conditions and medium attenuation characteristics. The primary cause of color distortion in underwater images is the selective absorption of depth-dependent light spectrums [28].

Color deformation causes color efficiency to deteriorate, turning objects into light and dark hues. Additionally, there is a decrease in average saturation and brightness. Consequently, it is necessary to enhance the image's brightness and saturation. The image is therefore first transformed into the Hue, Saturation, Value (HSV) color model before its brightness and S are adjusted. In this case, the S and V components are broken down and applied using linear contrast stretching, which is provided by (4), in the [1, 99] range. Equation (4) is applied to the histogram stretching given by

$$P_{\text{out}} = (P_{\text{in}} - i_{\text{in}})(\frac{o_{\text{max}} - o_{\text{min}}}{i_{\text{max}} - i_{\text{min}}}) + O_{\text{min}} \tag{4}$$

where P_{in} and P_{out} are the input and output pixels, respectively; and i_{min}, i_{max}, o_{max} and o_{min} are the minimum and maximum intensity level values for the input and output images, respectively.

As a result, the resulting image's standardized maximum range will be [0.01, 0.99]. The image elements S and V control the brightness and saturation of the image. To lessen the image's under- and over-saturation, the lowest and highest stretching values are set to 1 percent from both the bottom and higher boundaries. The most difficult to calculate is H, which establishes whether the H is red, blue, green, yellow, and so forth [29].

Once the image has been deblurred using a bilateral filter and saturation booster, the features are sharpened to further improve it. The finished image is altered in a way that highlights the edges and sharpens the features by applying a sharpening filter, which is intended to make the edges of the image more visible. An image crisper than the original will be produced by this step [20]. One of the differential operators frequently used in image sharpening is the Laplacian operator, which is a second derivative and has the following functional form:

$$\nabla^2 f(x, y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \tag{5}$$

Generally, when applied to image sharpening, (5) can also be defined as a discrete form (6):

$$\nabla^2 f(x, y) = f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) - 4f(x, y) \tag{6}$$

Where $f(x, y)$ denotes the pixel value of one image. The value of the gradient $\nabla f(x, y)$ is related to the grayscale difference of adjacent pixels. $\nabla^2 f(x, y)$ is the Laplacian operator [30].

Enhancing the image's edges to make it more distinct is the aim of the sharpening procedure. This process enhances the image's overall visual impact by fortifying the inside edges and making the details more visible. Fig. 2 illustrates the process of the proposed image enhancement technique, which involves first applying a denoising filter to the images before applying saturation and sharpening to improve them.

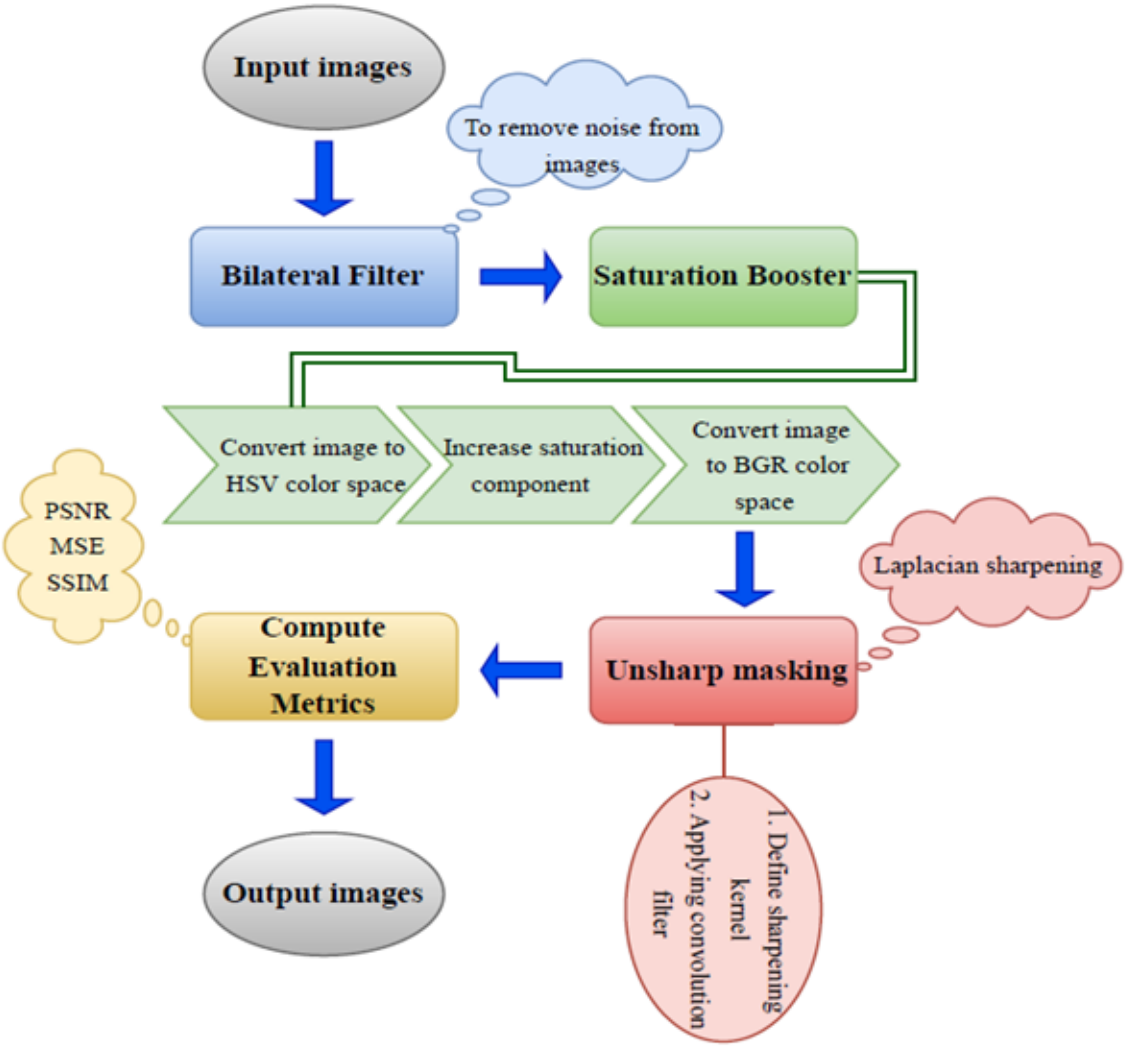

Figure 2: Methodology of the proposed method

4 Results

We discuss the results of simulating the suggested method for a standard image in this section. We use the Python 3.12.7 program to simulate the expected process. One popular tool for putting such algorithms into practice in image and video processing is Jupyter Notebook. The results of the suggested technique for improving underwater images are displayed in Tables 2, 3, 4, and 5, together with the simulation and result computations. A range of color images from the Fish4Knowledge and FishImg datasets is used to evaluate the proposed approach. The enhanced images are displayed using the evaluation matrices PSNR, MSE, and SSIM.

4.1 Evaluation Metrics

PSNR is calculated using the logarithmic ratio of the greatest achievable pixel density to the MSE between both pictures, where the summing approach has historically been the primary component of MSE. While RGB MSE color images can be computed using $M \times N \times O$ dimensions, MSE grayscale images are computed using $M \times N$ dimensions in (7).

$$\text{MSE} = \frac{1}{M \times N \times O} \sum_{x=1}^{M} \sum_{y=1}^{N} \sum_{z=1}^{O} \left[I_{(x,y,z)} - \hat{I}_{(x,y,z)} \right]^2 \tag{7}$$

Where M and N are the image resolution, O is the number of image channels, $I_{(x,y,z)}$ is the pixel value of the original image at the x, y coordinates and channel z, $\hat{I}$ is the output image processing result. Equation (8), MSE, and PSNR are closely related.

$$\text{PSNR} = 10 \log_{10} \left(\frac{\max^2}{\text{MSE}} \right) \tag{8}$$

Where *max* is the highest scale value of the RGB image. It is evident from the PSNR calculation formula, which uses (7) and (8), that the error squared value is the main part of the PSNR. The discrepancy in the pixels at identical channels and locations produces the error value [31]. Otherwise, it will create an infinite value that likewise does not alter the pixel value.

According to this research, SSIM was developed using three primary factors: structure, contrast, and brightness. SSIM was initially published by [32]. The summing method that served as the foundation for determining PSNR is replaced by these three components. Equation (9) allows for the definition of SSIM in RGB color images.

$$\text{SSIM}(i, i') = l(i, i')\, c(i, i')\, s(i, i') \tag{9}$$

Keep in mind that the first factor in (9) is $l(i, i^{'})$, which is a function that compares the luminance of an image i and image $i^{'}$.The second factor is $c(i, i^{'})$, which is a function that compares the contrast of an image i and image $i^{'}$. The third factor is $s(i, i^{'})$, which is a function that compares the structures of the image i and image $i^{'}$ based on the correlation coefficient.

4.2 Simulation Outcomes of Dataset Images

The modeling stage of the suggested method made use of the publicly accessible datasets Fish4Knowledge [33] and FishImg [34], which can be accessed via the Kaggle platform. Use ten images from the Fish4Knowledge and ten images from the FishImg datasets to gauge the effectiveness of the proposed approach. The sharpness of these underwater test images is impacted by noise. A bilateral filter is used to lessen this noise, producing denoised visuals. However, vivid colors and edge crispness are slightly lost during the elimination process.

Underwater light absorbs wavelengths, making the images resemble low-saturation and lifeless. Saturation enrichment is used to remedy this, improving object distinguishability. Lastly, Laplacian sharpening is applied to restore edge details, improving the image's definition and clarity.

Fig. 3 illustrates this clearly. Because blue light has the shortest wavelength, it travels the furthest in water. This is the reason why blue is the single colour that dominates underwater images. Along with an overabundance of blue, blurry images also have low contrast, low brightness, and other issues [10].

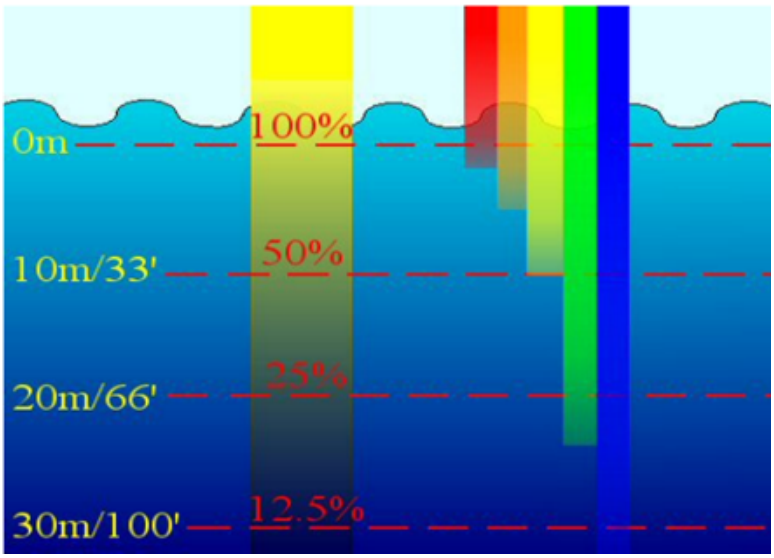

Figure 3: Colour wavelength in underwater images

The anticipated results can be seen in the underwater image in Table 2 that displays the original images, which are of poor quality. The raw underwater image, which is the test image obtained by the dataset, has some problems, including noise, low contrast, color fading, and blurriness. The first result is a smoother and sharper image when the noise is removed using the filter; nevertheless, the noise removal method may cause outlines to seem a bit blurred. Bilateral filtering refers to domain and range filtering combined. It substitutes an average of adjacent and comparable pixel values for the pixel value at x. In smooth areas, where pixel values in a local neighbourhood are comparable to one another. The bilateral filter fundamentally performs as a typical domain filter, removing the tiny, weakly correlated noise-induced variations in pixel values. One non-iterative technique is bilateral filtering. In contrast to conventional filters, it eliminates noise while maintaining edge information. However, the filter's parameters determine the bilateral filter's best performance.

Since underwater images lose red and yellow hues owing to wavelength absorption, applied saturation augmentation helps restore better color contrast. Laplacian sharpening was used to restore lost details and improve edges in the final images. With improved colors and sharper edges, the finished image seems competent and is more suited for analysis and object detection. Particularly in scenes with turbidity, the upgraded photos show better color balance and contrast. Fish edges seem more defined, which could help with tasks involving behavior analysis.

Table 3: Evaluation metrices outcomes of the proposed method for Fish4Knowledge dataset images

Images	**PSNR**	**MSE**	**SSIM**
Image1	40.14	6.30	0.9638
Image2	41.75	4.34	0.9755
Image3	42.96	3.29	0.9803
Image4	41.89	4.21	0.9675
Image5	42.88	3.35	0.9808
Image6	45.38	1.88	0.9888
Image7	43.58	2.85	0.9849
Image8	41.71	4.38	0.9710
Image9	40.43	5.89	0.9656
Image10	42.80	3.41	0.9766

The outcome metrics for the suggested image enhancement technique applied to images from the Fish4Knowledge dataset are shown in Table 3. To quantify the quality enhancements, PSNR, MSE, and SSIM are used to evaluate effectiveness. A high-quality augmentation with little distortion is shown by the PSNR values, which range from 40.14 dB to 45.38 dB. Better image restoration and detail preservation are indicated by a higher PSNR. The suggested approach successfully lowers noise while preserving significant image features, as evidenced by the comparatively low MSE values, which range from 1.88 to 6.30. Better image quality is indicated by lower MSE values. Between 0.9638 and 0.9888, the SSIM values are continuously high, indicating that the images' contrast, texture, and overall strength are all well-preserved following augmentation.

The images in Table 4 are raw underwater images that were obtained using FishImg data collection. Filtering was used to eliminate the noise from these raw images, and the first output was the filtered images. The more widely used color scheme that can distinguish between hue and level of intensity is the HSV color space. Compared to the RGB color space, HSV is more effective in reconstructing images. Hue is the color type or shade, like yellow, blue, or red. The hue runs from 0 to 1.0, while the associated colors encompass red to yellow, green, cyan, blue, and magenta. The brightness of a color is known as saturation. The related colors go from unsaturated (0), which is a grayscale variation between black and white, to completely saturated (1), which denotes strong color, since saturation varies from 0 to 1.0. Value is the color's brightness. The appropriate hues get brighter as the brightness, or value, increases from 0 to 1.0. Saturation augmentation is used because underwater images lose color due to wavelength absorption.

To measure the edges of the submerged images, Laplacian sharpening is used. To determine the saliency weight, it takes into account the tone planning and the field's extended probity, the weight of integration. Laplacian channels are used in this process to provide an improved submerged image. It provides the sum of the procedure's outcome. It is employed to examine the picture distribution at low levels. Laplacian sharpening, which improves sharpness and makes fish and other things in the image more visible, was added to the resulting images. With improved colors and sharper edges, the finished image seems sharper and is more suited for analysis and object detection.

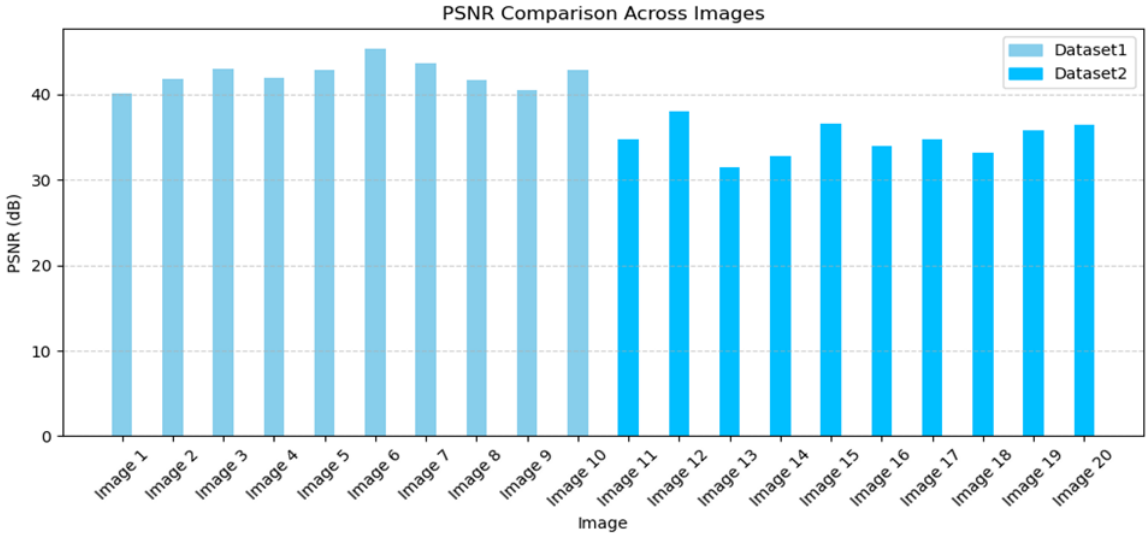

Figure 4: Metric PSNR comparison across Fish4Knowledge and FishImg datasets images

Table 5: Evaluation metrices outcomes of proposed method for FishImg dataset images

Images	**PSNR**	**MSE**	**SSIM**
Image11	34.72	21.94	0.9284
Image12	37.98	10.36	0.9095
Image13	31.49	46.16	0.8604
Image14	32.78	34.26	0.8750
Image15	36.63	14.13	0.9439
Image16	34.01	25.82	0.8881
Image17	34.71	22.00	0.9059
Image18	33.18	31.24	0.8256
Image19	35.78	17.17	0.9311
Image20	36.42	14.81	0.9232

The parameters for assessment for the FishImg dataset are shown in Table 5. A better outcome is indicated by a higher PSNR. A score around 1 indicates a better outcome. SSIM calculates the structural distinction among both images and assigns a score between 0 and 1. Effective noise reduction is indicated by PSNR values, which vary from 31.49 dB to 37.98 dB; however, some images have lower values because of starting quality variances. Better enhancement and noise reduction are indicated by lower MSE values, which range from 10.36 to 46.16. SSIM values between 0.8604 and 0.9439 attest to the suggested method's ability to preserve structural integrity while enhancing clarity. The outcomes in Fig. 4, Fig. 5, and Fig. 6 depict the PSNR, SSIM, and MSE values for the Fish4Knowledge and FishImg datasets, showcasing the efficacy of the suggested strategy in improving the clarity of images while maintaining structural integrity and reducing distortion.

In recent years, the study of submerged imaging techniques has grown. However, because of the complex physical characteristics of underwater settings, which cause vision loss and color aberration in underwater photographs, underwater image improvement is difficult. We have increasingly higher standards for the visual appeal of the photos we take as a result of technological advancements and ongoing improvements to photographic tools, yet environmental considerations frequently make it difficult to get acceptable shots. Low illumination, uneven lighting, and other elements like backlighting can all lead to faulty image information, which lowers the overall caliber of photos that are taken. As a result, these problems may ripple down to more

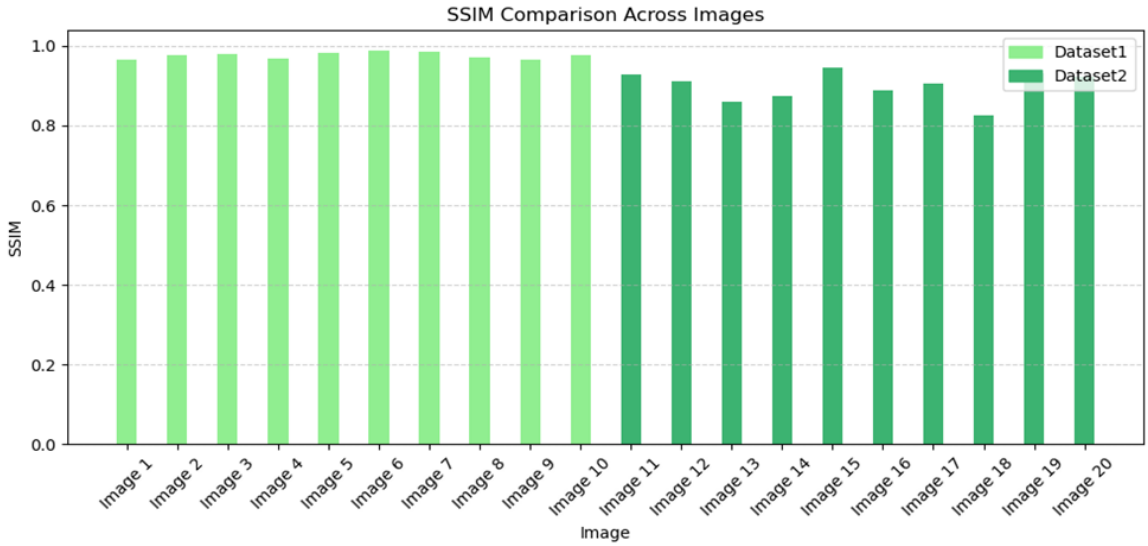

Figure 5: Metric SSIM comparison across Fish4Knowledge and FishImg datasets images

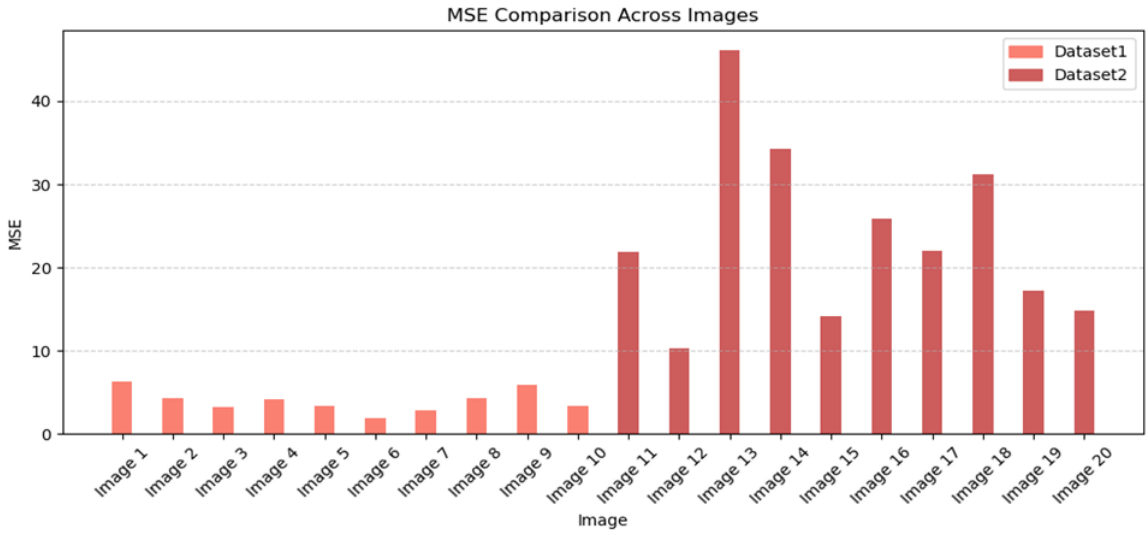

Figure 6: Metric MSE comparison across Fish4Knowledge and FishImg datasets images

complex tasks like object identification, categorization, and recognition [35].

In this work, twenty images were used from two distinct datasets. The Fish4knowledge dataset contains the first 10 images, whereas the FishImg dataset contains the following ten. We compare which dataset performs best after applying image-enhancing algorithms to these images.

The PSNR, MSE, and SSIM metrics were calculated across augmented images from two different underwater datasets in order to assess the efficacy of the suggested enhancement technique. Restoring clean images from the unprocessed ones is the goal of image enhancement, which is essential for low-level visual tasks. Decreased clarity and higher noise levels are two of the many aberrations that frequently affect images taken in low-light conditions. Information transmission is hampered by this deterioration, which has an adverse effect on many ensuing high-level visual tasks [36]. The Fish4Knowledge dataset typically produced higher PSNR and SSIM scores with low MSE values, indicating superior noise elimination and structure preservation. These images could include some brightness, noise, and a clearer background. The enhancing technique has a high PSNR and performs well with them, as seen in Fig. 3. However, the FishImg dataset likewise sustained satisfactory ratings for all samples, showing that the suggested method works consistently even in the face of changing underwater factors such as color exaggeration, viscosity, and illumination. In contrast to having lesser quality along with greater noise, blur, and underwater color cast, these photos additionally exhibit higher distortion. Despite improving visibility, improvement leads to good PSNR.

This comparison examination demonstrates the enhancement algorithm's resilience. Although the Fish4Knowledge dataset took quantitative advantage, the FishImg dataset's constant trends confirm the approach's versatility across a range of underwater sceneries, making it a workable option for real-world fish monitoring applications. Images from the Fish4Knowledge dataset showed improved PSNR values using the suggested enhancement strategy, suggesting little distortion and excellent detail in comparison to the original images. However, compared to the Fish4Knowledge dataset, the FishImg dataset yielded lesser PSNR values. This is mainly because the FishImg dataset had more difficult conditions, like inadequate lighting and greater baseline noise levels. The visual quality was nevertheless greatly enhanced in spite of this, indicating that the technique works even with lower-quality components, even though the PSNR shows the increased pixel-level discrepancy. All things considered, the technique improves underwater images by sharpening edges, lowering noise, and enhancing color quality, which improves the images' suitability for analysis, object detection, and more research.

4.3 Performance Comparison

The quantitative numerical metrics of our approach, Semantic Guided Underwater Image Enhancement Network (SGUIE-Net) [37], ResNet-Transformer-Attention (RTA) [38], Kuo-Jui's technique [39], and the Deep See Color (DSC) [40] model were compared. The comparative findings for various datasets are shown in Table 6. In recent years, several comparable approaches have been put out. Using region-wise semantic information, SGUIE-Net is a semantic-guided image improvement network that achieves reliable and aesthetically attractive regeneration across a variety of degraded types [37]. To increase the quality of vision and object detection, RTA, a transformer-based technique for underwater image improvement, combines multi-color-space inputs with multi-dimensional attention to correct color, contrast, and blurring [38]. In order to boost dynamic range and brilliance in subsea pictures and infer deterioration models, the Kuo-Jui Hu approach is a network-guided framework for underwater image processing which employs convolutional media transfer with multicolour space insertion [39]. DSC is an image improvement approach that effectively restores natural colors by addressing irregular reflections of light and color changes by combining deep learning with a visual generation model [40].

Overall, the proposed approach produces greater improvements when considering the outcomes of all measures combined in Table 6. The proposed approach gets the highest SSIM and PSNR values. The highest ratings indicate that there is an appropriate variance among the reference image and the water-based images that were enhanced using the proposed technology. The outcomes of the experiment show how well our approach preserves the texture of the images.

Table 6: Comparison between proposed method with state-of-art image enhancement approaches

Model Name	**PSNR**	**SSIM**
SGUIE-Net [37]	24.82	0.928
RTA [38]	24.87	0.935
Kuo-Jui Hu method [39]	20.93	0.877
DSC [40]	25.78	0.8752
Proposed method (ours)	**45.38**	**0.9888**

The proposed approach and a number of cutting-edge underwater visual improvements are quantitatively compared in Table 6, utilizing image quality assessment parameters including PSNR and SSIM.

5 Conclusion

To overcome the typical difficulties in acquiring images of underwater fish, a systematic and efficient image-enhancing technique has been put forth in this study. Environmental elements that impede accurate assessment, along with subsequent processing duties, such as low contrast, noise, color distortion, and inadequate illumination, frequently deteriorate underwater photographs. The suggested method overcomes these drawbacks by sequentially combining many enhancing approaches to greatly increase the visibility and graphic quality of underwater images. In order to reduce noise and minimize artifacts that are commonly present in underwater photography, the methodology starts with the deployment of a dual filtering procedure. The saturation augmentation stage comes next, which intensifies the color content to bring back the image's vitality and authentic look. Lastly, to improve the borders and minor details and produce sharper, more visually meaningful images, Laplacian sharpening is used. Standard picture quality assessment criteria like MSE, PSNR, and SSIM are used to numerically and visually analyze the improved images. The suggested approach performs noticeably better than existing underwater image enhancement algorithms, showing both quantitative supremacy and visually enhanced image quality with a PSNR of 45.38, SSIM of 0.9888, and MSE of 1.88. Further study could examine the method's efficacy in an expanded variety of underwater settings to verify reliability, even though its findings are encouraging.

Although the present findings are encouraging, this study clearly acknowledges its shortcomings and need for development. Future research will concentrate on adaptive enhancement methods that use deep learning for rapid optimization and real-time deployment on aquatic vehicles, taking into consideration changing underwater variables, including depth, turbidity, and lighting. To further determine the benefits and drawbacks of the suggested approach, future research will also include a thorough comparison with cutting-edge augmentation algorithms. The goal of these advancements is to provide a more resilient and intelligent enhancement framework that can serve a variety of real-time underwater image applications, especially in fish behavior evaluation and marine research.

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Table 2: Outcome of proposed method on Fish4Knowledge test images

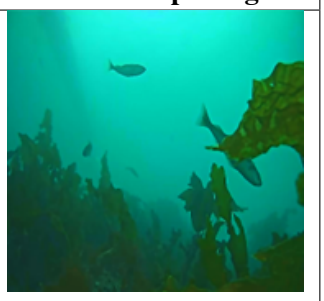
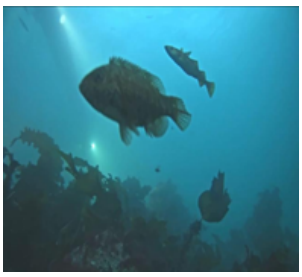
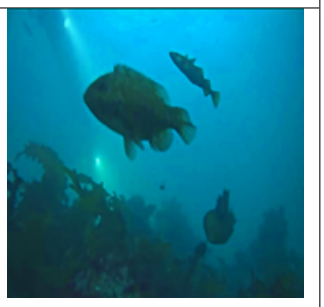
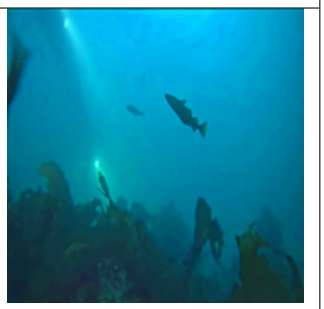
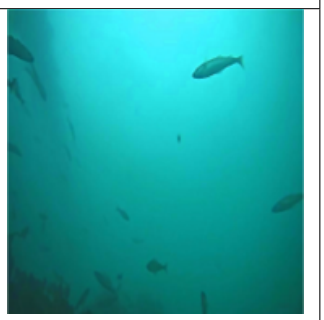
Original Image	Denoised Image	Saturation Enhanced Image	Final Sharp Image
			
			
			
			
			
			

Table 2: Outcome of proposed method on Fish4Knowledge test images (continued)

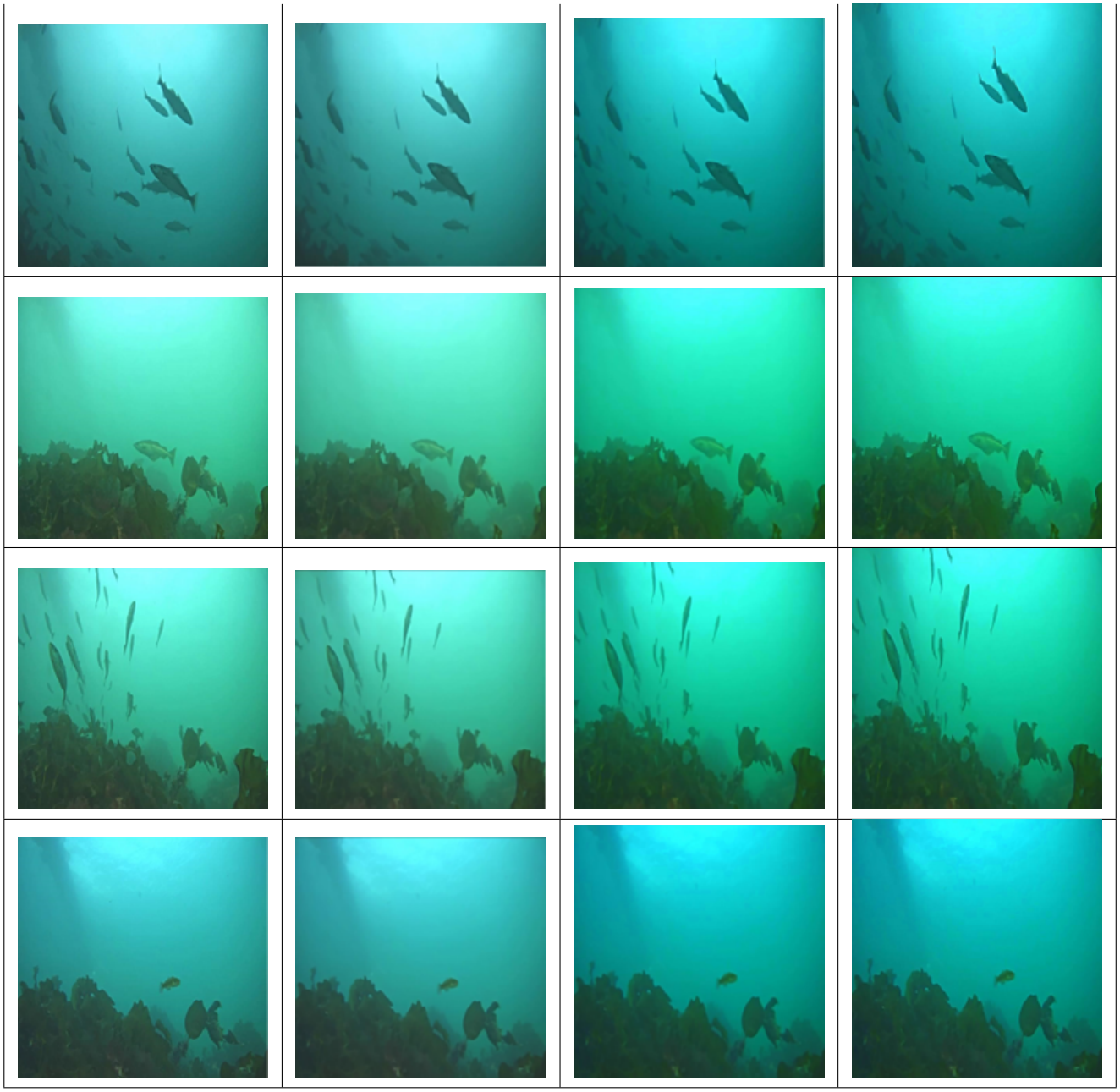


Table 4: Outcome of proposed method on FishImg test images

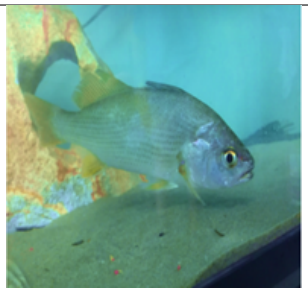
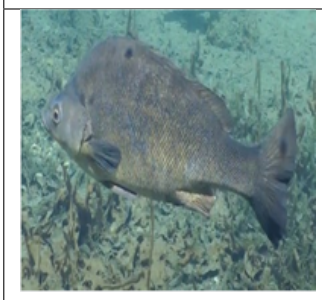
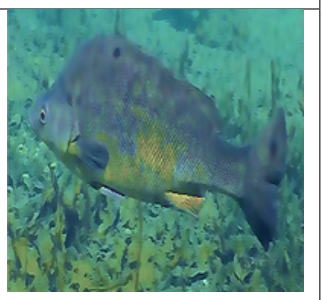
Original Image	Denoised Image	Saturation Enhanced Image	Final Sharp Image
			
			
			
			
			
			

Table 4: Outcome of proposed method on FishImg test images (continued)

