I.J. Information Technology and Computer Science, **2026, 2, 31-48**
Published Online on April 8, 2026 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijitcs.2026.02.03

Underwater Image Dehazing: A Comprehensive Approach

Sumalatha A.*
Department of Computer Science and Engineering, School of Engineering and Technology, Christ University, Bengaluru, Karnataka, India
E-mail: sumalathaa@res.christuniversity.in; sumanstars123@gmail.com
ORCID iD: https://orcid.org/0000-0002-3519-3063
*Corresponding author

Aruna S. K.
Department of AI and Data Science Engineering, School of Engineering and Technology, Christ University, Bengaluru, Karnataka, India
E-mail: aruna.sk@christuniversity.in
ORCID iD: https://orcid.org/0000-0002-6638-2772

Received: 24 October 2025; Revised: 30 January 2026; Accepted: 24 February 2026; Published: 08 April 2026

Abstract: Underwater imaging in recent times has advanced by trying to correct color distortion, increase contrast, and increase image clarity when light availability is low. The use of deep learning has been effective in enhancing image quality, but challenges persist in the decomposition process due to data inconsistencies. In order to do this a new scheme is proposed in this study. Unlike other methods which depend only on the single images captured, here an attempt is made to use images taken in other conditions to overcome this limitation, by using the model to try and improve such underwater images in general irrespective of the water conditions. A key innovation is the disassembly and synthesis of multi-channel illuminance data. Specifically, we decompose the input image into its red, green, and blue channels, and then approximate the illuminance component within each channel. By independently manipulating and reconstructing these channel-specific illuminance maps, we can effectively address the non-uniform light scattering and absorption that are characteristic of underwater environments. This allows us to correct for the inherent color casts and haze that degrade image quality. To further refine the enhancement, we incorporate, advanced color correction methods such as image saliency exploration and white balance adjustment to compensate for color attenuation caused by light absorption at different depths. These techniques effectively restore lost colors and enhance contrast, thereby improving image clarity and sharpness. This is helpful in the field of engineering and also forms the foundation for further exploring methods of improving images captured underwater. Investigational outcomes demonstrate that the intended method significantly augments image quality, making it highly effective for underwater detection and exploration tasks, offering an innovative solution for hazy images in various conditions and advancing underwater monitoring and exploration technologies.

Index Terms: Illuminance Reconstruction, Artifacts, Color Distortion, Underwater Monitoring, Exploration.

1. Introduction

Underwater images frequently experience diminished reflectivity as a result of environmental elements, including light immersion, scattering, as well as backscattering from suspended constituent parts in the water [1]. The degradation phenomena can lead to the non-appearance of objective contours, loss of operative details, and loss of complex semantic information, making it challenging to perform underwater entity recognition and other computer vision tasks. As an outcome, the improvement of submerged images has developed a vital area of exploration in current years [2,3]. Submarine image augmentation strategies are mainly categorized into the physical model technique and the deep learning technique [4]. Physical model methods aim to restore the original image by inverting the underwater image formation model, which requires knowledge of various parameters such as the complexity of the scene and optical properties of water. Conversely, deep learning methodologies utilize neural networks to understand intricate non-linear connections between corrupted input data and the improved output, eliminating the need for explicit physical models. This document presents a new technique for improving visibility in

This work is open access and licensed under the Creative Commons CC BY 4.0 License.

underwater images by breaking down and merging multiple illuminance data channels [4]. Due to the difficulties in acquiring paired underwater images, it is designed as a single-image approach. The technique uses a multiple resolution blend approach controlled by a weight map to decrease artifacts and inconsistencies [5]. Submerged images often suffer from extreme color distortion owing to the selective absorption and scattering of light in water. As water absorbs different wavelengths at varying rates, red light disappears first, followed by green, leaving images dominated by blue tones. This distortion results in low contrast and poor color representation, making underwater object detection and classification challenging. To overcome these issues, various color correction techniques have been introduced. Customary methods, such as histogram equalization and contrast stretching, fail to address wavelength-dependent attenuation. The proposed approach leverages image saliency exploration and white balance correction to enhance color fidelity. White balance correction adjusts color tones by compensating for excessive blue and green dominance, while saliency-based enhancement highlights key image features against the background. By applying these techniques in a structured manner, the proposed model improves color consistency and restores visibility, making it a robust solution for underwater imaging.

This study presents an innovative technique for augmenting submarine images. It involves breaking down and combining multiple illuminance data channels to enhance visibility. This technology is used in engineering and is the foundation for future research on improving submarine images. To improve submarine scene quality, two main strategies are utilized: enhancing imaging hardware and integrating software technology. Hardware methods, such as using polarized lenses and altering sensors, are commonly used initially. Software techniques are simple, affordable, and can overcome environmental limitations, unlike complex, expensive hardware methods. A cost-effective approach is needed due to challenges in obtaining underwater image pairs. This paper proposes a technique that enhances submarine images without the need for intricate changes, providing clarity using standard equipment. This paper introduces significant contributions in the arena of submarine image augmentation techniques[6] as depicted in Fig.1. Firstly, it discusses excavating hidden information in images by treating RGB channels as separate bands to rebuild image illuminance through multiple resolution synthesis, preserving details and improving visibility. Secondly, improved white balance is utilized for color improvement and perfecting, improving red channel restoration method and adapting blue or green channels based on image appearance[7]. Thirdly, Saliency detection is employed to enhance underwater image quality by highlighting objects against the background. The paper also includes a comparison with existing submarine image enhancement approaches.

Outline

The present research is structured as follows: Section 2 evaluates the most recent developments in submarine image augmentation. In Section 3, the procedure for restructuring submarine image brightness is outlined, involving the consolidation of data from the RGB frequencies. This involves developing a weight map for multiple resolutions and adjusting colors after restoring illuminance. The subsequent section provides an in-depth evaluation contrasting the suggested submarine image enhancement system with traditional methods in relation of qualitative and quantitative criteria.

2. Related Study

2.1. Physical Model Technique

Physical model methodologies rely on modeling the physical processes that cause image degradation in underwater environments[3]. These models account for aspects such as light attenuation, scattering and also color distortion due to different wavelengths of light being absorbed at varying depths. The majority of physical models derive from the Jaffe-McGlamery framework [5], which elucidates the interactions between light and underwater particles. This model encompasses direct transmission, forward scattering, and backscattering phenomena associated with light[8] as depicted in Fig.2. The restoration techniques seek to undo or minimize the effects of degradation phenomena such as scattering and absorption by quantifying their effects to reverse the image [9].

The methods based on physical models frequently necessitate an understanding of environmental variables such as water depth, illumination conditions, or attenuation coefficients[10]. Grounded in scientific principles, it is able to produce accurate improvements if the environment variables are known[11]. It works well with a clear physical understanding of underwater light propagation [12]. It requires accurate estimation of environmental parameters, which is quite difficult in real-world conditions and may experience difficulties in intricate or significantly variable underwater environments. Incorporating atmospheric light into the DCP model, Drews et al. built upon previous research [13]. Jones et al introduced a new underwater dark channel prior tailored for use in aquatic environments.

This conceptual framework enabled a more accurate assessment of the initial visualization in submarine settings. In 2015, Galdran et al. conducted a study [14] that introduced a technique utilizing the red channel, followed by an examination of potential anomalies resulting from color exploiting in red phantom band. Tang et al. conducted a study and proposed an enhanced procedure for submarine image enhancement using a sophisticated dark channel prior algorithm [15]. An approach of adaptive measure assortment was employed to improve the brightness of the diffusion map, along with color correction to eradicate any color discrepancies.

The technique adopted by Peng et al. [16] was derived from DCP. The Generalized Dark Channel Prior (GDCP) is employed to improve and repair images that have been degraded by fog, haze, sandstorms, or submarine conditions, without being restricted by lighting levels. In 2020, the research by Hou et al. focused on creating a submarine total variation model that incorporates the underwater dark channel prior. The recommended technique has the capability to deliver high performance in dehazing, enhancing contrast, preserving edges, and suppressing noise. In 2021, Xie et al. conducted a study [17] which proposed incorporating a red channel in the channeled deviation basis to enhance submarine image dehazing.

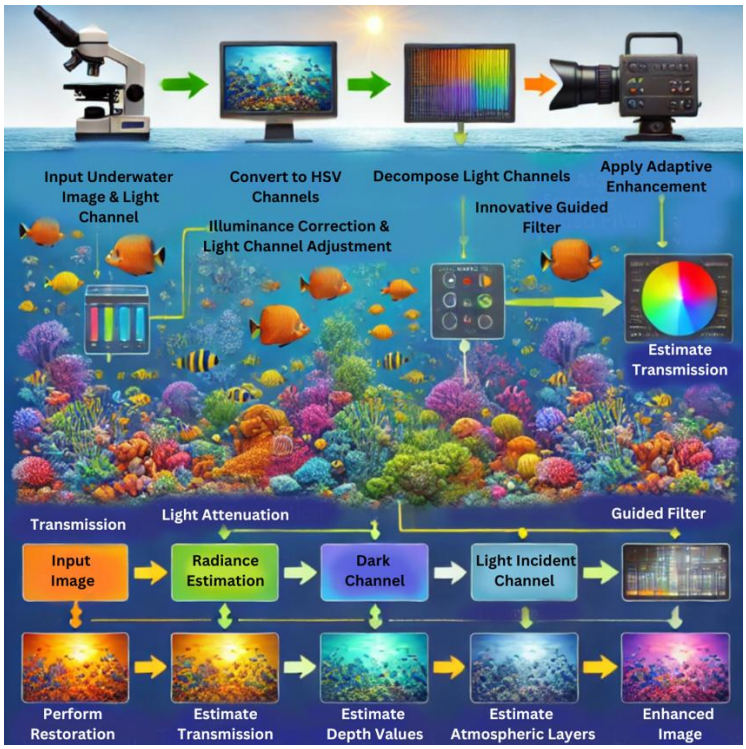


Fig. 1. Overall architecture of the EDUI system.

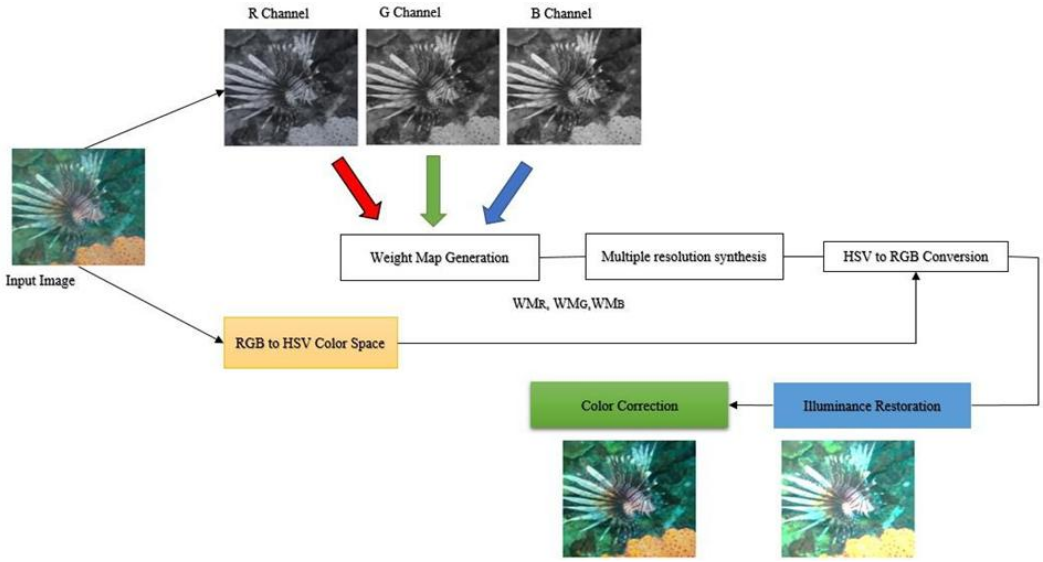


Fig.2. Method Proposed.

2.2. Non-Physical Model Technique

Submarine image processing often relies on non-physical based methods to overcome challenges like poor visibility, color bias, and low contrast caused by light immersion and scattering. These methods utilize computational techniques rather than physical models of light propagation in water[18]. Common non-physical based methods include Histogram Equalization, which aims to enhance image contrast by redistributing intensity values, and White Balance Correction, which adjusts colors to appear more natural by compensating for color loss underwater[19].

Variants of Histogram Equalization such as Adaptive Histogram Equalization (AHE) in addition to Contrast Limited Adaptive Histogram Equalization (CLAHE) are commonly used to prevent excessive noise amplification in submarine imagery[20]. Retinex-based techniques improve contrast and color in submarine images, simulating human visual perception[21]. Single-Scale Retinex and Multi-Scale Retinex improve luminance and maintain detail. Submarine image methods using other than the physical models aim to improve image eminence through a sequential stacking approach[22]. Current methods often depend too much on pixel- level processing, overlooking fundamental principles of submarine visual imaging. This results in improved imagery that does not entirely adhere to the guidelines for submarine photography [23].

2.3. Deep Learning Techniques

Deep learning methods for submarine image augmentation are utilized to tackle issues like light immersion, scattering, color distortion, and minimal contrast[24]. CNNs, with multiple layers, learn spatial hierarchies of features from underwater images, enhancing visibility, color correction, and contrast. Examples include UIE-Net, which enhances images directly from data, and multi-scale CNNs, which capture features at different scales to handle diverse underwater conditions. Generative Adversarial Networks (GANs) are designed for scene-to-scene transformation, recovery, or improvement by concurrently training a generator and a discriminator [25]. The generator spawns authentic scenes, whilst the discriminator distinguishes between real and generated scenes to improve the generator's effectiveness. Examples include WaterGAN for underwater image synthesis and UGAN for enhancing underwater images by mapping little quality to excellent quality domains, compensating for color distortion and restoring clarity. Current research struggles to obtain sufficient paired imageries for training deep learning approaches in immersed image augmentation[26]. Various procedures have been explored, but limitations exist, prompting the need for more efficient methods.

3. Proposed Methodology

Fig. 1 displays a new submarine scene enhancement technique that is independent of the visual model of submarine images named EDUI(Enhanced Dehazed Underwater Image). The process involves two phases: illuminance restoration and color rectification. The illuminance restoration decomposes the primary image into red, green, and blue channels using a multiple resolution synthesis technique. This is followed by color correction using a saliency map to improve white balance and recompense for color dilution in submarine settings, yielding overall scene augmentation.

3.1. Disintegration of Scene Color Space

Scientists have incorporated near-infrared imagery into dehazing techniques for atmospheric images to counteract cloud and haze attenuation, thereby enhancing visibility. This technique has motivated enhancements in underwater image quality, as not all submarine images possess visible light and near-infrared image pairs like those found in atmospheric images. The study purpose is to extract relevant data directly from original submarine scenes to replicate fusion effects. Underwater images experience varied attenuation levels across visible light bands, with the green band retaining the most information. Decomposing underwater images into RGB color channels highlights red attenuation in regions of high luminance but lacks detail in lower luminance areas [27, 28]. The original submarine image loses detail in the green and blue frequencies, while preserving more detail around the stones. This research seeks to enhance the essence of submarine images by enhancing them whilst maintaining important details, with a high focus on brightness. The HSV color space is used to separate luminance from color, preserving color saturation. The RGB color space is broken down, and brightness information is rebuilt in HSV using the decomposed RGB data. Color correction techniques are then applied for enhancement. Fig.3 illustrates the diminution. The red frequency provides more reliable data in areas with complex luminance. However, it lacks specific data concerning low luminance effects in areas adjacent to the rocks. The primary submarine image exhibits a loss of detail in the green and blue frequencies as a result of excessive brightness. Additional details become evident upon closer inspection. This initiative seeks to improve the quality of submarine images while maintaining important data at each frequency, especially regarding illuminance. For this we recommend the HSV color space, that acts effectually that splits illuminance from the color and provides improved color permeation conservancy as compared to others colour spaces. Building on the prior analysis of color using the RGB model, the subsequent step entails reconstructing the illuminance data inside the HSV color by separating the frequency bands of the RGB color. Later, color amendment methods can be applied on the reconstructed submerged portrait to obtain the refine results.

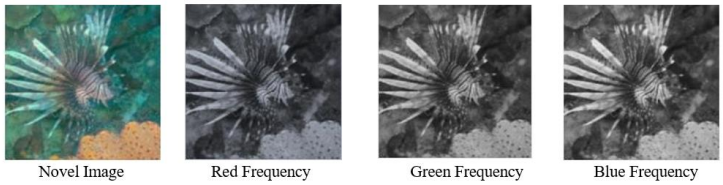


Fig.3. RGB decomposition of the submarine image

3.2. Multiple Resolution Synthesis Illuminance Restoration

This section introduces a novel approach for illuminance restoration by extracting discrete RGB submarine images and creating a weight map using local entropy, contrast, and discernibility measures. The weight map is essential in guiding the multiple resolution synthesis process to maintain the clearer and more detailed aspects of each frequency in the submarine image. This approach differs from a basic weighted average blending technique by guaranteeing that weight values for each pixel in the three channels fall within the range of 0 to 1, and their sum totals to 1. This approach enhances the precision of the fusion process, improves the quality of the final fused image, and effectively retains important features by integrating native entropy, contrast, and prominence metrics during the creation of the weight map. Multiple resolution synthesis is a technique used to combine information from different frequency components of an image. It involves decomposing the image into multiple layers of varying detail, allowing for processing at different scales. This is particularly useful in underwater images where illumination and visibility can fluctuate significantly throughout the image. Multiple resolution synthesis is more effective than other methods because it allows for more precise control over the fusion process. The weight map ensures that the most informative components from each frequency are preserved, while less informative components are discarded. This leads to a higher quality final image with better detail and contrast. Image entropy is a measure that assesses the informational data of a submarine image by determining the average amount of information it communicates [29]. It pertains to the distribution of gray levels, offering insight into spatial characteristics and clustering properties. The subjective measure W represents the normalized native entropy around a precise pixel by utilizing the neighboring region R. Local entropy measures the amount of information in a specific region of the image. It is considered by computing the quantity of pixels in the region that have the same value as the center pixel. Higher local entropy specifies more information. Local contrast measures the variance in intensity between neighboring pixels. It is considered by taking the square root of the average square off variance amongst each pixel and the average of its neighbors. Higher local contrast indicates more detail. Local visibility measures the ability of a frequency to capture precise facts in mediums like water. It is calculated by blurring the image with a Gaussian function and then taking the square root of the variance between the original image and the blurred image. Higher local visibility indicates more ability to capture specific facts. The local entropy, divergence, and visibility measures are united by multiplying them together. This gives each pixel a weight that represents its importance. The weight map is then used to guide the fusion process, giving more weight to pixels with higher weights. Eq.(1) calculates the local entropy at a pixel, which indicates the amount of information it contains.

$$W(i,j) = -\sum_{(k,l)\in N} x(f,(k,l))\ Dg_2(p) f(k,l) \tag{1}$$

To calculate $x(f)$, count the pixels in the 8x8 surrounding area that share the same value as the pixel placed at (k,l). Divide by total pixels in the neighborhood for the desired probability Eq.(2). Apply transformations for accurate calculations of W.

$$W(i,j) = -\sum_{(k,l)\in N} x(f,(k,l)) log_2(p)(f(k,l)) + \sum_{(k,l)\in N} x(f,(k,l)) \log_2(n) \tag{2}$$

The equation denotes $num(f,(k,l))$ as the number of pixels in the 8 × 8 vicinity around pixel (k,l) that have the equivalent value as pixel (k,l), comprising pixel (k,l). n indicates the overall pixels in the native region N to guarantee computational precision. Local contrast evaluates the intensity differences between the subject and the background in an image, thereby emphasizing details and lessening the background's effect. The divergence coefficient (C) is determined within a region (N) at the pixel coordinates (i,j) Eq. (3).

$$C(i,j) = \sqrt{\frac{1}{n}\sum_{(k,l)\in N} \ln(k,l) - (\mu(i,j))^2} \tag{3}$$

where, Eq. (4)

$$\mu(i,j) = \sum_{(k,l)\in N} \ln(k,l) \tag{4}$$

The pixel value of input images is represented as $\ln(i,j)$ with greater weights and contrasts signifying intricate details in the area when adjacent pixels differ more from the mean. This study utilizes an 8x8 static neighborhood. Local perceptibility is determined by assessing a frequency's ability to capture specific details in media like water using a vague assessment method with a Gaussian function. This function creates a blur effect in the image Eq.(5), leading to B_{img}.Visibility (V) is quantitatively assessed as the square root of the difference between the original submarine image and B_{img} Eq. (6).

$$B_{img}(i,j) = \ln(i,j) \otimes g(W(i,j),\sigma 1) \tag{5}$$

$$V(i,j) = \sqrt{\ln(i,j) - B_{img}(i,j)^2 \otimes g(W(i,j)),\sigma 2)} \tag{6}$$

The function $g(W(i,j,\sigma))$ defines a 2D circular proportionate Gaussian weighted function, specified by a frame size of A x A and a standard deviation of σ2. The function carries out 2D convolution. In this process, the value of A is fixed at 8, and σ1 and σ2 are each assigned a value of 2. Normalization is applied to entropy, contrast, and discernibility weights before multiplication to regulate the outcome weight. Each weight has an equivalent effect on the result. The weight allocated to individual pixel is illustrated as Eq.(7):

$$W_p(r,s) = W_{k(r,s)} * C_k(r,s) * V_k(r,s) \tag{7}$$

where $k \in (R,G,B)$. The above equation discusses normalizing weights for R, G, and B frequencies to ensure their total sum is 1 at each pixel. A weight plot is created for each frequency of a submarine image, with lighter areas indicating higher weights as depicted in Fig.4. Multiple resolution synthesis is then performed using Laplacian and Gaussian pyramid decomposition.

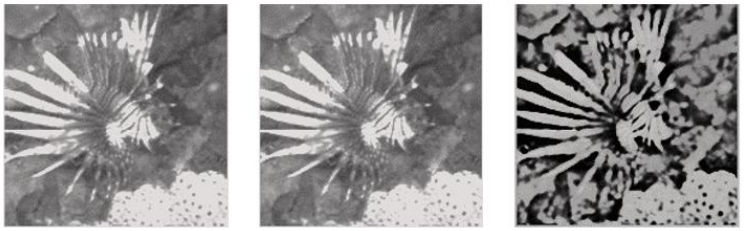


Fig.4. RGB frequencies of submarine scenes and its weight maps.

The weight map in the lth-level Gaussian pyramid decomposition is denoted as follows in Eq.:

$$GK\left\{W_p(k,l)\right\}l = \left[GK(k,l) \otimes GK\left\{W_p(k,l)\right\}_{l-1}\right]_{\downarrow_2} \tag{8}$$

The Gaussian Kernel embodied by $GK(k,l)$ is approximated by $GK\left\{W_p(k,l)\right\}l$ from the earlier level. Down sampling operation ↓2 reduces the image area to 1/4. Gaussian function separability abridges the procedure with an 8x8 Gaussian filter. The image disintegration at the lth level using the Laplacian pyramid is illustrated in Eq.(9).

$$L\left\{I(k,l)\right\}_l = G\left\{I(k,l)\right\}_{l-1} - IF(k,l) \otimes \left[G\left\{I(k,l)\right\}_l\right]_{\uparrow_2} \tag{9}$$

Interpolation filter $IF(k,l)$ and up sampling operation ↑2 are used to create a Laplacian pyramid with three novel scenes. Each scene level is multiplied by a weight map, then summated together. Reconstruction follows the Laplacian pyramid technique, starting from the maximum level and adding gradually to minor levels till attaining the lowermost Eq.(10).

$$L\{R_i(k,l)\}_l = G\{W_R(k,l)\}_l L\{I_R(k,l)\}_l + G\{W_G(k,l)\}_l L\{I_G(k,l)\}_l + G\{W_B(k,l)\}_l L\{I_B(k,l)\}_l \tag{10}$$

Reconstructed image (R_i) has the same dimensions as the source image. Pixel values are scaled linearly from $[0, max(R_i)]^{to}$ to $[0,1]$ representing the luminance component effectively as in Eq.(11).

$$L_{recon(u,v)} = \gamma(R_i(u,v),l) \tag{11}$$

where correction function $\gamma(R_i(u,v),l)$ is used for gamma adjustment with factor 1.

3.3. Color Correction

Following the integration of illuminance restoration, color correction is applied to the merged image to ensure natural color representation and contrast improvement applying a technique that fuses RGB and HSV color spaces.

Underwater images exhibit significant red-light absorption, causing a bluish-green tint that reduces image clarity. The proposed method applies a two-step color correction approach such as white balance adjustment and saliency detection-based enhancement.

3.3.1. White Balance Adjustment

The red frequency is enhanced based on the attenuation levels in the blue and green channels. By evaluating pixel-wise attenuation, the method selectively amplifies red tones to restore color balance. This ensures that objects appear more natural and enhances visibility for objects at different depths.

3.3.2. Saliency Detection-Based Enhancement

Saliency detection identifies important regions within the image and enhances their prominence by adjusting brightness and contrast dynamically. This technique reduces background noise and improves object distinguishability in murky waters. Additionally, histogram equalization is applied in the HSV color space to further refine saturation and luminance. By combining these methods, the proposed technique ensures enhanced color representation and structural details, surpassing conventional enhancement techniques. The submarine image is transmuted from HSV to RGB, with preliminary color correction applied to each component (R, G, B) to compensate for disparities in illuminance (Eq.(12)).

$$I_{T,RGB(c,d)}\left(\frac{R_{i,RGB(c,d)}}{L_{econ(c,d)}}\right)^{a}\left(\frac{I_{R(c,d)}+I_{G(c,d)}+I_{B(c,d)}}{3}\right) \tag{12}$$

During the color correction of underwater images, the red component experiences significant attenuation, while the blue and green constituents stay unaffected. A refined white balance method corrects for red tones based on the levels of the green and blue frequencies. Recompense levels are evaluated by the red frequency pixel cost and the data available in the frequencies of blue and green. Smaller compensation values are needed for high red frequency pixel values or limited data in blue and green frequencies. Increased recompense is required for pixels exhibiting lower red frequency while displaying greater blue and green frequency information. Compensation with the green frequency is required when the blue constituent is significantly reduced. Artificial diminution is implemented on the green or blue frequency as needed in this process. The recompense formula for the red frequency is established by normalizing the RGB image values to a range of $[0,1]$ Eq.(13).

$$I_{c,r}=I_{t,r}+\frac{1}{2}*\left(\frac{avg(I_{t,g})-avg(I_{t,r})}{avg(I_{t,r})+avg(I_{t,g})+avg(I_{t,b})}\right)*\left(1-I_{t,g}\right)+\frac{1}{2}\left(\frac{avg(I_{t,b})-avg(I_{t,r})}{avg(I_{t,r})+avg(I_{t,g})+avg(I_{t,b})}\right)*\left(1-I_{t,r}\right)*I_{t,b} \tag{13}$$

where $I_{c,r}$ is the amended red frequency and $avg(I)$ is the average pixel strength. Higher $avg(I_{t,g})$ than $avg(I_{t,b})$ designates higher attenuation of blue constituent with explicit formulations as in (Eqs.(14),(15)).

$$I_{c,b}=I_{t,b}+\left(\frac{avg(I_{t,g})-avg(I_{t,b})}{avg(I_{t,r})+avg(I_{t,g})+avg(I_{t,b})}\right)*\left(1-I_{t,b}\right)*I_{t,g} \tag{14}$$

$$I_{c,b}=I_{t,b}+\left(\frac{avg(I_{t,g})-avg(I_{t,b})}{avg(I_{t,r})+avg(I_{t,g})+avg(I_{t,b})}\right)*I_{t,g} \tag{15}$$

Formulation for blue constituent attenuation is depicted as follows (Eq.(16)):

$$I_{c,b}=I_{t,b}+\left(\frac{avg(I_{t,b})-avg(I_{t,g})}{avg(I_{t,r})+avg(I_{t,g})+avg(I_{t,b})}\right)*I_{t,b} \tag{16}$$

After adjusting pixels with artificial systems, we incorporated the saliency detection method by Hou et al. [30] to classify crucial areas in submarine scenes by analysing spectral residue. The aim is to augment visually crucial areas in submarine scenes. Amended white balance submarine image $\left(I_{WBal}\right)$ is grounded on the saliency map $(salMap)$ as in Eq.(17).

$$\left(I_{WBal}\right)=I_C+salMap*I_C \tag{17}$$

The saliency map is used to preserve sections surpassing a specified threshold, followed by a non-masked perfecting procedure.

$$\left(I_p\right) = I_{WBal} + \frac{1}{4} Norm\left(I_{WNal} - g \otimes I_{WBal}\right) \tag{18}$$

Linear normalization of a submarine scene is represented by $Norm(I)$, while a Gaussian filter is denoted by g in (Eq.(18)). A submarine scene can seem hazy owing to similar colors and reduced saturation. Histogram equalization is utilized to improve image acuity and enhance contrast, leading to a distinct and more appealing submarine image. Nevertheless, this technique may result in considerable color alterations and diminished detail in definite regions. To accomplish this, histogram equalized and optimized submarine scenes are converted into the HSV space, combined with original restored illuminance, and then subjected to gamma rectification to attain the preferred enhancements in the ultimate submarine scene.

$$H_{enh} = H_{perf} \tag{19}$$

$$S_{enh} = \gamma\left(\lambda_1 * S_{perf} + \left(1-\lambda_1\right) S_{histq}, \alpha\right) \tag{20}$$

$$V_{enh} = \gamma\left(\lambda_2 * V_{perf} + \lambda_3 * V_{histq} + \left(1-\lambda_1-\lambda_3\right) R_i, \beta\right) \tag{21}$$

In HSV color space, H_{perf}, S_{perf}, and V_{perf} are elements of perfected image. S_{histq} and V_{histq} are saturation and illuminance components post-histogram equalization. Correction coefficients α, β weighting factors λ_1, λ_2 and λ_3 are used. λ_1, λ_2, λ_3 must be within $[0,1]$ range, sum of λ_2 and λ_3 should also be in range(Eqs.(19)-(21)) . Image converted to RGB as I_{enh}. The submarine image is processed based on the gray world principle [31] for improved performance in submarine conditions. To achieve this, a scaling factor F is calculated by identifying the maximum mean intensity across the color channels, capped at a threshold of 0.375 and adjusted by a 1.2 gain (Eq.(22)).

$$F = 1.2 * \min(\max(\overline{I_{enh,r}}, \overline{I_{enh,g}}, \overline{I_{enh,b}}), 0.375) \tag{22}$$

Wherein $S \in \{R, G, B\}$ and $I_{enh,r}$, $I_{enh,g}$, $I_{enh,b}$ depicts the consequential image that represent the mean frequencies of the RGB channels in the enhanced submarine scene I_{enh} and I_{res} signifies the resulting scene (Eq.(23)).

$$I_{res,s} = \frac{F * I_{enh,s}}{I_{enh,s}} \tag{23}$$

4. Application in Real-World Scenarios and Scalability

The applicability of the suggested process in actual underwater imaging settings is of great importance, particularly in fields such as aquatic biology, underwater surveillance, and autonomous vehicle navigation. In practical underwater environments, factors such as varying lighting conditions, depth-dependent color attenuation, and turbidity introduce challenges that can degrade image quality. The proposed enhancement approach addresses these challenges by dynamically adjusting to different water conditions, ensuring robust performance across assorted underwater settings. For real-world deployment, the method can be integrated into underwater camera schemes used in remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs). By implementing the enhancement model in onboard processing units, real-time image correction can be achieved, facilitating clearer underwater visual feedback for navigation and exploration. Furthermore, the method's adaptability makes it suitable for applications in underwater archaeology, deep-sea exploration, and fisheries monitoring, where image clarity is crucial for data interpretation. Regarding scalability, the proposed approach is designed to handle large-scale datasets effectively.

The model's multi-resolution synthesis framework ensures efficient processing of high-resolution underwater images without excessive computational overhead. Additionally, the method's modular design allows for parallelized implementation, making it feasible for large-scale underwater data analysis tasks. This is particularly useful in applications involving extensive datasets, such as coral reef monitoring programs and oceanographic surveys, where large volumes of underwater imagery need to be processed efficiently. Future work will explore optimizing computational efficiency further, enabling real-time enhancement on embedded hardware with limited processing capabilities. By improving scalability, the proposed method can be extended to large-scale underwater monitoring

systems, supporting abiding studies of aquatic biotas and improving the accuracy of underwater visual sensing technologies.

5. Limitations of the Proposed Method

Regardless of its effectiveness, the proposed method has some limitations. Computational complexity remains a challenge, as the multi-resolution synthesis and illuminance reconstruction require substantial processing power, limiting real-time deployment on low-power systems. While optimizations are in progress, high-resolution image processing remains resource-intensive. Another issue is over-enhancement, where certain images may exhibit excessive sharpening or unnatural color corrections, particularly in extremely turbid waters. This can be mitigated by further tuning adaptive parameters based on water conditions. Rapid changes in ambient lighting due to moving waves or artificial sources may affect enhancement consistency. Future improvements in exposure correction mechanisms could help address this issue. Despite these limitations, the projected technique represents a substantial advancement in subaquatic image augmentation. Ongoing research will focus on improving computational efficiency, refining adaptive enhancement strategies, and enhancing generalizability across diverse underwater conditions.

6. Trade-off Between Image Quality Enhancement and Information Loss

While improving image quality is the primary goal of enhancement techniques, there exists a critical trade-off amongst augmentation and potential data loss. Excessive enhancement, particularly in deep learning-based methods, may lead to artifacts, over-saturation, and the suppression of subtle details present in the original image. In contrast, under-enhancement may fail to adequately restore degraded images, leaving them with poor visibility and insufficient contrast. The proposed method balances this trade-off by implementing an adaptive enhancement strategy. The weight map-based fusion strategy selectively enhances high-information regions while preserving low-contrast areas that might otherwise be lost due to aggressive enhancement. This approach prevents unwanted artifacts and ensures that fine details, such as texture and object boundaries, are retained.

Furthermore, the incorporation of multi-resolution synthesis allows for localized enhancement, avoiding over-processing of homogeneous regions while improving contrast in critical areas. Quantitative evaluations support this balance, as indicated by the method's superior performance across multiple perceptual metrics (UIQM, NIQE, PCQI, and MUSIQ). As shown in Tables 1 and 2, the proposed technique consistently outperforms traditional methods while maintaining image fidelity. The results demonstrate that the method effectively enhances contrast, sharpness, and color consistency without introducing significant information loss.

Additionally, visual assessments reveal that enhanced images maintain their structural integrity, ensuring that objects and textures remain clear and discernible. Future research will explore further refinements, including adaptive parameter tuning based on image content, to dynamically control the level of enhancement applied to different underwater scenes. By optimizing the balance between enhancement and information preservation, the proposed method provides a reliable and adaptable solution for underwater imaging challenges.

7. Results and Discussion

The effectiveness of the proposed color correction strategy is demonstrated through qualitative and quantitative evaluations. The white balance correction significantly improves the natural appearance of underwater images by counteracting excessive blue and green dominance. Figures 7 and 8 illustrate that the projected method successfully restores color tones while maintaining high contrast and detail preservation using datasets provided by Li et al. [32] and Liu et al. [33]. These databases include 950 real underwater images, alongside 200 images and 2,840 images, respectively. Li et al. 's method encounters challenges with 60 difficult images. The study will perform a detailed analysis and assessment of the efficacy of several methods by examining generated submarine images across diverse ecological environments, using both impartial and independent evaluations on different standard and challenging datasets.

7.1. Evaluation of Luminosity Reconstruction

Luminosity reformation is utilized to retain the essential details in every frequency and improve quality and dependability. Fig.5 exhibits instances of the illuminance restoration outcomes for various images from the dataset. In Fig.5(i), the original image required excessive illuminance, causing a loss of details, which was corrected in the restoration. Fig.5(ii) depicts white substances that are immersed and affected by high exposure in the original map but highlighted in the reconstruction. In Fig.5(iii), the restored illuminance augments contrast amongst the fragments. Lastly, Fig.5(iv) depicts improved texture discernibility from the previously unclear in the original submarine image illuminance. Experimental results in Fig.5(v) support the theory in the third section, depicting the restored illuminance map advances discernibility by conserving blue and green frequency information near rocks and adding red channel information as required.

7.2. Qualitative Evaluation

Throughout the testing period, the model was assessed solely using low-quality images to determine its efficacy in improving image resolution and color accuracy. The model presented in this paper, as depicted in Fig.6(i) & (ii), exhibited remarkable performance by successfully eliminating common underwater image distortions such as whitening, graying, and bluing phenomena, while also significantly enhancing color restoration. The model demonstrated the ability to restore the smoothness of objects. Furthermore, our system demonstrated exceptional proficiency in the reinstatement of fine details. As presented in Fig.6(iii) & (iv) the prototype effectively preserved and enhanced the multifaceted and diverse rectilinear and arched surfaces present in submarine images, resulting in a noticeable super-resolution effect. Subsequent experimentation involved a comparative analysis of the efficacy of various methods for enhancing underwater images in real-world scenarios, including approaches based on diffusion models like DM_uw [34], IDDPM [35], FUnIE-GAN [36] and TACL [37]. In order to facilitate a reasonable evaluation, a standardized selection of submarine images was chosen as the consistent test set. Fig.7 depicts that our exploration revealed that certain models exhibited shortcomings in color restoration, characterized by either excessive color saturation or insufficient submarine image brightness.

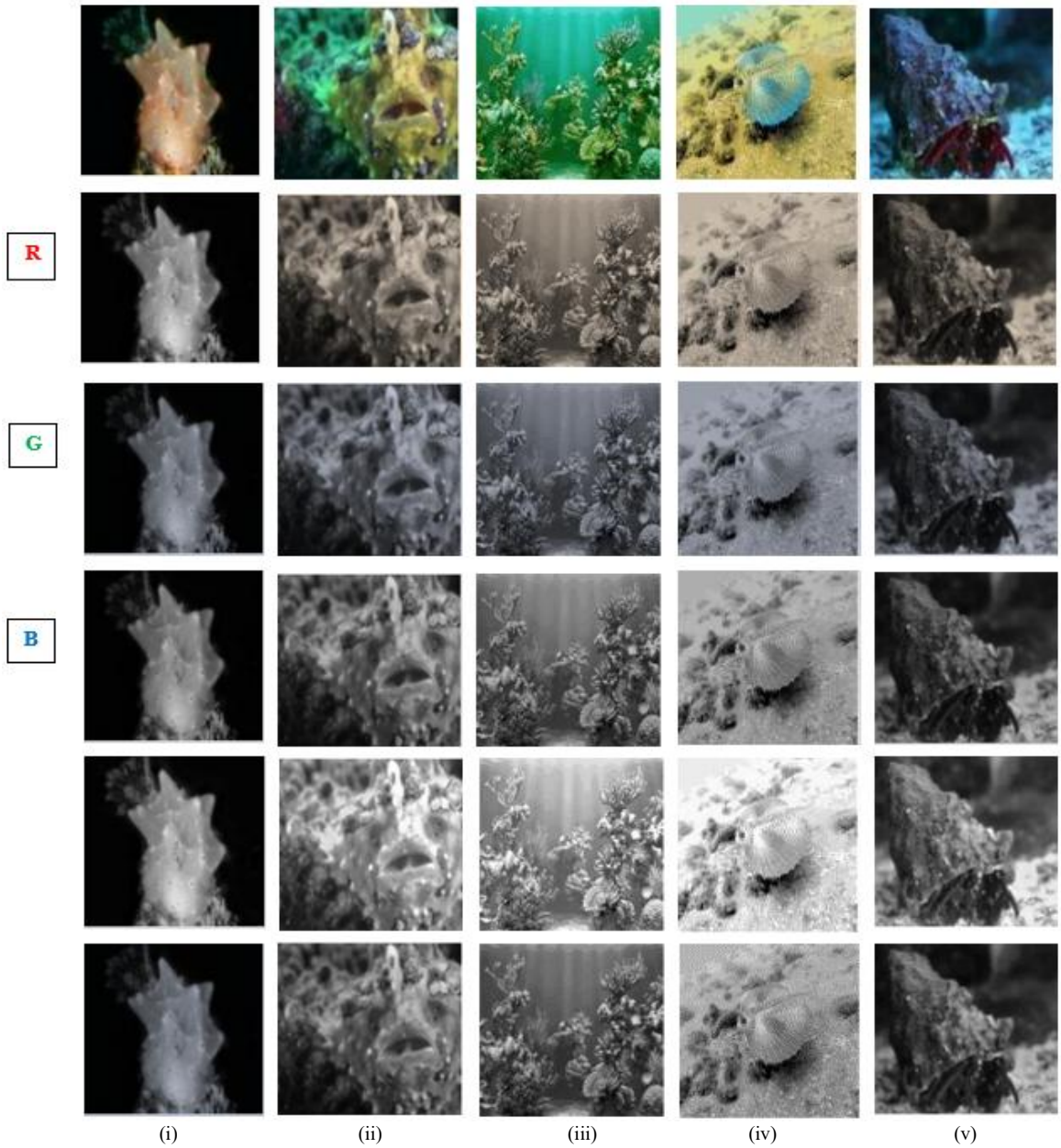


Fig.5. Illustration of illuminance restoration. Arranged horizontally are five submarine images (i-v) and organized vertically as follows: original submarine images, RGB components of the original submarine images, the novel illuminance components of the submarine portrait, and the restored luminance constituents

7.3. Quantitative Evaluation

In addition, extensive comparative experiments were performed based on the U45 and UIEB datasets in testing the efficiency of the proposed EDUI framework. So far, the effectiveness of the EDUI framework has been tested in an objective manner by using UIQM [38], MUSIQ [39], NIQE [40], and PCQI [41]. The quantitative results of the two data sets are presented in Table 1. and Table 2.

A. Performance on the U45 Dataset

As may be deduced from Table 1 above, the proposed EDUI scheme exhibits a competitive advantage. This is because the high level of naturalness is attained by the scheme, evidenced by the NIQE of 4.406 compared to other complex models such as the Ucolor [42], with only 4.761. MUSIQ attains the highest score of 47.169 compared to other schemes. Furthermore, the PCQI attains the highest value of 1.16 compared to other schemes. Though the UIQM attains a comparable value, the balanced analysis shows that the realism is achieved without saturation. In addition, conventional methods such as UDCP show poor efficiency in enhancing the brightness and color qualities, as seen in Fig. 7. Although the IBLA method in [48] is operational, it produces blurring and color bias effects. In addition, the efficiency of the UWCNN and FUnIE-GAN methods is hindered in the case of high turbidity and illumination, and the efficiency of the Ucolor and UDNet methods is not adequate in eliminating color casts.

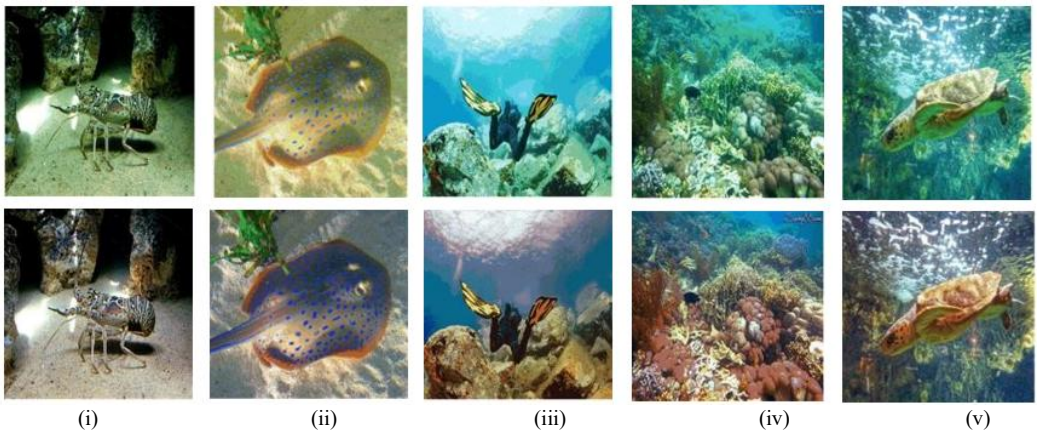


Fig. 6. The influence of our model EDUI on augmenting the quality of underwater images. The addition of components (i,ii) greatly enhances the color lushness of the new image, while (iii,iv) augment the image clarity

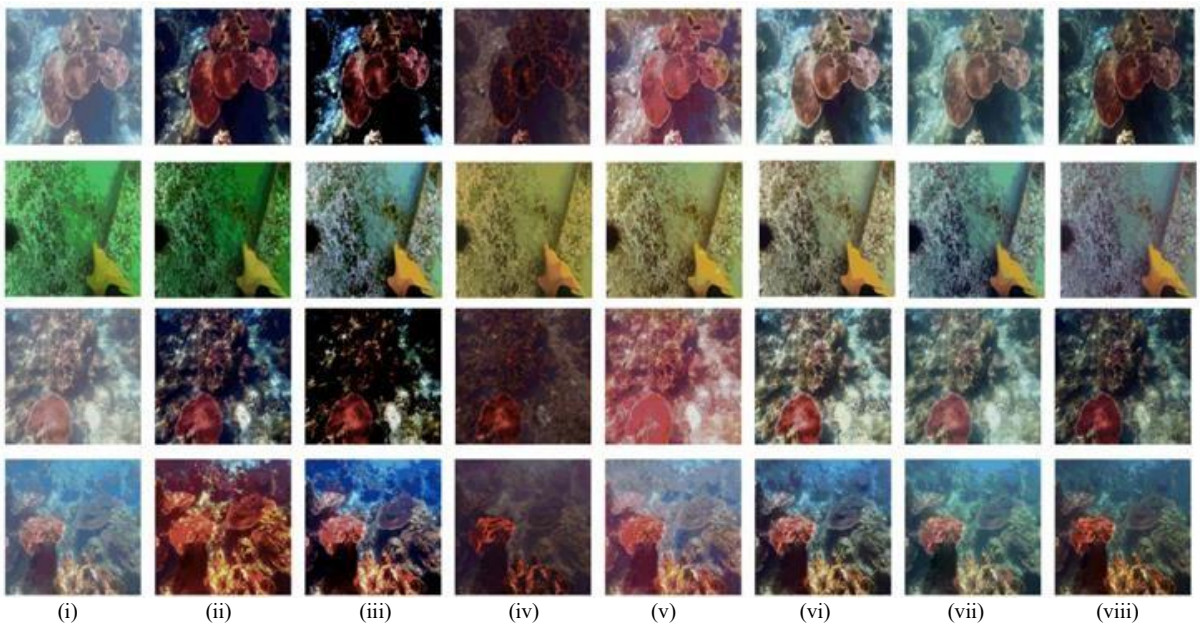


Fig. 7. Assessment of various techniques on the U45 database. (i) Original image (ii)UDCP (iii) IBLA (iv)UWCNN (v)FUnIEGAN (vi)Ucolor (vii)UDNet (viii)EDUI (Proposed)

B. Performance on the UIEB Dataset

The efficiency of the EDUI approach is again validated by its performance on a larger UIEB dataset, which is

shown in Table 2. The proposed approach again outperforms all the conventional baselines in the important evaluation criteria. Specifically, it has achieved the highest UIQM score, which is 5.00, compared to other state-of-the-art FUnIE-GAN, which has a score of 4.97. Furthermore, the lowest NIQE score of 4.30 is reported, verifying that the enhancement process retains the natural statistical characteristics of the image without artificially introducing artifacts. The efficacy of the framework is also established by attaining MUSIQ scores of 49.56 and PCQI scores of 1.19, thereby validating the efficiency of the channel decoupling method in detecting changes in the lighting.

C. Histogram Analysis and Visual Validation

Fig.8. presents a comparative histogram analysis between the raw underwater images and the enhanced results using the proposed EDUI framework. It can be seen that the histograms of the original images, shown in Fig. 8.(i) and Fig.8.(iii), are narrow and skewed, primarily concentrated in the blue and green channels, indicating a severe color cast and a lack of dynamic range. After the EDUI method has been applied, from Fig. 8.(ii) and 8.(iv), it is observed that the histograms show a much wider distribution over the dynamic range. Indeed, the red channel has been successfully restored and aligned with the other two green and blue channels. The re-distribution of the pixel intensities agrees with our objective metric gains; higher UIQM score indicates better perceptual quality while lower NIQE values confirm the suppression of the artifacts. These results validate that the coupled illuminance reconstruction and color correction effectively suppress the optical distortions specific to water.

D. Generalizability and Dataset Limitations

While the experiments were conducted on widely used underwater datasets such as U45 and UIEB, it is essential to evaluate the method's performance on a broader range of underwater datasets. Different underwater environments exhibit varying optical properties due to differences in water clarity, depth, turbidity, and lighting conditions. To further establish the robustness and generalizability of the proposed method, future work will focus on testing additional datasets such as Seathru[43], EUVP[44], and UFO-120[45]. These datasets provide a diverse range of real-world underwater conditions, enabling a more comprehensive validation of the proposed approach. Moreover, incorporating synthetic datasets can help in training deep learning model under controlled conditions, ensuring adaptability to a wide range of underwater scenarios. The ability of the model to generalize across different water conditions makes it suitable for applications such as marine exploration, underwater robotics, and environmental monitoring. Future extensions of this work will aim to improve adaptability by integrating domain adaptation techniques and evaluating cross-dataset performance metrics. By integrating illuminance reconstruction with advanced color correction and emphasizing dataset diversity, the proposed system augments underwater image quality more effectively than traditional dehazing or contrast-enhancement techniques, making it suitable for real-world applications in underwater monitoring and exploration.

Table 1. Quantitative assessment of U45 database using UIQM, NIQE, PCQI and MUSIQ metrics. Blue color represents the highest level of performance, while purple indicates the second highest level. An upward arrow indicates superior algorithm performance with higher values, while a downward arrow signifies improved performance with lower values

Metrics	UDCP	IBLA	UWCNN	FUnIEGAN	Ucolor	UDNet	(EDUI) Proposed
NIQE ↓	4.413	4.937	4.912	3.535	4.761	4.642	4.406
MUSIQ ↑	44.893	44.046	40.674	45.348	47.047	44.634	47.169
UIQM ↑	3.553	3.024	3.836	4.629	4.724	4.456	4.273
PCQI ↑	0.72	0.65	0.73	0.62	0.96	0.86	1.16

Table 2. Quantitative assessment of UIEB database using UIQM, NIQE, PCQI and MUSIQ metrics. Blue color represents the highest level of performance, while purple indicates the second highest level. An upward arrow indicates superior algorithm performance with higher values, while a downward arrow signifies improved performance with lower values

Metrics	UDCP	IBLA	UWCNN	FUnIEGAN	Ucolor	UDNet	(EDUI) Proposed
NIQE ↓	4.91	5.38	5.31	4.64	5.18	4.78	4.3
MUSIQ ↑	46.99	42.04	42.57	47.54	44.74	46.73	49.56
UIQM ↑	3.96	3.4	4.19	4.97	4.38	4.78	5.00
PCQI ↑	0.79	0.71	0.81	0.69	1.05	0.94	1.19

E. Statistical Validation of Experimental Results

We conducted the Wilcoxon Signed-Rank Test[46] and the Paired t-test[47] between our method's scores and the second-best performing method to verify that improvements are statistically significant and not based on random variance. As shown in Table III, the results report p-values less than the threshold of α=0.05, with $p \leq 0.005$ for all considered metrics. Hence, the null hypothesis is rejected with 95% confidence, confirming that the performance gains offered by the proposed framework "EDUI" are statistically significant.

Table 3. Statistical Validation of Experimental Results. An upward arrow indicates superior algorithm performance with higher values, while a downward arrow signifies improved performance with lower values

Metrics	Proposed (Mean)	Second Best Method	Paired	Wilcoxon Test (p)
NIQE↓	**4.30**	4.64 (FUnIEGAN)	0.002	0.004
MUSIQ↑	**49.56**	47.54 (FUnIEGAN)	0.002	0.004
UIQM ↑	**5.00**	4.97 (FUnIEGAN)	0.003	0.005
PCQI ↑	**1.19**	1.05 (Ucolor)	0.001	0.003

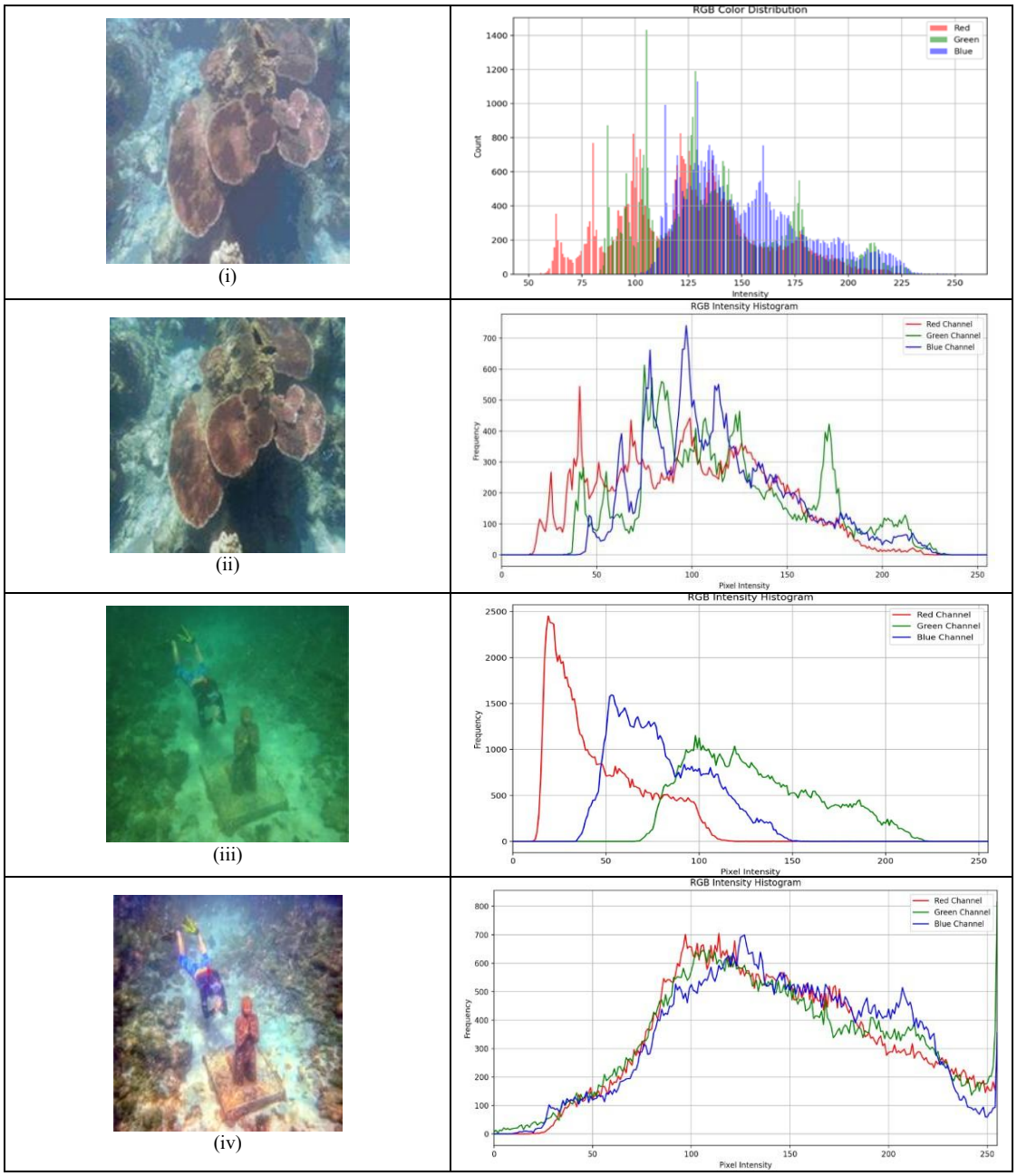


Fig.8. Histogram analysis of underwater image enhancement. (i) and (iii) represent the original underwater images and their respective skewed RGB distributions. (ii) and (iv) illustrate the enhanced results and the balanced color histograms achieved by the proposed EDUI framework

F. Analysis of Constraints and Limitations

Despite its effectiveness, the proposed method has some limitations. Computational complexity remains a challenge, as the multi-resolution synthesis and illuminance reconstruction require substantial processing power, limiting real-time deployment on low-power systems. While optimizations are in progress, high-resolution image processing remains resource-intensive. Another issue is over-enhancement, where certain images may exhibit excessive sharpening or unnatural color corrections, particularly in extremely turbid waters. This can be mitigated by further tuning adaptive parameters based on water conditions. Rapid changes in ambient lighting due to moving waves or

artificial sources may affect enhancement consistency. Future improvements in exposure correction mechanisms could help address this issue. Despite these limitations, the projected technique represents a substantial advancement in subaquatic image augmentation. Ongoing research will focus on improving computational efficiency, refining adaptive enhancement strategies, and enhancing generalizability across diverse underwater conditions.

8. Implementation Details of the Proposed Algorithm

To facilitate reproducibility, the following details elaborate on the implementation of the proposed method. The overall logic is summarized in Algorithm 1.

Step 1: Preprocessing:

Transform the input submarine image to the HSV or LAB color space and apply a guided filter to reduce noise while preserving edges.

Step 2: Light Attenuation Estimation

Compute the dark channel of the image as defined in Algorithm 2 to estimate the level of light absorption

Step 3: Transmission Map Calculation

Compute the transmission map as detailed in Algorithm 3 and then apply guided filtering to refine the transmission map.

Step 4: Restoration of the Image

Perform inverse haze removal and clip values to ensure pixel intensity remains in the valid range [0, 255].

Algorithm 1 Enhanced Dehazed Underwater Image (EDUI)

Input: Hazy Underwater Image (I)

Output: Dehazed Image I_{final}

1: $I_{hsv} = Convert\,To\,Color\,Space(I, "HSV")$
2: $D_{channel} = Compute\,Dark\,Channel(I_{hsv})$
3: $A = Estimate\,Atmospheric\,Light(I, D_{channel})$
4: $t = Estimate\,Transmission\,Map(I, A)$
5: $\omega = 0.95; //\ Haze\,\text{inf}\,luencecontsant$
6: $for\ each\ pixel(s,u)\ in\ I\ do$
7: $I_{dehazed}(s,u) = \dfrac{I(s,u) - A}{t(s,u)}$
8: $I_{dehazed}(s,u) = Clip(I_{dehazed}(s,u), 0, 255)$
9: $end\ for$
10: $I_{en} = Apply\,Contrst\,Adjustment(I_{dehazed})$
11: $I_{final} = Apply\,Color\,Correction(I_{en})$
12: $renturn\,I_{final}$

Fig.9. EDUI algorithm

Algorithm 2 Compute Dark Channel

Input: Image (I)

Output: Dark Channel Map $D_{channel}$

1: $D_{channel} = Initialize\,Dark\,Channel(I)$
2: $for\ each\ pixel(s,u)\ in\ I\ do$
3: $D_{channel}(s,u) = \min(I(s,u).R, I(s,u).G, I(s,u), B)$
4: $end\ for$
5: $return\,D_{channel}$

Fig.10. Compute dark channel algorithm

Algorithm 3 Estimate Transmission Map

Input: Image (I), Atmospheric Light A

Output: Refined Transmission Map $t_{refined}$

$\omega = 0.95;$ // *Constant to retain a small amount of haze*

$t = InitializeTransmissionMap(I)$

for each $pixel(s,u)$ *in* I *do*

$t(s,u) = 1 - \omega \cdot \left(\frac{D_{channel}(s,u)}{A} \right)$

end for

$t_{refined} = RefineTransmissionMap(t);$ // *Using guided filter*

return $t_{refined}$

Fig.11. Transmission map estimation algorithm

Step 5: Post-processing

Apply contrast enhancement (histogram equalization or contrast stretching). Perform color correction using white balance adjustment. Transform the processed submarine image into the RGB space.

The execution was carried out using Python with OpenCV and NumPy for image processing tasks. For deep learning components, PyTorch was used to fine-tune enhancement parameters dynamically. The algorithm was tested on an NVIDIA RTX GPU to accelerate computation, with processing times averaging 0.5 seconds per image for 1080p resolution.

9. Conclusion and Future Directions

In the present study, an innovative system for enhancing underwater images, referred to as EDUI, has been proposed to address the challenges of color distortion, poor contrast, and image degradation due to the scattering and absorption of light. Specifically, the novelty of the presented approach has been highlighted in the application of Multi-Channel Illuminance Reconstruction, Enhanced Color Correction, and Scalability of the technique, which have been validated through experimental tests using the datasets of U45 and UIEB, in addition to the statistically rigorous performance verification using the Wilcoxon Test and the Paired t-Test. The novelty of the image enhancement technique would be particularly beneficial in the field of submarine exploration and subaqueous investigation using autonomous devices and systems, which has been addressed while proposing the possibilities of enhancing the computational efficiency, diversity of the dataset, and the inclusion of adaptive learning techniques to address the challenges of image enhancement, which would further propel the field of underwater image restoration for various engineering and scientific applications.

Author Contributions Statement

Sumalatha A: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data Curation, and Writing – Original Draft: Conducted the entire research process, including the development of the EDUI framework, model implementation, data processing, experimental analysis, and drafting the manuscript.
Aruna S. K: Supervision and Writing – Review & Editing: Provided oversight for the research project and contributed to the final review and refinement of the manuscript.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Declaration

The authors received no financial support for the research, authorship, and/or publication of this article.

Data Availability Statement

This study analyzed publicly available datasets. The results obtained and datasets can be found here: “UIEB Dataset: https://li-chongyi.github.io/proj_benchmark.html. U45 Dataset: https://github.com/IPUI-Lab/U45”, accessed on January 20, 2026.

Ethical Declarations

The authors declare that this study did not involve human subjects and/or animals.

Acknowledgments
We sincerely thank the experts for their professional evaluation and valuable recommendations, which have contributed to improving the quality of the experiment and the reliability of its results.

Declaration of Generative AI in Scholarly Writing
The authors declare that no AI or AI-assisted technologies were used during the writing process of this manuscript.

Abbreviations
The following abbreviations are used in this manuscript:

RGB – Red, Green, Blue
HSV – Hue, Saturation, Value
DCP – Dark Channel Prior
GDCP – Generalized Dark Channel Prior
AHE – Adaptive Histogram Equalization
CLAHE – Contrast Limited Adaptive Histogram Equalization
CNN – Convolutional Neural Network
GAN – Generative Adversarial Network
UIE-Net – Underwater Image Enhancement Network
UGAN – Underwater Generative Adversarial Network
EDUI – Enhanced Dehazed Underwater Image
ROV – Remotely Operated Vehicle
AUV – Autonomous Underwater Vehicle
SSIM - Structural Similarity Index
UCIQE - Underwater Color Image Quality Evaluation
UIEB - Underwater Image Enhancement Benchmark
U45 - Underwater 45 Dataset

References

[1] Nnolim, Uche. (2017). Improved underwater image enhancement algorithms based on partial differential equations (PDEs). https://doi.org/10.48550/arXiv.1705.04272
[2] Han, M.; Lyu, Z.; Qiu, T.; Xu, M. A Review on Intelligence Dehazing and Color Restoration for Underwater Images. IEEE Trans. Syst. Man Cybern. Syst. 2020, 50, 1820–1832. https://doi.org/10.1109/TSMC.2017.2788902
[3] Ma, J.; Fan, X.; Wu, Z.; Zhang, X.; Shi, P.; Gengren, W. Underwater dam crack image enhancement algorithm based on improved dark channel prior. J. Image Graph. 2016, 21, 1574–1584. https://dx.doi.org/10.11834/jig.20161202
[4] Zhang, W.; Dong, L.; Pan, X.; Zou, P.; Qin, L.; Xu, W. A Survey of Restoration and Enhancement for Underwater Images. IEEE Access 2019, 7, 182259–182279. https://doi.org/10.1109/ACCESS.2019.2959560
[5] McGlamery, B. A Computer Model for Underwater Camera Systems; SPIE: Bellingham, WA, USA, 1980; Volume 0208. https://doi.org/10.1117/12.958279
[6] Deluxni, N.; Sudhakaran, P.; Kitmo; Ndiaye, M.F. A Review on Image Enhancement and Restoration Techniques for Underwater Optical Imaging Applications. IEEE Access 2023, 11, 111715–111737. https://doi.org/10.1109/ACCESS.2023.3322153
[7] Wang, N.; Zheng, H.; Zheng, B. Underwater Image Restoration via Maximum Attenuation Identification. IEEE Access 2017, 5, 18941–18952. https://doi.org/10.1109/ACCESS.2017.2753796
[8] Singh, N., Bhat, A. A systematic review of the methodologies for the processing and enhancement of the underwater images. Multimed Tools Appl 82, 38371–38396 (2023). https://doi.org/10.1007/s11042-023-15156-9
[9] Y. Wang, H. Liu and L. -P. Chau, "Single underwater image restoration using attenuation-curve prior," 2017 IEEE International Symposium on Circuits and Systems (ISCAS), Baltimore, MD, USA, 2017, pp. 1-4. https://doi.org/10.1109/ISCAS.2017.8050994
[10] Hou, G.; Li, J.; Wang, G.; Yang, H.; Huang, B.; Pan, Z. A novel dark channel prior guided variational framework for underwater image restoration. J. Vis. Commun. Image Represent. 2020, 66, 102732. https://doi.org/10.1016/j.jvcir.2019.102732
[11] Ebner, M. Color Constancy; Wiley Publishing: Hoboken, NJ, USA, 2007. https://doi.org/10.1002/9780470510490
[12] Kaiming, H.; Jian, S.; Xiaoou, T. Single image haze removal using dark channel prior. In Proceedings of the 2009 IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, USA, 20–25 June 2009; pp. 1956–1963. https://doi.org/10.1109/CVPRW.2009.5206515
[13] Drews, P., Jr.; Nascimento, E.d.; Moraes, F.; Botelho, S.; Campos, M. Transmission Estimation in Underwater Single Images. In Proceedings of the 2013 IEEE International Conference on Computer Vision Workshops, Sydney, Australia, 2–8 December 2013; pp. 825–830. https://doi.org/10.1109/ICCVW.2013.113
[14] Galdran, A.; Pardo, D.; Picón, A.; Alvarez-Gila, A. Automatic Red-Channel underwater image restoration. J. Vis. Commun. Image Represent. 2015, 26, 132–145. https://doi.org/10.1016/j.jvcir.2014.11.006

[15] Tang, Z.; Zhou, B.; Dai, X.; Gu, H. Underwater Robot Visual Enhancements Based on the Improved DCP Algorithm. Jiqiren/Robot 2018, 40, 222–230. https://doi.org/10.13973/j.cnki.robot.170251
[16] Peng, Y.T.; Cao, K.; Cosman, P.C. Generalization of the Dark Channel Prior for Single Image Restoration. IEEE Trans. Image Process. 2018, 27, 2856–2868. https://doi.org/10.1109/TIP.2018.2813092
[17] Tao, Yu & Chen, Honggang & Peng, Zijun & Tan, Renxuan. (2023). Underwater image enhancement via red channel maximum attenuation prior and multi-scale detail fusion. Optics Express. 31. 26697-26723. https://doi.org/10.1364/OE.494638
[18] Hu, Kai & Weng, Chenghang & Zhang, Yanwen & Jin, Junlan & Xia, Qingfeng. (2022). An Overview of Underwater Vision Enhancement: From Traditional Methods to Recent Deep Learning. Journal of Marine Science and Engineering. https://doi.org/10.3390/jmse10020241
[19] Trucco, E.; Olmos-Antillon, A.T. Self-Tuning Underwater Image Restoration. IEEE J. Ocean. Eng. 2006, 31, 511–519. https://doi.org/10.1109/JOE.2004.836395
[20] S. M. Pizer, E. P. Amburn, J. D. Austin, et al.: Adaptive Histogram Equalization and Its Variations. Computer Vision, Graphics, and Image Processing 39 (1987) 355-368. https://doi.org/10.1016/S0734-189X(87)80186-X
[21] Z. Mahmood, N. Muhammad, N. Bibi, Y. M. Malik, and N. Ahmed, "Human visual enhancement using Multi Scale Retinex," Informatics in Medicine Unlocked, vol. 13, pp. 9–20, 2018, https://doi.org/10.1016/j.imu.2018.09.001
[22] Liang, Dan, et al. “NPT-UL: An Underwater Image Enhancement Framework Based on Non-Physical Transformation and Unsupervised Learning.” IEEE Transactions on Geoscience and Remote Sensing, 1 Jan. 2024, pp. 1–1. https://doi.org/10.1109/tgrs.2024.3363037
[23] Zhu, Daqi, et al. “Underwater Image Enhancement Based on Colour Correction and Fusion.” IET Image Processing, 2 May 2021. https://doi.org/10.1049/ipr2.12247
[24] Zhu Shidong, et al. Enhancement of Underwater Images by CNN-Based Color Balance and Dehazing. Vol. 11, no. 16, 13 Aug. 2022, pp. 2537–2537. https://doi.org/10.3390/electronics11162537
[25] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y., "Generative Adversarial Networks," Advances in Neural Information Processing Systems, vol. 27, pp. 2672–2680, 2014. https://doi.org/10.1145/3422622
[26] Zhang, Weidong, et al. “Color Correction and Adaptive Contrast Enhancement for Underwater Image Enhancement.” Computers & Electrical Engineering, vol. 91, 1 May 2021, pp. 106981–106981. https://doi.org/10.1016/j.compeleceng.2021.106981
[27] Espinosa, A.R.; McIntosh, D.; Albu, A.B. An Efficient Approach for Underwater Image Improvement: Deblurring, Dehazing, and Color Correction. In Proceedings of the 2023 IEEE/CVF Winter Conference on Applications of Computer Vision Workshops (WACVW), Waikoloa, HI, USA, 3–7 January 2023; pp. 206–215. https://doi.org/10.1109/WACVW58289.2023.00026
[28] Abu, A., and Diamant, R. (2023). Underwater object classification combining SAS and transferred optical-to-SAS Imagery. Pattern Recognit. 144, 109868. https://doi.org/10.1016/j.patcog.2023.109868
[29] C. E. Shannon, "A mathematical theory of communication," Bell Syst. Tech. J., vol. 27, no. 3, pp. 379–423, Jul. 1948. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x
[30] X. Hou and L. Zhang, "Saliency Detection: A Spectral Residual Approach," in 2007 IEEE Conf. Comput. Vis. Pattern Recognit., Minneapolis, MN, USA, 2007, pp. 1-8. https://doi.org/10.1109/CVPR.2007.383267
[31] G. Buchsbaum, "A spatial processor model for object colour constancy," J. Frankl. Inst., vol. 310, no. 1, pp. 1-26, 1980. https://doi.org/10.1016/0016-0032(80)90058-7
[32] C. Li, C. Guo, W. Ren, R. Cong, J. Hou, S. Kwong, and D. Tao, "An Underwater Image Enhancement Benchmark Dataset and Beyond," IEEE Trans. Image Process., vol. 29, pp. 4376-4389, 2020. https://doi.org/10.1109/TIP.2019.2955241
[33] R. Liu, X. Fan, M. Zhu, M. Hou, and Z. Luo, "Real-world Underwater Enhancement: Challenges, Benchmarks, and Solutions Under Natural Light," IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 12, pp. 4861-4875, Dec. 2020, https://doi.org/10.1109/TCSVT.2019.2963772
[34] Y. Tang, H. Kawasaki, and T. Iwaguchi, "Underwater Image Enhancement by Transformer-based Diffusion Model with Non-uniform Sampling for Skip Strategy," in Proc. 31st ACM Int. Conf. Multimedia (MM '23), Ottawa, ON, Canada, 2023, pp. 5419–5427. https://doi.org/10.1145/3581783.3612378
[35] A. Q. Nichol and P. Dhariwal, "Improved Denoising Diffusion Probabilistic Models," in Proc. 38th Int. Conf. Mach. Learn. (ICML), 2021, vol. 139, pp. 8162-8171. https://doi.org/10.48550/arXiv.2102.09672
[36] C. Li, S. Anwar, and F. Porikli, "Underwater scene prior inspired deep underwater image and video enhancement," Pattern Recognit., vol. 98, p. 107038, Feb. 2020. https://doi.org/10.1016/j.patcog.2019.107038
[37] Y. Liu, S. Zhao, and Y. Cheng, "TACL: Twin Adversarial Contrastive Learning for Underwater Image Enhancement," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2022. https://doi.org/10.1109/TIP.2022.3190209
[38] K. Panetta, C. Gao, and S. Agaian, "Human-Visual-System-Inspired Underwater Image Quality Measures," IEEE J. Ocean. Eng., vol. 41, no. 3, pp. 541–551, Jul. 2016. https://doi.org/10.1109/JOE.2015.2469915
[39] J. Ke, Q. Wang, Y. Wang, P. Peyrard, C. K. Tang, and F. Lau, "MUSIQ: Multi-scale image quality transformer," in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), 2021, pp. 5148–5157. https://doi.org/10.1109/ICCV48922.2021.00510
[40] A. Mittal, R. Soundararajan, and A. C. Bovik, "Making a 'completely blind' quality analyzer," IEEE Signal Process. Lett., vol. 20, no. 3, pp. 209–212, Mar. 2012. https://doi.org/10.1109/LSP.2012.2227726
[41] S. Wang, K. Ma, H. Yeganeh, Z. Wang, and L. Lin, "A Patch-Structure Representation Method for Quality Assessment of Contrast Changed Images," IEEE Signal Process. Lett., vol. 22, no. 12, pp. 2387–2390, Dec. 2015. https://doi.org/10.1109/LSP.2015.2487369
[42] C. Li, S. Anwar, J. Hou, R. Cong, C. Guo, and W. Ren, "Underwater image enhancement via medium transmission-guided multi-color space embedding," IEEE Trans. Image Process., vol. 30, pp. 4985–5000, 2021. https://doi.org/10.1109/TIP.2021.3076367
[43] D. Akkaynak and T. Treibitz, "Sea-thru: A method for removing water from underwater images," in Proc. IEEE/CVF Conf.

Comput. Vis. Pattern Recognit. (CVPR), 2019, pp. 1682–1691. https://doi.org/10.1109/CVPR.2019.00178
[44] M. J. Islam, Y. Xia, and J. Sattar, "Fast underwater image enhancement for improved visual perception," IEEE Robot. Autom. Lett., vol. 5, no. 2, pp. 3227–3234, Apr. 2020. https://doi.org/10.1109/LRA.2020.2974710
[45] M. J. Islam, S. S. Enan, P. Luo, and J. Sattar, "Underwater image super-resolution using deep residual multipliers," in 2020 IEEE Int. Conf. Robot. Autom. (ICRA), Paris, France, 2020, pp. 900–906. https://doi.org/10.1109/ICRA40945.2020.9197213
[46] F. Wilcoxon, "Individual comparisons by ranking methods," Biometrics Bull., vol. 1, no. 6, pp. 80–83, Dec. 1945. https://doi.org/10.2307/3001968
[47] T. K. Kim, "T test as a parametric statistic," Korean J. Anesthesiol., vol. 68, no. 6, pp. 540–544, Dec. 2015. https://doi.org/10.4097/kjae.2015.68.6.540
[48] Peng, Y.T.; Cosman, P.C. Underwater Image Restoration Based on Image Blurriness and Light Absorption. IEEE Trans. Image Process. 2017, 26, 1579–1594. https://doi.org/10.1109/TIP.2017.2663846

Authors' Profiles



Sumalatha A. is a Researcher in Image Processing, Deep Learning, and Cyber Security. Holds a master's degree in Computer Science and Engineering from Visvesvaraya Technological University, Belgaum. Presently pursuing her Ph.D. in Computer Science and Engineering at CHRIST University - Kengeri Campus, Bengaluru, and her area of research lies in applying Deep Learning algorithms for Underwater Image Processing. Having a background of more than ten years in academia, Sumalatha has an excellent background in research as well.



Aruna S. K. is an Associate Professor at the Department of AI and Data Science Engineering, School of Engineering and Technology, CHRIST University - Kengeri Campus, Bengaluru and is a researcher in Machine Learning, Deep Learning, and Image Processing. She has completed her Ph.D in Information and Communication Engineering from Anna University, Chennai. She is one of the co-founders of the government funded project, "Biodegradable Hydrogel gauze from Nano Sericin and Gelatin", which has been selected by the Ministry of Micro, Small & Medium Enterprises (MSME), Government of India in August, 2022. She has over 20 years of experience in academics and has a strong passion for research and academics. She has published over 25 papers in various international and domestic journals.

How to cite this paper: Sumalatha A., Aruna S. K., "Underwater Image Dehazing: A Comprehensive Approach", International Journal of Information Technology and Computer Science(IJITCS), Vol.18, No.2, pp.31-48, 2026. DOI:10.5815/ijitcs.2026.02.03