Systematic review and analysis on underwater image enhancement methods, datasets, and evaluation metrics

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Abstract. Underwater environments can be used to explore new resources that can be employed in the fields of medical science and energy resources. Humans are dependent on the valuable resources that exist beneath Earth's surface. Underwater exploration requires enhanced images that are obtained using enhancement methods. So, it is important that underwater image enhancement (UIE) methods work well in terms of performance and accuracy. As a result, research in UIE has increased in the past few years. An extensive survey is conducted on existing UIE methods along with their broad classification, underwater datasets, and evaluation metrics, respectively. The experimental analysis is conducted to compare the existing UIE methods in terms of qualitative and quantitative evaluation metrics. The real-world applications and future scope of existing enhancement methods are highlighted and discussed. © *2022 SPIE and IS&T* [DOI: 10.1117/1.JEI.31.6.060901]

1 Introduction

Recently, exploration of the deep world below the water surface has captured the attention of scientists. The analysis of underwater images is important due to its numerous applications, such as oceanography, monitoring underwater life, and underwater military. Thus, underwater robots such as autonomous underwater vehicles and remote-controlled vehicles equipped with high-resolution imaging techniques are necessary for conducting effective research in the underwater world. Computer systems that are used to visually inspect underwater images fail as a result of poor-quality acquisition and processing of underwater images. Therefore, it is crucial to develop and improve underwater images with the help of underwater image enhancement (UIE) methods that can be used in challenging underwater conditions. Thus, this review article presents a detailed description of the existing UIE methods.

The UIE method is a way of improving the visual content of degraded underwater images that is necessary for both humans and machines to extract useful data. For example, detecting sub-sea pipeline cracks and studying marine life are heavily reliant on the captured underwater images.[1] The captured underwater image is influenced by a variety of factors, including limited visibility, uneven lighting, and faded color.[2]

The captured underwater images include important information that can be used in a variety of applications in current times.[3] However, despite the fact that there are numerous techniques for image enhancement available, these are primarily restricted to specific scenes. Moreover, the captured underwater images deteriorate because of the water medium.[4] However, with the advancement in deep learning approaches, UIE has shown great improvements.

Figure 1 shows the taxonomy of the review article. The objective of the survey is to provide an exhaustive overview of the different factors that are involved in the process of UIE and their impacts. This survey paper includes an in-depth introduction covering the features of the underwater environment. These features include the underwater image formation model (UIFM), and

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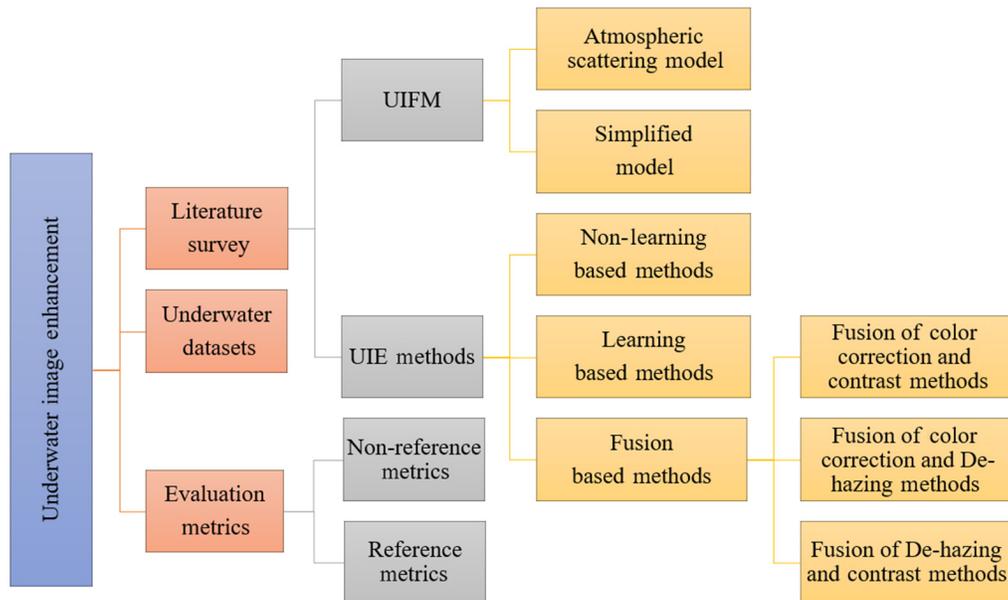*Address all correspondence to Manoj Kumar, manoj.kumar@gla.ac.in

Fig. 1 Taxonomy of the systematic review article.

the challenges in the underwater medium. This paper describes a broad classification of UIE techniques that are based on learning, non-learning, and fusion techniques. The existing UIE methods have been evaluated based on qualitative and quantitative analyses. In addition, different evaluation metrics are described in detail along with the datasets available. Finally, the applications in which UIE methods can be expected to make substantial contributions are discussed in depth.

1.1 Motivation

Underwater applications highly rely on high-quality underwater images that are obtained using the UIE methods.[5] As shown in Fig. 2, these methods can be used in marine animal detection, archaeology, and oceanography. Thus, the UIE approaches need to be adaptive as well as fast in terms of complexity for better performance. The purpose of the study is to present the latest and conventional UIE approaches for improving the performance and evaluation of UIE methods.

Schettini and Corchs[6] discussed the UIE methods based on UIFM. The authors categorized the algorithms by the type of physical UIFM used. The performance of existing UIE methods was evaluated on qualitative evaluation metrics. Lu et al.[7] presented a detailed review of UIE methods based on the imaging types. The fundamental concepts and classification methods were illustrated by the authors, who primarily used physical models to illustrate their points. In contrast, the main focus was to highlight the methods that do not rely on the physical UIFM method.
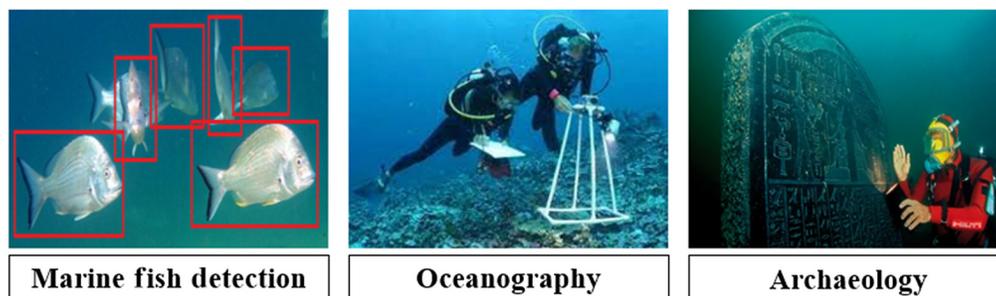

Fig. 2 Various applications of UIE in real-time processing.

Han et al.[8] categorized UIE methods as underwater de-haze and underwater color restoration. Furthermore, the reasons for the underwater image degradation were presented. The authors also focused on deep-learning-based UIE methods and provided their advantages and disadvantages. Finally, image quality assessment metrics and applications were described.

Yang et al.[9] analyzed various underwater scenarios, which have been found to be helpful in UIE approach selection depending on different underwater environments. The authors reviewed 120 research papers to analyze the UIE methods and provided qualitative and quantitative analyses based on an underwater dataset (UD). The paper was concluded with the future directions.

Anwar and Li[10] focused on only deep-learning networks, including convolutional neural network (CNN) and generative adversarial networks (GAN), presented in the field of UIE. Wang et al.[11] classified UIE methods as image formation free and image formation dependent models. The authors also performed an evaluation analysis on both categories and provided future gaps.

Moghimi and Mohanna[1] reviewed the field of the UIE as hardware and software tools used for acquisition and enhancement, existing UIE methods, discussion on different parameters for real-time enhancement and image quality evaluation metrics. Raveendran et al.[12] reviewed existing UIE methods, quality assessment metrics along with the applications and future directions. Hu et al.[13] reviewed existing UIFM, UD, and evaluation metrics and discussed issues and challenges in enhancing underwater images. The authors focused on neural networks based methods and video enhancement methods.

Zhou et al.[14] proposed a review on existing UIE methods based on hardware and software methods. In this paper, UIE categorization was done along with a discussion on UDs and evaluation metrics. Finally, the authors provided the limitations of UIE methods and experimentally analyzed the effectiveness of UIE methods.

Table 1 gives the existing review papers for UIE. The existing survey articles either focused on conventional approaches or learning approaches. However, they did not consider fusion-based methods. Moreover, a few existing evaluation metrics were discussed. This review article provides a background study on non-learning, learning, and fusion-based methods from the past two decades, as well as the issues and challenges in the field of UIE and a brief discussion on UIFM based on a real underwater environment. The main contributions of the review article are highlighted below:

Table 1 Existing review articles based on UIE from 2010–2022.

Author	Year	Review
Schettini and Corchs[6]	2010	Under-water image processing: state of the art of restoration and image enhancement method
Lu et al.[7]	2017	Under-water optical image processing: a comprehensive review
Han et al.[8]	2017	A review on intelligence dehazing and color restoration for under-water images
Yang et al.[9]	2019	An in-depth survey of under-water image enhancement and restoration
Anwar and Li[10]	2019	Diving deeper into under-water image enhancement: a survey
Wang et al.[11]	2019	An experimental-based review of image enhancement and image restoration methods for under-water imaging
Moghimi and Mohanna[1]	2021	Real-time under-water image enhancement: a systematic review
Raveendran et al.[12]	2021	Under-water image enhancement: a comprehensive review, recent trends, challenges, and applications
Hu et al.[13]	2022	An overview of under-water vision enhancement: from traditional methods to recent deep learning
Zhou et al.[14]	2022	Under-water vision enhancement technologies: a comprehensive review, challenges, and recent trends

1. A total of ~110 research papers are reviewed to understand the recent trends in the field of UIE, and a brief discussion on UIFM is given. A summary is presented to understand the underwater environment along with the issues and challenges.
2. The survey includes a discussion on the image quality assessment metrics and UD that are currently being used in UIE.
3. An experimental analysis is presented on a real UD using existing UIE approaches, and the results are presented based on qualitative and quantitative analyses.
4. The survey article includes the importance of UIE in underwater applications.

The remainder of the paper is as follows: Sec. 2 includes the discussion on the role of the underwater environment in the UIFM along with the issues and challenges and presents a classification of existing UIE approaches based on recent works. Section 3 includes the summary of the UD and the underwater evaluation metrics. Section 4 presents the experimental comparison of UIE methods based on qualitative and quantitative analyses. Section 5 discusses the applications of UIE in the field of underwater imaging and highlights the limitations of existing UIE methods, the UD, and evaluation metrics. Section 6 concludes the paper.

2 Background of UIE Methods

In this section, the underwater environment and optical characteristics are discussed in detail to help researchers to understand the role of different parameters and their impacts on the UIFM. Furthermore, various issues and challenges are included that will help future researchers to resolve them. Then, various UIE methods are discussed and analyzed based on the issues and challenges with respect to the underwater environment.

2.1 Underwater Image Formation Models

An underwater environment is the region of land that is immersed in water, such as a reservoir, lake, ocean, pond, or sea. The undersea environment is said to be the genesis of life on Earth. It is also important for the survival of living organisms on Earth. Diverse human activities, including fishing and diving, are conducted in the accessible region of the undersea.[15] The properties of the UIFM must therefore be understood for research in the range of underwater fields to be performed.

Figure 3 shows the overall process of image formation in the underwater environment. The UIFM comprises three main components:

i. Direct component: the amount of light that reaches the camera without any dispersion.
ii. Forward component: the amount of light that changes its direction from the real path and falls accidentally on the camera.
iii. Back component: the light that is dispersed by the water particles.

Underwater imaging does not perform well because of the high absorption and dispersion of light by the water particles. Further, an artificial source of light is required in the underwater environment to reduce darkness, which results in added noise.[16] The water particles consume most of the light obtained from different sources. The dispersion deviates the path of the light. This optical phenomenon leads to faded, blurred, dull, and dark images. The amount and nature of degradation depend upon the illumination and intensity of light in the underwater environment.

Next, a significant amount of uniform light generates in the scene due to scattering. Due to the wavelength dependency of the scattering, wavelengths with a higher frequency (such as blue and green) reach greater depths than those with a lower frequency (such as red), which disappears after about 4 to 5 m, resulting in bluish and greenish tinted images.[17] Further, the turbidity (the quality of water measured by the amount of clear visibility perceived by humans) of the water also affects the amount of scattering. Small water particles make the underwater environment cloudy, which results in the heterogeneous scattering of natural light. The turbidity is challenging in the UIE process.[18]
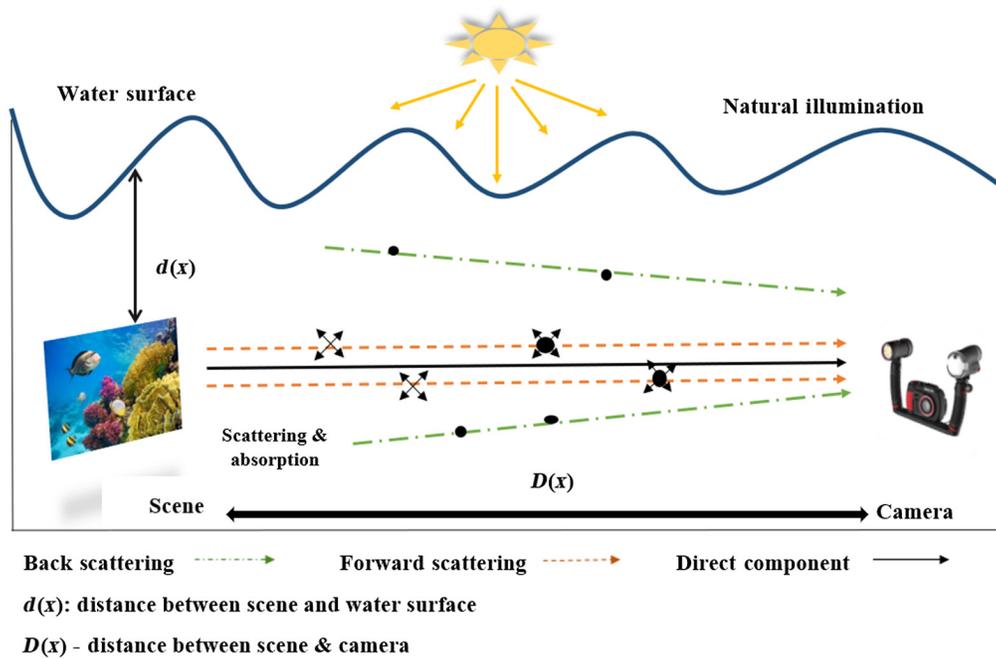
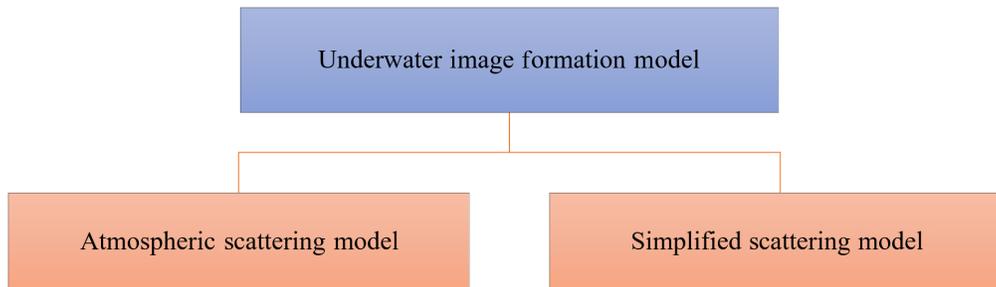Fig. 3 Process of image formation in an underwater environment.

Fig. 4 Different types of UIFMs.

Normally, an artificial light source is attached to camera devices[19] to make the underwater objects more visible. However, there are a few problems with artificial light, such as the cost of generating artificial light in the underwater scene for consistent long-term usage. Furthermore, underwater image quality deteriorates due to the irregular distribution of light as well as the illumination sometimes having heterogeneous characteristics. Moreover, the visibility of the underwater scene decreases rapidly after a distance of 4 to 5 m below the underwater surface. In recent years, researchers and scientists have designed different types of hardware platforms and camera devices to improve underwater visibility.[20]

Figure 4 shows the categorization of UIFM based on the parameters considered for degradation. The UIFM is beneficial in analyzing the process of deterioration in underwater images.

2.1.1 Atmospheric scattering model

Usually, a small amount of light goes into an image sensor for an image taken in a disperse medium because of absorption, such as for an underwater image. The atmospheric scattering model (ASM)[21] is a conventional model that considers the images obtained under the water to be equivalent to the image captured in a hazy environment. The ASM is defined in Eq. (1) as

$$U(x, y) = I(x, y)T(x, y) + B(1 - T(x, y)),\qquad(1)$$

where (x, y) is denoted as the location of the pixel, $U(x, y)$ is a human perceived image, $I(x, y)$ is a clear underwater image, B is the environmental illumination, and $T(x, y)$ is the transmission map (the amount of light that reaches the camera without dispersion) between the scene and camera and lies between (0, 1). The transmission varies according to Eq. (2) as

$$T(x, y) = \exp(-\beta D(x)), \tag{2}$$

where β is the attenuation coefficient and $D(x)$ is the depth information (distance between the scene and camera).

However, ASM differs from the real-world UIFM in which visual representation is much more complex because of limited underwater attenuation. Hence, the simplified model of image formation is more practical.

2.1.2 *Simplified Model*

Most physical-based models adopt a simplified undersea image creation model known as the simplified model.[22] Here, the captured image is denoted as $U_\lambda(x)$, and $I_\lambda(x)$ is the scene radiance. The non-heterogeneous background illumination is represented as $B_\lambda(x)$. It is formulated as shown in Eq. (3):

$$U_\lambda(x, y) = I_\lambda(x, y) \cdot T_\lambda(x, y) + B_\lambda(x, y) \cdot (1 - T_\lambda(x, y)), \tag{3}$$

where λ is represented as the wavelength of the RGB channel and $T_\lambda(x, y)$ is expressed as a medium energy ratio (the percentage of the scene radiance captured by the camera), which degrades contrast and color cast. The value of $T_\lambda(x, y)$ varies with $d(x)$ and λ as represented by Eq. (4):

$$T_\lambda(x, y) = 10^{-\beta_\lambda d(x)} = \frac{E_\lambda(x, d(x))}{E_\lambda(x, 0)} = N_\lambda(d(x)), \tag{4}$$

where the medium attenuation coefficient is denoted as β_λ and relies on wavelength (λ). Moreover, $E_\lambda(x, 0)$ is the light energy passing from a distance $d(x)$ through the transmitting medium, and $E_\lambda(x, d(x))$ is the light intensity obtained after absorption through transmitting medium. N_λ is the normalized residual energy (the ratio of leftover energy after absorption to the total energy in terms of distance).

In summary, the ASM deals in limited underwater scenarios such as in deep water with very little back-scatter, whereas the SM introduces a limited attenuation for a broad range of wavelengths. The SM assumes that the coefficients of attenuation differ with the image sensor, ambient light, etc. In addition, SM neglects that the back-scattering is different from the attenuation coefficient of the direct light.

2.2 *Issues and Challenges*

The underwater image is captured using the sensors in optical cameras and unmanned vehicles. These sensors have some limitations, such as limited visibility of the seafloor and depth restrictions.[23] The operation of unmanned vehicles fails because of hydro-dynamic effects that are non-linear in nature.

The exploration of the underwater world is expensive in terms of skilled divers.[24] There is a time limit that can be spent by an individual in an underwater environment for inspections that are done by divers. Thus, the exploration of underwater resources highly relies on the time spent by divers under the water. This disadvantage can be lessened to a large extent using UIE techniques.

When light travels from air to water the quality of the captured image reduces due to the optical characteristics of water. As a result, focusing on the region of interest by the camera in the water medium becomes difficult, resulting in deteriorated images.[25] The visual appeal of underwater images is impacted by light absorption and scattering. To overcome these issues, research to develop an efficient and high-performance UIE approach must be conducted.

S.no.	Issues	Challenges	Pictorial representation
1	Low visibility	Difficult to measure amount of scattering.	
2	Color cast	To restore attenuated color.	
3	Unavailability of ground truth	Proper evaluation of the UIE methods.	

Fig. 5 (1–3) shows the issues and challenges in the underwater image processing field.

The major issues and challenges in underwater image processing are presented in Fig. 5. The water medium serves as a natural light filter as it absorbs a large portion of light while travelling. After 10 m, approximately half of the light is attenuated, leaving only one-fourth of the total light at 20 m. The availability of light depends on the weather and time of the day, and it is not constant throughout the day. The surface of the water reflects the low portion light when it is noon and thus increases the undersea visibility during the day. Weather, such as storms, leads to water disturbances that cause reduced visibility. Color attenuation is also a challenge that is caused due to the wavelength of light. The blue and green colors penetrate deeper due to having higher wavelengths.[26] Thus, the captured underwater images are blue and green in color.

Scattering and absorption are two optical phenomena that cause low contrast and blurry images. These issues are considerably more aggravated in high turbidity environments or with the presence of artificial light sources. The non-uniform illumination in the undersea scene is caused by natural illumination and artificial light, which leads to reflection, thus obscuring the important details of the scene,[6] as shown in Fig. 3. This could lead to the data being interpreted incorrectly. Underwater images degrade as a result of fluorescence due to biological objects as well as undersea particles. Thus, an efficient UIE approach for extracting useful information from the undersea world will be helpful.

2.3 Existing UIE Methods

The quality of underwater images is essential for understanding the real-life marine environment. Therefore, high-quality images are required to explore marine life. Zhan et al.[27] demonstrated the impact of color cast in underwater images that leads to information loss. However, an improved underwater image that contains more information and better visual quality in comparison with the deteriorated underwater image is required. Figure 6 shows the categorization of UIE methods.
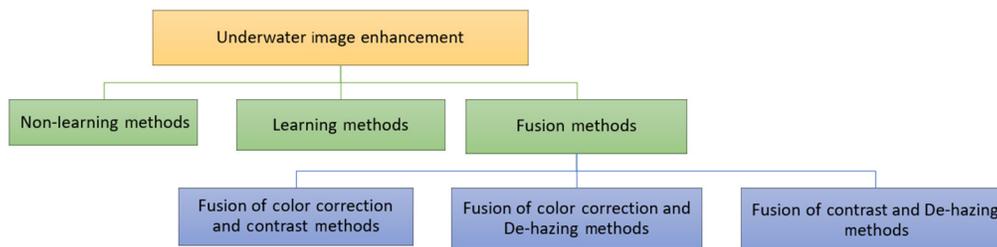

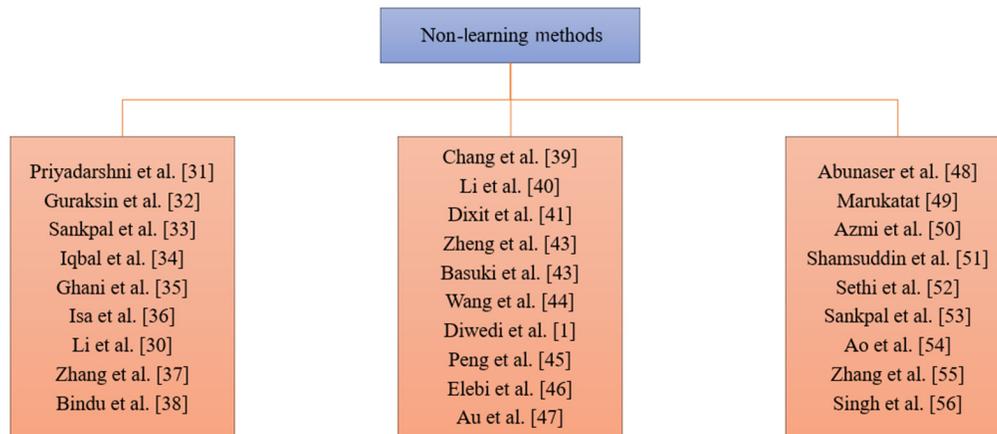**Fig. 6** Categorization of UIE methods.

Fig. 7 Different types of non-learning-based methods.

2.3.1 *Non-learning-based methods*

Non-learning-based methods are based on the traditional approaches that are used for UIE. Figure 7 shows the approaches used by authors to enhance underwater images. These methods use traditional image processing methods such as de-blurring and contrast methods for quality improvement. However, they use the ASM and SM to obtain clear underwater images. In the past, many authors focused on contrast improvement and color restoration for overall enhancement.

The human vision system is more sensitive to contrast in comparison with brightness. For example, if the image is dark, the contrast is high, resulting in information loss.[28] On the other hand, if the brightness is varied, humans can still obtain information. Thus, it is important to improve the contrast by representing the details of the underwater image. In the past few years, many UIE methods based on contrast enhancement have been proposed.

For underwater sonar images, Priyadharshni et al.[29] used the stationary wavelet transform. Further, they modified the low-frequency sub-band by applying a mask and Laplacian filter. The results showed high values of the peak-signal-to-noise ratio (PSNR) and structural-similarity-index-measure (SSIM).

Guraksin et al.[30] enhanced the degraded image that used the discrete wavelet transform along with a differential evolution approach. First, the contrast was improved, and then the homomorphic filter was used, resulting in enhanced brightness and contrast. The contrast-enhanced image was then decomposed using the discrete wavelet transform. Then, the optimal parameters for each of the performance evaluation criteria were determined using a differential evolution approach.

Sankpal and Deshpande[31] proposed an approach that utilizes the Rayleigh stretch method for enhancing contrast. It used maximum-likelihood estimation to reduce the loss, leading to better performance in terms of entropy. Iqbal et al.[32] focused on contrast and lighting problems and presented an integrated color model by stretching the RGB and hue-saturation-intensity color models.

Ghani and Isa[33] improved contrast using the Rayleigh distribution and averaging the RGB and hue-saturation-value (HSV) color models. Liu and Chau[28] presented an UIE method for turbid images and proposed an evaluation metric for evaluating the quality of underwater images.

The CIELab color space includes three channels: one luminance and two chromatic channels that are similar to the HVS. Zhang et al.[34] suggested an UIE approach formulated on CIELab. The authors modified the original retinex algorithm technique that minimized halo artifacts and named it multi-scale retinex, in which bilateral and trilateral filters were combined.

Bindhu and Maheswari[35] used linear image interpolation and an enhancer that eliminated noise and enhanced contrast, resulting in a high quality image. The quantitative results showed high entropy, PSNR, and mean-square-error (MSE) values. Chang et al.[36] presented a modified guided filter that reduced the computational complexity. However, Li et al.[37] utilized dark-

channel-prior that consisted of luminance adjustments that improved overall contrast. Also, the edge and image information were preserved.

Dixit et al.[38] estimated the blur regions using a contrast limited adaptive histogram equalization (CLAHE) that was combined with a dark-channel-prior. The edges were preserved using the homomorphic filter, and the noise was removed with a median filter. Zheng et al.[39] proposed a weighted blending approach that combined CLAHE and an unsharp mask and obtained better results.

Basuki and Ramadijanti[40] presented an UIE method that improved the contrast by increasing the auto level of the RGB color channel. Further, this method can be utilized to capture images in an underwater environment. Wang et al.[41] employed a virtual retina framework. It improved contrast while recovering the true colors of the underwater objects. Image quality assessment techniques based on the patch discrete cosine transform were also employed.

Dwivedi et al.[42] presented a distance factor estimation technique to remove underwater haze. The authors obtained significant results by estimating the object's distance from a particular point based on the intensity of every pixel. Peng et al.[43] estimated the depth map using the blur information to enhance the degraded image. The UIFM was used along with the blurriness information to compute the distance between the camera and a particular point, which resulted in improved underwater scene representations.

Çelebi and Ertürk,[44] utilized empirical mode decomposition that increased the inter-pretability of the input image by enhancing its visibility. The input image was broken down into intrinsic mode functions and individual color channels. The intrinsic mode functions were further combined with varied weights to obtain an improved underwater image. The weights were estimated using the genetic algorithm. The method performed better when compared with histogram-equalization and contrast stretching methods.

Au et al.[45] developed an UIE approach for enhancing the color quality of images by employing HVS. The color was improved in the compressed domain, where chromatic components were focused. The Weber-Fechner law was utilized to remove halo artifacts. Abunaser et al.[46] presented an UIE method based on a nature-inspired algorithm. It utilized particle swarm optimization and corrected RGB with the optimization process. The strategy resulted in a considerable improvement in the illumination and real colors of the underwater images.

Marukatat[47] presented an approach based on a parametric model known as local intensity distribution equalization, which resulted in less memory consumption and low complexity. Azmi et al.[48] presented a nature-based UIE approach to remove the color cast and enhance contrast. It also used swarm intelligence along with unsharp masking to enhance the sharpness of the input image.

Shamsuddin et al.[49] compared automatic (ACC) and manual color correction (MCC) approaches to get the average value of the stretched histogram and to improve color information. It was observed that the MCC outperformed the ACC. Sethi et al.[50] introduced an enhancement approach that employed fuzzy-logic to estimate color cast as well as bacterial foraging optimization. The adaptability of the method improved the degraded image. The method was compared with unsupervised-color-correction and gray-world approaches and outperformed them. Bacterial foraging, according to the findings of the performance evaluation, produced the best color balance and enhanced the contrast of the images.

Sankpal and Deshpande[51] presented an approach to correct the heterogeneous lighting. The maximum-likelihood estimation was employed and provided the best feasible fit when mapping the image to the Rayleigh-distribution. The scaling parameter was determined from the RGB color channels once the input image was separated into red, blue, and green color channels. Further histogram stretching was performed on separated channels, and finally, the channels were combined to obtain an enhanced image.

In terms of performance, Ao and Ma[52] presented an adaptive linear stretch approach, which outperformed linear stretching. It was found that this method enhanced the visual quality with low computation. According to the histogram, the threshold was changed for regions with poor light distributions.

Zhang et al.[53] proposed a retinex-based framework to adjust illumination. This model extracted the illumination map and then used gamma correction. With the utilization of a special normalization approach, the color cast was improved. During the illumination adjustment stage,

the edges were preserved, and the smoothing of the texture was performed. The method was better in terms of run time complexity and quantitative analysis.

Singh et al.[54] used a wavelet-based technique for color correction using the discrete-wavelet-transform on the input image, further computing the results. Two coefficients, including the approximation coefficients and detailed coefficients for color correction, were used, and the structure of the input image was maintained. The results proved that it outperformed other methods in terms of PSNR and SSIM.

Although non-learning-based UIE methods can enhance the contrast of underwater images, these methods generate red artifacts in the enhanced image and are unable to completely remove the color cast. Non-learning-based methods do not consider color cast and do-not have prior knowledge of the scene; therefore, noise removal filters and white balance methods are often used to obtain better results.

2.3.2 Learning-based methods

Learning is a process through which neural networks try to improve their performance using prior knowledge. This improvement happens over time and according to a set of rules. Thus, a neural network learns and extracts important features about its environment using a learning process.[55] The goal of learning methods is to extract high-level features from the input image and obtain an enhanced image as an output.[56]

In recent years, research proved that the efficiency of learning-based methods in various fields[57] such as image segmentation[58] and speech recognition[59] is better than that of non-learning methods. The learning-based methods improve the ability of feature extraction because of the deep neural network framework. Hence, they are useful in applications such as object detection[60] and image defogging.[61] Figure 8 shows the classification of learning-based methods, including CNN and GAN.

Convolutional neural network. CNN aims to be faithful to the original underwater image,[62] whereas GAN aims to improve the perceptual quality of the image. In image-based challenges, CNN is highly effective. Many popular deep neural network-based frameworks are based on CNN and applied on low-level images,[63] image de-blurring,[64–66] image de-raining,[67] image denoising,[68,69] low-light image enhancement[70,71] and image de-hazing.[72,73] Yet, very few methods are effective in the case of UIE, such as for low-light underwater images.[74]
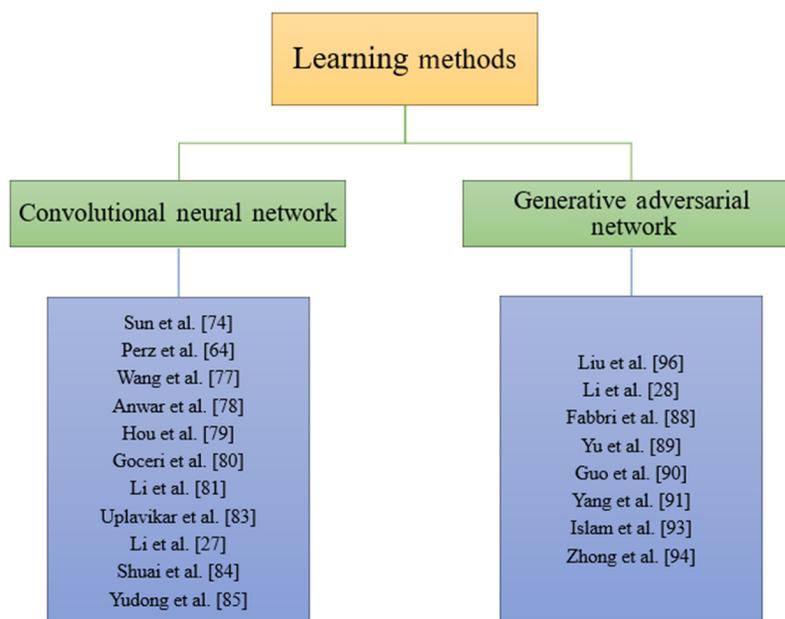

Fig. 8 Different types of learning-based methods.
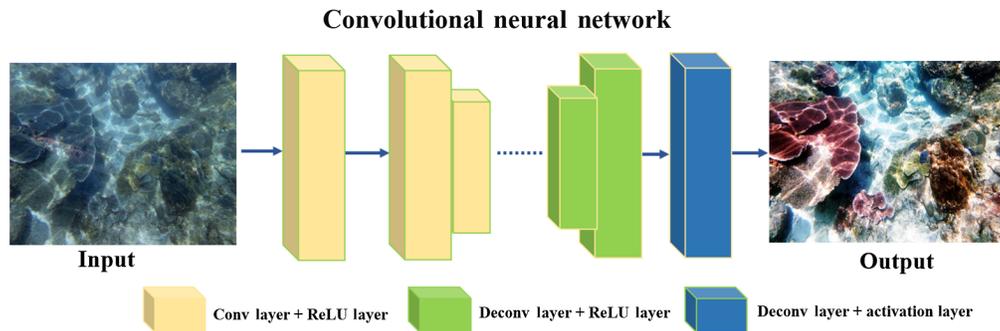
Convolutional neural network

Fig. 9 Basic CNN architecture for UIE.

According to Sun et al.,[75] in CNN, convolution layers are employed for encoding and deconvolution layers are employed for decoding; CNNs have been applied widely for different types of images, including colored photographs. The basic CNN architecture is shown in Fig. 9, where an image is fed to the network that extracts feature maps from the input and results in learned patterns. These learned patterns are used to obtain enhanced underwater images. The enhancement is achieved in an adaptive manner without taking the physical environment into consideration.

Perez et al.[62] suggested an UIE method based on CNN that trains the end-to-end (E2E) transformation model between the hazy images and the resulting enhanced image using combinations of distorted and restored underwater images. Li et al.[76] proposed underwater-CNN (UWCNN) trained by synthetic underwater images. The UWCNN was trained for ten different types of water. The kernel size of 3×3 was fixed at each layer, and it consisted of 10 layers. The UWCNN was evaluated on real UD and synthetic datasets.

At the same time, Wang et al.[77] suggested an end-to-end, underwater image-enhancing framework based on CNN, called underwater image enhancement net (UIE-net), to improve color and eliminate haze. The UIE-net used a pixel disrupt technique to eliminate inherent characteristics of local image patches, which significantly improved the system consistency and enhanced reliability.

Hou et al.[78] presented a residual CNN that used prior knowledge and different UDs for training, named the framework underwater residual CNN. It resolved the uneven underwater light issue, eliminated haze, and improved contrast. Further, Goceri[79] compared four existing UIE approaches based on residual networks and used RGB images for testing.

Li et al.[80] presented an underwater color correction model comprised mainly of the adversarial framework and multi-term loss mechanisms, including adversarial loss, cycle consistency loss,[81] and SSIM loss. This approach restored the input underwater image content and structure and corrected the color distortion.

In addition, Uplavikar et al.[82] presented a framework based on dominance learning that was capable of handling several different types of underwater images and producing visible images with the help of agnostic features. The author named the model underwater image enhancement-deep adversarial loss.

Li et al.[74] obtained a dataset known as the underwater image enhancement benchmark dataset. The author also presented Water-Net for enhancing underwater images. The dataset was used in training WaterNet and was designed to learn three consistency maps to overcome challenges faced during UIE.

Yuan et al.[83] proposed a tracking approach for unmanned aerial vehicles that considered factors including small scales and aerial views. The authors named the method adaptive spatial-temporal context-aware that computes spatial-temporal context weight. The method can be used in an underwater environment to track different types of organisms. With the help of spatial-temporal context weight, the target and background were distinguished in marine tracking.

Yuan et al.[84] presented a self-supervised learning-based tracker in a deep correlation framework that trains a feature extraction network that does not require labeled samples. It generated pseudo-labels using the Siamese framework and utilized multi-cycle consistency loss for training. The robustness of the network was improved using a low similarity dropout strategy and a cycle-trajectory consistency loss.

Yang et al.[85] presented a SiamCorners approach based on a learning-based method. It can be used in marine-life tracking and human body detection in crowded scenes. The method included three phases: tracking corner loss, corner pooling, and decoding for corner heatmaps and offsets. The advantage of the SiamCorners is that it does not require pre-defined anchor boxes, and it performs well in terms of efficiency.

Liu et al.[86] introduced a dual-level feature framework including thermal infrared specific discriminative and correlation features. These two feature models are jointly optimized in the thermal infrared for tracking with the help of a multi-task matching framework. The method can be used for fish detection and object tracking. The authors also presented a training dataset to compute the effectiveness of the method in comparison with the existing methods.

Xu et al.[87] employed a retinex method in their learning method and presented a deep-retinex-decomposition network for enhancing underwater images. The authors focused on improving the color, contrast, and brightness and estimated the illumination using a CNN as the baseline model. Wang et al.[88] used an HSV color model for enhancing the degraded image. The authors used convolutional neural networks and presented an E2E network by employing RGB and HSV color models. Furthermore, they used piece-wise-linear scaling, which helps in learning the properties of HSV.

Generative adversarial network. The GAN[89] is a mini–max mathematical function between the generator and discriminator via adversarial training. The discriminator learns to distinguish between an original image and a fake image. Further, the generator learns to fool the discriminator. The GAN has shown great success in underwater image generation that includes ground truth information also. Moreover, GAN has been utilized for improving the overall quality of degraded underwater images.[90] Figure 10 shows the basic architecture for enhancing underwater images using GAN.

Li et al.[26] proposed a GAN approach, named WaterGAN, through which artificial but more realistic images were obtained with the help of in-air images along with their depth maps, as shown in Fig. 11. Then, a two-step CNN was used to enhance the color cast, with both real-underwater and depth maps being used.

Fabbri et al.[91] similarly implemented GAN as a way of enhancing an underwater image. First, they reconstructed degraded images based on clear images by cycle-consistent generative
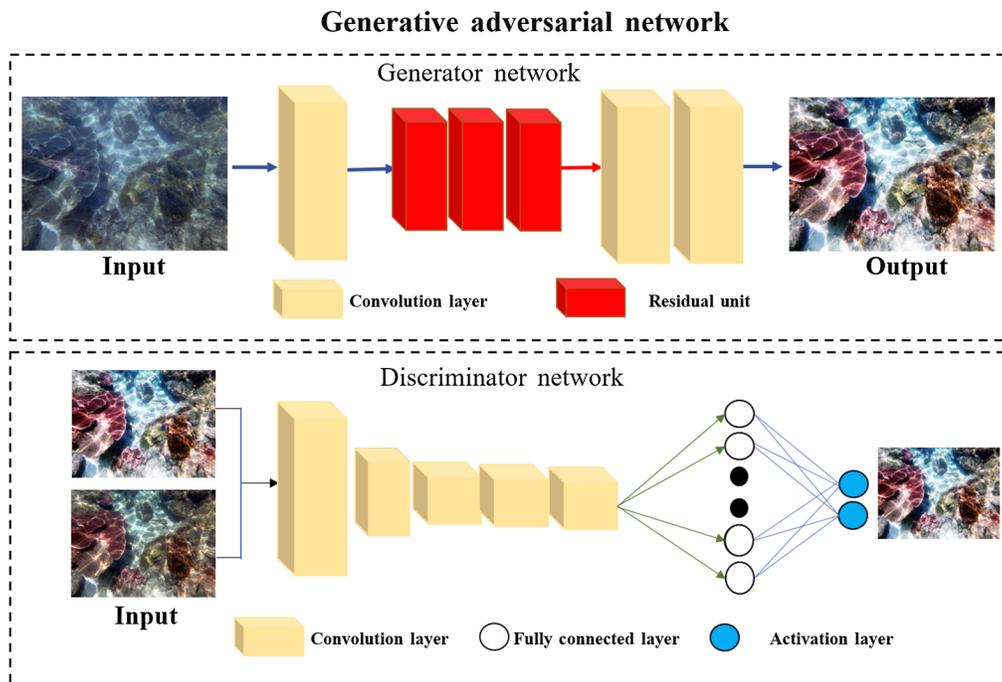
Generative adversarial network

Fig. 10 Basic architecture of GAN for UIE.
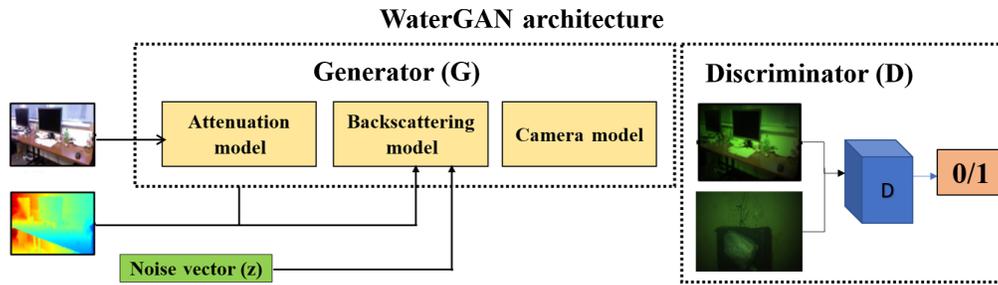
WaterGAN architecture

Fig. 11 Working architecture of WaterGAN.[26]

adversarial networks (CycleGAN). Then they fed pairs of underwater images to train an under-water-GAN (UW-GAN), which in turn transformed hazy images into more visible and high-resolution images.

Guo et al.[92] presented a multi-scale dense model named UW-GAN. In the generator network the residual multi-scale dense block is added. Whereas, to stabilize the discriminator training the light spectral normalization is used. Yu et al.[93] designed a loss function named Wasserstein GAN. It utilized a convolution patch GAN classifier as the discriminator of UW-GAN.[91]

Yang et al.[94] proposed a lightweight adaptive feature fusion network (LAFFENet). This model contained adaptive feature fusion modules that help to obtain feature maps, thus fusing them with channel attenuation. Moreover, it did not restrict attenuation coefficients along with veiling light. The number of parameters in the LAFFENet was reduced by 0.94%, from 2.5 million to 0.15 million.

Yang et al.[95] employed a conditional-generative-adversarial network, multi-scale generator, and dual discriminator. The dual discriminator extracted both local and global data, giving the image a natural appearance. It worked well in terms of PSNR and SSIM.

Islam et al.[96] presented FUnIE-GAN. First, they introduced a fully convolutional conditional GAN-based model. Then, they proposed a multi-model objective function to train FunIE-GAN. The authors also presented an enhancing underwater visual perception (EUVP) dataset that contained 20,000 paired and unpaired images generated using cycleGAN. The FunIE-GAN trains the model based on the global content, color, local texture, and style information of the input image.

Zong et al.[97] presented local-cycleGAN. It is a combination of local and global discriminators. Also they utilized a feedback mechanism that controlled the training of local-cycleGAN and a quality monitor loss function along with local and domain style loss. However, local-cycleGAN was unable to preserve image details.

Huang et al.[98] used GAN along with dual image wavelet fusion to improve the edge information and contrast. The authors introduced adaptive color compensation for obtaining attenuated color information. The goal was to improve different types of underwater images.

Liu et al.[99] utilized a deep residual framework for improving underwater images. The authors employed cycleGAN and a reconstruction model known as the very-deep super-resolution reconstruction model. The task of improving the model was carried out using an underwater ResNet framework. The method demonstrated that batch normalization layers can accelerate the rate of convergence and are extremely useful in the enhancement of models and algorithms. The high underwater image quality measure (UIQM) score also demonstrated a significant improvement in visual effects.

Although learning-based methods for UIE can enhance contrast and restore attenuated color by learning features and patterns from input images. deep-learning-based UIE methods have requirements, such as training data, hardware devices, and hyper-parameters (such as the learning rate and Adam optimizer).

2.3.3 Fusion-based Methods

The fusion methods are combinations of different image enhancement approaches for better performance. The results of fusion methods are a higher level of enhancement, which improves
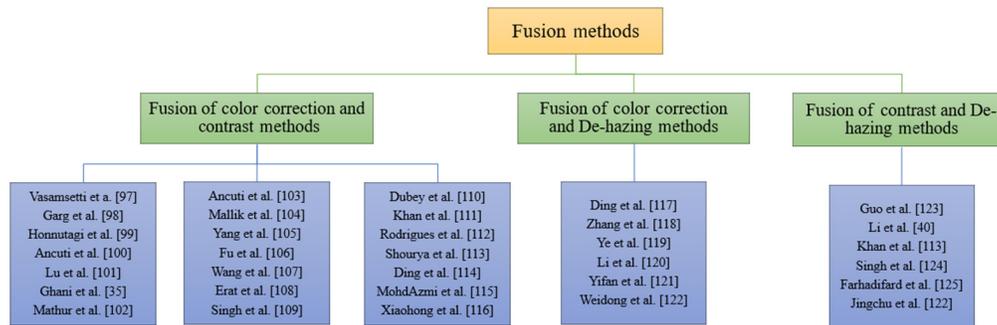
Fig. 12 Classification of fusion-based methods for UIE.

the visibility of the underwater deteriorated image. Figure 12 shows the broad classification of fusion-based methods.

Fusion of color correction and contrast enhancement. Vasamsetti et al.[100] obtained approximation and detailed coefficients with the help of the discrete wavelet transform. In this method, color correction and contrast improvement were modified individually. Also, the color casting factor was set for each RGB channel to change the value of the intensity.

Garg et al.[101] combined CLAHE and percentile methodology to improve the contrast and restore attenuated color. Honnutagi et al.[102] improved the color and contrast with the help of a salient weight map, estimation of luminance, and laplacian pyramid. To compare quantitatively, three evaluation metrics were used: PSNR, MSE, and entropy.

Ancuti et al.[103] presented a fusion approach to enhance underwater images and videos. To improve distant object visibility, four separate weight maps were estimated and used. This method can be used in underwater image segmentation, matching, and de-hazing. Ghani et al.[104] presented a dual image Rayleigh stretched contrast limited adaptive histogram specification approach for degraded underwater images. It fused local and global contrast, resulting in improved contrast.

Lu et al.[105] used three steps to enhance underwater images, especially those with turbidity. The three steps comprised the de-vignette method, the de-scattering method, and the weighted guided trigonometric filter. With these steps, noise was removed, color was corrected, and the vignette effect was removed. The results showed a significant difference in PSNR values when compared with existing UIE methods.

Ghani and Isa[106] used Rayleigh distribution and presented recursive-adaptive-histogram-modification. It was performed in the HSV color space by modifying the histogram of the image. Ghani and Isa[107] presented the UIE approach that included two stages: color correction and contrast improvement to further transform the image into the HSV color space. The edges were preserved with the help of Rayleigh stretching.

Mathur and Goel[108] used Rayleigh stretching for single UIE. It used white balancing as well as gamma correction to resolve the color cast issue. The findings of qualitative and quantitative research demonstrated that the effects of over and under exposed areas on images were reduced.

Ancuti et al.[109] presented a multi-scale fusion technique that improved global contrast and sharpness of the edge by blending images produced from a white-balancing method. Mallik et al.[110] presented an approach based on empirical mode decomposition. It removed the scattering and blurring caused by limited light in the underwater environment. Further, the authors used the white balancing method to remove color cast and enhance the contrast of the degraded image.

Yang et al.[111] presented a structured texture decomposition framework for underwater images without generating artifacts. The authors used histogram equalization to improve the color. Further, they used total variation and $L1$ norm on the input image to break the image into layers comprising the structure layer and decomposition layer. Finally, the noise was removed from both layers, and then enhancement was performed separately on each layer to generate a texture mask.

Fu et al.[112] used piece-wise linear transformation for UIE that resolved the color degradation issue and presented an optimal approach for contrast enhancement. It eliminated the artifacts and improved the overall quality of the input-degraded image. The method is better in terms of time complexity and can be used in real-life underwater applications.

Wang et al.[113] presented a method based on fusion for the frequency domain. The authors fused wavelet decomposition, weighted average, and local variance approaches. Erat et al.[114] presented an algorithm for the frequency domain that was based on histogram equalization and improved contrast. The color of the input images was corrected using the DCT method.

Singh and Biswas[115] proposed a method that utilized underwater images, including haze. It generated two images: contrast-enhanced and white-balanced images. These images were used as the input. The chrominance, saliency, and luminance weight maps were used on the generated images. The final de-hazed image was obtained through a multi-scale fusion of weight maps. Dubey et al.[116] proposed a fusion method in which RGB images were converted to a green-blue-red (YCBCR) model. The method was based on the wavelet domain as well as the used dynamic histogram equalization filter, and performance was evaluated on PSNR and entropy.

Rodrigues et al.[117] applied a non-filter on turbid images. The authors used an automatic technique for the estimation of the saturation map. The method improved the colors, contrast, and brightness of degraded images. Moreover, evaluation was performed on absolute mean brightness error (AMBE) and showed better performance.

Mohd Azmi et al.[118] introduced an UIE method that restored the red color and reduced the low lighting impact, and the contrast was improved using particle swarm optimization. Also, the performance was evaluated on the natural-image-quality-evaluator and entropy.

Yan et al.[119] presented a fusion approach for enhancing underwater images. The authors designed an adaptive-white balancing method and obtained two output images based on local and global contrast enhancement. Furthermore, to compute the weight maps, particle swarm optimization was used. Finally, the computed weight maps were refined using the guided filters. The enhanced image was obtained with the fusion of global and local contrast-enhanced images along with the refined weights.

Fusion of color correction and de-hazing. Ding et al.[120] presented a super-resolution CNN to demonstrate a two-step UIE technique. An adaptive color-correcting algorithm was utilized in the initial step to provide naturally colored corrected images while balancing color casts. Then, to eliminate the effects of blurring, color-corrected images were fed into a super-resolution CNN.

Zhang et al.[121] introduced de-hazing and color restoration techniques to improve the quality of underwater images. The experimental analysis was conducted based on qualitative and quantitative analyses.

Ye et al.[122] used a stacked conditional GAN framework to illustrate an underwater image de-hazing and color correction method. The framework was divided into two parts: a color correction sub-network and a haze detection sub-network, each including a generator and discriminator. De-hazing and color correction of underwater images were accomplished by estimating medium transmission and detecting a global background light.

Using a regression model to combine the characteristics of light in an underwater medium with background light estimation, Li et al.[123] proposed an image de-hazing and color correction technique. For the purpose of evaluating the performance of the method, many qualitative measures, such as the underwater color image quality assessment metric, were computed.

Huang et al.[98] fused the learning-based methods and the non-learning-based methods to restore the color along with the de-hazing. The authors designed an adaptive color compensation approach to restore the attenuated color information. To remove the effect of haze and blurring, the dual image wavelet fusion and GAN was proposed. The qualitative and quantitative results proved that the fusion method outperformed the existing UIE methods in terms of de-hazing and color restoration.

Weidong et al.[124] used a retinex-based method to improve the color of input images by removing the color cast. Furthermore, three inputs were obtained using detail enhancement and local and global contrast enhancement. The experimental analysis proved that the method worked well in diverse underwater scenes.

Fusion of contrast enhancement and de-hazing. Guo et al.[125] presented an improved segmentation dark channel prior method to remove fog and enhance contrast for underwater images. De-hazing occurs because of light refraction, and contrast degradation occurs because attenuation varies with wavelength. The method was the first method that cleared the fog in an underwater environment. Also, contrast enhancement was achieved by utilizing histogram stretching in the RGB channels for better visibility.

Khan et al.[126] utilized a de-haze and enhancement approach to estimate the amount of corrosion for underwater pipelines. The color correction and contrast were improved by utilizing a wavelet transform method in a fusion approach. The accuracy of the pipeline estimation was maintained using the method with the help of a segmentation method.

Singh and Biswas[127] introduced a multi-scale fusion approach that generated de-hazed images by combining the input images and the weight maps associated with each of those images. The usefulness of this approach was demonstrated by the high levels of entropy and the low values of the AMBE.

Farhadifard et al.[128] introduced an effective UIE method that does not rely on prior information. The color cast was corrected using a color correction approach based on a guided color mapping scheme. Moreover, singular value decomposition was utilized to remove blurring from images. The findings indicated that the natural color map was retained in a significant way.

Zhou et al.[124] used fusion approach for enhancing underwater images and named it multi-feature-prior-fusion. The authors used a color correction method to enhance the deteriorated image. The enhanced image was used to obtain two outputs using the guided filter and to estimate the artificial exposure map. Then, different weights, namely, global-contrast, saliency, saturation, and exposure weight, were extracted from both outputs. Finally, weights were normalized and the fusion was performed using normalized weights.

The fusion-based methods perform better in terms of color restoration, de-hazing, and contrast. However, the enhanced image obtained using fusion methods have some information loss compared with the input underwater image. The fusion-based methods fail in real-time image processing and should consider UIFM for better performance.

3 Underwater Dataset and Evaluation Metrics

In this section, the available underwater datasets and evaluation metrics are presented. The underwater datasets are used to train learning-based methods and improve the quality of existing UIE methods. By contrast, the evaluation metrics are used to compute the performance of the state-of-the-art UIE methods. The description of both along with their limitations are presented below.

3.1 *Underwater Dataset*

The UD plays a significant role in the growth and success of UIE methods. Therefore, the UD needs to be updated and improved continuously. The UD is used to train the learning-based methods, and it helps to boost the performance and efficiency of learning-based UIE methods. The performance of the learning-based UIE methods highly relies on the large number of images and high quality of images. The details of frequently used datasets in the UIE processes are given in Table 2. The size of the available real-world dataset is limited due to the problem of gathering underwater images.

In Fig. 13, some sample images from different datasets are shown. The sample images display a range of underwater environmental characteristics, including color cast, haziness to differing degrees, different types of water, and low lighting conditions. However, although a lot of work, including a large number of UDs for underwater imaging, has been presented, there are still some significant limitations, which are stated below.

i. The color of the deep sea scene and the images in the dataset are both monochromatic, which makes it unsuitable for computing the performance of UIE methods under color casts and natural lighting.

Table 2 Detailed summary of existing underwater datasets.

S.No.	Dataset	Year	Size	Scene diversity	Image resolution
1	F4K[129]	2013	6514 (video clips)	Marine fishes, underwater life and fish tracking	Diverse
2	MARIS[130]	2015	10,123	Multiple color pipes in water pool	1292 × 964
3	TURBID[25]	2016	82	Seabed, coral reef, underwater rocks, and human-made artifacts	3000 × 4000
4	ULFID[131]	2017	96	Man-made objects and varied degree of haziness	Diverse
5	UPFD [132]	2018	8995	Corals, nudibranches, octopus, and different species of reef fish	Diverse
6	URID[26]	2018	15,057	Rocks in the pool	1360 × 1024
7	RGBD[133]	2018	1100	Waterproof color charts in underwater atmosphere	1369 × 914
8	HL[134]	2018	57	Multiple color charts in real underwater scene, water-body types and haziness	5454 × 3653
9	HC[135]	2019	10,465	Scallops, sand dollars, rocks, and the occasional fishes	2720 × 1024
10	AFSC[136]	2019	571	Fishes and other related species	2112 × 2816
11	MBARI[137]	2019	666	Fishes	1920 × 1080
12	RUIE[24]	2019	4230	Scallops, sea cucumbers, and sea urchins	400 × 300
13	UIEB[74]	2019	950	Coral reef, Fish, marine life, rocks, sculpture, wreckage, and others	Diverse
14	OD[138]	2019	183	Low lighting conditions, fish, urchins, man-made objects, and effect of artificial light	1280 × 720
15	EUVP[96]	2020	20,000	Scenes, water-body types and lighting conditions	Diverse
16	U45[139]	2020	6368	Color casts, low contrast, and haze	Diverse

ii. The dispersion effect cannot be seen because the scene depth is not very small, which leads to an incorrect evaluation of UIE approaches.

iii. Images taken under the water sometimes include a few aquatic mammals, which limits their use in multiple object detection.

iv. Due to natural limitations, it is challenging to collect ground truth photos. It is impractical to obtain both the damaged underwater image as well as the ground truth image of the same environment at the same time.

3.2 Evaluation Metrics

The performance and accuracy of UIE methods can be assessed qualitatively and quantitatively. The evaluation metrics for UIE approaches must be able to compare the quality of enhancement to the human visual system, must be fast in terms of computation, and must be able to measure the degree of deterioration. Additionally, it must be useful in choosing the best variables and be suitable for practically all types of underwater images and color restoration techniques. Despite the fact that there are numerous evaluation metrics for air images such as discussed in Refs. 140 and 141, they are inappropriate for underwater images due to underwater optical properties.

The qualitative analysis is conducted based on visual results. Human participants are used for image quality evaluation because reference images are not available. However, quantitative analysis is a better way of computing the performance of UIE methods. They are typically
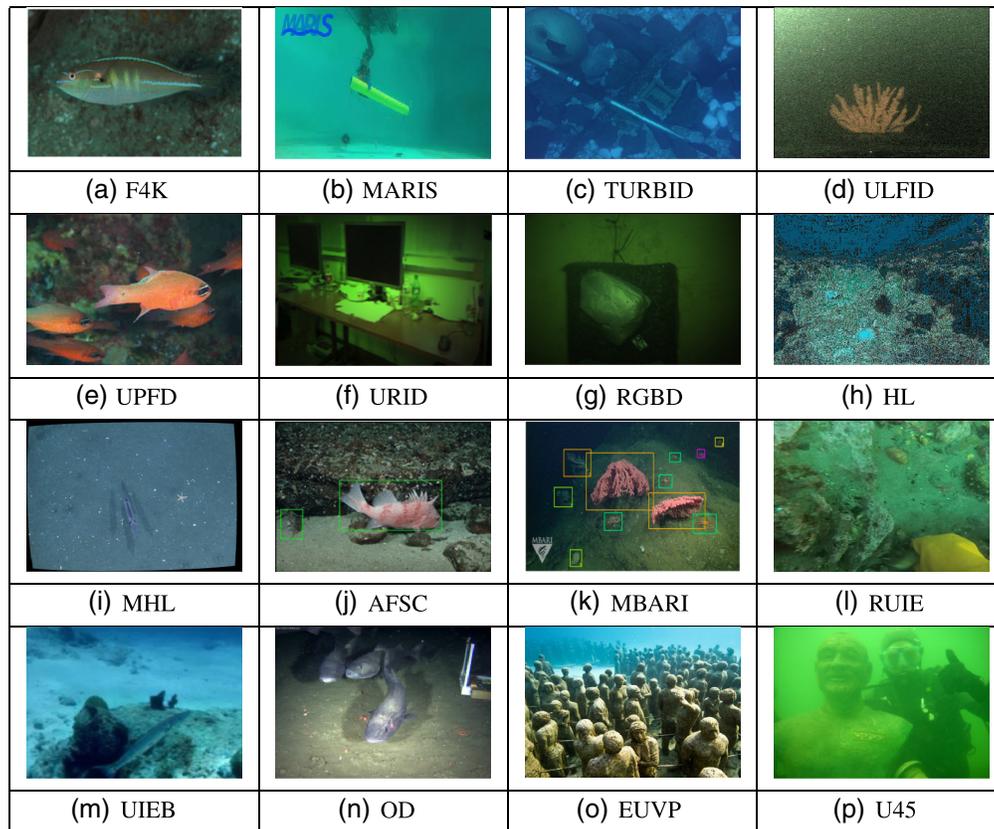
(a) F4K	(b) MARIS	(c) TURBID	(d) ULFID
(e) UPFD	(f) URID	(g) RGBD	(h) HL
(i) MHL	(j) AFSC	(k) MBARI	(l) RUIE
(m) UIEB	(n) OD	(o) EUVP	(p) U45

Fig. 13 (a–i) shows the samples of underwater images from the discussed datasets, with different amounts of light, color cast, haze, marine animals, marine objects, and turbidity.

affordable and simple to calculate. Additionally, they are unaffected by any specific observational case or circumstance. Therefore, quantitative analysis is essential.

3.2.1 Full-reference metric

Full-reference-based metrics need a high-quality reference image, which is difficult in underwater environments. Color boards are used to obtain images of an underwater scene to obtain reference images. For example, Zhou et al.[142] captured an underwater image of a plastic color disk in a swimming pool as a test image, considering the plastic color disk to be its reference image. Mostly, MSE, PSNR, SSIM, contrast noise ratio (CNR), and AMBE are used to evaluate the performance of UIE methods. Table 3 gives the summary of full-reference image-based metrics along with their mathematical formulas.

3.2.2 No-reference metric

The evaluation of UIE methods on real-world underwater images is evaluated using no-reference-based metrics. In no-reference image-based metrics, the reference image is not required. The degraded image is used as the reference image for evaluation purposes. Usually, these metrics are used to evaluate blurred and foggy underwater images.[143,144]

For greyscale images, Kanaev et al.[145] proposed a structure tensor-oriented image quality method for underwater image quality evaluation. Some other evaluation metrics for grey-scale images are contrast[146,147] and edge sharpening.[148] The natural image quality evaluator (NIQE),[60] blind/reference-less image spatial quality evaluator (BRISQUE),[61] UIQM,[55] underwater color image quality evaluation (UCIQE),[149] and patch-based contrast quality index (PCQI)[150] are some important no-reference-based evaluation parameters. Table 4 gives the summary of no-reference image-based metrics along with their formulas.

Table 3 Detailed summary of full-reference image-based parameters.

Metric	Formula	Detail	Comment
MSE	$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[F(i,j) - E(i,j)]^2$	$F(i,j)$ = underwater image, $E(i,j)$ = enhanced image, and $M \times N$ = image size	The quality improves as the MSE decreases
SSIM	$SSIM(F,E) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2\mu_y^2 + C_1)(\sigma_x^2\sigma_y^2 + C_2)}$	μ_x, μ_y = mean values of the pixel and σ_x, σ_y = standard deviation values of the intensity value	Higher value of SSIM denotes better quality of the image
PSNR	$PSNR = 20\log_{10}\left(\frac{F^2}{\sqrt{MSE}}\right)$	F^2 = maximum pixel value	The quality improves as the PSNR increases
CNR	$CNR = \frac{(\mu_i - \mu_n)}{\sigma_n}$	$\mu_i\mu_n$ = mean value in a region of interest for i and n	The quality improves as the CNR increases
AMBE	$AMBE = Z_1 - Z_2$	Z_1 = mean value of underwater image, Z_2 = mean value of enhanced image	AMBE median values indicates that brightness values are well preserved

Table 4 Summary of no-reference image-based parameters.

Metric	Formula	Detail	Comments
UIQM	$UIQM = const_1 \times UICM + const_2 \times UISM + const_3 \times UIConM$	$UIQM$ = underwater image colorfulness measure, $UISM$ = underwater image sharpness measure, and $UIConM$ = underwater image contrast measure	The quality improves as the UIQM increases
UCIQE	$UCIQE = c_1 \times \sigma_c + c_2 \times con + c_3 \times \mu_{saturation}$	$c_1, c_2 c_3$ = weighted coefficients, σ_{c} = standard deviation, con = contrast and $\mu_{saturation}$ = average value of saturation	The quality improves as the UCIQE increases
PCQI	$PCQI = \frac{1}{P}\sum_{n=1}^{P} l_r(i_n, j_n) \cdot l_s(i_n, j_n) \cdot l_t(i_n, j_n)$	P = number of patches in underwater image, l_r, l_s and l_t = comparison functions	The quality improves as the PCQI increases
BRISQUE	$BRISQUE = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C}$	$I(i,j)$ = intensity value of image, $\mu(i,j)$ = mean, $\sigma(i,j)$ = standard deviation and C = constant. Here if $I(i,j) = 0$ the value of C is 1 else 1/255	The lower the BRISQUE value, the better the enhancement
NIQE	$NIQE = \sqrt{\left((\nu_1 - \nu_2)^T \left(\frac{\Sigma_1 + \Sigma_2}{2}\right)^{-1} (\nu_1 - \nu_2)\right)}$	ν_1, ν_2 = mean and Σ_1, Σ_2 = covariance-matrices	Lower NIQE values indicate good preservation of brightness values

A lot of work has been presented in terms of evaluation metrics. However, it has limitations, which are mentioned below, and thus the UIE methods fail to enhance the images in different scenarios such as hazy environments and with different parameters such as haze, contrast, saturation, and brightness. The limitations of underwater evaluation metrics are as follows:

a. The results obtained from no-reference evaluation metrics have poor correlation with subjective results. It shows that they are unable to estimate the quality of input image accurately.

  b. Some of the evaluation metrics are restricted to the type of distortions such as color distortion, limited contrast, and low visibility that are observed due to absorption and scattering.

4 Evaluation Analysis

In this section, the performance of existing UIE methods is evaluated, compared, and analyzed. The evaluation is conducted using the benchmark real-world underwater image enhance (RUIE)[24] dataset, which is one of the most used UDs. The images of the RUIE dataset includes underwater issues such as color cast, haze, and limited visibility. The UIE methods are analyzed using qualitative and quantitative analyses.

4.1 Qualitative Analysis

Qualitative analysis has great importance in underwater image processing applications such as image enhancement. It relies on the content of the image and the type of distortion present in the image. The existing Histogram Equalization (HE),[151] CLAHE,[152] Integrated Color Model (ICM),[32] Unsupervised Color Model (UCM),[153] Relative Global Histogram Stretching (RGHS),[154] Rayleigh Distribution (RD),[107] Fusion,[103] EUIE,[155] UWCNN,[76] ShallowNet,[156] and WaterNet[74] are compared and analyzed based on qualitative analysis and histogram distribution, as shown in Fig. 14. The existing UIE methods are evaluated on the RUIE dataset.

Figure 14 shows the comparison of existing UIE methods based on the visual quality and histogram distribution. In Fig. 14(b), it can be observed that HE produces artifacts and unwanted noise and loses real underwater colors, whereas CLAHE and ICM are unable to remove color cast or haze from the input image, as shown in Figs. 14(c) and 14(d), as they rely on adaptive parameters that avoid global histogram stretching and contrast stretching, respectively. In Figs. 14(e) and 14(i), both UCM and EUIE are able to remove color cast and haze from the input image as UCM is based on Rayleigh distribution in HSV and EUIE considers UIFM. The enhanced image by RGHS, as shown in Fig. 14(h), partly removes color cast, but fails in restoring real color information. However, the fusion-based enhancement successfully removes the color cast and restores original color information as it considers color and contrast to be the main parameters during enhancement. However, as shown in Fig. 14(j), it fails to improve the overall brightness of the degraded input image.

Figures 14(f), 14(g), and 14(i) show the comparison of learning-based methods such as ShallowNet, WaterNet, and UWCNN, which work well in terms of removing the color cast. But WaterNet and UWCNN fail to eliminate the haze effect in the input image as UWCNN does not consider a physical model. However, WaterGAN is trained with color-cast images only and did not consider haze while training the network. It can be observed that ShallowNet outperforms existing methods in terms of qualitative analysis as it is trained on a large number of datasets and uses VGG perceptual loss while training.

4.2 Quantitative Analysis

Quantitative analysis is used to evaluate the image quality accurately. It is based on a mathematical model, and the goal is to provide quality predictions as per human observation. So, it helps improve the efficiency of UIE methods. The existing HE,[151] CLAHE,[152] ICM,[32] UCM,[153] RGHS,[154] RD,[107] Fusion,[103] EUIE,[155] UWCNN,[76] ShallowNet,[156] and WaterNet[74] methods are compared based on quantitative analysis using the UIQM, UCIQE, BRISQUE, PCQI, NIQE, and AG evaluation metrics are used. No-reference evaluation metrics are used to evaluate the performance, for ground truth information of real underwater datasets is not available.

Figures 15(a) and 15(c) show that WaterNet outperforms existing methods in terms of UIQM and BRSIQUE as it was able to remove the color cast and improve sharpness due to the training dataset. Figure 15(b) shows that EUIE obtains the highest value in terms of UCIQE as it considers a statistical model for enhancing the image. However, Fig. 15(c) proves that HE obtains
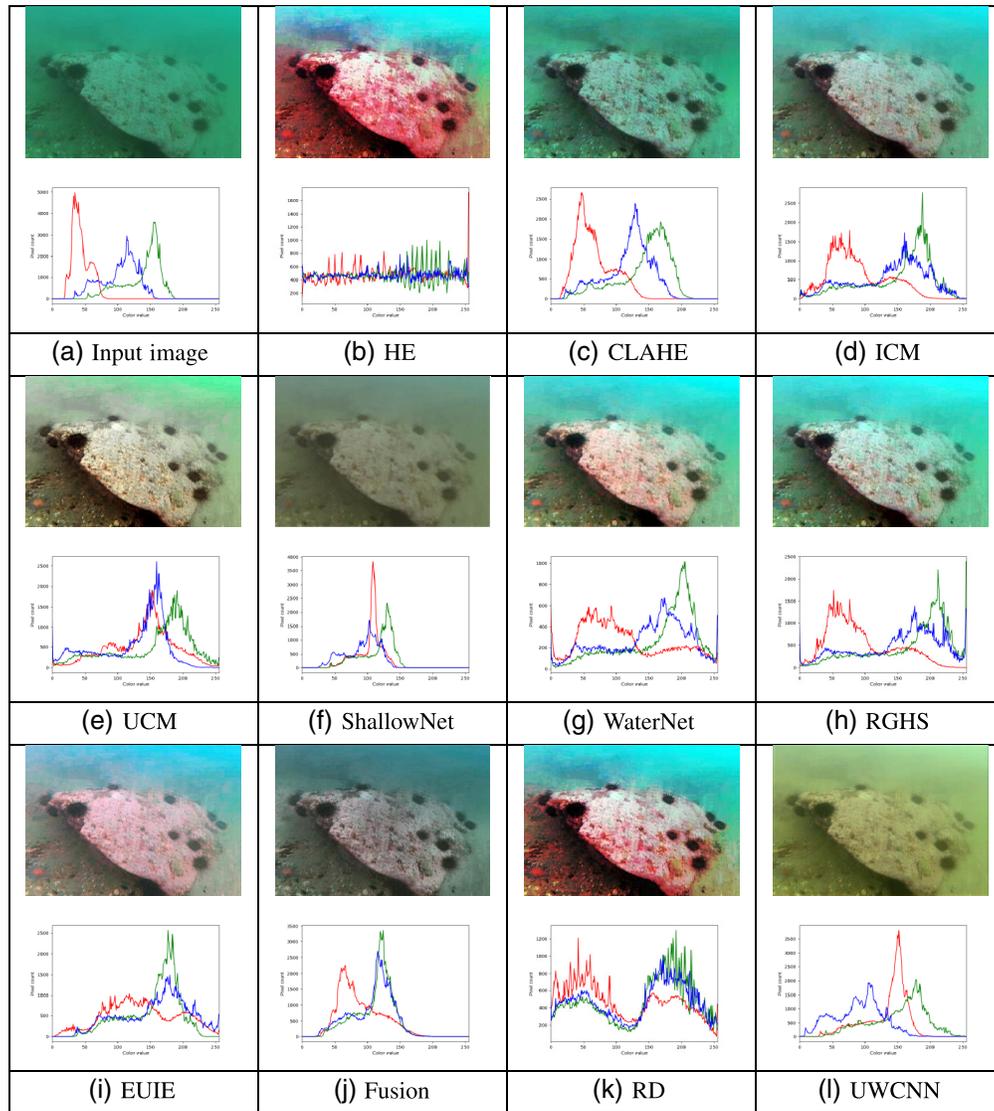
Fig. 14 (a–l) presents the qualitative analysis and comparisons of existing UIE methods on the RUIE dataset.

the highest value for PCQI but fails in terms of qualitative analysis as the HE algorithm does not consider attenuation and scattering to be important parameters for enhancement. Figures 15(e) and 15(f) show that ShallowNet obtains the lowest value in terms of NIQE due to its training loss functions, whereas the highest value in terms of AG signifies that ShallowNet works well in terms of contrast and texture.

Table 5 presents the quantitative results of HE, CLAHE, ICM, UCM, Shallow-Net, WaterNet, RGHS, EUIE, Fusion, RD and UWCNN. The bold values shows that WaterNet out-performs the other methods in terms of BRISQUE, PCQI, and UIQM, which proves that WaterNet is able to regain the colors, saturation, and naturalness of the degraded image, for it is trained with a large number of synthetic datasets that include ground truth information. Moreover, the bold value of ShallowNet proves that it outperforms the other UIE methods in terms of NIQE and AG, which shows that it can improve the contrast and clarity of the image. As, ShallowNet uses three different types of training datasets, including real and synthetic. The bold values in EUIE shows that it outperforms the existing methods in terms of UCIQE, which means that it can improve contrast as well as saturation, for EUIE estimated statistical and transmission maps based on UIFM.
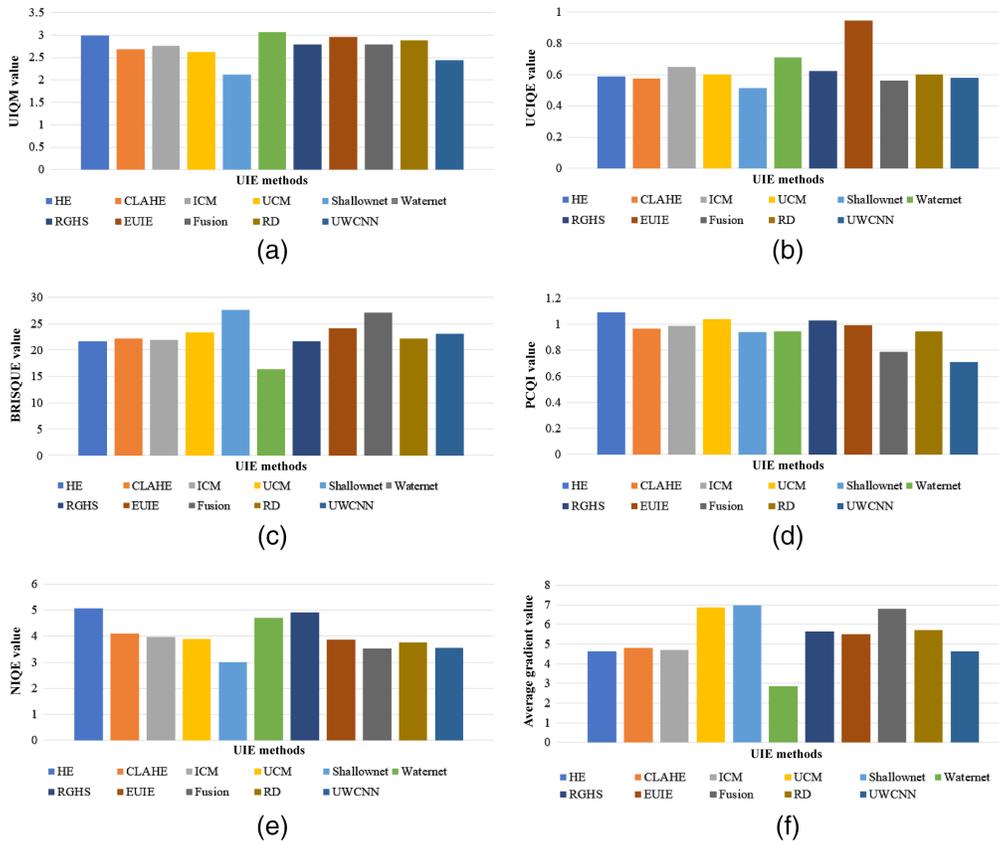
Fig. 15 (a–f) presents the graphical representation of the existing UIE methods in terms of no-reference evaluation metrics.

Table 5 Quantitative results of the compared UIE methods based on no-reference evaluation metrics.

Metrics	HE	CLAHE	ICM	UCM	Shallow-net	Water-net	RGHS	EUIE	Fusion	RD	UWCNN
BRISQUE	21.70	22.15	21.87	23.27	27.64	**16.33**	21.67	24.07	27.13	22.12	23.05
PCQI	0.92	0.96	0.98	1.03	0.94	**1.09**	1.03	0.99	0.78	0.93	0.71
UIQM	2.99	2.68	2.76	2.62	2.11	**3.06**	2.78	2.95	2.79	2.88	2.43
NIQE	5.07	4.11	3.96	3.89	**3.01**	4.69	4.91	3.86	3.51	3.75	3.55
UCIQE	0.58	0.57	0.64	0.60	0.51	0.71	0.62	**0.94**	0.56	0.60	0.58
AG	4.64	4.82	4.70	6.88	**6.97**	2.84	5.65	5.50	6.80	5.72	4.63

5 Applications and Future Gaps

In this section, different real-world underwater applications are provided to help researchers to understand the use of UIE in real-life situations, further improving the performance of UIE methods. Then, future gaps are included to highlight the limitations of the UIE methods, underwater datasets, and evaluation metrics.

5.1 Applications

In underwater image processing, obtaining a high-quality image plays an important role in areas such as monitoring and tracking marine life and the environment. It is expected that underwater
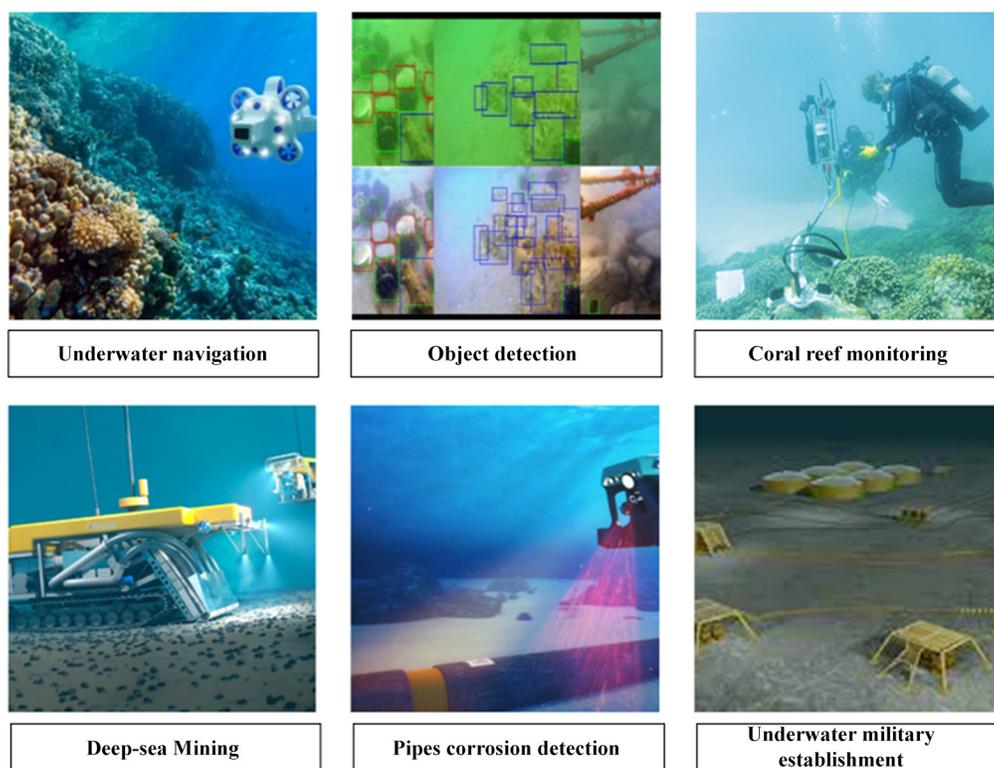
Fig. 16 Applications of UIE in a real-life scenario.[23,24]

Table 6 Different UIE approaches for underwater applications.

S.No.	Author	Method	Applications
1	Li et al.[74]	UIEB	Marine biology and archaeology
2	Islam et al.[96]	FUnIE-GAN	Coral reef monitoring and seabed mapping
3	Zong et al.[97]	Local-cycleGAN	Marine vehicle navigation and seafloor mapping
4	Song et al.[155]	EUIE	Marine surveillance and scene understanding
5	Hassan et al.[158]	Retinex enhancement	Military surveillance and marine networks
6	Yang et al.[94]	LAFFENet	Marine docking and salience object detection
7	Liu et al.[24]	RUIE	Object detection and environmental sensing
8	Xu et al.[87]	Deep-Retinex	Bathymetry and target detection

research centers will adopt intelligent underwater image processing methods in the future. For instance, color correlation in the underwater image may be utilized in real-time object detection, and underwater image registration can be employed to obtain mineral resource information.[157]

A large number of UIE approaches have been proposed for these applications. Intelligent underwater image de-hazing and attenuated color restoration are used to enhance the visibility and color, which in turn helps researchers to better investigate underwater ecosystems. The various applications of UIE are shown in Fig. 16. Table 6 shows the different underwater image enhancement methods developed for real-water underwater applications.

    a. Underwater navigation

It is used to explore the underwater world with the help of underwater robots and scuba divers.[23]

   b. Object detection

It is used to study marine life and science with the help of pose and structure estimation.[9]

   c. Coral reef monitoring

It is used to monitor and track the underwater territories, climate, and health of coral reefs as they are the source of food and shelter for marine life.[27]

   d. Deep sea mining

It is used to extract minerals such as metals and important resources from the deep sea.[8]

   e. Pipes corrosion detection

It is used to maintain the undersea pipes and estimate the amount of corrosion.[7]

   f. Underwater military establishment

It is used to establish military camps under the water for marine warfare.[157]

5.2 Discussion on Future Gaps

The results of this study show that the UIE field needs more research and investigation. The UIE methods fail due to underwater inherent characteristics, such as absorption, scattering, and attenuation. Even with the great progress in UIE methods, datasets, and evaluation metrics, obtaining high quality images remains difficult. The limitations of the review are mentioned below.

1. Human perception is primarily influenced by prior knowledge of the environment. An individual describes a scene or image quality that is primarily based on existing information and not on the visual content. An underwater environment should be explored using modern technology such as automated robots having prior knowledge. As a result, efficiency and performance of UIE methods will increase.

2. In the case of the marine environment, the natural light that propagates from the sun gets entirely absorbed below a depth of 1000 m. The only light source at greater depths is artificial light, which is required to understand the underwater scene. The majority of UIE techniques are unable to fully recover undersea images or recover information from degraded images. Thus, a new image formation model that considers irregular lighting, limited brightness, and light attenuation is required to improve scene interpretation.

3. Existing evaluation metrics are limited to some factors including contrast, sharpness, brightness, and saturation. However, no evaluation metric that considers all important factors of the underwater environment exists. Thus, considerable efforts are required to develop more accurate evaluation metrics.

4. Due to the lack of ground truth, synthetic images have been utilized to train learning-based methods. However, the UIE methods trained on synthetic images sometimes fail to enhance real underwater images. Thus, the obtained accuracy of the UIE model is poor.

5. The majority of UIE methods focus on single or multiple images rather than videos. Underwater videos play a major role in applications such as understanding marine life. However, high-resolution underwater videos are required for extracting important features of the marine world. Moreover, pretrained UIE methods are needed to improve the quality of underwater videos.

6 Conclusion

This review provided a thorough analysis of the research that has been done in the field of UIE. The role of optical properties in the underwater environment was discussed to understand the parameters used in UIFM. Further, UIE approaches that are employed by researchers were analyzed and then categorized into three broad categories: non-learning, learning, and fusion-based methods. This paper also reviewed different kinds of underwater datasets and evaluation metrics

that researchers use to perform experimental analysis and validation. The performance of UIE methods was analyzed and compared using the RUIE dataset. Also, real-world underwater applications were discussed. Finally, various limitations of UIE methods, datasets, and evaluation metrics were highlighted and discussed in detail. Although single UIE method algorithms have made great progress in recent years, no algorithm that can be utilized to enhance underwater images at varying depths has been created. There are still options to improve the performance of UIE methods in terms of flexibility, robustness, and complexity for real-life applications.

Acknowledgments

Data, Materials, and Code Availability

The datasets used to analyze the findings of this study are publicly available at [https://github.com/xahidbuffon/Awesome_Underwater_Datasets].

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