العددِ 21A ايار 2026
NO.21A May 2026
المجلة العراقية للبحوث الانسانية والاجتماعية والعلمية
Iraqi Journal of Humanitarian, Social and Scientific Research
Print ISSN 2710-0952 Electronic ISSN2790-1254

Underwater Image Enhancement: A Comparative Review of Traditional, Optimization-Based, Deep Learning, and Hybrid Methods

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Abstract

In this study, we compare and evaluate four major categories of underwater image enhancement methods: traditional, optimization-based, deep learning-based, and hybrid methods. Traditional methods of underwater image enhancement (e.g., histogram equalization and Retinex based methods) provide an effective means of enhancing low-light images; however, these methods tend to fail when attempting to solve the more complex issues associated with underwater imagery. Optimization-based methods represent an improvement over the traditional methods of enhancement, as optimization-based methods dynamically adjust the enhancement parameters to achieve improved image quality. However, optimization-based methods require pre-defined objective functions, which limits the applicability of these methods to solving real-world image enhancement problems. Deep learning models (e.g., CNN's and GAN's) have demonstrated great potential for solving a wide range of image processing tasks including image enhancement, by exploiting complex spatial and spectral patterns in images and providing high quality enhanced images. However, hybrid approaches to underwater image enhancement integrate the feature extraction capabilities of deep learning models and the optimization capability of optimization-based methods. Overall, our comparisons demonstrate that hybrid approaches to underwater image enhancement generally provide the highest quality enhancements, and offer great promise for practical applications requiring high-quality enhanced images of underwater scenes**.**

Keywords: Histogram Equalization, Retinex, Deep Learning, CNNs, GAN.

1. Introduction

Quality degradation due to absorption and scattering of light is a major obstacle to using underwater images in marine exploration, monitoring of environments, underwater robotic systems and science. Absorption and scattering are both responsible for image quality degradation in the form of color distortion, reduced contrast, haze and loss of detail. Water depth, water clarity (turbidity), lighting and proximity of the camera to the subject can all significantly impact the amount of image quality degradation that occurs[1]. The degradation in Figure 1 is typical when viewing underwater images as they will typically appear blue/green, be less bright, and contain fewer fine details. The extent of these effects will vary based on factors such as depth, water clarity (turbidity), suspended sediment and lighting. Therefore, enhancing underwater images is a highly challenging and complex process. Figure1 illustrates some images that are collected from various underwater images datasets[2].

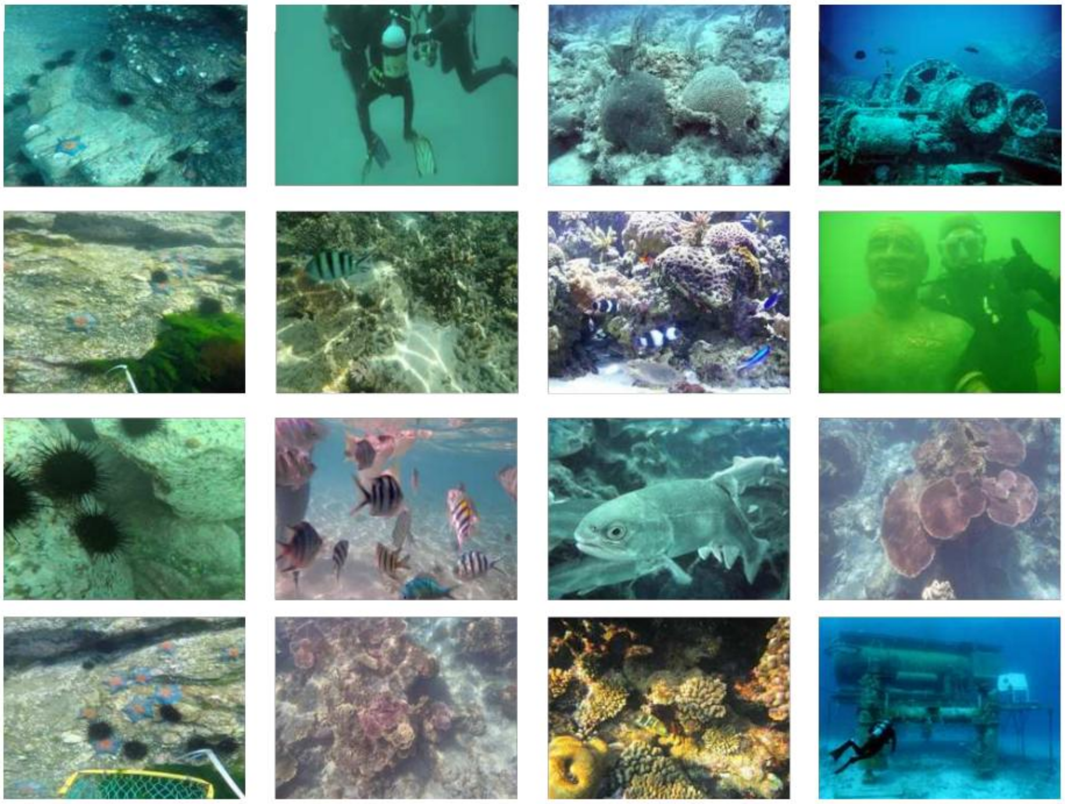

Figure 1. Examples of underwater images

There are many types of enhancement methods available to improve the quality of underwater images. Traditional techniques such as histogram equalization, Retinex-based enhancement and image fusion involve applying predefined formulas to adjust individual pixel values in the image[3]. While these methods are quick and easy to implement they often fail to address the complexity of the problem and can lead to excessive enhancements and color errors.

In comparison, optimization-based methods employ some form of traditional technique and then utilize an algorithm to optimize the parameters involved in enhancing the image; this allows for a better balance of contrast, color and visuality when enhancing images. Optimization-based techniques can produce high-quality images, however, the effectiveness of the optimization-based technique relies heavily upon the design of the objective function(s) used within the technique and therefore may not always be effective in every type of underwater environment. In recent years, there has been significant interest in developing data-driven models using deep learning techniques such as CNN's, GAN's and transformer-based architectures to create models that can learn to apply complex enhancement patterns to underwater images[4]. Deep learning based models often perform well at correcting color, increasing contrast and preserving details in underwater images when utilizing large datasets. However, the development of deep learning models requires large amounts of labeled data, high-performance computing resources and careful model training to prevent the occurrence of artifacts and/or overfitting.

To address the limitations associated with the use of single-method enhancement techniques, hybrid frameworks have been developed that integrate optimization and deep learning techniques into a single framework[5]. These hybrid systems leverage the feature extraction capabilities of deep learning techniques and the parameter fine-tuning capabilities of optimization techniques to provide the benefits of both paradigms. As a result of integrating the two paradigms into a single system, hybrid models are particularly effective at producing clear images while maintaining detail and correct color in a variety of underwater environments.

This research provides a comprehensive comparison of four major techniques for enhancing underwater images: traditional, optimization-based, deep learning and hybrid. Through the evaluation of the strengths and weaknesses of each technique and the resultant image quality of each, this research demonstrates the progression of each technique and concludes that hybrid techniques generally produce the most effective results. This research aims to assist researchers and practitioners in selecting the most appropriate technique to use for real-world applications involving underwater imaging.

2. Literature Review

Underwater image enhancement has become a subject of substantial interest for several reasons. It is well-known that images taken under water are typically degraded by the loss of clarity, and color information through light absorption and scattering; this can also be seen through changes in color, which results from color distortion. The degradation of image quality hinders the ability of underwater vision systems to perform in numerous applications such as marine exploration, object detection, and autonomous underwater vehicles. In order to improve image quality, researchers have developed a variety of techniques for improving image quality, with many researchers using optimization-based models (OBMs) to optimize image quality[6]. OBMs use an optimization process to identify the optimal values for enhancing image contrast, correcting color distortion, and reducing noise. The purpose of this literature review is to provide an overview of existing underwater image enhancement methods, focusing on the underlying processes employed to operate the enhancements, as well as the primary limitations associated with the enhancements.

2.1 Traditional Methods of Underwater Image Enhancement

The majority of current underwater image-enhancement methods utilize a variety of classical image processing methods to resolve problems related to light loss, scattering, low contrast and color distortion in underwater environments. Classical image processing methods do not require learning-based models since they apply adjustments to either individual pixel values or individual color-channels. Due to this reason, classical image processing methods have been used efficiently in a large number of underwater vision studies during early years of underwater vision research.

In addition to being able to minimize color loss and perform locally adaptive contrast enhancement, Santhi Priya et al. (2023) proposed a new underwater image enhancement method which utilized a maximum attenuation map for guiding local color corrections, and integral maps for adaptively adjusting contrast. Following local color corrections, a color balance technique was employed to minimize color discrepancies and improve the visual naturalness of the underwater image [7].

Wang et al. (2023) proposed a new underwater image enhancement method which incorporates adaptive color correction and stationary wavelet detail enhancement. In their method, a stationary wavelet transform was first used to enhance the image details and clarity, and then channel similarity was used to guide pixel level color compensation in order to prevent red-channel artifacts[6].

Experimental results demonstrated that Wang's (2024) method significantly improved the color fidelity, detail preservation and overall image quality when compared to a number of other state-of-the-art underwater image enhancement methods[8].

Based on global and local histogram equalization and dual-image multi-scale fusion (GLHDF), Bai et al. (2022) proposed a new underwater image enhancement method. The GLHDF method utilized pixel intensity center regionalization in conjunction with global and local histogram equalization to adjust color casts and increase the contrast of the images, while also integrating saliency, contrast and exposure information using multi-scale fusion. Experimental results demonstrated that the GLHDF method effectively improved the visibility, color naturalness and sharpness of underwater images, and significantly outperformed a number of other state-of-the-art underwater image enhancement techniques[9].

Utilizing a combination of adaptive color and contrast enhancement with denoising (ACCE-D), Li et al. (2023) developed an underwater image enhancement framework. The ACCE-D method decomposed images into high-and low-frequency components using Difference of Gaussian and bilateral filtering, respectively. Then, noise was reduced from the high-frequency component of each image using soft-thresholding, and the color and contrast of each image was adaptively adjusted in the HSI color space using a variational model. Experimental results demonstrated that the ACCE-D method effectively corrected colors, improved the visibility of underwater images and preserved image details, and significantly outperformed a number of other state-of-the-art underwater image enhancement methods[10].

Using a combination of minimal color loss and locally adaptive contrast enhancement (MLLE), Yasaswini et al. (2022) proposed a new underwater image enhancement method. The MLLE method utilized map-guided fusion to enhance the local color correction of images, and integral and squared integral maps to adaptively adjust the contrast of the images. Then, a color balance technique was used in the CIELAB color space to further improve the color balance and richness of the images. Experimental results demonstrated that the MLLE method effectively improved the color richness, contrast and detail preservation of underwater images, and significantly outperformed a number of other state-of-the-art underwater image enhancement methods[11].

Using a combination of multi-domain fusion and dynamic color compensation, Tian et al. (2024) proposed an adaptive underwater image enhancement framework. The method utilized illumination compensation, spatial and frequency-domain filtering, and a dynamic color compensation model that combined RCP, DCP and MUDCP in accordance with water type. Experimental results demonstrated that the method significantly outperformed a number of state-of-the-art methods in terms of contrast enhancement, color correction and structural preservation[12].

Using a combination of multi-resolution fusion of RGB channels and luminance reconstruction, Wang et al. (2023) proposed a new underwater image enhancement method. The method decomposed RGB channels and reconstructed luminance information using Laplacian-Gaussian pyramids weighted by weight maps to eliminate artifacts. Experimental results demonstrated that the method significantly improved the visibility in dark regions and the color consistency, contrast and sharpness of underwater images when compared to a number of state-of-the-art methods[6].

Using a combination of histogram equalization approximation and a physics-based dichromatic model, Peng et al. (2024) proposed a new underwater image enhancement method. The authors developed a physical model of the underwater image formation process that included the effects of light attenuation and scattering. Using this physical model, they approximated the conventional histogram equalization within a convex optimization framework to restore color balance and enhance contrast simultaneously without requiring paired reference images. This method provided a unique advantage of restoring color balance and enhancing contrast simultaneously[13].

Although the above-mentioned classical underwater image restoration methods produced visually appealing images, it can be observed from Table 1 that even the best performing underwater image restoration methods contain both advantages and disadvantages.

Therefore, the primary disadvantage of the classical underwater image enhancement methods is that they cannot provide the same degree of objectivity as learning-based methods, due to the fact that the parameters of classical image processing methods are difficult to optimize and the parameters are typically manually set by researchers. Therefore, the development of a new learning-based underwater image enhancement method that provides a higher degree of objectivity than the classical methods is required.

Table 1. A comparative of the Traditional methods of Underwater Image Enhancement

No	Research Title	Reference no.	year	Method	Strengths	Weaknesses
1	Underwater mage Enhancement via Minimal Color Loss and Locally Adaptive Contrast Enhancement	[7]	2023	MLLE: Minimal Color Loss–based Fusion with Local Adaptive Contrast Enhancement	Preserves color and mproves ocal contrast using a single image	Less effective in highly turbid or very low-visibility water
2	Underwater mage	[8]	2024	Adaptive color correction with	Reduces color	Higher computational

	Enhancement via Adaptive Color Correction and Stationary Wavelet Detail Enhancement			stationary wavelet detail enhancement	artifacts and mproves mage details	cost
3	Underwater mage Enhancement Based on Global and Local Equalization of Histogram and Dual-Image Multi-Scale Fusion	[9]	2020	Global–local histogram equalization combined with dual-mage multi-scale usion (GLHDF)	Improves visibility, contrast, and color balance across diverse underwater scenes	Increased complexity and limited robustness to varying urbidity levels
4	Enhancing Underwater Image via Adaptive Color and Contrast Enhancement, and Denoising	[14]	2022	ACCE in HSI with DoG & Bilateral Filter	Enhances color, contrast, and details; denoises	High computation; parameter sensitivity
5	Underwater Picture mprovement with Locally Adaptive Contrast Augmentation and Minimal Color Loss	[11]	2024	MLLE: Min Color Loss + Map-Guided Fusion + Local Contrast	Enhances color, contrast, details; fast CPU processing	Limited in ow-light mages
6	An Adaptive Underwater Image Enhancement Framework via Multi-Domain Fusion and Color Compensation	[12]		Multi-domain fusion with adaptive color compensation	Improves visibility, contrast, and color idelity across different water conditions	High computational complexity and dependence on accurate parameter estimation
7	Underwater mage Enhancement Using Multi-Task usion	[13]	2024	Multi-task fusion combining color correction, fuzzy visibility enhancement, and contrast enhancement	High visual quality and mproved eature detection	Higher computational complexity
8	Underwater mage Enhancement Based on Luminance Reconstruction by	[15]	2021	2021 Luminance econstruction using multi-resolution fusion	Enhances dark egions, mproves contrast and sharpness,	Performance depends on handcrafted usion rules and may ncrease

	Multi-Resolution Fusion of RGB Channels				educes usion artifacts	computational cost
9	Underwater mage Enhancement Based on Histogram-Equalization Approximation Using Physics-Based Dichromatic Modeling	[16]	2021	Physics-based Dichromatic Model + Histogram Equalization Approximation + Convex Optimization	Restores color and contrast jointly, no paired data equired	Depends on physical model assumptions

Underwater image enhancements traditionally have been done using a series of steps that use pre-determined rules and that include minimizing color loss, adjusting contrast, histogram equalization, and merging images taken at multiple scales[17]. While these traditional enhancements are easy to understand and will generally provide good results in most cases where the degradation of the image due to water effects is moderate, they suffer from being "hard-wired" and therefore fail to adapt to significant levels of turbidity and/or low light. However, while these traditional methods are straightforward in concept, the fact that they depend on assumptions that may not reflect the actual conditions under which an image was captured, means they may not be effective in all cases. In addition to traditional rule based methods, some other approaches use physics-based models such as the Dark Channel Prior (DCP) and its variants for estimating how light travels and is bent through water based on its optical properties. DCP and its underwater variants were initially developed to remove haze from the atmosphere but are now also being applied to remove backscatter from underwater images. Like the traditional method-based enhancements, however, if the assumptions regarding how light behaves in the underwater environment are incorrect, then this type of method-based enhancement will also not perform well. Researchers have attempted to address some of the limitations of traditional image enhancements in recent years, but so far the limitations of assumption-based enhancements and the need for manual step-by-step processing continue to limit their effectiveness[18]. The variability of underwater conditions with respect to depth, turbidity, and lighting, make classical enhancements inherently non-robust. Therefore, researchers are increasingly focused on developing new adaptive, learning-based image enhancements for underwater environments.

2.2. Optimization-Based Methods of Underwater Image Enhancement

Optimization-based methods for enhancing underwater images treat the restoration of an image as an optimization problem[12]. They seek to restore an image to its original state through the minimization or maximization of an objective function that satisfies one or more of three types of requirements: physical, statistical, and perceptual. Optimization-based methods produce estimates of the original image by balancing the degree to which the estimated image resembles the observed underwater image and the degree to which the estimated image conforms to the constraints imposed by the characteristics of natural images and/or the physics of underwater imaging. A typical approach involves the application of an inverse imaging model. Inverse imaging models simulate the process of forming an underwater image by simulating the effects of transmission through water (i.e., the attenuation of light due to water), the effects of ambient illumination, and the effects of water absorbing light. Typically, the restoration of an image is accomplished by solving constrained optimization problems that include prior knowledge about the image, such as the smoothness of a transmission map and/or the sparsity of the gradient of a transmission map.

Rana Ghalib and Alyasseri (2023) developed a new method for enhancing underwater images that used the Coronavirus Herd Immunity Optimizer (CHIO) to optimize an image's visual quality. Their method converted images from RGB to HSV color space, optimized their visual quality using CHIO, and then changed them back to RGB. The authors tested their method on four benchmark underwater image datasets and found that their method produced images that had significantly higher contrast, improved color corrections, and greater detail than did images enhanced using the optimization methods that they evaluated against; however, the authors also noted that their method could sometimes have difficulty producing high-quality enhancements when the images were primarily green in color and that their method could be computationally intensive[19].

Zhang et al. (2023) developed a framework for enhancing underwater images that addressed degradation caused by the absorption and scattering of light by applying piecewise color correction and dual-prior contrast optimization to the images. The authors applied color correction to the base layer of the images after splitting them into two layers (a base layer and a detail layer). They applied contrast optimization to both layers. The authors tested their method on multiple benchmark underwater image datasets and demonstrated that their method produces images that are more accurate in terms of color, have higher contrast levels, and preserve textures better than do images that are enhanced using current leading methods, particularly in foggy or low-light underwater environments[10].

Chen et al. (2023) developed "Underwater-YCC: Underwater Target Detection Optimization Algorithm Based on YOLOv7," which integrates color correction and attention-based feature optimization into YOLOv7 to enhance underwater target detection. Chen et al. conducted experiments using the test sets in the datasets that they used to develop their algorithm, and concluded that their algorithm can detect underwater targets more accurately and robustly than the standard YOLO models, particularly for small or blurry targets[6].

Demir, Aktas, and Eksioglu (2025) have proposed a deep learning framework that integrates pixel-level color correction and physical-channel based dehazing techniques. The model uses a joint loss function to jointly train and optimize both modules. Experimental results show improved performance over other traditional and state-of-the-art methods in terms of qualitative and quantitative evaluation metrics[20].

Recently, a research article titled "Underwater Image Enhancement Using Improved Colony Heuristic Particle Swarm Optimization" was published by Dajian Yi (2025). In this study, Colony Heuristic Particle Swarm Optimization (CHPSO) was used as an image enhancement technique. CHPSO is a hybrid metaheuristic method that incorporates particle swarm optimization (PSO) and ant colony optimization (ACO) to enhance collaboration and information sharing among particles. The Adaptive Weight Adjustment and Pheromone-Based Heuristic Algorithm were employed to increase the convergence speed and PSNR and SSIM by 8.7%, 7.2%, and 9.4% respectively. Therefore, the hybrid metaheuristic method demonstrated a significant improvement in real-time image enhancement and optimization efficiency[21].

Isa et al. (2022) also improved the YOLOv5 framework for underwater object detection by adjusting some hyperparameters, including the learning rate and momentum. The authors used the ADAM optimizer with a reduce-learning-rate-on-plateau strategy, which allows the model to converge faster. The improved model (YOLOv5s-bA-LRP) achieved a high mean average precision (mAP) of 98.6% and detected objects at 106 FPS, thus indicating superior convergence and detection capabilities on low-contrast and blurry underwater images[22]. In addition, Zhang, Bi, and Li (2025) have proposed a new underwater image processing and target detection method. Their method consists of three main components: Visual Saliency Analysis (VSA), Particle Swarm Optimization (PSO), and blockchain technology. The use of these technologies has shown to significantly improve the quality of underwater images, their brightness, and color, while also improving the effectiveness of target detection and tracking. Experimental results showed higher values of F-values, lower values of mean absolute error, and higher values of image entropy as compared to other VSA-based methods[23]. Table 2 in the following shows a comparison of optimization-based underwater image enhancement methods.

Table 2. A comparative analysis of the optimization Underwater Image Enhancement

No	Research Title	Reference No.	Year	The Method	strengths	Weaknesses
1	An optimization method for underwater images enhancement.	[19]	2022	CHIO metaheuristic with RGB–HSV color space conversion	Effective color correction, contrast and detail enhancement; outperforms traditional optimizers	Less effective for green-dominant images; high computational time
2	Underwater image Enhancement via Piecewise Color Correction and Dual Prior Optimized Contrast	[24]	2023	Piecewise color correction + dual-prior contrast optimization	High color fidelity and contrast in low-light underwater scenes	High computational cost; handcrafted priors

	nhancement					
3	Enhancement and ptimization of nderwater Images nd Videos apping	[25]	2023	Dark hannel Prior DCP), ransmission ap ptimization, daptive aturation ap	Improved isibility and olor fidelity; pplicable to mages and ideos; real-ime erformance	Sensitive to epth estimation ccuracy; educed ffectiveness in ighly complex nderwater cenes
4	Underwater-CC: Underwater arget Detection ptimization lgorithm Based n YOLOv7	[6]	2023	YOLOv7 + nderwater olor orrection + ttention	High ccuracy for mall targets	Higher omputational ost
5	Optimizing nderwater Image uality	[17]	2023	Median ilter, Gamma orrection, CP, LAHE	High-quality nhancement, ast rocessing, eal-time uitable	Limited daptability to xtremely turbid ater; may need arameter tuning
6	EFFICIENT NDERWATER MAGE LASSIFICATIO N WITH NHANCED OLOV5 AND EARDED RAGON PTIMIZATION BeardYOLO)	[26]	2025	YOLOv5 + earded ragon ptimization BDO)	High lassification ccuracy; mproved lustering; obust for omplex nderwater asks	Increased odel omplexity; omputationally ntensive
7	Joint ptimization in nderwater Image nhancement: A raining ramework ntegrating Pixel-evel and hysical-Channel echniques	[20]	2025	HUWIE-et: Pixel-evel color orrection + hysics-nformed ehazing	Improved larity and tability; joint ptimization; eep learning-ased	Higher omputational equirements; omplex training
8	Image nhancement HPSO Processing echnology Based n Improved article Swarm ptimization	[21]	2025	CHPSO: SO + Ant olony ptimization	Faster onvergence; igher PSNR & SSIM; mproved ptimization	Increased omputational omplexity; equires careful arameter tuning

	Algorithm.					
9	Optimizing the Hyperparameter Tuning of YOLOv5 for Underwater Detection	[22]	2022	YOLOv5 + ADAM optimizer + Reduce-earning-rate-on-plateau	High mAP 98.6%), fast nference (106 FPS), mproved convergence	Sensitive to hyperparameter election; challenging in varied underwater conditions
10	Underwater mage processing and target detection rom particle swarm optimization algorithm	[27]	2025	VSA + PSO + Blockchain	Improved mage quality, brightness, color, and arget detection; higher F-value, lower MAE	Limited ample size; hort research ime; further validation equired

Optimization-based methods for improving the quality of underwater images provide an organized approach to restoring images using objective function-based methods. However, optimization-based methods have limitations related to model-based assumptions that must be made; the sensitivity of parameters chosen; and the need for significant computing resources. Therefore, researchers have begun to study both hybrid and deep-learning based models that allow for more flexibility and a better understanding of underwater environments.

2.3 Deep-Learning Based Methods for Underwater Image Enhancement

Due to its ability to capture complex degradation patterns within data sets, deep-learning has become increasingly popular in underwater image enhancement. Many recent studies have focused on transformer-based architectures to capture both local and global degradation characteristics across a variety of underwater images. Other studies have focused on developing lightweight models and unsupervised models to improve performance under reduced computational loads and reduced reliance on large amounts of labeled data, which will be necessary for real-time applications of underwater systems. In total, there are several forms of deep-learning based models available including convolutional neural networks (CNNs); attention networks; generative adversarial networks (GANs); and models based on transformers, all of which represent strong and evolving solutions for underwater image enhancement [28].

Saleh et al. (2022) presented an unsupervised deep learning framework for the enhancement of underwater images based on an adaptive distribution of uncertainty. Their proposed method, UDnet, utilizes a statistically guided multi-color space stretch for generating pseudo-reference maps; it also employs a U-Net–based conditional variational autoencoder for modeling feature uncertainty. Thus, this framework eliminates the need for paired training data and adaptively enhances the contrast, color saturation, and illumination of the images.

Evaluations on multiple public datasets have shown that the UDnet framework demonstrates com 023+petitive state-of-the-art performance in both qualitative visual quality and quantitative measures; these results support the use of uncertainty-aware unsupervised learning for the enhancement of underwater images[29].

Chandra et al. (2023) proposed a CNN-based method called CNN-CBDT for the enhancement of underwater images which provides an improvement in color balance and reduction of noise. The method utilized deep convolutional features with ReLU or PReLU activation to simultaneously address both color distortion and noise. The experiments demonstrated that CNN-CBDT provided improvements in peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) over the traditional methods while providing the ability to perform in real-time[30].

Yadav et al. (2021) proposed a CNN-based method for the enhancement of underwater images which used histogram equalization to correct for the dominant color and low contrast. The method applied histogram equalization to the grayscale version of the image and then employed a trained convolutional neural network to preserve the color information. The experimental results showed that the proposed method recovered better contrast than traditional correction methods as well as lower mean squared error (MSE) and higher PSNR[31].

Chen et al. (2021) developed an underwater image enhancement method which combined deep learning with an image formation model to correct for color distortion and low contrast in images captured by robots under water. The method used PReLU activation and dilated convolution to provide greater flexibility in fitting features and preserving detail. The experimental results showed richer colors, higher PSNR and SSIM, faster processing times, and better results in later feature matching tasks[32].

Wang et al. (2022) proposed the UIEC^2-Net, a CNN-based framework for the enhancement of underwater images which utilized both RGB and HSV color spaces within a single end-to-end network. The model enhanced the RGB values, adjusted the luminance and saturation values in HSV, and utilized an attention mechanism to combine the results. Tests on synthetic and real underwater images showed that UIEC^2-Net was able to effectively remove color casts from the images, improve their visual quality, and achieve better evaluation metrics[33].

El Rejal et al. (2023) proposed the WGH-Net, an end-to-end CNN-based framework for the enhancement of underwater images which utilized both spatial and frequency domain processing to correct for color casts, low contrast, and blurring in images taken at great depths. WGH-Net produced good results on several datasets and achieved better results than most other state-of-the-art methods in both full-reference and non-reference metrics[34].

Xie et al. (2022) proposed a deep learning framework for enhancing low-light underwater images and introduced the first specifically designed low-light underwater image dataset (LUIE) along with a dual-network model named LDS-Net. The method jointly addressed low-light degradation and scattering effects using image decomposition and restoration. Experimental results showed that LDS-Net exhibited robust performance across a wide range of illumination levels and outperformed all other underwater and low-light enhancement methods[35].

Shi et al., (2022) - Shi et al. (2022) presented an Underwater Image Enhancement Framework, which utilized both Deep Learning and Conventional Image Enhancement Techniques. Shi's method used Attention-Guided Residual Learning for Color Compensation of Red & Green Channels and Combined CLAHE and Gamma Correction in a Multi-Scale CNN to Enhance Contrast and Deblur Images. The experimental results showed that their method was able to enhance both synthetic and real-world images[33].

Shanmugavalli et al., (2025) - Shanmugavalli et al. (2025) proposed a Generative Adversarial Network (GAN) based on a U-Net architecture to address Low Contrast, Color Distortion and Noise in Underwater Images. Their method integrated the U-Net Architecture as Feature Extractor with GAN-based Realism Learning and therefore Enhanced Visibility and Restored Natural Colors to the images. Experimental Results on both UIEB and EUVP Datasets demonstrated that their method produced Superior PSNR, SSIM and UIQM than Traditional Methods[36].

Jayasurya et al., (2025) - Jayasurya et al. (2025) presented a Novel Underwater Image Enhancement Method called UWE-Net, which is based on a Deep Learning Architecture. UWE-Net is based on a Pre-trained VGG16 Encoder with a Convolutional Block Attention Module (CBAM), and uses the Charbonnier Loss Function. As a result of using Channel-Wise and Spatial Attention together, the method effectively reduces Color Distortion, Low Contrast and Degradation of Visibility of Underwater Images. The results of experiments performed on the UIEB Dataset have shown Improved Visual Quality with Superior PSNR and SSIM Values compared to other State-of-the-Art Methods[37].

Table 3. A comparative of the Deep Learning Underwater Image Enhancement Methods.

No	Research itle	Ref.	Year	Method	Strengths	Weaknesses
1	Adaptive ncertainty istribution in eep Learning or nsupervised nderwater mage nhancement	[29]	2023	UDnet with GMCS, cVAE, nd Probabilistic daptive Instance ormalization	Fully nsupervised ramework; no aired data equired; obust color nd contrast estoration; trong eneralization cross datasets	Increased omputational omplexity; erformance ensitivity to eference map uality
2	CNN based olor alancing and enoising echnique for nderwater	[30]	2023	CNN-CBDT Color Balancing + enoising)	Improved olor and noise uppression; eal-time speed	Reduced obustness in ighly turbid cenes

	mages: CNN-CBDT					
3	UNDERWATER IMAGE ENHANCEMENT USING CONVOLUTIONAL NEURAL NETWORK	[31]	2021	CNN + Histogram Equalization	Improved contrast and edge recovery; ow MSE and high PSNR	Limited handling of evere color distortio
4	Underwater mage Enhancement based on Deep Learning and mage Formation Model	[32]	2021	Deep Learning + mage Formation Model	Accurate color correction; high PSNR/SSIM; fast computation	Relies on supervised training data
5	UIEC^2-Net: CNN-based Underwater mage Enhancement Using Two Color Space	[38]	2021	UIEC²-Net (RGB + HSV CNN)	Effective color cast emoval; global uminance and saturation control; detail preservation	Higher model complexity han single color-space CNNs
6	An End-to-End CNN Approach for Enhancing Underwater mages Using Spatial and Frequency Domain Techniques	[34]	2023	WGH-Net (CNN + Spatial/Frequency Domains)	Handles deep-sea degradation; strong quantitative and qualitative esults	Not yet validated on eal-time video
7	Lighting the darkness in the ea: A deep earning model or underwater mage nhancement	[35]	2022	LDS-Net + LUIE Dataset	Effective ow-light and scattering emoval; obust under varying llumination	Two-stage network ncreases training complexity
8	Integrating deep learning and traditional mage nhancement echniques for nderwater	[33]	2022	DL + CLAHE + Gamma (Attention-based MSCNN)	Accurate color correction; enhanced contrast and brightness; strong	Increased pipeline complexity due to hybrid design

	mage nhancement				eneralization	
9	A Deep earning pproach for nhanced larity: ransforming nderwater magery with -Net GAN	[36]	2025	U-Net GAN	Strong detail reservation; atural color estoration; igh SNR/SSIM/U QM	High raining omplexity nd omputational ost
10	UWE-Net: A eep Learning ramework for nderwater mage nhancement ntegrating BAM and harbonnier oss	[37]	2025	UWE-Net VGG16 + CBAM Charbonnier oss)	Effective ttention-based nhancement; igh SNR/SSIM; ood eneralization	Computatio ally ntensive; imited real- ime alidation

Deep learning methods help improve underwater images by addressing the common challenges of color distortion, low contrast, and light scattering in underwater images. CNNs are capable of extracting the relevant features in underwater images, however, most deep learning models require large amounts of training data which is typically labeled. GANs can generate high-quality images that closely resemble real-world images; however, they require a significant amount of computational resources to operate. In addition to the above-mentioned deep learning models, there are other approaches including attention-based models, models that utilize multiple color spaces, hybrid models and unsupervised models that provide greater adaptability and generalizability[39]. However, achieving both robustness and efficiency in highly degraded underwater images is still a challenging problem.

2.4 Hybrid Optimization and Deep Learning Methods

In recent years, researchers have been increasingly employing hybrid optimization and deep learning methods to enhance underwater images. The hybrid models utilize both the physics-based and data-driven paradigms, i.e., the mathematical optimization and the data-driven learning, respectively. Therefore, the hybrid models are able to improve the visual quality of underwater images and address some of the problems, e.g., color distortion, low contrast, and scattering, associated with underwater images more effectively than the individual deep learning and optimization methods. Recently, researchers have proposed various types of hybrid models based on transformers that utilize self-attention and optimization to improve the feature representation. By integrating deep learning to extract features from the images with parameter optimization, the hybrid models are capable of capturing the global information in the images and preserving the fine details of the images. Consequently, these models are suitable for processing the complex underwater images. In summary, the hybrid optimization and deep learning methods demonstrate considerable promise by combining the flexibility of deep learning and the accuracy of optimization to improve the quality of underwater images[40].

Kaur et al. (2025) introduced a hybrid underwater image dehazing framework that integrates a GAN model with bottleneck attention and enhanced Retinex optimization to simultaneously tackle haze, color distortion, and low visibility. The framework utilizes the combination of the data-driven learning paradigm and the physics-based enhancement paradigm to produce higher perceptual quality and structural consistency of the underwater images produced from the framework than those generated by traditional and deep learning methods from the UIEB datase[5].

Kumar et al. (2025) have developed a hybrid underwater image enhancement framework that uses hierarchical transformers with Particle Swarm Optimization (HTN-PSO) to model both local features and long-range dependencies. By combining transformer-based attention with evolutionary optimization, this method has significantly enhanced the quality of perception and no-reference metric values on a variety of benchmark datasets and demonstrated better generalization and robustness than previous CNN- and transformer-based methods[41].

Abirami et al. (2025) proposed an ensemble deep learning framework with hybrid optimization (UODC-EDLHOA) for underwater object detection and classification. The model uses EfficientNetB7 with attention mechanisms for feature extraction, YOLOv9 for detection, and an ensemble of DNN, DBN, and LSTM, optimized with a hybrid STSC algorithm. Tests have shown a classification accuracy of 92.78%, strong performance in various underwater conditions, and effective detection of small, overlapping, or hidden objects[40].

Peng et al. (2025) presented PBDNet, a polarization bi-decoder network for underwater salient object detection (USOD). The model includes dual decoders and utilizes polarization information along with Feature Interacting Spatial Attention Fusion (FISAF) and Residual Spatial Pyramid Feature Aggregation (RSPFA) to efficiently capture both local and global features. Experimental results demonstrate high detection accuracy with low parameters (14.7M) and low computational costs (9.7G FLOPS). Nevertheless, it shows limitations in terms of object distance sensitivity and difficulty in generalizing to multiple different modalities[42].

Mu et al. (2025) have introduced MUGAN, a mixed generative adversarial network for underwater image enhancement. The model includes convolutional operation and self-attention within a U-shaped generator and employed a dual discriminator to optimize both global and local image features. A multi-term loss function is applied to guarantee both perceptual quality and color fidelity. Experimental results indicate improved contrast, natural color reproduction, and robust performance in different types of underwater conditions. Research directions for future studies include video enhancement and the utilization of extended datasets[10].

Sahu and Swarnkar (2024) have tackled the issue of underwater image degradation due to light absorption, scattering, and turbidity by presenting a hybrid deep learning architecture that couples Convolutional Neural Networks (CNNs) with Transformer-based models. The framework was trained by means of supervised and unsupervised learning techniques to improve robustness in a wide range of underwater scenarios. Although it is effective, the study points out still existing limitations of the framework in extremely turbid water conditions and in terms of domain generalization, highlighting the need for further studies concerning lightweight and adaptive models[41].

Narla et al. (2025) have also proposed a hybrid non-learning-based enhancement framework for underwater images based on the integration of White Balancing (WB), Contrast Limited Adaptive Histogram Equalization (CLAHE), and Dark Channel Prior (DCP). In comparison to traditional learning-based frameworks that rely on data-driven approaches, this framework relies on physical priors, thereby providing robustness and computational efficiency. On the other hand, the use of handcrafted priors represents a limitation regarding adaptability to complex underwater degradations and generalization over highly diverse environments[43].

Geng et al. (2025) introduced an architecture combining a U-Net and a Transformer for the purpose of enhancing underwater images, which are the shortcomings of present models for their inability to retain fine detail while preventing visual artifact generation; this architecture includes multi-scale local feature extraction utilizing a U-Net and global context modeling utilizing a Transformer. In addition, the authors provided a novel Recurrent Multi-Scale Feature Modulation (R-MSFM) technique, which was utilized to improve the architecture; however, the authors noted that while the model is capable of producing high-quality results under normal water conditions, it has difficulty adapting to extreme water conditions, thus demonstrating a need for enhanced domain adaptation and reduced computational overhead to facilitate lightweight deployment[39].

Noor and Ruhaiyem (2025) developed an underwater image enhancement framework integrating traditional image processing techniques with deep learning architectures to address color distortion, haze, and loss of resolution resulting from imaging underwater. The framework is designed as a multi-stage pipeline; the first stage removes haze from the image through the application of a dark channel filtering strategy prior to applying Retinex-based color correction to provide consistent chromaticity. Although the multi-stage nature of the framework enables the sequential e execution of each stage, the sequential nature of the hand-crafted stages limits the ability to adapt to highly dynamic underwater environments and provides cumulative error sensitivity[1].

Table 4. Comparison of hybrid optimization and deep learning based techniques for underwater image enhancement, including methodologies, techniques used, findings, and limitations.

The umber	Search Name	Authors	Year	The echnology sed	strengths	Weaknesses

1	Underwater mage lehazing ising a ıybrid GAN vith ottleneck ttention and mproved Retinex ased ptimization	[28]	2025	GAN + Bottleneck Attention + Retinex	High erceptual uality; trong color estoration; obust lehazing	Increased raining omplexity; arameter tuning equired
2	Underwater mage nhancement ising hybrid ransformers nd volutionary article warm ptimization	[5]	2025	Hierarchical Transformers - PSO (HTN-PSO)	Strong lobal feature nodeling; daptive ptimization; igh UIQM mprovement	Reduced ffectiveness in xtreme urbidity; added omputational verhead
3	An ntegration of nsemble leep learning vith hybrid ptimization pproaches or effective nderwater bject letection and lassification nodel	[40]	2025	Ensemble DL (DNN + DBN + LSTM) + EfficientNetB 7 + YOLOv9 - Hybrid STSC Optimization	High ccuracy 92.78%); obust under hallenging nderwater onditions; handles small nd verlapping bjects	Computational y intensive; equires multiple nodel training tages
4	PIC-GAN: Symmetry-Driven Underwater mage Enhancement vith Partial nstance Normalisatio n and Colour Detail Modulation	[23]	2025	GAN + Symmetric U-Net + PIN + CDM	High PSNR/SSIM; preserves extures and lobal eatures; mproved erceptual uality (low LPIPS)	Limited daptability for non-paired data; educed erformance in xtreme or nighly turbid vaters
5	PBDNet: a polarization bi-decoder	[42]	2025	Dual-lecoder CNN - Polarization	High ccuracy; fficient	Sensitive to bject distance; imited multi-

	etwork with eature nteracting usion for wo-modality nderwater alient object etection			- FISAF + RSPFA	eature usion; low omputationa cost	nodality eneralization
6	Underwater mage nhancement sing a nixed enerative dversarial etwork	[10]	2023	U-shaped AN + Convolution + Self-Attention - Dual Discriminator - Multi-term Loss	Enhanced olor fidelity; mproved ontrast and larity; robust cross scales	High training omplexity; not et validated for ideo or real-ime deployment
7	Advancing Underwater mage Quality Enhancement hrough Hybrid Deep Learning Architectures	[41]	2025	Hybrid CNN–Transformer Deep Learning	High erceptual uality, ffective olor and tructure estoration	Limited erformance in xtreme urbidity, domain eneralization ssues
8	A Hybrid Approach with CLAHE and Dark Channel Prior for Enhancing Underwater mages	[43]	2025	WB + CLAHE + DCP with multi-scale usion	Effective olor orrection and de-hazing, low omputationa cost	Limited daptability to omplex and arying nderwater onditions
9	Underwater mage Enhancement with a Hybrid U-Net-Transformer and Recurrent Multi-Scale Modulation	[39]	2025	Hybrid U-Net–Transformer with R-MSFM	High detail reservation, trong PSNR/UIQM ains, ffective lobal–local usion	Performance egradation in xtreme water onditions
10	Hybrid Approach for Enhancing Underwater	[1]	2025	Dark iltering + Retinex + Super-	Improved esolution and color onsistency,	Error ccumulation rom multi-stage rocessing,

	mage Based on Deep Learning Techniques			Resolution + CNN	ffective hybrid pipeline	imited adaptability

3. Result and Analysis

Underwater image enhancement methods have been reviewed more frequently in the last couple of years. Table 5 compares different underwater image enhancement techniques to show how they work and what advantages they offer in terms of their capabilities, limitations, and comparable features. These are some newer techniques that use deep learning and physical modeling as a hybrid approach to enhance underwater images. For example, DPF-Net, PhaseFormer, UIE-UnFold and Swin CNet use both deep networks and physical modeling. They have been developed to enhance image quality in underwater environments and are able to provide realistic images.

Table 5. Comparison of Underwater Image Enhancement Approaches

Approach	Strengths	Weaknesses	Typical Outcome
Traditional Methods	Fast, simple, interpretable	Limited modeling of underwater physics, can over- or under-enhance	Basic contrast and color improvement; inconsistent on complex images
Optimization-Based Methods	Adaptive parameter tuning, objective-focused	Computation heavy, dependent on objective design	Better balance of enhancement criteria than traditional
Deep Learning Models	Strong nonlinear modeling, perceptual quality	Requires large datasets, training complexity	High visual quality, good generalization with sufficient data
Hybrid Optimization + Deep Learning	Combines deep feature learning with adaptive optimization	More complex design	Best overall performance in quality and robustness

Recent studies have shown that new underwater image enhancements are better than old ones at both measurable performance (in terms of objective measures) and visual appearance (as judged by humans). Hybrid approaches that incorporate physics-based modeling, multi-scale feature extraction, and deep learning have been shown to be more robust against large color changes and scattering effects than other approaches[4]. Task-oriented datasets are becoming increasingly popular as the trend shifts from image quality improvement toward improving both the quality of the image and the performance in tasks such as object detection and segmentation. Additionally, smaller and less computationally expensive networks can now produce high-quality results with lower processing power, enabling the possibility of near-real time operation on small embedded systems or remote-operated vehicles. However, there are still many barriers to overcome before such frameworks can be widely adopted, including the need for larger and more diverse datasets, the current reliance on synthetic training data, and the computationally intensive nature of many hybrid and Transformer-based architectures. This research proposes a method to address each of these issues through the application of physics-guided deep learning, multi-objective optimization, and efficient design techniques to enhance generalizability, task performance, and real-time capability. Overall, this research concludes that hybrid and task-oriented frameworks are likely the most effective and practical approach to underwater image enhancement.

4. Conclusion

Recent advancements in underwater image improvement have been achieved through the combination of physics-based and optimization methods along with deep learning. As shown in studies, hybrid models, Transformer architectures, multi-scale or task-aware techniques can enhance both underwater image quality and performance of tasks such as object detection and segmentation. The challenge is in achieving generalization to a variety of underwater environments; achieving real time operation; and having sufficient large datasets to label that contain a wide range of underwater conditions, depths, and lighting. The proposed framework will address these limitations by utilizing an adaptive, physics-based and optimization guided deep learning framework that improves both underwater image quality and performance in associated tasks while using a large and diverse dataset. The lightweight models in this framework will allow for real time execution on embedded devices and remote operated vehicles (ROVs). Ultimately, current research indicates that hybrid, task aware frameworks are the most viable approach toward developing a reliable and practical method for enhancing underwater imagery. This is because hybrid, task aware methods provide the ability to utilize the strengths of deep learning and adaptive optimization to produce high quality images while maintaining structural detail.

ACKNOWLEDGMENT

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

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