IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 1 September 2024, accepted 14 September 2024, date of publication 23 September 2024,
date of current version 14 October 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3465550

TOPICAL REVIEW

Seeing Through the Haze: A Comprehensive Review of Underwater Image Enhancement Techniques

LYES SAAD SAOUD, MAHMOUD ELMEZAIN, ATIF SULTAN, MOHAMED HESHMAT, LAKMAL SENEVIRATNE, AND IRFAN HUSSAIN
Khalifa University Center for Autonomous and Robotic Systems, Khalifa University, Abu Dhabi, United Arab Emirates

Corresponding author: Irfan Hussain (irfan.hussain@ku.ac.ae)

This work was supported by the Khalifa University of Science and Technology under Award CIRA-2021-085, Award No. 8434000534 and Award RC1-2018-KUCARS.

ABSTRACT Underwater imaging suffers from significant quality degradation due to light scattering and absorption by water molecules, leading to color cast and reduced visibility. This hinders the ability to analyze and interpret the underwater world. Image dehazing techniques have emerged as a crucial component for underwater image enhancement (UIE). This review comprehensively examines both traditional methods, rooted in the physics of light transmission in water, and recent advances in learning-based approaches, particularly deep learning architectures like Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Transformers. We conduct a comparative analysis across various metrics, including visual quality, color fidelity, robustness to noise, and computational efficiency, to highlight the strengths and weaknesses of each approach. Furthermore, we address key challenges and future directions for traditional and learning-based methods, focusing on domain adaptation, real-time processing, and integrating physical priors into deep learning models. This review provides valuable insights and recommendations for researchers and practitioners in underwater image enhancement.

INDEX TERMS Underwater image enhancement, traditional dehazing methods, learning-based dehazing methods, deep learning for underwater imaging.

I. INTRODUCTION

The underwater environment holds immense scientific and ecological significance, sheltering diverse habitats across over 71% of Earth's surface [1]. However, capturing clear images underwater presents a significant challenge as a result of complex light interaction with water. As illustrated in Figure 1, light scattering, absorption, and attenuation degrade image quality, leading to limited visibility, color distortion, and reduced contrast [2], [3].

These limitations hinder the effectiveness of underwater image analysis in various applications, as crucial details and information are obscured. Image enhancement techniques, particularly dehazing, are essential to recover these details and improve image quality for visual interpretability [2], [4], [5].

Inspired by recent breakthroughs in deep learning in image processing tasks such as dehazing and low light enhancement, researchers have begun exploring its application in underwater image enhancement (e.g. [3], [6]). These approaches leverage the capabilities of deep neural networks to learn the complex transformations needed to recover the original scene from degraded underwater images. In particular, some studies integrate physics-based models that simulate underwater light behavior with deep image enhancement frameworks, achieving promising results (e.g., [3], [6]).

Over the past few decades, numerous image enhancement techniques have been proposed. Traditionally, dehazing methods, built on the principles of light transmission in water, have played a role in image enhancement efforts [7], [8].

The associate editor coordinating the review of this manuscript and approving it for publication was Tai Fei.

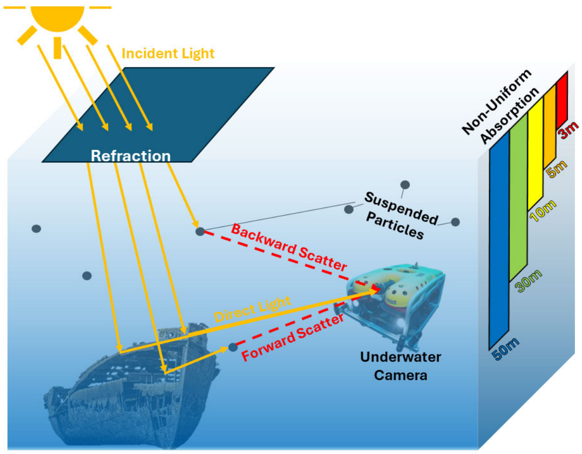

FIGURE 1. Underwater Light Attenuation and Scattering: Light in underwater environments is heavily influenced by wavelength-dependent absorption and scattering, severely limiting visibility and necessitating specialized image-processing techniques. Red wavelengths are quickly absorbed within a few meters of the light source, while blue and green wavelengths penetrate deeper because there is less attenuation. Suspended particles further scatter light, altering its direction and intensity.

More recently, the advent of deep learning, particularly Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), has revolutionized the field. They have demonstrated remarkable abilities in learning the complex features and patterns that characterize underwater imagery, achieving impressive dehazing results [9]. A conceptual framework for both traditional and deep-learning-based underwater image enhancement is depicted in Figure 2.

This study offers a comprehensive analysis of underwater image enhancement methodologies, encompassing both traditional and learning-based dehazing strategies. It also examines the evaluation criteria and contemplates prospective advancements in the field of underwater image enhancement and restoration, as illustrated in Figure 3.

A. MOTIVATION: BEYOND THE HAZE: A NEED FOR CLEAR UNDERWATER IMAGES

Beneath the ocean's surface lies a hidden world, teeming with life and holding the key to understanding our planet's past and shaping its future. However, capturing clear images in this underwater realm presents a formidable challenge.

Light, upon entering the water, undergoes a complex transformation. Scattering, absorption, and attenuation act as a distorting veil, obscuring crucial details and transforming vibrant underwater scenes into murky shadows. This significantly degrades image quality, leading to limited visibility, color distortion, and reduced contrast.

To address these challenges, researchers have increasingly focused on developing advanced image enhancement techniques. As illustrated in Figure 4, the number of publications on underwater image enhancement has shown a substantial increase over the past decade, indicating growing interest and advancements in this field.

To gauge the current research landscape, we conducted a thorough analysis of 167 high-quality, directly relevant research papers. From this pool, we identified the top 10% most cited papers and visualized their distribution on a bar chart, as illustrated in Figure 5. This surge in research activity is further corroborated by the publication venues of these highly cited works. Leading publications such as the *IEEE Transactions on Image Processing* and the *IEEE Access* play a critical role in disseminating these key findings and innovative techniques, solidifying their positions as prominent platforms within the field.

Furthermore, Figure 6 lists the journals and conferences with the highest number of publications in this domain, underscoring the widespread and multidisciplinary interest in overcoming the challenges of underwater imaging in the last decade.

Although general image enhancement techniques can be helpful, the unique challenges of underwater imaging often require customized dehazing techniques to effectively mitigate the effects of light scattering. Table 1 shows several recent reviews that have explored various underwater image enhancement techniques to address these issues (e.g., [10], [11], [12], [13], [14], [15], [16]). These reviews provide valuable insight into enhancement methods, including noise reduction and color correction, reinforcing the critical need for specialized solutions in underwater image processing.

B. MAIN CONTRIBUTIONS: UNVEILING THE DEPTHS OF DEHAZING TECHNIQUES

This review paper offers several key contributions to the field of underwater image dehazing:

- **Focused Analysis**: In contrast to existing reviews that encompass a broader scope of underwater image enhancement, this paper narrows its focus specifically on dehazing techniques. This concentrated examination provides a deeper understanding of the intricacies and challenges unique to underwater dehazing.
- **Comparative Insights**: Through a meticulous comparative analysis of both traditional and cutting-edge learning-based dehazing approaches, this review sheds light on the strengths, limitations, and potential future directions of these techniques. By gleaning insights from seminal works and exploring advancements at the forefront of the field, we aim to provide a comprehensive roadmap for researchers and practitioners.
- **Rigorous Evaluation**: This review goes beyond mere description. We delve into the theoretical frameworks that underpin dehazing techniques and analyze empirical evidence to understand their comparative performance across key metrics. This rigorous evaluation helps identify the trade-offs inherent in different approaches and reveals the challenges that remain in unlocking the full potential of underwater dehazing.
- **Captivating Guide**: This review aspires to be more than just a dry academic exercise. It strives to be a captivating guide, navigating the intricate interplay of physics,

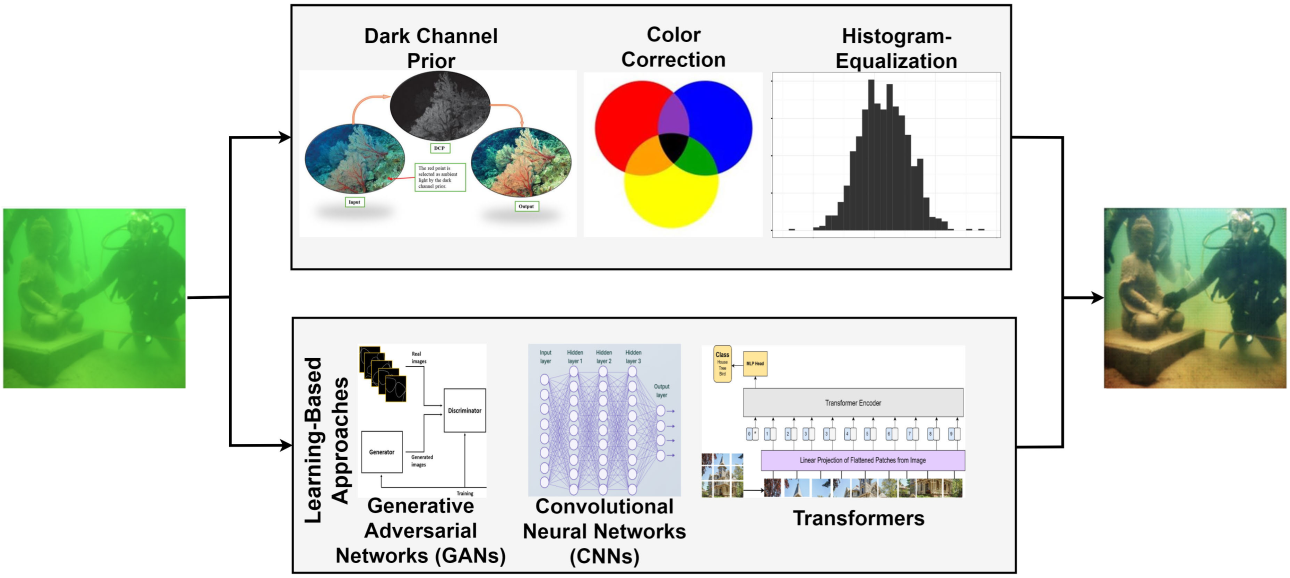

FIGURE 2. Conceptual Framework of Underwater Image Enhancement: The left side depicts the degraded underwater image with low contrast and color distortion. The center is divided into two modules that list traditional dehazing methods (e.g., Dark Channel Prior, Color Correction, Histogram Equalization) and learning-based approaches (e.g., Convolutional Neural Networks, Generative Adversarial Networks). The right side shows the enhanced image.

TABLE 1. Summary of selected reviews on underwater image enhancement (UIE).

Reference	Classification Framework	Key Elements
Lepcha et al. [11] (2023)	Image enhancement (both in air and underwater)	Discussion of available models and datasets as well as unresolved issues for image enhancement.
Shuang et al. [12] (2024)	Quality improvement of underwater optical images	Discussion of various algorithm ideologies
Raveendran et al. [13] (2021)	UIE by hardware and software methods	Summary of underwater datasets and applications areas of IE
Jian et al. [14] (2021)	Underwater image processing and analysis	Discussion of image processing models and their classification
Han et al. [15] (2020)	Deep learning methods for dehazing and color restoration of underwater images	Classification of image quality evaluation metrics
Deluxni et al. [16] (2023)	UIE and restoration	Categorization of UIE techniques. Highlighting of problems and solutions of UIE
Song et al. [17] (2023)	Deep sea image restoration	Comparison of shallow sea, deep learning based deep sea unsupervised learning methods for deep-sea image restoration

computation, and human perception. By presenting the complexities of underwater dehazing clearly and engagingly, we aim to equip researchers and practitioners with a deeper understanding of the current state-of-the-art and pave the way for further advancements in this critical field.

These contributions collectively aim to provide a valuable resource for researchers and practitioners working in the field of underwater image dehazing. By offering a focused analysis, comparative insights, rigorous evaluation, and a captivating presentation, this review paper seeks to illuminate the path toward a clearer understanding and future advancements in underwater exploration and analysis.

II. TRADITIONAL DEHAZING APPROACHES

Underwater environments pose significant challenges for image acquisition due to the scattering and absorption of light by water molecules, as shown in Figure 1. These phenomena attenuate light, alter its spectral composition, and introduce backscatter, resulting in limited visibility, reduced contrast, and color-cast images [38], [39]. Overcoming these limitations has been a central focus of underwater image enhancement research, leading to diverse techniques. Traditional approaches include methods that were most frequently employed before the development of modern machine learning and deep learning algorithms. These approaches rely on mathematical formulations, physics-based models, and image-processing techniques to improve the visibility of underwater photos [40], [41].

A. CATEGORIZATION OF TRADITIONAL APPROACHES BASED ON CHALLENGES ADDRESSED

Various methods have been developed to address the challenges of underwater imaging, each tailored to address specific aspects of improving enhancement performance.

1) METHODS ADDRESSING SCATTERING MODELS

Methods focusing on scattering models aim to enhance visibility by effectively mitigating light scattering and absorption

TABLE 2. **Polarized light, compensation techniques, fusion-based methods, prior-guided, and homomorphic filtering approaches.**

Reference	Problem	Method	Findings	Limitations
Schechner et al. [18] (2004)	Poor visibility and color distortion	Utilizing polarized light	Enhanced scene contrast, color correction, and overall improved underwater visibility	Sensitivity to lighting conditions
Schechner et al. [19] (2005)	Poor visibility and color distortion	Recovery of visibility and structure by polarization analysis	Improved contrast and color correction in underwater scenes	Limited applicability in dynamic underwater environments
Iqbal et al. [20] (2010)	Reduced contrast and color cast	Unsupervised color correction method (UCM)	Superior underwater image quality with enhanced natural color reproduction	Sensitivity to scene complexity
Chiang et al. [21] (2012)	Light scattering, color change, and artificial lighting influence	Wavelength Compensation and Dehazing (WCID)	Improved underwater image visibility and color fidelity	Sensitivity to artificial light variations
Ancuti et al. [22] (2012)	Limited visibility due to scattering and absorption	Fusion-based enhancement strategy	Reduced noise, improved exposure, and increased contrast	Complexity in fusion parameter tuning
Drews et al. [23] (2013)	Limitations of existing transmission estimation methods	Underwater Dark Channel Prior (UDCP)	Outperformed several techniques for transmission estimation	Sensitivity to scene composition
Li et al. [24] (2016)	Ill-posed single image restoration problem	Background light estimation using quad-tree subdivision	Better image quality with natural color and improved contrast	Dependency on accurate segmentation
Li et al. [25] (2016)	Low contrast, color cast, and limited visibility	Two-step approach for dehazing and contrast enhancement	Natural color and high contrast versions	Dependency on accurate transmission estimation
Li et al. [26] (2016)	Challenges in single-image restoration	Blue-green channel dehazing method	Improved visibility, contrast, and reduced light absorption effects	Sensitivity to scene complexity
Huang et al. [27] (2018)	Low contrast, bad color balance, and bluish-green cast	Relative global histogram stretching	Better perceptual quality and less noise	Limited applicability to highly turbid waters
Ancuti et al. [28] (2018)	Degraded exposure, low contrast, and blurred edges	Single-image method using color-compensated images	Improvements in exposure, contrast, and sharpness	Sensitivity to image quality
Akkaynak et al. [29] (2018)	Errors in current image formation models	Revised model considering wavelength-dependent attenuation and backscatter	More accurate restoration and better color reconstruction	Dependency on accurate environmental data
Protasiuk et al. [30] (2019)	Color correction and color transfer challenges	Local color mapping and color covariance mapping	Enhanced performance in underwater image correction	Sensitivity to scene variations
Sethi et al. [31] (2019)	Low contrast, bad color balance, and bluish-green cast	Enhancement using Multi-Objective Particle Swarm Optimization (MOPSO)	Good contrast, color correction	Sensitivity to parameter tuning
Yang et al. [32] (2020)	Color distortion and limited visibility	Underwater image enhancement based on salient object detection	Improves contrast and visibility by focusing enhancement on salient regions	Dependency on accurate salient object detection
Li et al. [33] (2020)	Color distortion and low contrast	Underwater image enhancement using adaptive color correction	Achieves better color balance and contrast enhancement	Sensitivity to complex scenes
Fu et al. [34] (2020)	Visibility and color degradation in underwater images	Fusion-based enhancement method combining multiple inputs	Enhanced detail and color in images	May require multiple input images for best results
Chong et al. [35] (2021)	Limited visibility, color distortion, and loss of detail	Underwater Image Enhancement by Noise-Aware Homomorphic Filtering	Removes noise and enhances visibility in underwater images	Sensitivity to noise
Zhang et al. [36] (2023)	Color distortion and low contrast in underwater images	Piecewise color correction and dual prior optimized contrast enhancement	Outperformed state-of-the-art methods in benchmark tests	Potential challenges in extreme lighting conditions
Hou et al. [37] (2023)	Non-uniform illumination in underwater images	Illumination Channel Sparsity Prior (ICSP) guided variational framework	Enhanced brightness, corrected color distortion, revealed fine details	Performance dependent on accurate modeling of illumination channel
An et al. [38] (2024)	Color shift, reduced visibility, and low contrast in underwater images	Hybrid Fusion Method (HFM) using type-II fuzzy sets and curve transformation	Superior results in visibility and contrast restoration	May have limitations in real-time processing

effects (see Table 2). These approaches leverage techniques such as polarized light utilization [17], [18] and wavelength compensation and dehazing (WCID) [20] to enhance scene contrast and improve overall underwater visibility. However, they often exhibit sensitivity to changing lighting conditions and may have limited applicability in dynamic underwater environments.

In contrast, adaptive algorithms such as dark channel prior (DCP) have been integrated into various enhancement strategies, demonstrating their effectiveness in improving image

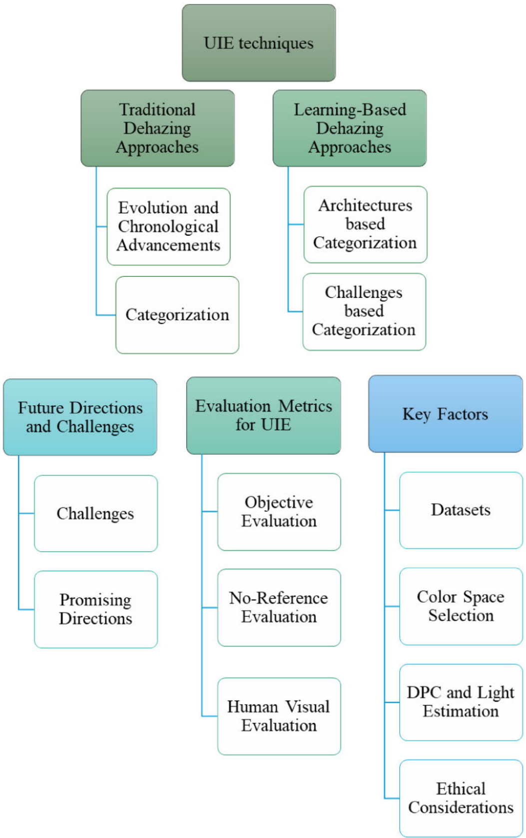

FIGURE 3. Hierarchical Structure of Underwater Image dehazing Review: This figure illustrates the breakdown of the review paper, including traditional and learning-based dehazing approaches, evaluation metrics, and future directions in underwater image enhancement and restoration.

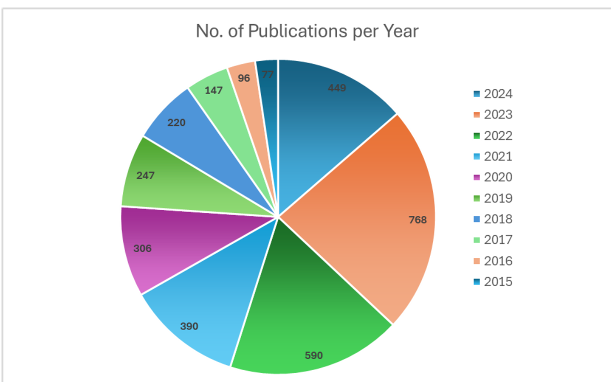

FIGURE 4. Number of publications per year in underwater image enhancement research over the last decade.

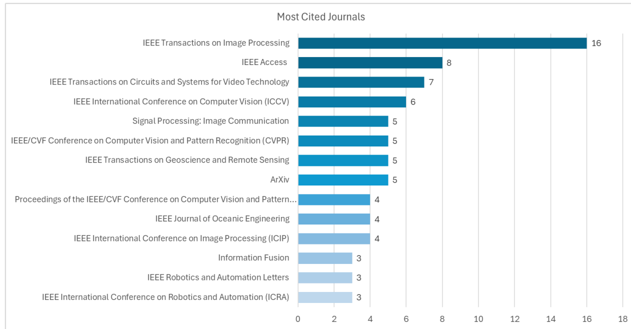

FIGURE 5. Distribution of Highly Cited Papers by Publication Venue in our Review.

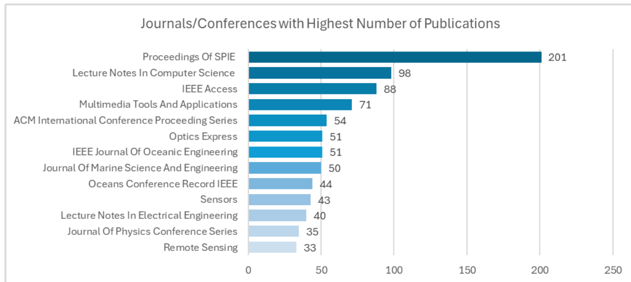

FIGURE 6. Journals/Conferences with the highest number of publications in underwater image enhancement research.

quality through noise-aware homomorphic filtering [34] and depth map estimation techniques [42], [43]. These methods excel in removing noise artifacts, enhancing visibility, and preserving fine details, although they can be sensitive to noise levels and require accurate parameter tuning for optimal performance.

Moreover, recent advancements have explored integration strategies that combine dehazing with techniques such as homomorphic filtering and image fusion. These hybrid approaches have shown promise in achieving comprehensive improvements by leveraging the strengths of each technique—enhanced visibility and contrast through dehazing, coupled with detailed restoration and noise reduction through fusion-based methods [24], [33]. A significant recent contribution to this field is the frequency and content dual stream network for image dehazing [44], which enhances edge information and texture details by using a frequency stream based on attention octave convolution and fuses these with a content stream to improve overall dehazing performance.

2) TRADITIONAL METHODS ADDRESSING COLOR DISTORTIONS

Underwater color distortion is another major obstacle to achieving realistic image quality. To address this challenge, Akkaynak et al. [28] revised image formation models to account for how different wavelengths of light are attenuated and scattered underwater. This approach leads to more accurate restoration and color reconstruction, but requires precise environmental data, which may not always be available. Furthermore, restoring high-quality images from a single captured image presents another significant hurdle. Li et al. [23] addressed this by proposing a method that estimates background light using a quad-tree subdivision.

While this approach effectively preserves natural colors and improves contrast, it relies heavily on accurate image segmentation. Protasiuk et al. [29] focused on local color mapping and covariance mapping. Their approach demonstrates superior performance in correcting underwater image coloration, but remains sensitive to variations within the underwater scene. In this direction, too, Akkaynak et al. [45] proposed a method that utilizes revised image formation models and RGBD images to address this issue. This approach outperformed other techniques based on atmospheric models and opened new avenues for research. However, it relies on accurate registration of RGBD images, which can be challenging in underwater environments. Additionally, Sekeroglu [41] proposed a time-shift image enhancement method, which enhances images by representing them in spacetime, deriving associated events at a specified time, and using them to improve degraded images. This approach is particularly useful for addressing constant images in underwater environments.

3) METHODS ADDRESSING REAL-TIME DEHAZING

While the aforementioned traditional dehazing methods have shown promise, their computational complexity often limits their real-time applicability. Efforts to improve processing speed and accuracy have led to innovations in parameter estimation and overall algorithm efficiency. This is crucial for real-time applications, especially in high-turbidity water environments where rapid processing is essential [46]. For example, Roznere et al. [47] proposed a real-time color correction method that uses depth sensors to account for variations in the type of water and depth. This approach particularly benefits underwater robots that require robust navigation, but is based on accurate depth estimation. James et al. [48] addressed the problem of wavy water surfaces that can cause non-rigid distortions in underwater videos, compromising image quality. The method is comprised of a two-step method that combines compressed sensing and optical flow.

B. EVOLUTION AND CHRONOLOGICAL ADVANCEMENTS OF TRADITIONAL APPROACHES

Traditional dehazing approaches face multifaceted challenges in improving underwater image quality. However, through specialized methods, enhanced computational efficiency, and rigorous evaluation, researchers continue to make strides in overcoming these obstacles and advancing the field of underwater image enhancement. As we delve deeper into the historical evolution and recent advancements of traditional dehazing techniques, it becomes evident that continuous refinements have been made to address the complexities of underwater imaging. Pioneering efforts in the early 2000s, such as polarization-based techniques, laid the groundwork for subsequent advancements. These early studies introduced innovative computer vision methodologies that analyzed images captured through polarizers at different orientations, exploiting the inherent properties of polarized light to improve scene contrast, color correction, and overall underwater visibility [17], [18].

In 2010, the Unsupervised Colour Correction Method (UCM) addressed issues like reduced contrast and color cast prevalent in underwater imagery. UCM leveraged advanced color balancing and contrast correction techniques within the RGB and HSI color models, surpassing conventional methods and delivering superior underwater image quality with enhanced natural color reproduction [19]. These early techniques paved the way for further innovations in underwater image enhancement, including introducing the WCID algorithm in 2012, which marked another significant advancement. This novel method combined dehazing techniques with wavelength compensation specifically tailored for underwater environments, leading to improved color fidelity and substantial enhancements in visibility [20]. The same year saw the rise of image fusion techniques, which effectively utilized weight maps and multi-directional illumination fusion to create enhanced versions of underwater images and videos [21].

A breakthrough occurred in 2013 with the introduction of the Underwater Dark Channel Prior (UDCP) method, which adapted the dark channel prior concept specifically for underwater environments by leveraging the observation that blue and green color channels hold significant underwater visual information, leading to superior transmission estimation [22]. Subsequent years witnessed further enrichment of the underwater image enhancement algorithms, including Retinex-based enhancement methods that achieved remarkable improvements in color accuracy, detail preservation, and overall image quality [49], as well as holistic approaches that facilitated simultaneous quality assessment, visibility enhancement, and stereo vision disparity computation [53].

In 2015, depth estimation-based techniques emerged, exploiting image blurriness as a proxy of depth and offering superior underwater image enhancement capabilities (see Table 3) [42]. That year also saw the development of automatic red-channel restoration methods that focused on mitigating color distortion and contrast deficiencies by restoring the red channel, which is significantly attenuated underwater, resulting in improved color balance and enhanced image fidelity [54].

Researchers have recently continued to refine traditional dehazing methods by incorporating underwater-specific characteristics. These include underwater light attenuation models, more sophisticated scattering models, and joint dehazing and denoising techniques [40], [55], [56], [57], [58], [59], [60]. Building on these foundations, the period 2021 to 2023 saw further advancements, including underwater color restoration techniques leveraging color constancy assumptions and image statistics, models that account for multiple light scattering, and the integration of dehazing with other image processing techniques for enhanced results [61], [62], [63], [64], [65], [66], [67].

In summary, traditional methods include diverse approaches that address the complex challenges of underwater image enhancement, emphasizing advancements in visibility, color

TABLE 3. Depth estimation and detail restoration approaches.

Reference	Problem	Method	Findings	Limitations
Peng et al. [43] (2015)	Challenges in single-image restoration	Depth estimation-based technique	Superior restoration results compared to previous methods	Sensitivity to depth estimation accuracy
Fu et al. [50] (2014)	Color distortion and low contrast	Retinex-based enhancement method	Improvements in color accuracy, detail preservation, and overall image quality	Computational complexity
Peng et al. [44] (2017)	Color distortion and low contrast due to light attenuation	Depth estimation based on blurriness and light absorption	Superior restoration results compared to previous methods	Sensitivity to noise
Tian et al. [51] (2017)	Image degradation due to scattering	Restoration and depth estimation using light field imaging	Improved image quality through backscatter removal and better depth estimation	Complexity in light field data processing
Zhang et al. [52] (2017)	Blurry images with low contrast and reduced visibility	Multi-Scale Retinex approach	Significant improvements in color and detail enhancement	Sensitivity to noise
Akkaynak et al. [46] (2019)	True color recovery is difficult due to existing models	Color recovery using revised image formation model and RGBD images	Outperformed atmospheric model methods and opened new research possibilities	Dependency on accurate RGBD image registration
Roznere et al. [48] (2019)	Color correction challenges due to water type and depth	Real-time color correction method using depth sensors	Improved performance and robust navigation for robots	Dependency on accurate depth estimation
Zhou et al. [53] (2023)	Underwater image degradation due to solid-colored objects and backscatter	Depth map estimation with Channel Intensity Prior (CIP) and Adaptive Dark Pixels (ADP)	Improved handling of uneven lighting and diverse environments	Complexity in estimating accurate depth maps

fidelity, and detail preservation, which are all crucial for underwater imaging applications. However, these methods often simplify assumptions about the underwater environment, which may not be valid in all scenarios. Techniques developed for specific underwater and lighting conditions might not perform well under different water properties or lighting conditions, and some methods can be computationally expensive, limiting their real-time applicability. Given these limitations, researchers have increasingly turned to deep learning techniques, which offer a data-driven and adaptable approach to underwater image enhancement capable of handling the complexities of diverse underwater environments.

The next section will explore deep-learning techniques for underwater image enhancement. These techniques offer promising avenues for overcoming the limitations of traditional methods and achieving superior image quality in challenging underwater environments.

III. LEARNING-BASED DEHAZING APPROACHES

Enhancing underwater images is challenging due to the complex interplay of light scattering, absorption, and reflection in underwater environments. Traditional dehazing methods, which rely on hand-crafted algorithms and models, often fall short when addressing these complexities effectively. In contrast, learning-based approaches, particularly those leveraging Deep Learning (DL), have demonstrated significant promise in overcoming these challenges [68], [69], [70], [71], [72], [73], [74], [75]. Learning-based approaches, particularly those leveraging deep learning, have emerged as powerful tools for underwater image enhancement. Their strength lies in handling the non-linear and intricate relationships inherent in underwater image degradation. By training on large datasets of underwater images and their corresponding clear versions, deep learning models can extract intricate features that capture the complex interplay of light scattering, absorption, and color cast affecting underwater images. This capability translates to superior performance in restored image quality, color fidelity, and visibility improvement. Additionally, these models can generalize well to unseen scenarios, performing effectively in diverse underwater environments where traditional methods may struggle with variations [76], [77], [78].

However, learning-based approaches face significant challenges, primarily the reliance on large, labeled underwater datasets, which are costly and time-consuming to collect due to the need for specialized equipment and professional divers. Additionally, the high computational demands of training and deploying deep learning models limit their suitability for real-time applications.

To mitigate these issues, researchers have explored various strategies. Data augmentation techniques, such as flipping, rotation, and color jittering, artificially expand training datasets, allowing models to learn from a broader range of examples [69]. Model compression and optimization aim to reduce computational complexity, making real-time processing more feasible [80].

Despite these advancements, limitations still need to be addressed, particularly concerning the generalizability of training models to real-world underwater images and accurately modeling the complex physics of underwater light scattering [76]. Further research is needed to incorporate underwater physics into DL architectures, develop unsupervised and weakly-supervised learning methods, and optimize DL models for real-time processing.

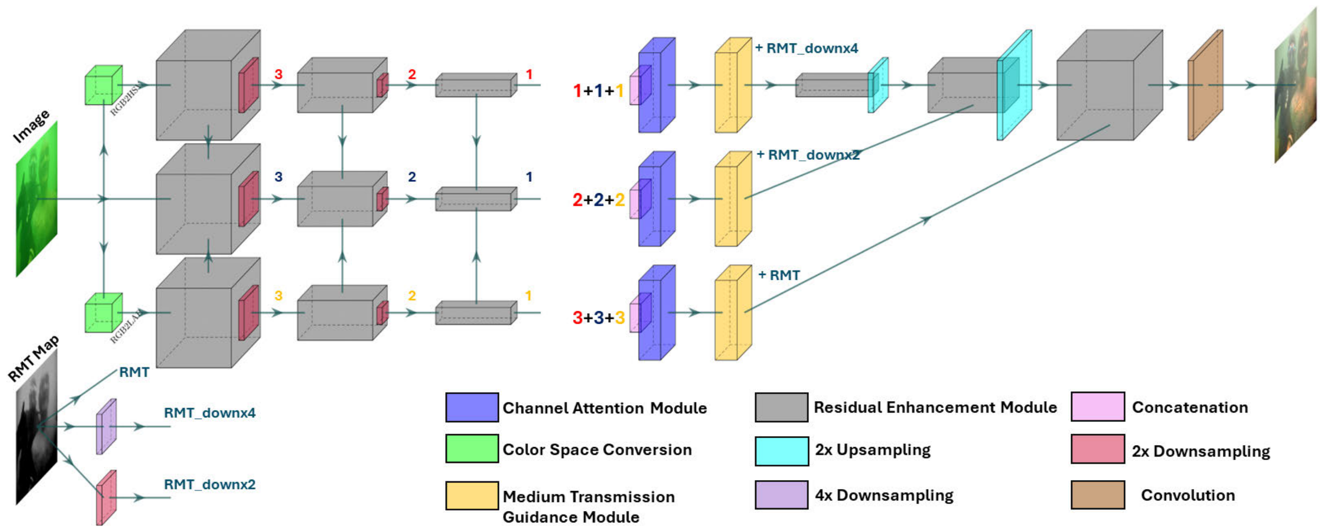

FIGURE 7. Architecture of Ucolor for underwater image enhancement [79] taking as input an RGB image and a reverse medium transmission (RMT) map.

In summary, learning-based dehazing approaches using deep learning techniques have shown significant potential in addressing the challenges of underwater image enhancement, often outperforming traditional methods. However, ongoing research is essential to overcome the remaining limitations and fully realize the potential of these approaches in practical applications.

A. CATEGORIZATION OF LEARNING-BASED APPROACHES BASED ON UTILIZED ARCHITECTURES

Recent advancements have brought deep learning to the forefront of underwater image dehazing. Popular architectures include:

- Convolutional Neural Networks (CNNs): exploiting convolutional layers to learn and remove haze features.
- Generative Adversarial Networks (GANs): learning to generate dehazed images through adversarial training.
- Transformers: Utilizing attention mechanisms for efficient feature extraction and representation.

We delve into the functionalities of these architectures, their adaptation for underwater tasks, training processes, datasets, and evaluation metrics. Challenges like data availability, generalization, and interpretability are also addressed.

1) CONVOLUTIONAL NEURAL NETWORKS (CNNS)

Convolutional Neural Networks (CNNs) have emerged as a powerful tool for addressing the challenges of underwater image dehazing [81]. CNN-based approaches have demonstrated superior performance in underwater image dehazing compared to traditional methods, exhibiting improvements in color balance, dehazing of degraded images, and reduction of color deviation, blur, and low contrast [78], [82].

Despite these advancements, CNN-based methods face limitations, including restricted receptive fields hindering the capture of long-range dependencies and difficulties in reconstructing intricate details often lost due to underwater light scattering [83], [84]. While recent research combining deep learning with computer vision techniques has yielded promising results in enhancing underwater image quality [82], [84], recovering natural and realistic dehazed results remains a challenging problem due to semantic confusion within hazy scenes [85].

To address this challenge, several advancements have been made:

- Ucolor (shown in Figure 7), an underwater image enhancement network, tackles color casts and low contrast using a multi-color space encoder and a medium transmission-guided decoder inspired by physical models. This approach outperforms state-of-the-art methods in improving visual quality [79].
- The Shallow-UWnet architecture addresses the limitations of deep CNNs and GANs by proposing a shallow neural network that maintains performance comparable to complex models but with significantly fewer parameters. This network exhibits good generalization across synthetic and real-world datasets, making it a practical solution for real-world applications [86].
- UICE^2-Net, the first deep learning method for underwater image enhancement that utilizes RGB and HSV color spaces, proposes a three-block architecture to improve subjective visual quality and objective metrics. These blocks include an RGB pixel-level block, an HSV global-adjust block, and an attention map block [87].
- LCNet [88] is a lightweight cascaded network based on Laplacian image pyramids, which reduces

computational complexity while enhancing underwater images. LCNet progressively predicts high-quality residuals in a coarse-to-fine manner with reduced complexity. The recursive nesting of sub-networks further reduces the computational cost.

By incorporating the limitation and addressing related research efforts, you provide a more comprehensive overview of the current state-of-the-art in CNN-based underwater image dehazing

2) GENERATIVE ADVERSARIAL NETWORKS (GANS)

GANs have been extensively utilized for underwater image dehazing, effectively addressing challenges and offering potential applications beyond visual enhancement. Underwater imagery often suffers from noise, haziness, and color loss, presenting difficulties for image enhancement [89], [90]. With their ability to generate realistic images, these networks have been employed to tackle these challenges, producing high-resolution images [90]. GANs have shown promising results in comparison, and GAN-DE demonstrates superiority over traditional methods in terms of visual enhancement, processing speed, and color-accuracy analyses [89], [90].

The proliferation of IoT devices equipped with visual sensors has led to their integration into various applications, including vehicle navigation and traffic management. However, the presence of atmospheric particles can significantly degrade image quality, hindering the performance of these systems. While deep learning has shown promise in addressing image dehazing, existing methods often struggle with generalizing from simulated to real-world conditions. To overcome these challenges, recent research has focused on developing techniques that can effectively restore clear images from degraded inputs. To overcome these limitations, a generative adversarial and self-supervised dehazing network has been introduced to enhance dehazing performance on real haze images [91]. This network leverages generative adversarial learning to establish a connection between dehazed and haze-free images, improving the natural appearance of dehazed results. Additionally, self-supervised learning is employed to reinforce the relationship between dehazed and hazy images, constraining the solution space for dehazing.

Furthermore, potential technical implications should be considered for using GANs for underwater image dehazing, such as the possible impact on the accuracy and authenticity of enhanced images. Beyond visual enhancement, GANs have potential applications in underwater image restoration for marine research, exploration, resource management, and automated tasks like Simultaneous Localization and Mapping (SLAM) in murky underwater environments [92]. The utilization of GANs, such as MuLA-GAN, has demonstrated superior performance in restoring color, contrast, texture, and saturation in underwater imagery, showcasing their value for marine research and exploration [93], [94]. Figure 8 shows [93] model architecture as an example of GANs used for underwater image dehazing.

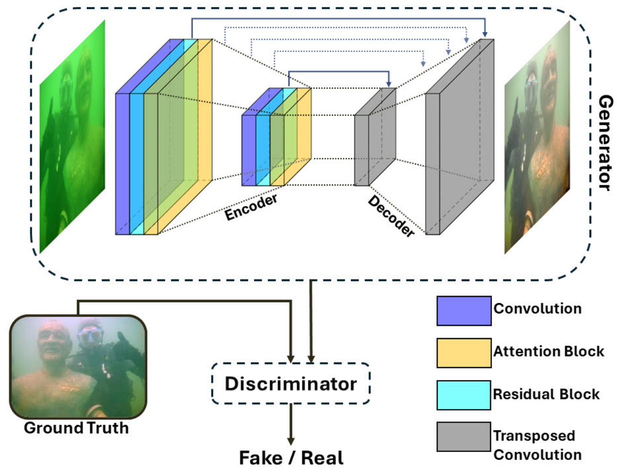

FIGURE 8. GAN network architecture for underwater image dehazing [93].

3) TRANSFORMERS

Transformers are emerging as a powerful tool for improving underwater image dehazing. These deep learning models address the unique challenges of underwater imaging, such as scattering and absorption of light particles, while leveraging its specific characteristics. This section formulates insights from recent research on applying transformers for underwater dehazing.

One key advantage of transformers is their ability to compute self-attention within localized areas (windows). This approach, including Vision Transformers (ViTs) and particularly Window-based Transformers (WTs), is well-suited for underwater image dehazing tasks [95]. It allows the model to focus on specific regions and capture relevant information for restoration. For example, the Underwater window-based Transformer Generative Adversarial Network (UwTGAN) demonstrates significant improvements in quantitative metrics and qualitative image quality assessment [95]. A novel transformer-based network (Figure 9) was proposed by [96] to effectively integrate both global context and local details through a global-local transformer (GL-Trans) block (Figure10) and a detail-enhanced skip connector (DESC). Recognizing the limitations of manual design and tuning in deep neural network-based underwater image enhancement, Tang et al. [97] propose a Neural Architecture Search (NAS) approach to automatically find the optimal U-Net architecture for this task, aiming for effective and lightweight models. The search space includes diverse operators to enhance representation capability. A selectable transformer structure with optional multi-head self-attention modules further expands the search space and improves learning capability.

However, despite the strengths of the self-attention mechanism, transformers can struggle with severe and unpredictable degradation in underwater images [98]. Multi-scale ViT (MViT) variants, such as Swin transformers, tackle this challenge by preserving long-range dependencies across different feature scales through evolving channel capacity [98]. This

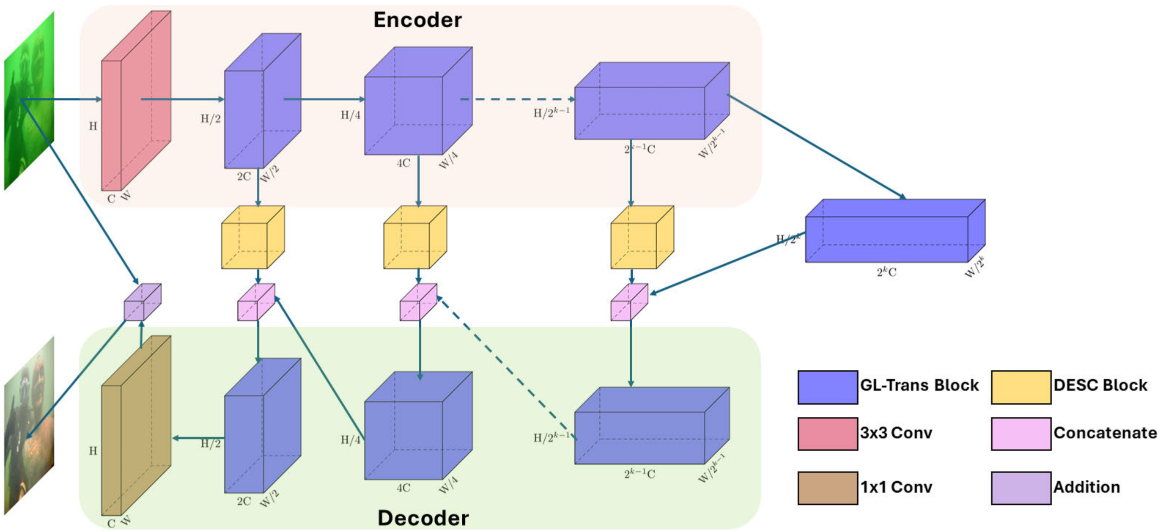

FIGURE 9. The overall architecture of the WaterFormer model for UIE [96].

allows the model to capture local and global information in the degraded image.

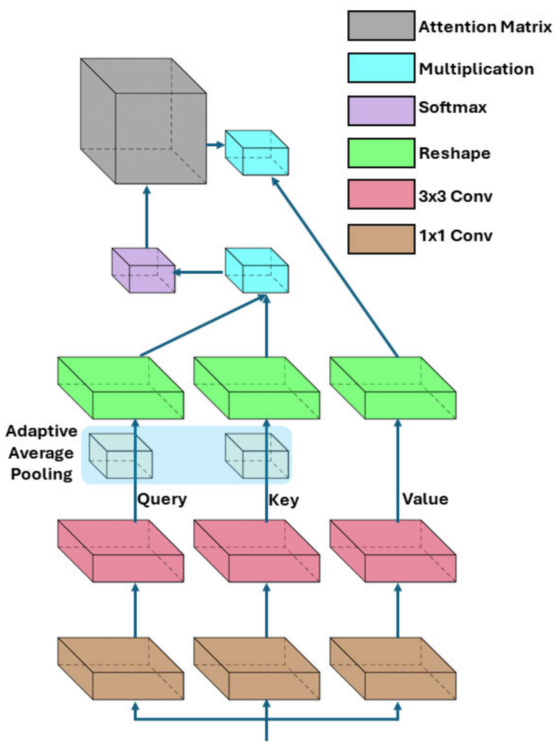

FIGURE 10. The details of the Multi-head Self-Attention (MSA) Module in the GL-Trans block [96]. Adaptive Average Pooling is Utilized only in Global MSA.

B. CATEGORIZATION OF LEARNING-BASED APPROACHES BASED ON CHALLENGES ADRESSED

1) METHODS ADDRESSING LIGHT ATTENUATION AND SCATTERING

In table 4, we can see that Wang et al. [99] developed UIE-Net, a CNN for color correction and haze removal, which outperformed existing methods on various scenes but with limited real-time capability. Li et al. [100] proposed a weakly supervised color transfer method, producing visually pleasing results but dependent on the quality of weak supervision. Wang et al. [101] used an unsupervised GAN for realistic underwater image generation, with U-Net trained on synthetic datasets performing well on real-world data but limited in robustness to diverse underwater conditions. Chen et al. [102] introduced a multi-branch GAN for image content preservation and noise removal, showing promising results in real-world seabed experiments but with high computational overhead for real-time applications. Guo et al. [103] proposed a multiscale dense GAN for enhancement, outperforming non-deep and deep learning approaches but with high computational cost. Han et al. [81] used unsupervised image-to-image translation with contrastive learning and GANs. This approach demonstrates superiority over existing methods by maximizing mutual information between raw and restored images and is trained on a large-scale real underwater dataset. Figure 11 shows an example of unsupervised image-to-image translation for underwater image dehazing. Ren et al. [84] introduced URSCT-SESR, a U-Net-based method with Swin-Convs Transformer blocks, excelling in Simultaneous Enhancement and Super-Resolution (SESR) tasks but with high computational cost.

2) METHODS ADDRESSING BLURRING AND LOW VISIBILITY

Yang et al. [31] used a conditional GAN with a multi-scale generator and dual discriminator, superior to state-of-the-art techniques on real-world and synthetic images but with high training complexity. Liu et al. [106] provided a comprehensive evaluation using the RUIE dataset, suggesting promising solutions and new directions but limited by the quality of the evaluation dataset. Zhu et al. [78] introduced an object-guided twin adversarial contrastive learning-based method, significantly improving visual quality and detection accuracy but

TABLE 4. Summary of learning-based approaches addressing light attenuation and scattering.

Reference	Problem	Method	Findings	Limitations
Li et al. [101] (2018)	Light attenuation and scattering	Weakly supervised color transfer method	Produces visually pleasing results	Depends on the quality of weak supervision
Wang et al. [102] (2019)	Light attenuation and backscattering issues	Unsupervised GAN for realistic underwater image generation	U-Net trained on synthetic datasets performs well on real-world data	Limited robustness to diverse underwater conditions
Chen et al. [103] (2019)	Low quality of underwater robotic vision	Multi-branch GAN for image content preservation and noise removal	Promising results in real-world seabed experiments	High computational overhead for real-time applications
Guo et al. [104] (2020)	Underexposure and fuzz	Multiscale dense GAN for enhancement	Leading performance at the time of publication	High computational cost
Han et al. [82] (2021)	Degradation from light absorption and scattering	Unsupervised image-to-image translation with contrastive learning and GANs	Large-scale dataset and superior performance	Dependence on the quality of contrastive learning
Ren et al. [85] (2022)	Degradation from light absorption and scattering	URSCT-SESR: U-Net-based method with Swin-Convs Transformer blocks	Excels in enhancement, super-resolution tasks	High computational cost

TABLE 5. Summary of learning-based approaches addressing blurring and low visibility.

Reference	Problem	Method	Findings	Limitations
Yang et al. [32] (2020)	Blurring, low light, and uneven illumination	Conditional GAN with multi-scale generator, dual discriminator	Superior to state-of-the-art techniques at the time of publication on real-world and synthetic images	High training complexity
Zhu et al. [79] (2022)	Visual appeal-focused methods reduce detection performance	CNN-based generative adversarial network	Significant improvements in visual quality, detection accuracy	High complexity and computational cost
Liu et al. [105] (2022)	Distortions and blurring affect object detection accuracy	Object-guided twin adversarial contrastive learning-based method	Improves visual quality, detection accuracy	High complexity and computational cost
Jiang et al. [106] (2022)	Degradations such as color cast, blur, low visibility	TOPAL: Target-oriented perceptual adversarial fusion network	Superior performance in image quality improvement	High complexity

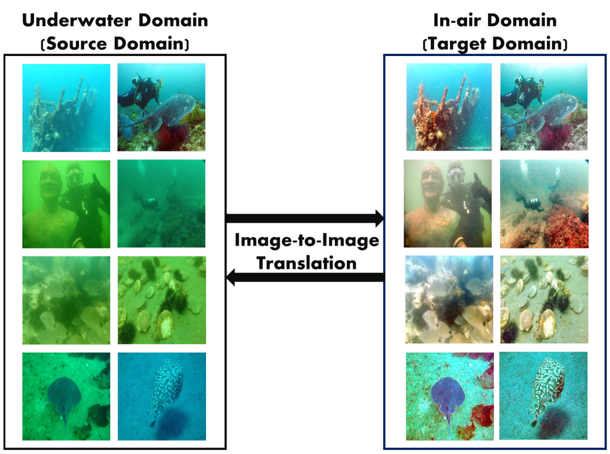

FIGURE 11. Example of unsupervised image-to-image translation for underwater images.

with high complexity and computational cost. Liu et al. [104] improved distortions affecting object detection accuracy with a similar method, achieving better detection accuracy but with high complexity and computational cost. Jiang et al. [105] proposed TOPAL, a target-oriented perceptual adversarial fusion network superior in image quality improvement but with high complexity. Blurring and low visibility mitigation methods are summarized in Table 5.

3) METHODS ADDRESSING LIMITED DATASETS AND GENERALIZABILITY

Li et al. [107] developed WaterGAN, a GAN for realistic underwater image generation, effective on pure water tank and field data but requiring high computational resources (refer to Table 6). Li et al. [108] evaluated algorithms mainly on synthetic datasets, highlighting performance and limitations in large-scale real-world underwater image benchmarks (UIEB). Uplavikar et al. [109] developed a model that adversarially learns content features and disentangles nuisances, outperforming previous methods on various water types but not evaluated in extremely murky waters. Li et al. [32] introduced UWCNN, a lightweight CNN based on underwater scene prior, generalizing well to different underwater scenes but limited to predefined scene priors. Li et al. [79] developed Ucolor, a network with a multi-color space encoder and transmission-guided decoder, outperforming state-of-the-art methods but limited in generalization to all underwater conditions. Lyu et al. [110] developed SCNet, using normalization schemes to learn water type-desensitized features, competitive in visual quality improvements but

TABLE 6. Summary of learning-based approaches addressing limited datasets and generalizability.

Reference	Problem	Method	Findings	Limitations
Li et al. [108] (2018)	Model dependency on numerous parameters	WaterGAN: GAN for realistic underwater image generation	Effective on pure water tank and field data	Requires high computational resources
Li et al. [109] (2019)	Algorithms mainly evaluated on synthetic datasets	Large-scale real-world underwater image benchmark (UIEB)	Highlights performance and limitations of algorithms	Limited to the quality of the benchmark dataset
Uplavikar et al. [110] (2019)	Diverse water types complicate enhancement	Model adversarially learns content features, disentangles nuisances	Outperforms previous methods on various water types	Performance in extremely murky waters not evaluated
Li et al. [33] (2020)	Diverse underwater scene types	UWCNN: Lightweight CNN based on underwater scene prior	Generalizes well to different underwater scenes	Limited to predefined scene priors
Li et al. [80] (2021)	Color casts and low contrast	Ucolor: Network with multi-color space encoder, transmission-guided decoder	State-of-the-art at the time of publication	Limited generalization to all underwater conditions
Fu et al. [111] (2022)	Diverse water conditions	SCNet: Normalization schemes to learn water type-desensitized features	Competitive visual quality improvements	May not cover all possible water conditions
Wang et al. [112] (2022)	Insufficient datasets, imperfect ground truths	High-level semantic-aware model with multi-path Contextual Feature Refinement Module (CFRM)	State-of-the-art at the time of publication	Limited by semantic annotation quality
Fu et al. [62] (2022)	Limited real-world paired data	USUIR leveraging homology between raw and re-degraded images	Promising restoration quality	Limited by unsupervised learning challenges
Qi et al. [113] (2022)	Limited paired images for training	SGUIE-Net: Unsupervised generative model with semantic region-wise enhancement	Impressive performance on various datasets	Limited by the unsupervised learning capability

may not cover all possible water conditions. Wang et al. [111] developed Semantic-aware Texture-Structure Feature Collaboration (STSC) which is a high-level semantic-aware model with a multi-path Contextual Feature Refinement Module (CFRM), outperforming state-of-the-art techniques but limited by semantic annotation quality. Fu et al. [61] used USUIR to restore quality and improve the original image by developing homology between raw and re-degraded images–promising restoration quality but limited by unsupervised learning challenges. Qi et al. [112] developed SGUIE-Net, an unsupervised generative model with semantic region-wise enhancement, demonstrating impressive performance on various datasets but limited by unsupervised learning capability.

4) DL METHODS ADDRESSING COLOR DISTORTION

Addressing color distortion (refer to Table. 7), Jamadandi et al. [113] used deep learning with wavelet-corrected transformations, achieving state-of-the-art results but with high complexity and computational cost. Uplavikar et al. [109] developed a model that adversarially learns content features and disentangles nuisances, outperforming previous methods on various water types but not evaluated in extremely murky waters. Islam et al. [114] proposed Deep SESR, a residual-in-residual network for simultaneous enhancement and super-resolution, outperforming existing solutions but with high computational complexity. Li et al. [32] designed UWCNN for generalizability to different underwater scenes. Yang et al. [31] applied a conditional GAN with a multi-scale generator and dual discriminator on real-world and synthetic images. Fu et al. [33] combined deep learning and conventional enhancement in a two-branch network, significantly improving performance but dependent on histogram equalization quality. Wang et al. [87] introduced UICE^2-Net, consisting of RGB pixel-level, HSV global-adjust, and attention map blocks, effective in improving visual quality and metrics but with high model complexity. Jiang et al. [105] proposed TOPAL for color correction, but with high model complexity. Ma et al. [115] used a wavelet-based dual-stream network, enhancing image quality but with high model complexity. SCNet [110] and LANet [63] generate promising results, but suffer from limited generalizability and model complexity, respectively. Wang et al. [99] developed UIE-Net, a CNN for color correction and haze removal, which outperformed existing methods on various scenes but with limited real-time capability.

Summary: This section presented an overview of learning-based methods categorized by their architectures and the addressed problems. Each method has distinct advantages and limitations, ranging from interpretability features to complexity and suitability for specific applications. CNNs excel in handling color balance and dehazing degraded underwater images, while GANs are proficient in synthesizing underwater images. Transformers show promise when integrated with CNNs for extensive-range data capture and image nuance retention. Performance differences among these methods highlight their nuanced strengths in achieving high-quality underwater image enhancement across various scenarios.

TABLE 7. Summary of learning-based approaches addressing color distortion.

Reference	Problem	Method	Findings	Limitations
Wang et al. [100] (2017)	Color distortion and haze removal	UIE-Net: CNN for color correction and haze removal	Leading performance on various scenes	Limited real-time capability
Jamadandi et al. [114] (2019)	Color distortion from light absorption	Deep learning with wavelet-corrected transformations	State-of-the-art at the time of publication on popular datasets	High complexity and computational cost
Uplavikar et al. [110] (2019)	Diverse water types complicate enhancement	Model adversarially learns content features, disentangles nuisances	Outperforms previous methods on various water types	Performance in extremely murky waters not evaluated
Islam et al. [115] (2020)	Simultaneous enhancement and super-resolution	Deep SESR: Residual-in-residual network for SESR	State-of-the-art at the time of publication across various test cases	High computational complexity
Li et al. [33] (2020)	Diverse underwater scene types	UWCNN: Lightweight CNN based on underwater scene prior	Generalizes well to different underwater scenes	Limited to predefined scene priors
Yang et al. [32] (2020)	Color distortion, blurring, low light, uneven illumination	Conditional GAN with multi-scale generator, dual discriminator	Superior to state-of-the-art techniques at the time of the publication on real-world and synthetic images	High training complexity
Fu et al. [34] (2020)	Global color distortion, local contrast reduction	Two-branch network combining deep learning and conventional enhancement	Significant performance improvements over state-of-the-art methods	Dependence on histogram equalization quality
Li et al. [80] (2021)	Color casts and low contrast	Ucolor: Network with multi-color space encoder, transmission-guided decoder	State-of-the-art at the time of publication	Limited generalization to all underwater conditions
Wang et al. [88] (2021)	Insensitivy of existing models to image properties such as luminance and saturation	UICE^2-Net: Consists of RGB pixel-level block, HSV global-adjust block, attention map block	Effective in improving visual quality metrics	High model complexity
Jiang et al. [106] (2022)	Degradations such as color cast, blur, low visibility	TOPAL: Target-oriented perceptual adversarial fusion network	Superior performance in image quality improvement	High model complexity
Ma et al. [116] (2022)	Color distortion, blurred details	Wavelet-based dual-stream network	Effective in enhancing image quality	High model complexity
Fu et al. [111] (2022)	Diverse water conditions	SCNet: Normalization schemes to learn water type-desensitized features	Competitive visual quality improvements	May not cover all possible water conditions
Liu et al. [64] (2022)	Color casts, low illumination	LANet with multiscale fusion, parallel attention, adaptive learning modules	Effective in improving color correction, detail restoration	High model complexity

IV. EVALUATION METRICS FOR UNDERWATER IMAGE ENHANCEMENT

Evaluating the quality of underwater images is essential for developing and benchmarking image enhancement algorithms. Underwater image enhancement metrics can be broadly divided into:

Non-Gradient-Based: These metrics assess fundamental aspects of underwater image enhancement, including color correction, contrast enhancement, noise reduction, visibility improvement, and overall image clarity [120], [121]. They specifically address challenges such as color cast, reduced visibility, and the need for accurate color restoration. Common examples include the Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Underwater Image Quality Measure (UIQM), which are detailed in subsequent subsections.

Gradient-Based: These metrics concentrate on enhancing sharpness and image detail in underwater environments [121]. They are critical for evaluating techniques that preserve and enhance image details typically compromised by underwater light scattering and absorption. Examples include Tenengrad (TENG), Variance of Laplacian (LAPV), and metrics based on Steerable Filters (SFIL).

The remainder of this section will go over the mathematical formulation of the metrics and their classification based on their evaluation method.

A. OBJECTIVE EVALUATION

1) MEAN SQUARED ERROR (MSE) AND PEAK SIGNAL-TO-NOISE RATIO (PSNR)

MSE quantifies the average squared error between the enhanced image $E(i, j)$ and the reference image $F(i, j)$:

$$\mathrm{MSE} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [F(i,j) - E(i,j)]^2 \tag{1}$$

where $M \times N$ is the image size.

PSNR, derived from MSE, measures the peak error:

$$\mathrm{PSNR} = 20 \log_{10} \left(\frac{\mathrm{MAX}_F}{\sqrt{\mathrm{MSE}}} \right) \tag{2}$$

where MAX_F is the maximum possible pixel value of the image (e.g., 255 for 8-bit images) [122].

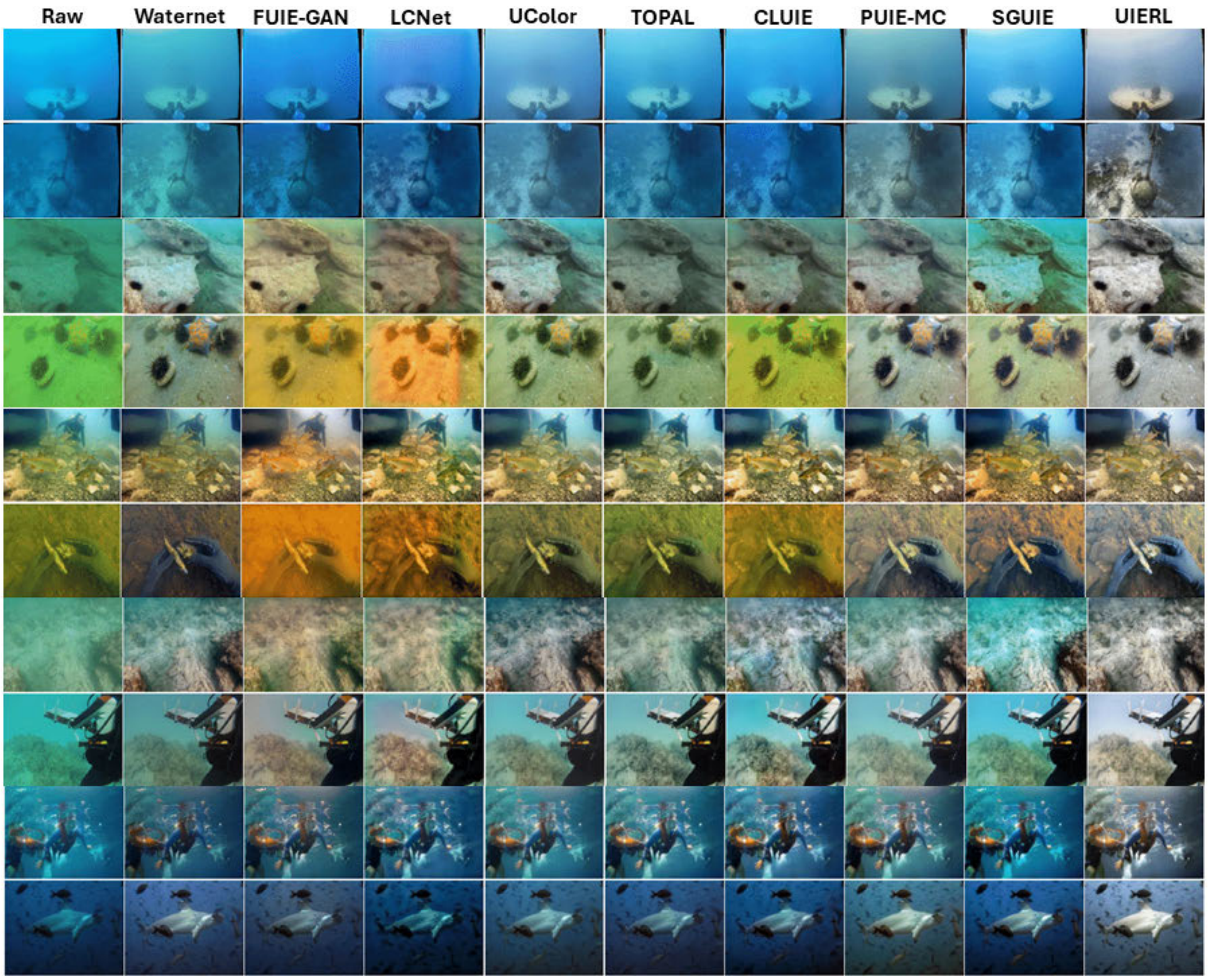

FIGURE 12. Sample Input-Output Images: This figure demonstrates the degradation effects of underwater environments and the improvement achieved by learning-based underwater image enhancement models. From left to right are raw underwater images, and the results of WaterNet [108], FUIEGAN [116], LCNet [88], Ucolor [79], TOPAL [105], CLUIE [117], PUIE-MC [118], SGUIE [112], and UIERL [119]. Findings are reported by [119].

2) ENTROPY

Entropy $H(F)$ measures the information content in an image, indicating its richness in details:

$$H(F) = -\sum_{i=0}^{255} p_i \log_2 p_i \tag{3}$$

where p_i is the probability of intensity level i [122].

3) STRUCTURAL SIMILARITY INDEX MEASURE (SSIM)

SSIM compares the structural similarity between the reference and enhanced images, considering luminance and contrast:

$$\mathrm{SSIM}(F, E) = \frac{(2\mu_F \mu_E + C_1)(2\sigma_{FE} + C_2)}{(\mu_F^2 + \mu_E^2 + C_1)(\sigma_F^2 + \sigma_E^2 + C_2)} \tag{4}$$

where μ_F and μ_E are the mean intensities, σ_F and σ_E are the variances, and σ_{FE} is the covariance of F and E. Constants C_1 and C_2 stabilize the division [122].

4) PATCH-BASED CONTRAST QUALITY INDEX (PCQI)

PCQI evaluates local contrast and structural distortion in image patches:

$$\mathrm{PCQI} = Q_1 \cdot Q_2 \cdot Q_3 \tag{5}$$

where Q_1, Q_2, and Q_3 assess mean intensity, structural distortion, and contrast change, respectively [122].

B. NO-REFERENCE EVALUATION

1) UNDERWATER COLOR IMAGE QUALITY EVALUATION (UCIQE)

UCIQE evaluates underwater image quality based on chroma, contrast, and saturation in the CIELab color space:

$$\mathrm{UCIQE} = c_1 \cdot \sigma_C + c_2 \cdot \mathrm{contrast}_L + c_3 \cdot \mu_S \tag{6}$$

where σ_C is the standard deviation of chroma, $\mathrm{contrast}_L$ is the contrast of luminance, and μ_S is the mean saturation.

The coefficients c_1, c_2, and c_3 are empirically determined weights [123].

2) UNDERWATER IMAGE QUALITY MEASURE (UIQM)

UIQM combines measures of Underwater Colorfulness (UICM), Image Sharpness (UISM), and Image Contrast (UIConM):

$$\text{UIQM} = c_1 \cdot \text{UICM} + c_2 \cdot \text{UISM} + c_3 \cdot \text{UIConM} \tag{7}$$

where c_1, c_2, and c_3 are weighting factors [124].

3) SPATIAL-SPECTRAL ENTROPY-BASED QUALITY (SSEQ)

SSEQ evaluates image quality based on spatial and spectral entropy features:

$$\text{SSEQ} = -\sum_i \sum_j p_{ij} \log_2 p_{ij} \tag{8}$$

where p_{ij} represents the joint probability distribution of spatial and spectral features [125].

4) MEASURE OF ENHANCEMENT (EME)

EME evaluates local contrast enhancement by measuring intensity differences within small image patches:

$$\text{EME} = \frac{1}{k} \sum_k \log \left(\frac{I_{\max}(k)}{I_{\min}(k)} \right) \tag{9}$$

where $I_{\max}(k)$ and $I_{\min}(k)$ are the maximum and minimum intensity values in the k-th patch, respectively [126].

5) COLORFULNESS, CONTRAST AND FOG DENSITY (CCF)

CCF measures overall colorfulness, contrast, and fog density in the image:

$$\text{CCF} = w_1 \cdot \text{Colorfulness} + w_2 \cdot \text{Contrast} - w_3 \cdot \text{FogDensity} \tag{10}$$

where w_1, w_2, and w_3 are weights assigned to each component based on importance [122].

6) AVERAGE GRADIENT (AG)

AG quantifies image sharpness by averaging gradient magnitudes:

$$\text{AG} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2} \tag{11}$$

where $\frac{\partial I}{\partial x}$ and $\frac{\partial I}{\partial y}$ are the gradients in the horizontal and vertical directions, respectively [127].

C. HUMAN VISUAL EVALUATION

Human visual assessments provide crucial insights that automatic metrics may overlook. While time-consuming and costly, subjective evaluations are essential for understanding the visual impact of image enhancement techniques.

In summary, underwater image quality metrics evaluate attributes such as color fidelity, sharpness, contrast, information content, and similarity to a reference image. The choice of metric depends on the specific application and the availability of a reference image [122], [123], [124], [125], [126], [127]. Effective evaluation metrics for underwater images remain challenging due to factors like low contrast, color degradation, and variations in underwater environments. Continued research and development are crucial for advancing the field of underwater image enhancement.

V. COMPARATIVE ANALYSIS AND DISCUSSION

In this section, we conduct a comparative analysis of traditional and recent learning-based approaches to the underwater dehazing problem. Learning-based methods demonstrate significant improvements in enhancing underwater images compared to traditional methods. We compare the main global techniques based on several performance metrics, including PSNR, SSIM, UCIQE, and UIQM. This analysis is structured into the following subsections:

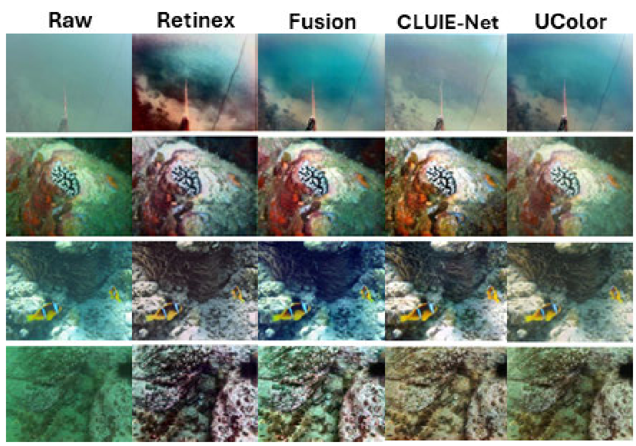

FIGURE 13. Sample Input-Output Images for Traditional Approaches (Retinex & Fusion Methods) and Learning-based Approaches (CLUIE-Net & UColor). From left to right are raw underwater images, and the results of Retinex Method [49], Fusion Method [21] CLUIE-Net [117], and UColor [79]. Findings are reported by [117].

A. VISUAL ANALYSIS OF LEARNING-BASED APPROACHES

Visual quality encompasses the overall perception of an image, including factors such as color fidelity, contrast, detail preservation, and naturalness. Recent advancements in deep learning-based underwater image enhancement have significantly improved visual quality compared to traditional methods.

Figure 12 (as reported in [119]) showcases the impact of various deep learning approaches on underwater image enhancement. The images represent a wide range of underwater environments, highlighting common challenges like blueish/greenish casts, low contrast, and blurred details. While deep learning has emerged as a powerful tool for underwater image enhancement, not all approaches

TABLE 8. Performance metrics of traditional dehazing approaches.

Reference	Method	Dataset	Evaluation Details
		UIEB	
Kang et al. [129] (2022)	Structural patch decomposition and fusion		PSNR = 23.34, SSIM = 0.87
Yuan et al. [130] (2020)	Contour Bougie & morphology		UCIQE = 0.64, UIQM = 5.62, PCQI = 1.27
Xie et al. [57] (2021)	Red channel prior guided	UIEB & RUIE	UCIQE = 0.58, UIQM = 1.54
		Other Datasets	
Schechner et al. [18] (2004)	Polarized light (enhancement)	Aqua-Polaricam images	Improved visibility range
Iqbal et al. [20] (2010)	Color correction method	Online-sampled images	Histograms and detected edges
Peng et al. [43] (2015)	Image formation model-based	Four underwater images	Dehazed images and depth maps
Fu et al. [50] (2014)	Retinex-based	Online-sampled images	Dehazed images
Chiang et al. [21] (2011)	Wavelength Compensation	Image of a board with six patches at 5m and 15m	PSNR = 19.72(5m), 18.42(15m)
Li et al. [25] (2016)	Histogram-based method	ColorChecker	PSNR = 19.08
Peng et al. [44] (2017)	Depth estimation	Various images	UIQM = 3.23, BRISQUE = 30.24
Zhang et al. [52] (2017)	Extended multi-scale Retinex	Five underwater images	MSE = 280.53
Ancuti et al. [28] (2017)	White-balanced input image fusion	Underwater videos/images	UCIQE = 0.651, UIQM = 0.67
Marques et al. [131] (2020)	Contrast and multi-scale fusion	OceanDark	UIQM = 1.38, PCQI = 1.17
Zhuang et al. [56] (2021)	Bayesian retinex algorithm	50 underwater images	UCIQE = 0.57, UIQM = 4.47
Li et al. [132] (2017)	Hybrid approach combining color correction and dehazing	45 degraded underwater images	UCIQE = 0.607, UIQM = 7.50
Huang et al. [27] (2018)	Relative global histogram stretching	YouTube images	PSNR = 18.64, UCIQE = 0.587
Song et al. [133] (2020)	Background light estimation	Background Lights	UCIQE = 0.63, BRISQUE = 31.78, SSIM = 0.75
Berman et al. [134] (2020)	Expanded haze-lines model	SQUID	Angular Error = 6.49

achieve equally impressive results. Techniques like WaterNet [108] and UColor [79] often struggle to restore realistic colors and introduce distortions in the foreground. Similarly, methods like FUIEGAN [116] and LCNet [88] can introduce unwanted color casts or fail to remove existing ones. Additionally, TOPAL [105] may enhance the image in a way that deviates from the natural underwater environment.

In contrast, deep learning-based methods generally outperform traditional approaches in terms of visual quality. As observed in Figure 12, methods such as CLUIE [117], PUIE-MC [118], and SGUIE [112] demonstrate notable improvements in both color correction and detail recovery. However, some limitations persist. For instance, PUIE-MC may not enhance contrast as effectively, while SGUIE can result in over-saturation, making the images less visually appealing.

The method proposed by [117], UIERL, excels in achieving balanced visual enhancements. It effectively corrects color casts, enhances contrast, and recovers details across diverse underwater scenes. This success is attributed to the design of internal and external representation learning stages within the model. The internal stage allows for differential enhancement of degraded regions, leading to a more natural-looking overall image. Additionally, the external information from related images facilitates the restoration of finer details in object structure and edges.

These findings highlight the advancements made by deep learning-based methods in enhancing the visual quality of underwater images. As the field progresses, further refinements in these models will continue to improve the accuracy and naturalness of underwater image restoration.

B. TRADITIONAL VS LEARNING-BASED APPROACHES

Color fidelity refers to the accuracy with which an image reflects the true colors of the underwater scene. Traditional methods for underwater image enhancement often struggle to maintain color fidelity, resulting in distortions and unrealistic color shifts.

Figure 13 provides a direct comparison of traditional methods (Retinex and Fusion) and deep learning approaches (CLUIE-Net and UColor) on sample underwater images. Traditional methods, as depicted in Figure 13, frequently introduce significant color distortions. The Retinex method [49] can produce reddish hues, while the Fusion method [21] may lead to unnatural color corrections.

In contrast, deep learning-based methods generally achieve superior color fidelity. As illustrated in Figure 13, CLUIE-Net [117] produces enhancements with a more balanced color distribution, natural color saturation, and clear details. This underscores the effectiveness of deep learning in preserving the true colors of underwater environments.

However, even within deep learning approaches, performance can vary. While CLUIE-Net achieves the best scores on color fidelity metrics, other models like UColor [79] may exhibit less effective recovery of local details, potentially affecting overall color accuracy.

Underwater images often suffer from various types of noise, and traditional methods can sometimes amplify this noise. For instance, the Retinex-based method [49] and the depth estimation method [43] result in MSE values of 280.53 and UIQM scores of 3.23, respectively, indicating suboptimal noise handling (Table 8).

Conversely, learning-based approaches demonstrate better robustness to noise. Deep SESR [114] achieves a PSNR

TABLE 9. Performance metrics of learning-based approaches - PSNR and SSIM.

Reference	Method	Dataset	PSNR	SSIM
		UIEB		
Li et al. [109] (2019)	Water-Net		19.11	0.797
Ren et al. [135] (2022)	URSCT-SESR		22.72	0.910
Tang et al. [98] (2022)	NAS-based U-Net		25.45	0.923
Yang et al. [32] (2020)	Conditional GAN		17.72	0.655
Wang et al. [88] (2021)	UICE^2-Net		24.56	0.934
Liu et al. [105] (2022)	TACL		22.30	0.888
Jiang et al. [106] (2022)	TOPAL		21.58	0.902
Fu et al. [119] (2022)	PUIE-Net		21.86	0.870
Liu et al. [66] (2023)	Boths		25.68	0.905
		UIEB Validation-90		
Huo et al. [63] (2021)	PRWNet		21.72	0.89
Li et al. [80] (2021)	Ucolor		20.63	0.770
Wei et al. [136] (2022)	Frequency-Spatial Domain Aware Network		25.20	0.943
Yan et al. [137] (2022)	Attention-guided dynamic network		24.52	0.813
Shen et al. [65] (2023)	UDAformer		23.48	0.920
Peng et al. [138] (2023)	U-shape Transformer		22.91	0.910
		EUVP		
Islam et al. [117] (2020)	FUnIE-GAN		21.92	0.887
Naik et al. [87] (2021)	Shallow UWnet		27.39	0.830
Liu et al. [64] (2022)	LANet		25.82	0.866
		Different Datasets		
Jamadandi et al. [114] (2019)	Modified VGG19 network	Subsets of Imagenet	29.71	0.854
Uplavikar et al. [110] (2019)	U-Net with adversarial loss (UIE-DAL)	NYU-V2 RGB-D	28.10	0.927
Islam et al. [115] (2020)	Deep SESR	UFO-120	27.15	0.840
Li et al. [33] (2020)	UWCNN	Synthetic Images	25.92	0.937
Fu et al. [34] (2020)	Global–local network	RUIE (UCCS)	18.10	0.660
Chen et al. [139] (2021)	Patch detection-based models	OUC Database	28.29	0.913
Han et al. [82] (2021)	Contrastive Underwater Restoration GAN	HICRD	26.88	0.834
Qi et al. [113] (2022)	SGUIE-Net	SUIM-E	24.82	0.928

TABLE 10. Performance metrics of learning-based approaches - UCIQE and UIQM.

Reference	Method	Dataset	UCIQE	UIQM
		UIEB		
Wang et al. [100] (2017)	UIE-Net		0.54	4.80
Zhu et al. [79] (2021)	Dense-fusion GAN		0.63	3.93
Li et al. [108] (2018)	WaterGAN		0.54	3.38
Chen et al. [103] (2019)	GAN-RS		0.61	4.04
Wang et al. [88] (2021)	UICE^2-Net		0.62	4.08
Jiang et al. [106] (2022)	TOPAL		0.62	4.02
Wang et al. [112] (2022)	STSC		-	3.76
		EUVP		
Li et al. [101] (2017)	Weakly supervised color transfer		0.56	3.55
Wang et al. [102] (2019)	UWGAN		0.59	3.93
Sharma et al. [140] (2023)	Deep WaveNet		0.56	3.04
		Different Datasets		
Liu et al. [66] (2023)	Boths	T40, U45, and C60	0.59	1.29

of 27.15 and an SSIM of 0.840, reflecting enhanced noise reduction capabilities (Table 9). PRWNet [62] achieves an SSIM of 0.900, further emphasizing the superior noise handling of learning-based methods. This robustness is primarily due to the noise reduction and feature extraction layers inherent in deep learning models.

Table 10 demonstrates that learning-based methods also yield robust performance in non-reference evaluations. UICE^2-Net [87] achieves an impressive a UCIQE of 0.62 and an UIQM of 4.08, using the end-to-end learning for adjusting underwater image luminance, color and saturation. TOPAL [105] achieves a UCIQE of 0.62 and UIQM of 4.08, To enhance the details and appearance of input images. Further solidifying the effectiveness of learning-based methods in refining the quality of underwater imagery.

These findings indicate that deep learning-based methods represent a significant advancement in underwater image enhancement, particularly in terms of color fidelity. However, further research is needed to refine existing models and achieve even more accurate color restoration across diverse underwater environments.

C. COMPUTATIONAL EFFICIENCY

Computational efficiency is a key consideration, especially for real-time applications. Traditional methods generally offer faster processing times due to their simpler algorithms. For example, histogram-based methods and color correction

TABLE 11. Comparison of computational metrics including GFLops, parameter counts (in millions), and inference times (in milliseconds) for various transformer-based networks. Findings are reported by [96].

METHOD	GFLOPS	PARAMETER (M)	TIME (MS)
UFormerB [141]	87.6	69.5	53.1
SwinIR [142]	202.1	31.4	53.2
Restormer [143]	87.2	16.9	59.1
UDAFormer [65]	41.6	**9.6**	48.4
UShapeTrans [138]	**3.03**	31.6	**28.5**
URSCT [135]	14.2	11.4	49.8
WaterFormer [97]	49.8	27.1	44.3

techniques can be executed quickly, making them suitable for real-time applications.

However, while offering superior enhancement quality, learning-based methods often require significant computational resources. Despite this, recent advancements have led to more efficient architectures. For instance, UWCNN achieves a balance between processing speed and enhancement quality with a PSNR of 25.92 and an SSIM of 0.937, making it more viable for real-time applications (Table 9). These advancements are a result of optimized network architectures and efficient training strategies.

Additionally, Table 11 [96] provides a comparison of computational metrics, including GFLops, parameter counts (in millions), and inference times (in milliseconds) for various transformer-based networks. This comparison highlights the ongoing efforts to improve computational efficiency in deep learning models for image enhancement tasks.

Among the transformer-based networks evaluated, SwinIR [141] stands out with the highest GFLOPs of 202.1 and a relatively low parameter count of 31.4 million. This combination suggests that SwinIR achieves a good balance between computational power and model complexity. UShapeTrans [137], on the other hand, demonstrates the lowest GFLOPs at 3.03, indicating significantly lower computational demands compared to other models. Despite this, it maintains a competitive parameter count of 31.6 million, suggesting efficient use of parameters.

In terms of inference time, UShapeTrans performs best with 28.5 milliseconds, highlighting its suitability for real-time applications. Conversely, Restormer [142] has the highest inference time at 59.1 milliseconds, indicating potential challenges in deploying it for real-time processing despite its moderate computational metrics.

Considering these factors, UShapeTrans emerges as a compelling choice for scenarios with critical low latency, such as interactive applications or embedded systems. SwinIR, with its high computational efficiency and balanced performance metrics, remains a strong contender for tasks requiring robust image enhancement capabilities without compromising on speed or quality.

D. EVALUATION OF UNDERWATER IMAGE ENHANCEMENT MODELS ON BENCHMARK DATASETS

To ensure a fair and comprehensive evaluation of the underwater image enhancement models, we conducted experiments on benchmark datasets, both with and without ground truth (GT) references. This approach allows for a robust assessment of the models' performance across different conditions and datasets.

1) BENCHMARK DATASETS

a: REFERENCE-BASED DATASETS

- **EUVP_Dataset** [116]: This dataset contains 12k paired for evaluating enhancement quality.
- **LSUI400** [137]: Features 400 underwater images with ground truth references for detailed performance analysis.
- **Ocean_Ex** [143]: A dataset with ground truth 40 images used to benchmark enhancement techniques under varied underwater conditions.
- **UIEB100** [108]: Includes 100 images with their corresponding references to assess the accuracy and effectiveness of enhancement algorithms. The original UIEB dataset contains 890 referenced images: 800 for training, and 90 for validation. 60 additional images are included for challenging non-referenced scenarios (Challenging-60).

b: NON-REFERENCE DATASETS

- **RUIE_Color90** [106]: Contains 90 images with challenging underwater scenarios to test the robustness of enhancement methods. The dataset is divided into three subsets, UIQS, UCCS, and UHTS, each targeting different aspects of image quality: visibility, color cast, and object detection/classification.
- **U45** [144]: Features 45 images from different underwater environments, providing a diverse set of conditions for model evaluation.
- **Upoor200** [143]: As a non-reference dataset in this context, it provides additional evaluation opportunities for models without ground truth comparisons with a total of 200 images.

E. EVALUATION METHODOLOGY

To ensure the validity of our comparisons, we applied state-of-the-art underwater image enhancement models - including Cycle-GAN [100], FUnIEGAN [116], RAUNE-Net [143], UT-UIE [137], and WaterNet [108] - to these benchmark datasets. This included running the models on both reference-based and non-reference datasets to assess their performance in enhancing visibility and color fidelity.

Our evaluation metrics focused on:

- **Image Quality**: Assessing the clarity and detail improvement achieved by each model, as seen in the figures.
- **Visibility Enhancement**: Evaluating how effectively each model improves underwater visibility.
- **Color Fidelity**: Measuring the accuracy of color reproduction in enhanced images.

By comparing the results across these datasets and figures, we provide a thorough analysis of each model's strengths and limitations. This approach ensures that the evaluation reflects

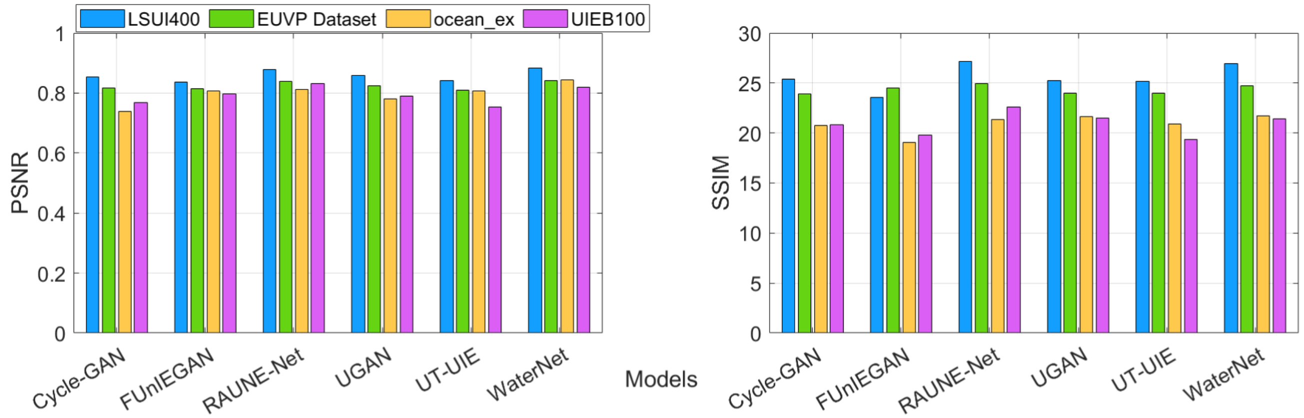

FIGURE 14. Comparison of PSNR and SSIM values for different models across various datasets. The PSNR values reflect the quality of the reconstructed images, while SSIM indicates structural similarity preservation.

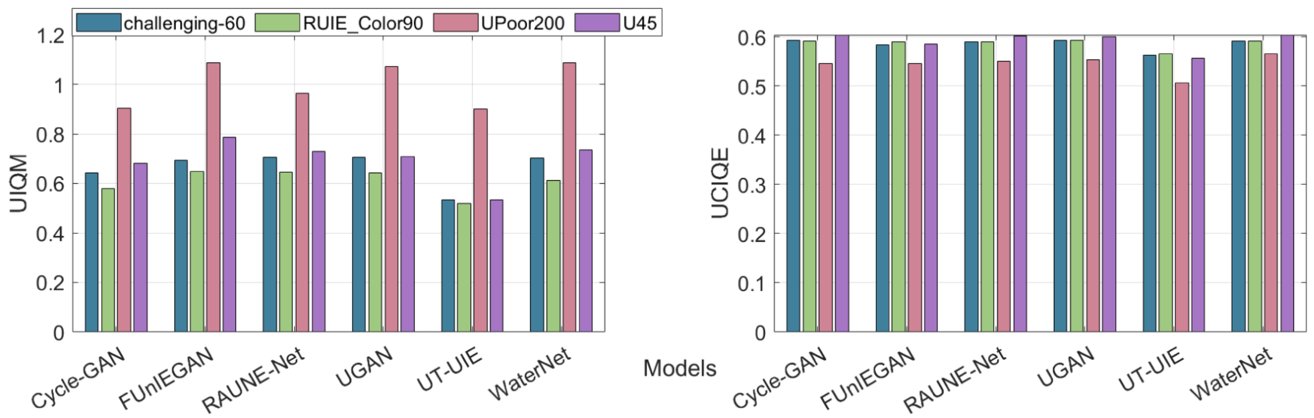

FIGURE 15. Comparison of UIQM and UCIQE values for different models across various datasets. UIQM measures perceptual image quality, while UCIQE evaluates color quality and contrast.

a broad range of underwater conditions and enhancement challenges, facilitating a fair and comprehensive assessment of the models' capabilities.

F. PERFORMANCE METRICS

1) IMAGE QUALITY (PSNR AND SSIM)

Figure 14 presents the comparison of PSNR and SSIM values across different models and datasets.

- **PSNR (Peak Signal-to-Noise Ratio)**: 'WaterNet' and 'RAUNE-Net' demonstrate competitive PSNR values, particularly in the LSUI400 dataset, where 'WaterNet' achieves the highest PSNR of 0.883. This suggests that these models are effective in reducing noise and preserving image quality. For the ocean_ex dataset, 'WaterNet' achieves a PSNR of 0.843, highlighting its robust performance in maintaining image quality.

- **SSIM (Structural Similarity Index)**: 'RAUNE-Net' and 'WaterNet' show strong performance in structural preservation, especially in the LSUI400 dataset with SSIM values of 27.198 and 26.922, respectively. This indicates that these models effectively preserve image structure and texture.

2) PERCEPTUAL AND COLOR QUALITY (UIQM AND UCIQE)

Figure 15 compares UIQM and UCIQE values across models and datasets.

- **UIQM (Unified Image Quality Measure)**: 'FUnIEGAN' and 'RAUNE-Net' perform well in terms of perceptual quality, particularly in the RUIE_Color90 dataset where 'RAUNE-Net' achieves a UIQM of 0.7296. This suggests that these models produce visually appealing results.

- **UCIQE (Uniform Chrominance Image Quality Evaluation)**: 'WaterNet' and 'Cycle-GAN' score high in the challenging-60 dataset, with UCIQE values of 0.5820 and 0.5790, respectively. This indicates strong performance in maintaining color quality and contrast.

3) VISUAL ASSESSMENT

Visual comparisons of the performance of the networks on various datasets are presented in figure 16 which includes datasets with ground truth images, and figure 17 which includes datasets with no reference images.

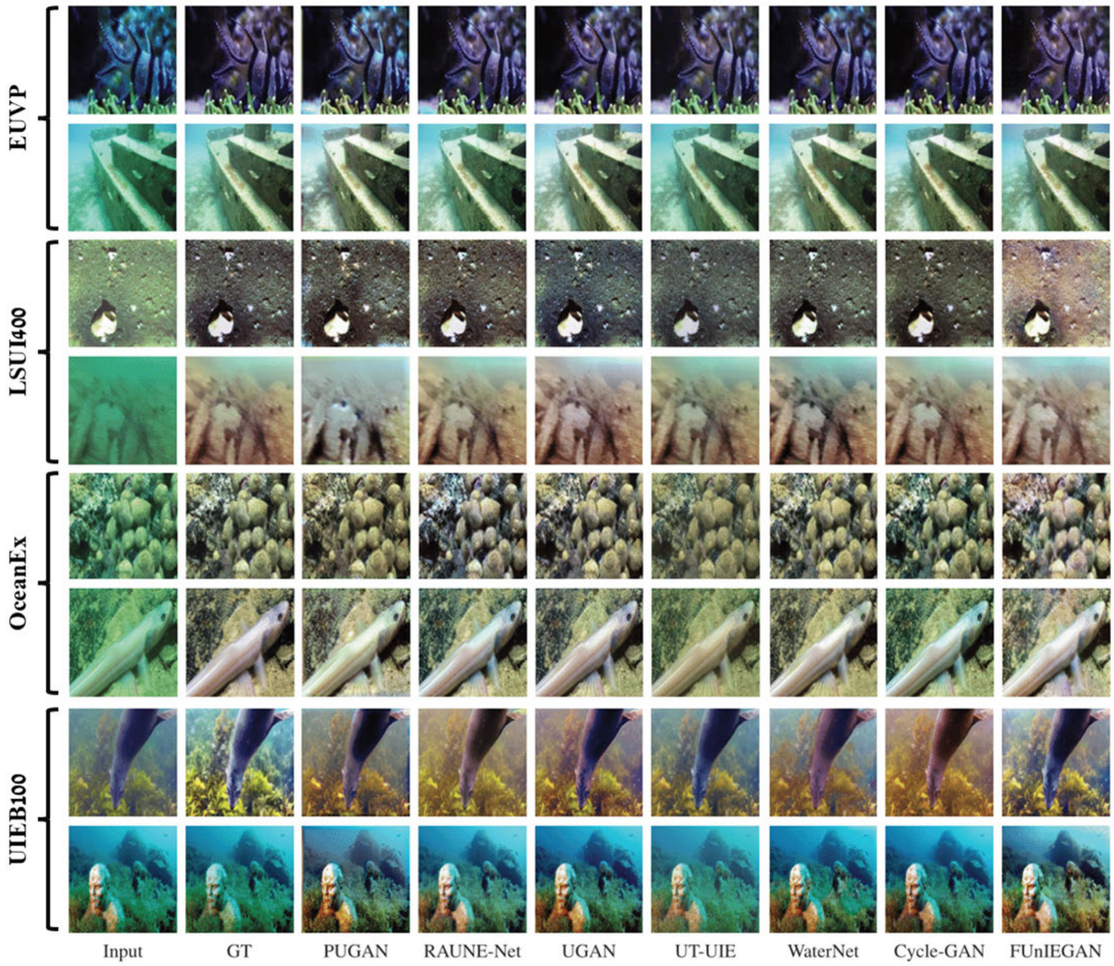

FIGURE 16. Comparative visual analysis of underwater image enhancement techniques on datasets with GT references including EUVP [116], LSUI400 [137], OceanEx [143], and UIEB100 [108]. From left to right, the images depict the original input image, ground truth (GT), followed by the results from PUGAN [145], RAUNE-Net [143], UGAN [146], UT-UIE [137], WaterNet [108], Cycle-GAN [100], and FUnIEGAN [116].

VI. FUTURE DIRECTIONS AND CHALLENGES IN UNDERWATER IMAGE ENHANCEMENT AND RESTORATION

Underwater image and video quality suffer significantly from light absorption and scattering by water molecules and suspended particles [147], [148]. This section explores the ongoing challenges in underwater image enhancement and restoration, promising future research directions, the potential of advanced machine learning techniques, and key factors affecting algorithm performance.

A. CHALLENGES IN UNDERWATER IMAGE ENHANCEMENT AND RESTORATION

1) LIGHT ABSORPTION AND SCATTERING

The inherent properties of water, including light absorption and scattering, significantly reduce visibility, introduce color cast, and decrease contrast in underwater images [7], [14], [148]. These effects make it challenging to capture clear and visually appealing underwater scenes.

2) BACKSCATTERING

In turbid water environments, backscattering caused by suspended particles further degrades image quality by introducing haze and obscuring details [148].

3) LIMITED EFFECTIVENESS OF EXISTING METHODS

While existing enhancement and restoration techniques have shown progress, they often struggle to preserve fine details and effectively remove distortions, particularly in challenging underwater conditions with high turbidity or non-uniform lighting [14].

4) DATA SCARCITY

A significant hurdle in developing robust image enhancement and restoration models is the limited availability of high-quality, well-annotated underwater image datasets [131]. This scarcity hinders the training and evaluation of deep learning models, which often require large amounts of labeled data.

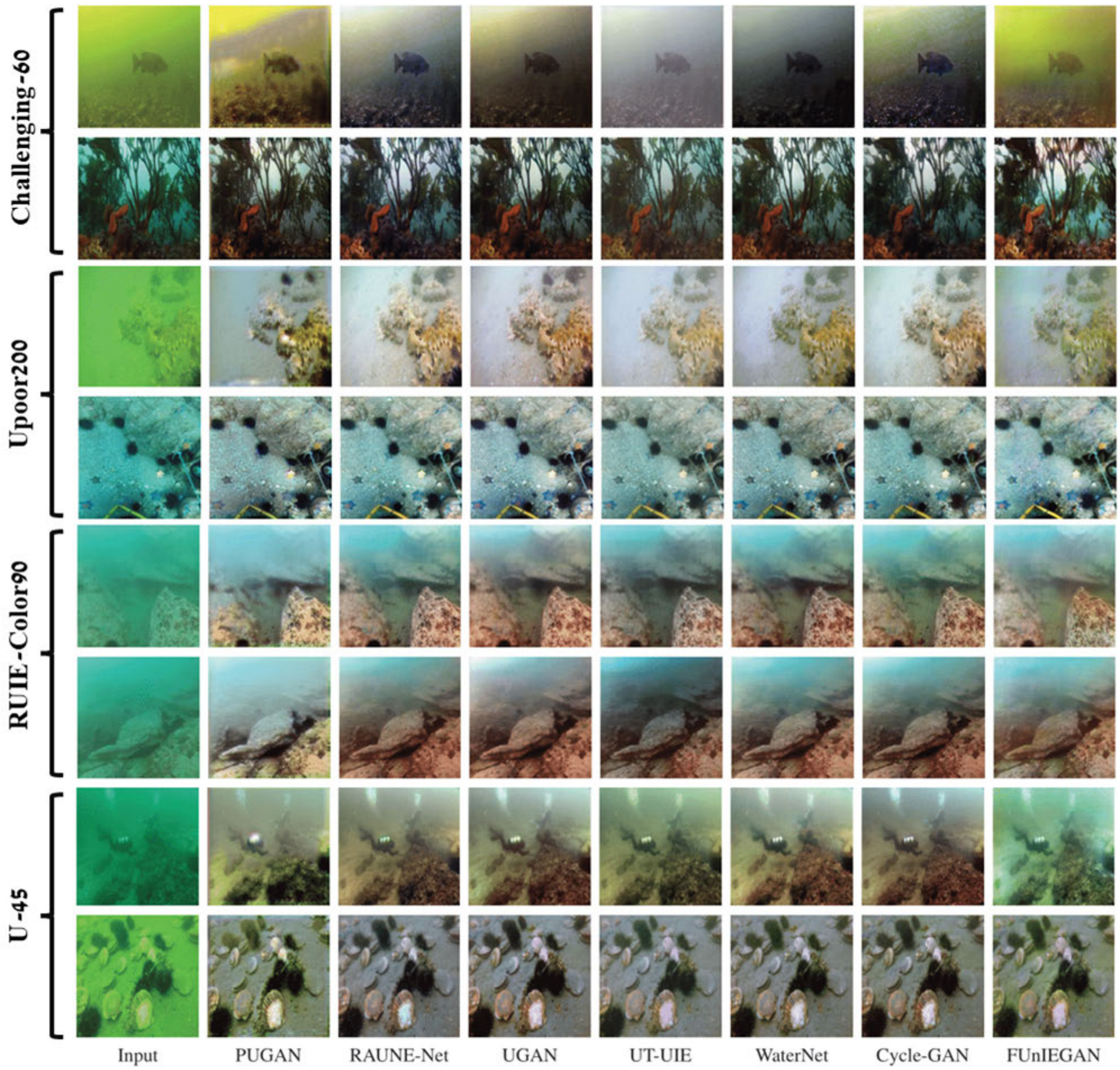

FIGURE 17. Comparative visual analysis of underwater image enhancement techniques on no reference datasets including Challenging-60 [116], Upoor200 [143], RUIE-Color90 [106], and U-45 [144]. From left to right, the images depict the original input image, followed by the results from PUGAN [145], RAUNE-Net [143], UGAN [146], UT-UIE [137], WaterNet [108], Cycle-GAN [100], and FUnIEGAN [116].

5) NETWORK EFFICIENCY FOR RESOURCE-LIMITED SCENARIOS

Many existing methods rely on complex network architectures to achieve desirable image quality improvement. However, these approaches often demand significant computational resources, making them impractical for deployment on underwater devices with limited processing power. Therefore, there is a need for lightweight networks that can achieve high performance with low computational requirements [65], [149].

6) EVALUATION METRICS

Existing objective quality metrics often fail to capture the nuances of human perception, leading to discrepancies between measured scores and actual perceived quality of enhanced images [150]. Further research is needed to develop task-oriented evaluation frameworks that better reflect the suitability of enhanced images for downstream computer vision applications, such as object detection and segmentation.

B. PROMISING RESEARCH DIRECTIONS

1) DEEP LEARNING FOR ENHANCEMENT AND RESTORATION

Deep learning approaches hold significant promise for underwater image enhancement and restoration tasks, demonstrating effectiveness in areas like noise reduction, color correction, and detail enhancement [151]. Advances in techniques like CNNs, GANs, and transformer networks present opportunities for pushing the boundaries of image quality improvement [152].

2) DOMAIN ADAPTATION TECHNIQUES
Domain adaptation techniques offer a promising solution to address the scarcity of labeled underwater image datasets. These methods enable models to learn from synthetic underwater images generated from in-air RGB images, allowing them to generalize to diverse underwater environments where real data collection might be limited [153].

A prominent technique within domain adaptation is CycleGAN [153]. By generating synthetic underwater images from RGB in-air images, CycleGAN allows models to train on a wider range of underwater conditions, enhancing their generalization ability and dehazing performance. However, the effectiveness of CycleGAN can be limited by the quality and representativeness of the in-air image datasets used for generation. Further research is needed to explore techniques for improving the realism and diversity of synthetic underwater images generated through domain adaptation [154].

3) REAL-TIME PROCESSING
Real-time processing capabilities are crucial for underwater monitoring, surveillance, and other practical applications [147], [155]. Developing efficient algorithms with low computational overhead is essential for real-time deployment. Recent advancements in techniques like non-local prior and air-light estimation (NLP-ALE) show promise in balancing image quality with processing speed [147]. Additionally, methods based on dark channel prior and Gaussian low pass filtering have demonstrated potential for real-time applications with minimal computational resources [155].

4) MULTI-TASK LEARNING
Exploring the potential of multitask learning paradigms represents a promising research direction. By leveraging advanced vision tasks (e.g., object detection, segmentation) to guide and optimize the underwater image enhancement process, multitask learning can lead to more effective and application-specific image quality improvements [156].

5) OTHER ADVANCED TECHNIQUES
In addition to deep learning and domain adaptation, other promising techniques are emerging in the field of underwater image enhancement and restoration. Here are a few examples:

a: NON-LOCAL MEANS FILTERING
This technique leverages the redundancy within an image to remove noise and enhance image details while preserving edges [157]. It achieves this by comparing image patches to similar patches throughout the image, utilizing weighted averaging to reduce noise and enhance details.

b: FUSION-BASED APPROACHES
Underwater images often suffer from low contrast and color distortion. Fusion-based techniques that combine multiple enhancement methods can help improve contrast, color balance, and overall visual quality. For example, a fusion algorithm that combines color balance, contrast optimization, and histogram equalization has been shown to effectively restore and enhance underwater images [37].

c: PARAMETRIC RESTORATION
Traditional restoration methods rely on physical models of light propagation in water, which require estimating parameters like attenuation coefficients. Recent work has proposed learning-based techniques to estimate these parameters, which can then be used as a ''clue'' to guide the restoration process. For instance, the AquaGAN model estimates attenuation coefficients and uses them to train a generative network for underwater image restoration [158].

d: FREQUENCY DOMAIN TECHNIQUES
Homomorphic filtering in the frequency domain can help correct uneven illumination and enhance contrast in underwater images [34]. This approach separates the illumination and reflectance components, allowing the use of high-pass filters to reduce the impact of low-frequency illumination variations.

e: BENCHMARK DATASETS
The development of large-scale, high-quality benchmark datasets for underwater image enhancement, such as UIEB, has enabled more rigorous evaluation and comparison of different restoration techniques [108].

C. KEY FACTORS AFFECTING ALGORITHM PERFORMANCE
1) DATASETS
The availability of high-quality underwater image datasets with diverse scene types, lighting conditions, and turbidity levels is crucial for training and evaluating image enhancement and restoration algorithms [131], [159]. Future research should focus on building larger, more comprehensive underwater image datasets to facilitate the development of robust models. These datasets should also be well-annotated with ground truth information relevant to the specific enhancement or restoration task (e.g., object segmentation masks, haze-free reference images). Annotations can include information about object boundaries, depth information, and the true color of objects underwater.

2) COLOR SPACE SELECTION
The choice of color space can impact algorithm performance. Techniques based on the YCbCr color space effectively separate image luminance and chrominance, allowing for targeted treatment of these elements to improve enhancement results [160]. Luminance refers to the brightness of an image, while chrominance represents color information.

By separating these components, algorithms can focus on enhancing brightness without affecting color information or vice versa. Other color spaces, such as HSV (hue, saturation, value), may also be beneficial depending on the specific task and image characteristics. HSV separates color information into hue (color tint), saturation (color intensity), and value (brightness), allowing for adjustments to specific aspects of color in underwater images.

3) DARK CHANNEL PRIOR AND ATMOSPHERIC LIGHT ESTIMATION

Techniques leveraging the dark channel prior and atmospheric light estimation have significantly improved underwater image quality by enhancing contrast, reducing noise and artifacts [161]. The dark channel prior is based on the observation that underwater scenes often have dark pixels in at least one color channel, corresponding to areas without direct light penetration. By analyzing these dark pixels, algorithms can estimate the atmospheric light affecting the entire image. However, these methods may not always perform well in challenging scenarios with severe backscattering or non-uniform illumination. Further research is needed to develop more robust and adaptable approaches for dark channel prior estimation and atmospheric light calculation, particularly for complex underwater environments [162].

D. ETHICAL CONSIDERATIONS

While advancements in underwater image enhancement offer exciting potential for various applications, ethical considerations must be addressed. Incorporating physical priors in image enhancement algorithms raises concerns regarding the accuracy and reliability of the resulting images, particularly in critical domains like marine biology and oceanography. Enhanced underwater images may not perfectly reflect the true underwater environment, potentially leading to misinterpretations of data. As research progresses, careful evaluation of the potential impact of enhanced underwater images on decision-making processes in marine environments is essential. This includes considerations of transparency, fairness, and potential biases introduced by the enhancement algorithms. Transparency requires documenting the algorithms used and their limitations, while fairness ensures the algorithms perform consistently across different underwater environments.

VII. CONCLUSION

Underwater image enhancement remains a critical challenge due to the severe degradation of image quality caused by light scattering and absorption. This review comprehensively examined traditional and learning-based approaches to address this issue. While traditional methods offer interpretability, their performance is limited under complex conditions. Conversely, learning-based methods excel in handling complex scenarios but often lack transparency and can be computationally demanding.

This review highlights the need for hybrid approaches that combine the strengths of both traditional and learning-based techniques. Future research should focus on developing robust models capable of handling diverse underwater environments, real-time processing for practical applications, and incorporating physical priors into deep learning frameworks. By addressing these challenges, researchers can significantly advance underwater imaging capabilities, enabling breakthroughs in marine biology, underwater archaeology, and other fields.

Quantifying the impact of poor underwater image quality on specific applications, such as marine biology or underwater archaeology, would further strengthen the conclusion. For instance, providing statistics on the economic losses due to inaccurate image interpretation or the limitations of current underwater exploration tools could emphasize the significance of this research area.

This review contributes to the field by providing a comprehensive overview of existing methods, identifying research gaps, and suggesting promising directions for future research. By building upon this foundation, researchers can develop innovative solutions to overcome the challenges of underwater imaging and unlock the full potential of this valuable resource.

REFERENCES

[1] M. Wang, K. Zhang, H. Wei, W. Chen, and T. Zhao, "Underwater image quality optimization: Researches, challenges, and future trends," *Image Vis. Comput.*, vol. 146, Jun. 2024, Art. no. 104995.

[2] W.-T. Lin, Y.-X. Lin, J.-W. Chen, and K.-L. Hua, "PixMamba: Leveraging state space models in a dual-level architecture for underwater image enhancement," 2024, *arXiv:2406.08444*.

[3] A. Chandrasekar, M. Sreenivas, and S. Biswas, "PhISH-Net: Physics inspired system for high resolution underwater image enhancement," in *Proc. IEEE/CVF Winter Conf. Appl. Comput. Vis. (WACV)*, Jan. 2024, pp. 1495–1505.

[4] M. K. Moghimi and F. Mohanna, "Real-time underwater image enhancement: A systematic review," *J. Real-Time Image Process.*, vol. 18, no. 5, pp. 1509–1525, Oct. 2021.

[5] X. Jiang, H. Yu, Y. Zhang, M. Pan, Z. Li, J. Liu, and S. Lv, "An underwater image enhancement method for a preprocessing framework based on generative adversarial network," *Sensors*, vol. 23, no. 13, p. 5774, Jun. 2023.

[6] X. Deng, T. Liu, S. He, X. Xiao, P. Li, and Y. Gu, "An underwater image enhancement model for domain adaptation," *Frontiers Mar. Sci.*, vol. 10, Apr. 2023, Art. no. 1138013.

[7] C. Li and J. Guo, "Underwater image enhancement by dehazing and color correction," *J. Electron. Imag.*, vol. 24, no. 3, Jun. 2015, Art. no. 033023.

[8] L. Li, H. Wang, and X. Liu, "Underwater image enhancement based on improved dark channel prior and color correction," *Guangxue Xuebao/Acta Optica Sinica*, vol. 37, no. 12, 2017, Art. no. 1211003.

[9] R. Thomas, L. Thampi, S. Kamal, A. A. Balakrishnan, T. P. M. Haridas, and M. H. Supriya, "Dehazing underwater images using encoder decoder based generic model-agnostic convolutional neural network," in *Proc. Int. Symp. Ocean Technol. (SYMPOL)*, Dec. 2021, pp. 1–4.

[10] D. C. Lepcha, B. Goyal, A. Dogra, K. P. Sharma, and D. N. Gupta, "A deep journey into image enhancement: A survey of current and emerging trends," *Inf. Fusion*, vol. 93, pp. 36–76, May 2023.

[11] X. Shuang, J. Zhang, and Y. Tian, "Algorithms for improving the quality of underwater optical images: A comprehensive review," *Signal Process.*, vol. 219, Jun. 2024, Art. no. 109408.

[12] S. Raveendran, M. D. Patil, and G. K. Birajdar, "Underwater image enhancement: A comprehensive review, recent trends, challenges and applications," *Artif. Intell. Rev.*, vol. 54, no. 7, pp. 5413–5467, Oct. 2021.

[13] M. Jian, X. Liu, H. Luo, X. Lu, H. Yu, and J. Dong, "Underwater image processing and analysis: A review," *Signal Process., Image Commun.*, vol. 91, Feb. 2021, Art. no. 116088.

[14] M. Han, Z. Lyu, T. Qiu, and M. Xu, "A review on intelligence dehazing and color restoration for underwater images," *IEEE Trans. Syst. Man, Cybern. Syst.*, vol. 50, no. 5, pp. 1820–1832, May 2020.

[15] N. Deluxni, P. Sudhakaran, and M. F. Ndiaye, "A review on image enhancement and restoration techniques for underwater optical imaging applications," *IEEE Access*, vol. 11, pp. 111715–111737, 2023.

[16] W. Song, Y. Liu, D. Huang, B. Zhang, Z. Shen, and H. Xu, "From shallow sea to deep sea: Research progress in underwater image restoration," *Frontiers Mar. Sci.*, vol. 10, May 2023, Art. no. 1163831.

[17] Y. Y. Schechner and N. Karpel, "Clear underwater vision," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, vol. 1, Sep. 2004, pp. 536–543.

[18] Y. Y. Schechner and N. Karpel, "Recovery of underwater visibility and structure by polarization analysis," *IEEE J. Ocean. Eng.*, vol. 30, no. 3, pp. 570–587, Jul. 2005.

[19] K. Iqbal, M. Odetayo, A. James, R. A. Salam, and A. Z. Hj Talib, "Enhancing the low quality images using unsupervised colour correction method," in *Proc. IEEE Int. Conf. Syst., Man Cybern.*, Oct. 2010, pp. 1703–1709.

[20] J. Y. Chiang and Y.-C. Chen, "Underwater image enhancement by wavelength compensation and dehazing," *IEEE Trans. Image Process.*, vol. 21, no. 4, pp. 1756–1769, Apr. 2012.

[21] C. Ancuti, C. O. Ancuti, T. Haber, and P. Bekaert, "Enhancing underwater images and videos by fusion," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2012, pp. 81–88.

[22] P. Drews Jr., E. do Nascimento, F. Moraes, S. Botelho, and M. Campos, "Transmission estimation in underwater single images," in *Proc. IEEE Int. Conf. Comput. Vis. Workshops*, Dec. 2013, pp. 825–830.

[23] C. Li, J. Guo, S. Chen, Y. Tang, Y. Pang, and J. Wang, "Underwater image restoration based on minimum information loss principle and optical properties of underwater imaging," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2016, pp. 1993–1997.

[24] C.-Y. Li, J.-C. Guo, R.-M. Cong, Y.-W. Pang, and B. Wang, "Underwater image enhancement by dehazing with minimum information loss and histogram distribution prior," *IEEE Trans. Image Process.*, vol. 25, no. 12, pp. 5664–5677, Dec. 2016.

[25] C. Li, J. Quo, Y. Pang, S. Chen, and J. Wang, "Single underwater image restoration by blue-green channels dehazing and red channel correction," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Mar. 2016, pp. 1731–1735.

[26] D. Huang, Y. Wang, W. Song, J. Sequeira, and S. Mavromatis, "Shallow-water image enhancement using relative global histogram stretching based on adaptive parameter acquisition," in *Proc. Int. Conf. Multimedia Modeling*, Bangkok, Thailand. Cham, Switzerland: Springer, 2018, pp. 453–465.

[27] C. O. Ancuti, C. Ancuti, C. De Vleeschouwer, and P. Bekaert, "Color balance and fusion for underwater image enhancement," *IEEE Trans. Image Process.*, vol. 27, no. 1, pp. 379–393, Jan. 2018.

[28] D. Akkaynak and T. Treibitz, "A revised underwater image formation model," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 6723–6732.

[29] R. Protasiuk, A. Bibi, and B. Ghanem, "Local color mapping combined with color transfer for underwater image enhancement," in *Proc. IEEE Winter Conf. Appl. Comput. Vis. (WACV)*, Jan. 2019, pp. 1433–1439.

[30] R. Sethi and I. Sreedevi, "Adaptive enhancement of underwater images using multi-objective PSO," *Multimedia Tools Appl.*, vol. 78, no. 22, pp. 31823–31845, Nov. 2019.

[31] M. Yang, K. Hu, Y. Du, Z. Wei, Z. Sheng, and J. Hu, "Underwater image enhancement based on conditional generative adversarial network," *Signal Process., Image Commun.*, vol. 81, Feb. 2020, Art. no. 115723.

[32] C. Li, S. Anwar, and F. Porikli, "Underwater scene prior inspired deep underwater image and video enhancement," *Pattern Recognit.*, vol. 98, Feb. 2020, Art. no. 107038.

[33] X. Fu and X. Cao, "Underwater image enhancement with global–local networks and compressed-histogram equalization," *Signal Process., Image Commun.*, vol. 86, Aug. 2020, Art. no. 115892.

[34] C. H. Chong, A. S. A. Ghani, and K. Z. M. Azmi, "Dual image fusion technique for underwater image contrast enhancement," in *Proc. 11th Nat. Tech. Seminar Unmanned Syst. Technol.*, 2021, pp. 57–72.

[35] W. Zhang, S. Jin, P. Zhuang, Z. Liang, and C. Li, "Underwater image enhancement via piecewise color correction and dual prior optimized contrast enhancement," *IEEE Signal Process. Lett.*, vol. 30, pp. 229–233, 2023.

[36] G. Hou, N. Li, P. Zhuang, K. Li, H. Sun, and C. Li, "Non-uniform illumination underwater image restoration via illumination channel sparsity prior," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 34, no. 2, pp. 799–814, Feb. 2024.

[37] S. An, L. Xu, Z. Deng, and H. Zhang, "HFM: A hybrid fusion method for underwater image enhancement," *Eng. Appl. Artif. Intell.*, vol. 127, Jan. 2024, Art. no. 107219.

[38] Y. Zhang, F. Yang, and W. He, "An approach for underwater image enhancement based on color correction and dehazing," *Int. J. Adv. Robotic Syst.*, vol. 17, no. 5, Sep. 2020, Art. no. 172988142096164.

[39] M. Žuži, J. Čejka, F. Bruno, D. Skarlatos, and F. Liarokapis, "Impact of dehazing on underwater marker detection for augmented reality," *Frontiers Robot. AI*, vol. 5, p. 92, Aug. 2018.

[40] E. N. Malamas, E. G. M. Petrakis, M. Zervakis, L. Petit, and J.-D. Legat, "A survey on industrial vision systems, applications and tools," *Image Vis. Comput.*, vol. 21, no. 2, pp. 171–188, Feb. 2003.

[41] B. Sekeroglu, "Time-shift image enhancement method," *Image Vis. Comput.*, vol. 138, Oct. 2023, Art. no. 104810.

[42] Y.-T. Peng, X. Zhao, and P. C. Cosman, "Single underwater image enhancement using depth estimation based on blurriness," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2015, pp. 4952–4956.

[43] Y.-T. Peng and P. C. Cosman, "Underwater image restoration based on image blurriness and light absorption," *IEEE Trans. Image Process.*, vol. 26, no. 4, pp. 1579–1594, Apr. 2017.

[44] M. Wang, L. Liao, D. Huang, Z. Fan, J. Zhuang, and W. Zhang, "Frequency and content dual stream network for image dehazing," *Image Vis. Comput.*, vol. 139, Nov. 2023, Art. no. 104820.

[45] D. Akkaynak and T. Treibitz, "Sea-thru: A method for removing water from underwater images," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 1682–1691.

[46] Y. Xiang, G. Wang, J. Gao, X. Wang, Y. Chen, K.-H. Chew, and R.-P. Chen, "Fast processing of underwater active polarimetric dehazing imaging without prior knowledge," *J. Electron. Imag.*, vol. 32, no. 3, Jun. 2023, Art. no. 033026.

[47] M. Roznere and A. Q. Li, "Real-time model-based image color correction for underwater robots," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Nov. 2019, pp. 7191–7196.

[48] J. G. James, P. Agrawal, and A. Rajwade, "Restoration of non-rigidly distorted underwater images using a combination of compressive sensing and local polynomial image representations," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, Oct. 2019, pp. 7838–7847.

[49] X. Fu, P. Zhuang, Y. Huang, Y. Liao, X.-P. Zhang, and X. Ding, "Depth and image restoration from light field in a scattering medium," in *Proc. IEEE Int. Conf. Image Proess. (ICIP)*, Oct. 2014, pp. 2401–2410.

[50] J. Tian, Z. Murez, T. Cui, Z. Zhang, D. Kriegman, and R. Ramamoorthi, "Depth and image restoration from light field in a scattering medium," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Oct. 2017, pp. 2420–2429.

[51] S. Zhang, T. Wang, J. Dong, and H. Yu, "Underwater image enhancement via extended multi-scale retinex," *Neurocomputing*, vol. 245, pp. 1–9, Jul. 2017.

[52] J. Zhou, Q. Liu, Q. Jiang, W. Ren, K.-M. Lam, and W. Zhang, "Underwater camera: Improving visual perception via adaptive dark pixel prior and color correction," *Int. J. Comput. Vis.*, Aug. 2023.

[53] M. Roser, M. Dunbabin, and A. Geiger, "Simultaneous underwater visibility assessment, enhancement and improved stereo," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2014, pp. 3840–3847.

[54] A. Galdran, D. Pardo, A. Picón, and A. Alvarez-Gila, "Automatic red-channel underwater image restoration," *J. Vis. Commun. Image Represent.*, vol. 26, pp. 132–145, Jan. 2015.

[55] P. Zhuang, C. Li, and J. Wu, "Bayesian retinex underwater image enhancement," *Eng. Appl. Artif. Intell.*, vol. 101, May 2021, Art. no. 104171.

[56] J. Xie, G. Hou, G. Wang, and Z. Pan, "A variational framework for underwater image dehazing and deblurring," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 32, no. 6, pp. 3514–3526, Jun. 2022.

[57] W. Zhang, P. Zhuang, H.-H. Sun, G. Li, S. Kwong, and C. Li, "Underwater image enhancement via minimal color loss and locally adaptive contrast enhancement," *IEEE Trans. Image Process.*, vol. 31, pp. 3997–4010, 2022.

[58] P. Zhuang, J. Wu, F. Porikli, and C. Li, "Underwater image enhancement with hyper-Laplacian reflectance priors," *IEEE Trans. Image Process.*, vol. 31, pp. 5442–5455, 2022.
[59] J. Yuan, Z. Cai, and W. Cao, "TEBCF: Real-world underwater image texture enhancement model based on blurriness and color fusion," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, 2022, Art. no. 4204315.
[60] W. Zhang, Y. Wang, and C. Li, "Underwater image enhancement by attenuated color channel correction and detail preserved contrast enhancement," *IEEE J. Ocean. Eng.*, vol. 47, no. 3, pp. 718–735, Jul. 2022.
[61] Z. Fu, H. Lin, Y. Yang, S. Chai, L. Sun, Y. Huang, and X. Ding, "Unsupervised underwater image restoration: From a homology perspective," in *Proc. AAAI Conf. Artif. Intell.*, 2022, pp. 643–651.
[62] F. Huo, B. Li, and X. Zhu, "Efficient wavelet boost learning-based multi-stage progressive refinement network for underwater image enhancement," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. Workshops (ICCVW)*, Oct. 2021, pp. 1944–1952.
[63] S. Liu, H. Fan, S. Lin, Q. Wang, N. Ding, and Y. Tang, "Adaptive learning attention network for underwater image enhancement," *IEEE Robot. Autom. Lett.*, vol. 7, no. 2, pp. 5326–5333, Apr. 2022.
[64] Z. Shen, H. Xu, T. Luo, Y. Song, and Z. He, "UDAformer: Underwater image enhancement based on dual attention transformer," *Comput. Graph.*, vol. 111, pp. 77–88, Apr. 2023.
[65] X. Liu, S. Lin, K. Chi, Z. Tao, and Y. Zhao, "Boths: Super lightweight network-enabled underwater image enhancement," *IEEE Geosci. Remote Sens. Lett.*, vol. 20, pp. 1–5, 2023.
[66] P. Mu, H. Xu, Z. Liu, Z. Wang, S. Chan, and C. Bai, "A generalized physical-knowledge-guided dynamic model for underwater image enhancement," in *Proc. 31st ACM Int. Conf. Multimedia*, vol. 43, Oct. 2023, pp. 7111–7120.
[67] J. Zhou, B. Li, D. Zhang, J. Yuan, W. Zhang, Z. Cai, and J. Shi, "UGIF-net: An efficient fully guided information flow network for underwater image enhancement," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023, Art. no. 4206117.
[68] S. Yang, Z. Chen, Z. Feng, and X. Ma, "Underwater image enhancement using scene depth-based adaptive background light estimation and dark channel prior algorithms," *IEEE Access*, vol. 7, pp. 165318–165327, 2019.
[69] Q. Jiang, Y. Zhang, F. Bao, X. Zhao, C. Zhang, and P. Liu, "Two-step domain adaptation for underwater image enhancement," *Pattern Recognit.*, vol. 122, Feb. 2022, Art. no. 108324.
[70] C. Wu, Z. Liu, L. Qian, and J. Zhou, "Depth-conditioned GAN for underwater image enhancement," *IEEE Access*, vol. 11, pp. 141789–141800, 2023.
[71] Y. Jeon and H. Kim, "Efficient image enhancement via representative color transform," *IEEE Access*, vol. 12, pp. 76458–76468, 2024.
[72] J. Qian, B. Kong, and J. Yang, "Underwater image clarification based on double-opponency light estimation and red channel prior," *IEEE Access*, vol. 11, pp. 64383–64396, 2023.
[73] A. Saleem, S. Paheding, N. Rawashdeh, A. Awad, and N. Kaur, "A non-reference evaluation of underwater image enhancement methods using a new underwater image dataset," *IEEE Access*, vol. 11, pp. 10412–10428, 2023.
[74] H. Zhao and H. Yuan, "Residual dense blocks and contrastive regularization integrated underwater image enhancement network," *IEEE Access*, vol. 11, pp. 113017–113026, 2023.
[75] T. Wang, L. Wang, E. Zhang, Y. Ma, Y. Wang, H. Xie, and M. Zhu, "Underwater image enhancement based on optimal contrast and attenuation difference," *IEEE Access*, vol. 11, pp. 68538–68549, 2023.
[76] J. Zhang, F. He, Y. Duan, and S. Yang, "AIDEDNet: Anti-interference and detail enhancement dehazing network for real-world scenes," *Frontiers Comput. Sci.*, vol. 17, no. 2, Apr. 2023, Art. no. 172703.
[77] S. Luchman and S. Viriri, "Underwater image enhancement using adaptive algorithms," in *Proc. Int. Workshop Artif. Intell. Pattern Recognit.*, 2021, pp. 316–326.
[78] S. Zhu, W. Luo, and S. Duan, "Enhancement of underwater images by CNN-based color balance and dehazing," *Electronics*, vol. 11, no. 16, p. 2537, Aug. 2022.
[79] C. Li, S. Anwar, J. Hou, R. Cong, C. Guo, and W. Ren, "Underwater image enhancement via medium transmission-guided multi-color space embedding," *IEEE Trans. Image Process.*, vol. 30, pp. 4985–5000, 2021.
[80] M. Mousavi, R. Estrada, and A. Ashok, "IDehaze: Supervised underwater image enhancement and dehazing via physically accurate photorealistic simulations," *Electronics*, vol. 12, no. 11, p. 2352, May 2023.
[81] J. Han, M. Shoeiby, T. Malthus, E. Botha, J. Anstee, S. Anwar, R. Wei, L. Petersson, and M. A. Armin, "Single underwater image restoration by contrastive learning," in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, Jul. 2021, pp. 2385–2388.
[82] V. Rajesh, S. Radhika, and S. Vishnu, "Comparing the performance measures of underwater image enhancement through improved CNN with Gaussian and Kalman filter method," in *Proc. Int. Conf. Syst., Comput., Autom. Netw. (ICSCAN)*, Nov. 2023, pp. 1–6.
[83] Z. Fu, X. Lin, W. Wang, Y. Huang, and X. Ding, "Underwater image enhancement via learning water type desensitized representations," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2022, pp. 2764–2768.
[84] X. Liu, B. Chen, and S. Wu, "A light-weight hybrid network for image dehazing," in *Proc. IEEE 18th Conf. Ind. Electron. Appl. (ICIEA)*, Aug. 2023, pp. 501–506.
[85] S. Zhang, W. Ren, X. Tan, Z.-J. Wang, Y. Liu, J. Zhang, X. Zhang, and X. Cao, "Semantic-aware dehazing network with adaptive feature fusion," *IEEE Trans. Cybern.*, vol. 53, no. 1, pp. 454–467, Jan. 2023.
[86] A. Naik, A. Swarnakar, and K. Mittal, "Shallow-UWNet: Compressed model for underwater image enhancement (student abstract)," in *Proc. AAAI Conf. Artif. Intell.*, 2021, pp. 15853–15854.
[87] Y. Wang, J. Guo, H. Gao, and H. Yue, "UIEC^2-Net: CNN-based underwater image enhancement using two color space," *Signal Process., Image Commun.*, vol. 96, Aug. 2021, Art. no. 116250.
[88] N. Jiang, W. Chen, Y. Lin, T. Zhao, and C.-W. Lin, "Underwater image enhancement with lightweight cascaded network," *IEEE Trans. Multimedia*, vol. 24, pp. 4301–4313, 2022.
[89] A. K. Cherian, J. Venugopal, R. Abishek, and F. Jabbar, "Survey on underwater image enhancement using deep learning," in *Proc. Int. Conf. Comput., Commun., Secur. Intell. Syst. (IC3SIS)*, Jun. 2022, pp. 1–6.
[90] H. Yu, X. Li, Y. Feng, and S. Han, "Underwater vision enhancement based on GAN with dehazing evaluation," *Appl. Intell.*, vol. 53, no. 5, pp. 5664–5680, Jul. 2022.
[91] S. Zhang, X. Zhang, S. Wan, W. Ren, L. Zhao, and L. Shen, "Generative adversarial and self-supervised dehazing network," *IEEE Trans. Ind. Informat.*, vol. 20, no. 3, pp. 4187–4197, Mar. 2024.
[92] W. Chen, M. Rahmati, V. Sadhu, and D. Pompili, "Real-time image enhancement for vision-based autonomous underwater vehicle navigation in murky waters," in *Proc. Int. Conf. Underwater Netw. Syst.*, vol. 1, Oct. 2019, pp. 1–8.
[93] A. B. Bakht, Z. Jia, M. U. Din, W. Akram, L. S. Saoud, L. Seneviratne, D. Lin, S. He, and I. Hussain, "MuLA-GAN: Multi-level attention GAN for enhanced underwater visibility," *Ecol. Informat.*, vol. 81, Jul. 2024, Art. no. 102631.
[94] D. Avola, I. Cannistraci, M. Cascio, and I. Scagnetto, "Real-time GAN-based model for underwater image enhancement," in *Proc. Int. Conf. Image Anal. Process.*, 2023, pp. 412–423.
[95] M. Ummar, F. A. Dharejo, B. Alawode, T. Mahbub, M. J. Piran, and S. Javed, "Window-based transformer generative adversarial network for autonomous underwater image enhancement," *Eng. Appl. Artif. Intell.*, vol. 126, Nov. 2023, Art. no. 107069.
[96] J. Wen, J. Cui, G. Yang, B. Zhao, Y. Zhai, Z. Gao, L. Dou, and B. M. Chen, "WaterFormer: A global–local transformer for underwater image enhancement with environment adaptor," *IEEE Robot. Autom. Mag.*, vol. 31, no. 1, pp. 29–40, Mar. 2024.
[97] Y. Tang, T. Iwaguchi, H. Kawasaki, R. Sagawa, and R. Furukawa, "AutoEnhancer: Transformer on U-Net architecture search for underwater image enhancement," in *Proc. Asian Conf. Comput. Vis. (ACCV)*, Dec. 2022, pp. 1403–1420.
[98] F. A. Dharejo, I. I. Ganapathi, M. Zawish, B. Alawode, M. Alathbah, N. Werghi, and S. Javed, "SwinWave-SR: Multi-scale lightweight underwater image super-resolution," *Inf. Fusion*, vol. 103, Mar. 2024, Art. no. 102127.
[99] Y. Wang, J. Zhang, Y. Cao, and Z. Wang, "A deep CNN method for underwater image enhancement," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2017, pp. 1382–1386.

[100] C. Li, J. Guo, and C. Guo, "Emerging from water: Underwater image color correction based on weakly supervised color transfer," *IEEE Signal Process. Lett.*, vol. 25, no. 3, pp. 323–327, Mar. 2018.

[101] N. Wang, Y. Zhou, F. Han, H. Zhu, and J. Yao, "UWGAN: Underwater GAN for real-world underwater color restoration and dehazing," 2019, *arXiv:1912.10269*.

[102] X. Chen, J. Yu, S. Kong, Z. Wu, X. Fang, and L. Wen, "Towards real-time advancement of underwater visual quality with GAN," *IEEE Trans. Ind. Electron.*, vol. 66, no. 12, pp. 9350–9359, Dec. 2019.

[103] Y. Guo, H. Li, and P. Zhuang, "Underwater image enhancement using a multiscale dense generative adversarial network," *IEEE J. Ocean. Eng.*, vol. 45, no. 3, pp. 862–870, Jul. 2020.

[104] R. Liu, Z. Jiang, S. Yang, and X. Fan, "Twin adversarial contrastive learning for underwater image enhancement and beyond," *IEEE Trans. Image Process.*, vol. 31, pp. 4922–4936, 2022.

[105] Z. Jiang, Z. Li, S. Yang, X. Fan, and R. Liu, "Target oriented perceptual adversarial fusion network for underwater image enhancement," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 32, no. 10, pp. 6584–6598, Oct. 2022.

[106] R. Liu, X. Fan, M. Zhu, M. Hou, and Z. Luo, "Real-world underwater enhancement: Challenges, benchmarks, and solutions under natural light," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 30, no. 12, pp. 4861–4875, Dec. 2020.

[107] J. Li, K. A. Skinner, R. M. Eustice, and M. Johnson-Roberson, "WaterGAN: Unsupervised generative network to enable real-time color correction of monocular underwater images," *IEEE Robot. Autom. Lett.*, vol. 3, no. 1, pp. 387–394, Jan. 2018.

[108] C. Li, C. Guo, W. Ren, R. Cong, J. Hou, S. Kwong, and D. Tao, "An underwater image enhancement benchmark dataset and beyond," *IEEE Trans. Image Process.*, vol. 29, pp. 4376–4389, 2020.

[109] P. M. Uplavikar, Z. Wu, and Z. Wang, "All-in-one underwater image enhancement using domain-adversarial learning," in *Proc. CVPR Workshops*, 2019, pp. 1–8.

[110] Z. Lyu, A. Peng, Q. Wang, and D. Ding, "An efficient learning-based method for underwater image enhancement," *Displays*, vol. 74, Sep. 2022, Art. no. 102174.

[111] D. Wang, L. Ma, R. Liu, and X. Fan, "Semantic-aware texture-structure feature collaboration for underwater image enhancement," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2022, pp. 4592–4598.

[112] Q. Qi, K. Li, H. Zheng, X. Gao, G. Hou, and K. Sun, "SGUIE-Net: Semantic attention guided underwater image enhancement with multi-scale perception," *IEEE Trans. Image Process.*, vol. 31, pp. 6816–6830, 2022.

[113] A. Jamadandi and U. Mudenagudi, "Exemplar-based underwater image enhancement augmented by wavelet corrected transforms," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR) Workshops*, Jun. 2019, pp. 11–17.

[114] M. Jahidul Islam, P. Luo, and J. Sattar, "Simultaneous enhancement and super-resolution of underwater imagery for improved visual perception," 2020, *arXiv:2002.01155*.

[115] Z. Ma and C. Oh, "A wavelet-based dual-stream network for underwater image enhancement," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2022, pp. 2769–2773.

[116] M. J. Islam, Y. Xia, and J. Sattar, "Fast underwater image enhancement for improved visual perception," *IEEE Robot. Autom. Lett.*, vol. 5, no. 2, pp. 3227–3234, Apr. 2020.

[117] K. Li, L. Wu, Q. Qi, W. Liu, X. Gao, L. Zhou, and D. Song, "Beyond single reference for training: Underwater image enhancement via comparative learning," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 33, no. 6, pp. 2561–2576, Jun. 2023.

[118] Z. Fu, W. Wang, Y. Huang, X. Ding, and K.-K. Ma, "Uncertainty inspired underwater image enhancement," in *Proc. Eur. Conf. Comput. Vis.* Cham, Switzerland: Springer, 2022, pp. 465–482.

[119] Z. Wang, L. Shen, Y. Yu, and Y. Hui, "UIERL: Internal-external representation learning network for underwater image enhancement," *IEEE Trans. Multimedia*, vol. 26, pp. 9252–9267, 2024.

[120] K. Purnima and C. S. Kumar, "Non-gradient based design metrics for underwater image enhancement," in *Proc. Int. Conf. Self Sustain. Artif. Intell. Syst. (ICSSAS)*, vol. 5, Oct. 2023, pp. 817–823.

[121] K. Purnima and C. S. Kumar, "Gradient-based design metrics for assessment of underwater image enhancement," in *Proc. Int. Conf. Self Sustain. Artif. Intell. Syst. (ICSSAS)*, Oct. 2023, pp. 783–788.

[122] T. Chen, X. Yang, N. Li, T. Wang, and G. Ji, "Underwater image quality assessment method based on color space multi-feature fusion," *Sci. Rep.*, vol. 13, no. 1, Oct. 2023, Art. no. 16838.

[123] K. Panetta, C. Gao, and S. Agaian, "Human-visual-system-inspired underwater image quality measures," *IEEE J. Ocean. Eng.*, vol. 41, no. 3, pp. 541–551, Jul. 2016.

[124] M. Yang and A. Sowmya, "An underwater color image quality evaluation metric," *IEEE Trans. Image Process.*, vol. 24, no. 12, pp. 6062–6071, Dec. 2015.

[125] L. Liu, B. Liu, H. Huang, and A. C. Bovik, "No-reference image quality assessment based on spatial and spectral entropies," *Signal Process., Image Commun.*, vol. 29, no. 8, pp. 856–863, Sep. 2014.

[126] Y. Zheng, W. Chen, R. Lin, T. Zhao, and P. Le Callet, "UIF: An objective quality assessment for underwater image enhancement," *IEEE Trans. Image Process.*, vol. 31, pp. 5456–5468, 2022.

[127] A. Mittal, A. K. Moorthy, and A. C. Bovik, "No-reference image quality assessment in the spatial domain," *IEEE Trans. Image Process.*, vol. 21, no. 12, pp. 4695–4708, Dec. 2012.

[128] Y. Kang, Q. Jiang, C. Li, W. Ren, H. Liu, and P. Wang, "A perception-aware decomposition and fusion framework for underwater image enhancement," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 33, no. 3, pp. 988–1002, Mar. 2023.

[129] J. Yuan, W. Cao, Z. Cai, and B. Su, "An underwater image vision enhancement algorithm based on contour bougie morphology," *IEEE Trans. Geosci. Remote Sens.*, vol. 59, no. 10, pp. 8117–8128, Oct. 2021.

[130] T. P. Marques and A. B. Albu, "L2UWE: A framework for the efficient enhancement of low-light underwater images using local contrast and multi-scale fusion," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2020, pp. 2286–2295.

[131] C. Li, J. Guo, C. Guo, R. Cong, and J. Gong, "A hybrid method for underwater image correction," *Pattern Recognit. Lett.*, vol. 94, pp. 62–67, Jul. 2017.

[132] W. Song, Y. Wang, D. Huang, A. Liotta, and C. Perra, "Enhancement of underwater images with statistical model of background light and optimization of transmission map," *IEEE Trans. Broadcast.*, vol. 66, no. 1, pp. 153–169, Mar. 2020.

[133] D. Berman, D. Levy, S. Avidan, and T. Treibitz, "Underwater single image color restoration using haze-lines and a new quantitative dataset," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 43, no. 8, pp. 2822–2837, Aug. 2021.

[134] T. Ren, H. Xu, G. Jiang, M. Yu, X. Zhang, B. Wang, and T. Luo, "Reinforced Swin-Convs transformer for simultaneous underwater sensing scene image enhancement and super-resolution," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, 2022, Art. no. 4209616.

[135] Y. Wei, Z. Zheng, and X. Jia, "UHD underwater image enhancement via frequency-spatial domain aware network," in *Proc. Asian Conf. Comput. Vis. (ACCV)*, Dec. 2022, pp. 299–314.

[136] X. Yan, W. Qin, Y. Wang, G. Wang, and X. Fu, "Attention-guided dynamic multi-branch neural network for underwater image enhancement," *Knowl.-Based Syst.*, vol. 258, Dec. 2022, Art. no. 110041.

[137] L. Peng, C. Zhu, and L. Bian, "U-shape transformer for underwater image enhancement," *IEEE Trans. Image Process.*, vol. 32, pp. 3066–3079, 2023.

[138] L. Chen, Z. Jiang, L. Tong, Z. Liu, A. Zhao, Q. Zhang, J. Dong, and H. Zhou, "Perceptual underwater image enhancement with deep learning and physical priors," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 31, no. 8, pp. 3078–3092, Aug. 2021.

[139] P. Sharma, I. Bisht, and A. Sur, "Wavelength-based attributed deep neural network for underwater image restoration," *ACM Trans. Multimedia Comput., Commun., Appl.*, vol. 19, no. 1, pp. 1–23, Jan. 2023.

[140] Z. Wang, X. Cun, J. Bao, W. Zhou, J. Liu, and H. Li, "Uformer: A general U-shaped transformer for image restoration," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2022, pp. 17683–17693.

[141] J. Liang, J. Cao, G. Sun, K. Zhang, L. Van Gool, and R. Timofte, "SwinIR: Image restoration using Swin transformer," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. Workshops (ICCVW)*, Oct. 2021, pp. 1833–1844.

[142] S. W. Zamir, A. Arora, S. Khan, M. Hayat, F. S. Khan, and M. Yang, "Restormer: Efficient transformer for high-resolution image restoration," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2022, pp. 5718–5729.
[143] W. Peng, C. Zhou, R. Hu, J. Cao, and Y. Liu, "RAUNE-Net: A residual and attention-driven underwater image enhancement method," in *Proc. Int. Forum Digital TV Wireless Multimedia Commun.* Cham, Switzerland: Springer, 2023, pp. 15–27.
[144] H. Li, J. Li, and W. Wang, "A fusion adversarial underwater image enhancement network with a public test dataset," 2019, *arXiv:1906.06819*.
[145] R. Cong, W. Yang, W. Zhang, C. Li, C.-L. Guo, Q. Huang, and S. Kwong, "PUGAN: Physical model-guided underwater image enhancement using GAN with dual-discriminators," *IEEE Trans. Image Process.*, vol. 32, pp. 4472–4485, 2023.
[146] C. Fabbri, M. J. Islam, and J. Sattar, "Enhancing underwater imagery using generative adversarial networks," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2018, pp. 7159–7165.
[147] A. Dogra, B. Goyal, D. C. Lepcha, and V. Kukreja, "Underwater image dehazing using non-local prior method and air-light estimation," in *Proc. Int. Conf. Intell. Perception Comput. Vis. (CIPCV)*, vol. 29, May 2023, pp. 68–73.
[148] T. Li, J. Wang, and K. Yao, "Visibility enhancement of underwater images based on active polarized illumination and average filtering technology," *Alexandria Eng. J.*, vol. 61, no. 1, pp. 701–708, Jan. 2022.
[149] H.-H. Yang, K.-C. Huang, and W.-T. Chen, "LAFFNet: A lightweight adaptive feature fusion network for underwater image enhancement," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2021, pp. 685–692.
[150] H. Chen and P. K. Varshney, "A human perception inspired quality metric for image fusion based on regional information," *Inf. Fusion*, vol. 8, no. 2, pp. 193–207, Apr. 2007.
[151] J. Perez, A. C. Attanasio, N. Nechyporenko, and P. J. Sanz, "A deep learning approach for underwater image enhancement," in *Biomedical Applications Based on Natural and Artificial Computing*, J. M. F. Vicente, J. R. Álvarez-Sánchez, F. de la Paz López, J. T. Moreo, and H. Adeli, Eds., Cham, Switzerland: Springer, 2017.
[152] Y.-S. Shin, Y. Cho, G. Pandey, and A. Kim, "Estimation of ambient light and transmission map with common convolutional architecture," in *Proc. OCEANS MTS/IEEE Monterey*, Sep. 2016, pp. 1–7.
[153] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Oct. 2017, pp. 2242–2251.
[154] L. S. Saoud, Z. Niu, A. Sultan, L. Seneviratne, and I. Hussain, "ADOD: Adaptive domain-aware object detection with residual attention for underwater environments," in *Proc. 21st Int. Conf. Adv. Robot. (ICAR)*, vol. 517, Dec. 2023, pp. 633–638.
[155] R. Verma, "Enhancing underwater images through non-local prior-based dehazing," in *Proc. 3rd Int. Conf. Technol. Advancements Comput. Sci. (ICTACS)*, vol. 55, Nov. 2023, pp. 1–6.
[156] H. Almarzouqi and L. S. Saoud, "Semantic labeling of high-resolution images using EfficientUNets and transformers," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023, Art. no. 4402913.
[157] A. Buades, B. Coll, and J.-M. Morel, "A non-local algorithm for image denoising," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2005, pp. 60–65.
[158] C. Desai, B. S. S. Reddy, R. A. Tabib, U. Patil, and U. Mudenagudi, "AquaGAN: Restoration of underwater images," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2022, pp. 295–303.
[159] X. Chen, P. Zhang, L. Quan, C. Yi, and C. Lu, "Underwater image enhancement based on deep learning and image formation model," 2021, *arXiv:2101.00991*.
[160] M. K. Das, N. V. Gaddala, P. R. Bommireddy, and R. Roy, "Underwater image dehazing in YCbCr color space using superpixel segmentation," in *Proc. 7th Int. Conf. Video Image Process.*, vol. 571, Dec. 2023, pp. 37–44.
[161] N. Muhammad and F. Fahrianto, "Underwater image enhancement using guided joint bilateral filter," in *Proc. 6th Int. Conf. Cyber IT Service Manage. (CITSM)*, Aug. 2018, pp. 1–6.
[162] B. Yao and J. Xiang, "Underwater image dehazing using modified dark channel prior," in *Proc. Chin. Control Decis. Conf. (CCDC)*, Jun. 2018, pp. 5792–5797.

LYES SAAD SAOUD received the Bachelor of Science degree in electronics engineering and the Master of Science degree in electronics from the University of Setif, Algeria, in 2003 and 2006, respectively, the Doctor of Philosophy (Ph.D.) degree in physics, with a specialization in renewable energies from the University of Boumerdès, Algeria, in January 2015, and the Empowerment to Direct Research degree, in February 2017. From February 2019 to October 2019, he was an Associate Professor and the Head of the Department of Electrical Systems Engineering, University of Boumerdès, where he was also a Scientific Member of the Faculty of Technology. He is currently a Postdoctoral Fellow with the Department of Mechanical Engineering, Khalifa University, United Arab Emirates. Previously, he has held his postdoctoral research positions in civil infrastructure and environmental engineering, mechanical engineering, and electrical engineering and computer science with Khalifa University. Additionally, he was a Visiting Postdoctoral Fellow with the REDLab, University of Hawai'i at Manoa, USA. His research interests include computer and robot vision, specifically for object detection and domain adaptation, advanced neural networks, fuzzy logic, hybrid systems, renewable energy to address challenges in sustainability, environmental impact, and energy engineering. He was a Senior Consultant in cybersecurity, predictive modeling, machine learning, and data science with IOTwitt Corporation, Hawaii, USA. He also served on the technical committee for several international conferences and as a Reviewer for journals, such as IEEE Transactions on Neural Networks and Learning Systems, IEEE Access, *Transactions of the Institute of Measurement and Control*, *Journal of Renewable and Sustainable Energy*, *Neurocomputing*, *Scientific Reports*, *Science Progress*, and *Neural Processing Letters*.

MAHMOUD ELMEZAIN received the Master of Science degree in electrical and computer engineering from Khalifa University, United Arab Emirates, where he is currently pursuing the Ph.D. degree in robotics engineering. His research interests include employing AI for marine monitoring and developing underwater computer vision techniques. His work involves creating algorithms to enhance the perception and navigation capabilities of autonomous and remotely operated underwater vehicles.

ATIF SULTAN received the bachelor's degree in mechatronics and the master's degree in biomedical engineering from the National University of Sciences and Technology, Pakistan. He is currently pursuing the Ph.D. degree in mechanical engineering with Khalifa University, Abu Dhabi, United Arab Emirates. Notably, he emerged victorious with the All Pakistan DICE Health Innovation Exhibition, in 2017. His doctoral research focuses on developing robotic systems for complex underwater conservation tasks, with a particular emphasis on coral reef monitoring.

MOHAMED HESHMAT received the joint Ph.D. degree in robotics from Egypt-Japan University of Science and Technology, Egypt, and Osaka University, Japan, in 2015. Prior to his current research focus, he was a Research Fellow with the University of Lincoln, the University of Surrey, and the University of the West of England, Bristol, U.K. During this time, he made significant contributions to advancements in industrial robotic inspection, elder monitoring systems, and offsite logistics AI platforms. He has extensive experience in developing computer vision and robotics solutions for the industry. His current research interests include developing cutting-edge navigation systems for underwater mobile robots and pioneering deep-learning models for inspection applications.

LAKMAL SENEVIRATNE is currently a Professor in mechanical engineering and the Founding Director of the Centre for Autonomous Robotic Systems (KUCARS), Khalifa University, United Arab Emirates. He was an Associate Provost in research and graduate studies and an Associate VP Research with Khalifa University. Before joining Khalifa University, he was a Professor in mechatronics, the Founding Director of the Centre for Robotics Research, and the Head of the Division of Engineering, King's College London, where he is also a Professor Emeritus. His main research interests include robotics and automation, with a particular emphasis on increasing the autonomy of robotic systems interacting with complex dynamic environments. He has published over 400 peer-reviewed publications on these topics. He is a member of the Mohammed Bin Rashid Academy of Scientists, United Arab Emirates.

IRFAN HUSSAIN received the B.E. degree in mechatronics engineering from Air University, Pakistan, the M.S. degree in mechatronics engineering from the National University of Sciences and Technology, Pakistan, the master's degree in automatica and control technologies from the Politecnico di Torino, Italy, and the Ph.D. degree in robotics from the University of Siena, Italy. He was a Postdoctorate Researcher with the Robotics Institute, Khalifa University of Science and Technology, Abu Dhabi, United Arab Emirates. He was also a Postdoctorate Researcher with Siena Robotics and System Laboratory (SIRSLab), Italy. He was a Research Assistant with Gyeongsang National University, South Korea, from 2012 to 2013. He was a Visiting Researcher with the Centro Ricerche Fiat (CRF), Italy. He was the Assistant Manager of engineering with Trojans Pakistan, from 2008 to 2011. He is currently an Assistant Professor in robotics and mechanical engineering with Khalifa University, Abu Dhabi, United Arab Emirates. He is the author of one book, more than 70 articles, and three inventions. His research interests include marine robotics, healthcare robotics, and industrial robotics. He is also an Associate Editor of *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, a Research Topic Editor on ''Wearable Robots and Sensorimotor Interfaces: Augmentation, Rehabilitation, Assistance or Substitution of Human Sensorimotor Function'' (ID 21096), *Frontiers in Neurorobotics*, and a Guest Editor of Special Issue ''Design and Development of Vision-Based Tactile Sensors'' A Special Issue of Sensors (ISSN 1424-8220). He is also an Associate Editor of IEEE/RAS ICRA-23, ICRA-22, ICRA-21, and RAS/EMBS BioRob-18.