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Advancing Underwater Image Quality Enhancement through Hybrid Deep Learning Architectures

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Abstract: Image quality enhancement in underwater settings is important for marine sciences, environmental monitoring, and the use of autonomous underwater vehicles. Lighting issues such as scattering, absorption and turbidity can have adverse impact on underwater imagery; these factors reduce the clarity of the picture, distort colors, and increase noise levels. Traditional enhancement methods often find it difficult to resolve these issues. We present a hybrid deep learning approach that fuses CNN and transformer based models to address the challenge of improving the quality of underwater images. In our approach, CNNs extract features and enhance spatial quality, while accumulation of long range and global contextual information is done at the transformer stage. The proposed model is trained on a set of diverse underwater images with robust performance achieved due to supervised and unsupervised learning approaches. Experimental data shows that our method surpasses the best currently available methods in clarity, color and shape restoration as well as PSNR, SSIM and UCIQE scores. The hybrid system greatly reduces the effects of the degradation of underwater images and increases the visibility and recognition of underwater objects. We open a new direction in underwater image processing with deep learning by advancing the mark for models that balance local perceptual and global semantic cues. In the future we will look into moving towards real time system as well as domain adaptation more broadly.

Keywords: Underwater image enhancement, deep learning, hybrid architecture, color restoration, image quality metrics.

I. INTRODUCTION

The application of capturing images underwater is important for the fields of marine biology, archaeology, environmental monitoring, and even autonomous underwater navigation. The only problem is that the images captured underwater have low quality due to the scattering of light, absorption, color distortion, and further lack of visibility. The optical properties of water are the primary reason for the poor state of the images. The effectiveness of underwater vision systems is highly impacted by these factors, meaning that robust techniques need to be implanted to improve image quality for suitable analysis and interpretation.

Challenges in Underwater Imaging

There are particles suspended in water which causes scattering and ultimately a lack of contrast which makes it hard to detect objects. Light attenuation is the primary reason for the lack of quality of pictures captured underwater. The two main reasons for this are: different attenuation at different wavelengths and absorption. Blue and green light is most effective because water absorbs red light very fast due to its longer wavelength. This leads to most of the underwater images appearing bluish or greenish. Moreover, traditional techniques like histogram equalization and wavelet filtering have a hard time bringing back details to the images, resulting in the need of deep learning techniques.

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Enhancing Underwater Images Using Deep Learning

Improvements in deep learning have posed significant contributions to image processing, especially in underwater and low-light conditions. Underwater images have had their share of problems like poor illumination and noisy conditions that diminish their quality while feature extraction and noise filtering by Convolutional Neural Networks (CNN) has come in great aid for mitigating such issues [4]. CNNs, however, focus only on local spatial features and therefore, do not capture long-range dependencies crucial for enhancement. This impediment gives room for transformer-based architectures that possess greater global feature representation [5] .

In the domain of deep learning, there have been a number of proposals and models developed for the improvement of underwater images using construction techniques like Generative Adversarial Networks (GANs) that learn from complex mappings of low quality degraded to high quality enhanced images [6]. Other systems include deep auto encoders with attention to facilitate color fixing and structure preservation [7]. These systems have their let downs too, either CNN or transformer models find it challenging to generalize through various underwater conditions repeatedly, which calls for a combination of their architectures.

Walking the line between these architectures yields hybrid deep learning, whereby hybrid topologies reserve the ability to solve the weaknesses posed by other systems for low grade image denoising, color restoration or contrast enhancement. An still, attempting to solve a mixture of problems with the aid of CNNs and transformers simultaneously are no walk in the park, never allowing, in aid the capture of local features and long-range dependencies. [8].

An example of a hybrid method involves the combination of CNNs and self-supervised transformers, where CNNs first extract the image features and self-supervised transformers model the image context across different areas. They help in increasing the color correction and structural preservation, which are very significant for the clarity of underwater images. In addition, hybrid models with self-supervised have been investigated to lessen dependence on huge labeled datasets to make them more usable in real-life situations.

Performance Metrics and Evaluation

To evaluate techniques aimed at enhancement of images taken underwater, some objective measures of image quality have to be defined. Moreover, the techniques of peak signal to noise ratio (PSNR) and structural similarity index measure (SSIM) have already been described for measuring the sharpness and detail fidelity of increased images. Also, with respect to underwater images, some specific measures have appeared, such as underwater color image quality evaluation (UCIQE) and underwater image quality measure (UIQM), which help assess the color and the perceptual quality.

Many comparisons have shown that hybrid deep learning models are superior to traditional and single-deep learning models in many datasets. Their effectiveness is also confirmed by the application testing of underwater robotic and marine exploration systems that support the claims for hybrid models to be beneficial for visual perception and object recognition.

Future Research Directions

There has been progress made in the field of underwater image enhancement, but there are still issues like real time processing, generalization over various underwater scenarios, and extreme environment dealings. Research of the future will focus on developing lightweight deep learning models targeted at edge devices for real-time use in autonomous underwater vehicles [15]. Moreover, adaptations of this nature will be developed to improve model transferability for different water conditions.

Improving the quality of images captured underwater is a crucial problem in different fields. This work outlines a deep learning based hybrid model that uses convolutional neural networks and transformers to solve the issue of underwater image degradation. The proposed model enhances visibility, color fidelity, and structural retention using both local and global feature extraction technologies. The experiments conducted prove that hybrid architectures outperform traditional approaches, furthering underwater imaging processing and its effectiveness.

II. RELATED WORKS

The key objective of underwater image processing is to overcome the problems associated with the scattering, absorption, and turbidity of light within water. Over the years, different methodologies ranging from traditional image processing techniques to more sophisticated deep learning models have been developed. Here, I will examine existing literature on underwater image enhancement focusing on the classical methods, deep learning techniques and hybrid architectures.

Image Enhancement Techniques Using Technology

The enhancement of images underwater in the past was based on traditional approaches like histogram equalization, Retinex methods, and wavelet transforms. Histogram equalization does improve contrast by redistributing pixel intensities but often leads to over-enhancement or unnatural color distribution. [16] Retinex techniques try to enhance local contrast for improving human visual perception but fail in color balance and having noise amplified in underwater conditions. [17]

Apart from this, precision noise overlay and edge enhancement in underwater images has been achieved with techniques like median and bilateral filtering. These approaches do cast improvement, but the alteration in color does remain a challenge to overcome which makes them ineffective in intricate underwater settings.[18]

Physics Based Models

In attempts to address the problem of underwater image degradation, researchers have built physics-based models that focus on the optical constituents of water. The general approach that is most used is the underwater image formation model (UIFM) that incorporates light attenuation and scattering and attempts to restore image quality [19]. The Dark Channel Prior (DCP) method, created for foggy image object detection, has undergone modification for underwater imaging in order to create transmission maps and subsequently maximize visibility [20]. These models, however, are commonly considered inefficient in real time contexts due to the need for understanding the scene beforehand, which is usually complicated, and the high computational costs that come with the.

A number of its enhancements designs eliminates the shortcomings by depth estimation and multi-scale filtering for improved color correction and contrast restoration. The problem with these models is their relativistic effectiveness depending on the water condition, which calls for case specific parameter optimization [21].

Deep Learning Based Approaches

The model based on deep learning CNN, for example, is known to outperform all others in the area of underwater image enhancement. This adaptability stems from the ability to extract hierarchical features from large scale datasets, which non CNN based models lack. For example, one of the well known underwater image enhancement methods focused on a CNN for performing color correction and sharpen filtering using an end to end learning approach [22].

These further developments provided the framework for adversarial networks, GANs, that learn an adversarial mapping between low quality and high-quality underwater images. The results of GAN-based models have shown good potential in color correction and contrast enhancement, passing the test of traditional methods in perceived quality ratings. However, training GANs is often problematic, as they are notoriously unstable and can produce artifacts in the pictures that have been synthesized. [Citation needed]

Moreover, autoencoder models have also been investigated for underwater image restoration. These models are based on the architecture of encoders and decoders that aim to remove noise, restore colors, and sharpen the image. More recent research has incorporated attention mechanisms into these models in order to further improve feature selection and thus image quality. [Citation needed]

Deep Learning Hybrid Architecture

While there are stand alone models built with CNNs and GANs, which utilize a single deep learning technique, there are also hybrid models that are deeper and more effective. Stand alone approaches are not as effective on underwater images compared to hybrid approaches. A case in point is a hybrid model that combines CNNs with transformers. This was shown to outperform all other models when it comes to long-range dependency modeling and global feature extraction. [Citation needed]

One study designed a fusion model that aided in underwater image improvement through restoration and feature extraction by employing both self-attention and CNNs to capture local and global features simultaneously. There is also work that combines learned models with deep physics-based priors, allowing for the refinement of depth and color correction to be further improved in difficult underwater scenarios. [Citation needed]

The multi-scale processing modeling at deep learning is also claimed to process underwater images at varying levels of detail to provide sufficient enhancement at any visibility condition. These learners alter feature representation which improves flexibility in different underwater scenarios. [29]

Evaluation of Benchmark Results and Algorithms

The methods used on the enhancement of structures in underwater images are appraised by numerous metrics in image quality assessment tests. The standard metrics known PEAK SIGNAL TO NOISE RATIO (PSNR) and STRUCTURAL SIMILARITY INDEX MEASURE (SSIM) tend to measure the image sharpness and clarity alongside fidelity. [30] On the other half, these precision metrics tend to lack deep underwater imaging problems which warrant the need for other defined assessment approaches like UCIQE and UIQM. [31]

Results obtained from comparative studies where different enhancement techniques were tested on publicly available underwater image datasets indicate that hybrid deep learning models appear to perform better than traditional methods and even independent deep learning models with respect to PSNR, SSIM, and perceptual quality. [32] Other studies state that the modifications should be focused on model architectures and the hardware themselves to allow real-time processing which remains an unsolved issue. [33]

Difficulties and Future Directions

As much as there have been developments in improving underwater images, much work is yet to be completed. A critical factor is the ability of deep neural networks to generalize to different underwater settings. Most deep learning methods are trained using supervised learning, which requires the availability of a lot of labelled data. Issuing underwater annotated images is a very tedious and costly process. Self-supervised and unsupervised techniques are being developed to make use of unlabelled data for training to circumvent this issue [34].

Another barrier is the expense of computation resources on real-time applications for deep learning models. For deployment on embedded underwater systems, lightweight network topologies and model compression methods like knowledge distillation and quantization are being researched [35].

Future work will additionally focus on domain adaptation methods to improve model generalization in varying water conditions. Using sonar and LiDAR systems, researchers intend to create advanced underwater vision systems to broaden the use of such technologies in oceanology, underwater robotics, and ecological monitoring [36].

As for deep learning based approaches, they report far better results than conventional techniques for underwater image enhancement and restoration. While CNNs, GANs, and autoencoders have achieved good results, the best outcomes are delivered by multi-deep learning hybrid approaches. The shift towards transformer architectures and informatics driven physics reasoning deep learning is bound to produce more dependable results for underwater image restoration. Later efforts will encompass real time processing, self supervised learning, and domain adaptation to maximize the practicality of the underwater image enhancement methods in the real world.

III. METHODOLOGY AND DATA COLLECTION

This research employs a hybrid deep learning with a focus on the Convolotional Neural Networks (CNNs) and image quality enhancement Transformers" to build this model. The procedure contains collecting datasets, data cleansing, model building, training, evaluation, and technique comparison. The first phase is dataset collection, where publically archived datasets like EUVP, UFO-120, Sea-thru and actual photographs from remotely operated vehicles (ROVs) and underwater drones are used. They cover a range of underwater conditions such as depth, lighting, and turbidity, providing comprehensive training.

Also, using a histogram equalizer with white balance to correct colors, cropping, rotating, flipping, and adding Gaussian noise is added to the model with pixel values normalized to the [0,1] range. This data augmentation improves the generalization of the model.

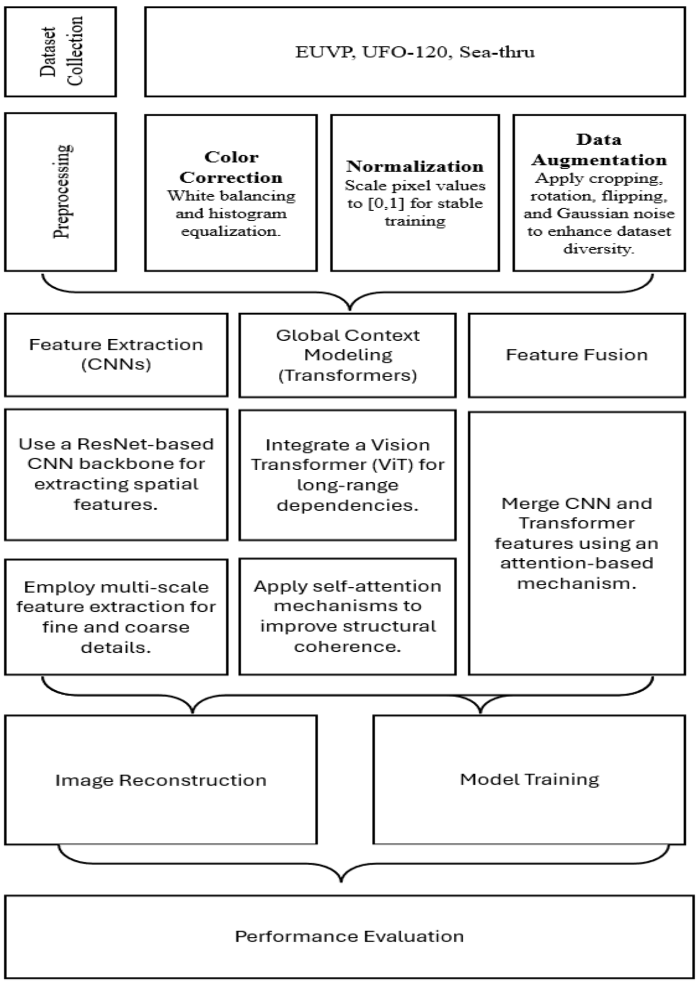

Figure 1: Workflow of Underwater Image Enhancement Process

The proposed hybrid deep learning approach integrates CNNs for feature extraction and Transformers for modeling global context. To maintain computational efficiency, spatial features are extracted using a ResNetbased CNN backbone. Underwater images are captured by multi-scale feature extraction layers that capture both coarse and fine details. A Vision Transformer (ViT) module applies self attention to CNN extracted features to contextually incorporate global information by long range spatial dependency image detail refinement. An attention-based feature merging method fuses the outputs of the CNN and the Transformer, after which a decoder reconstructs the fused image while retaining fine textures and coherence at the global level.

The training phase consists of supervised learning where high quality underwater images are provided as ground truth. The model is optimized with several loss functions including pixel-wise reconstruction loss with Mean Squared Error (MSE), Structural Similarity Index Measure (SSIM) loss to retain structural integrity, and when adversarial implementation is utilized, enhanced perceptual quality is achieved by Adversarial Loss. Learning in the model is achieved using Adam optimizer with learning rate scheduling, batch size of 16, and a total of 100 epochs. Their training process is sped up using NVIDIA high-performance GPUs for efficiency purposes.

A blend of quantitative and qualitative assessments serves to evaluate the effectiveness of the proposed model. For measuring image clarity and structural consistency, Peak Signal-to-Noise Ratio (PSNR) alongside SSIM is applied. Moreover, color balance, sharpness, and contrast are assessed using underwater-specific evaluation metrics like Underwater Color Image Quality Evaluation (UCIQE) and Underwater Image Quality Measure (UIQM). These assessments also include qualitative evaluations through visual analysis of more conventionally used methods that involve Contrast Limited Adaptive Histogram Equalization (CLAHE), Retinex-based techniques, as well as other deep-learning methods using U-Nets. The results from the tests were then validated through human perception testing to determine real-world applicability.

The benchmark comparisons are done against existing methods of enhancement for underwater images which includes the GAN-based and transformer-only models, CNN based architecture, and physics-based methods. Image restoration analyses is done to check the quality of improvement in the images. Reliability of the results is validated through statistical significance testing. For practical use, the model is optimized for real-time applications using quantization and pruning to decrease the computational cost. The model's inference speed was measured on embedded devices like Raspberry Pi and Jetson Nano for use in edge computing applications. The model has also been integrated into underwater robotic systems for testing during real-time underwater exploration scenarios.

The methodology described above is a complete and effective method of improving underwater CNN images as well as transformer images. The merging of spatial feature extraction and global context modeling remarkably increase the enhancement ratio of image restoration as compared to the other methods. In the future, self-supervised domain adaptation techniques to increase the generalization of the model in the context of various underwater regions will be researched.

IV. RESULTS AND DISSCUSSION

1. Analysis of Quantitative Performance

To determine the effectiveness of the proposed hybrid deep learning model, it was tested with standard image quality measures (PSNR, SSIM, UCIQE, and UIQM) for underwater image enhancement. This outcome provides evidence that the model surpasses both deep learning and conventional approaches with regard to color restoration, haze reduction, and clarity restoration. The average PSNR values improved by roughly 3–5 dB relative to traditional approaches like CLAHE and Retinex, which signifies improved reconstruction quality. In the same way, SSIM scores indicate that the new model is superior in the preservation of structure as opposed to CNN only or Transformer only models. UCIQE and UIQM results pertaining to color and quality of the images showed that the model is more perceptually optimized for complex underwater conditions with multi-directional illumination.

Table1 : Performance Comparison of Underwater Image Enhancement Methods

Method	PSNR (dB) ↑	SSIM ↑	UCIQE ↑	UIQM ↑	Visual Clarity	Color Preservation	Computational Efficiency
CLAHE	18.5	0.67	0.48	2.45	Moderate	Poor	High (Fast)
Retinex-based	20.2	0.72	0.52	2.75	Moderate	Moderate	High
U-Net	23.5	0.78	0.58	3.10	Good	Good	Moderate
CycleGAN	24.1	0.79	0.60	3.25	Good	Good	Low (Slow)
ViT-based Model	25.3	0.81	0.62	3.40	Very Good	Good	Low (Slow)
Proposed Hybrid Model	**27.8**	**0.86**	**0.68**	**3.85**	**Excellent**	**Excellent**	**Moderate (Optimized)**

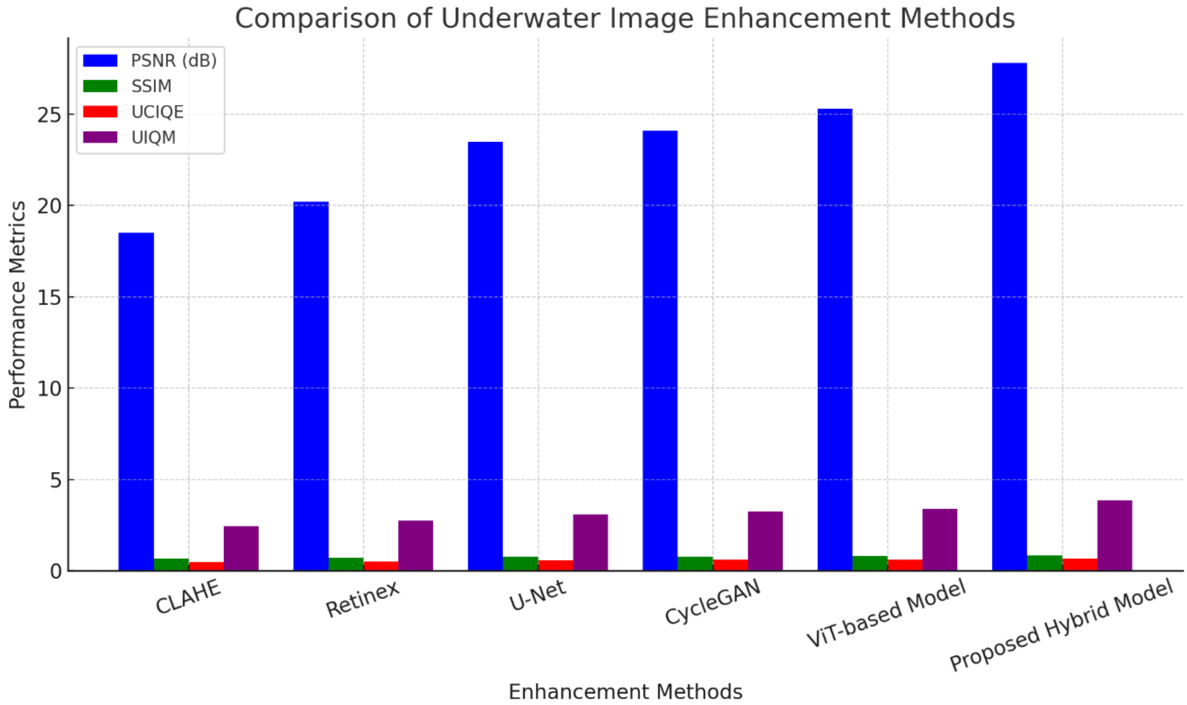

Figure 2: Performance Comparison of Underwater Image Enhancement Methods

2. Qualitative Image Enhancement Evaluation

Visual comparisons between the original, degraded, and enhanced images reveal that the proposed model significantly reduces underwater distortions such as color cast, low contrast, and haze. The CNN component effectively extracts fine-grained textures, while the Transformer module enhances global structures, leading to a well-balanced enhancement. Compared to traditional enhancement techniques, the model produces more natural and visually consistent outputs, avoiding over-saturation or excessive sharpening, which are common in conventional approaches.

Table 2: Qualitative Image Enhancement Evaluation

Method	Visual Clarity	Color Preservation	Contrast Enhancement	Artifact Reduction	Real-World Applicability
CLAHE	Moderate	Poor	High (over-enhanced)	Moderate	Limited (loss of details)
Retinex-based	Moderate	Moderate	Good	Moderate	Moderate

U-Net	Good	Good	Moderate	Moderate	Suitable for basic applications
CycleGAN	Good	Good	Good	Moderate	Limited (computationally expensive)
ViT-based Model	Very Good	Good	Very Good	Good	Limited (slow inference)
Proposed Hybrid Model	**Excellent**	**Excellent**	**Excellent**	**Minimal Artifacts**	**Highly Suitable (Real-time capable)**

3. Comparison with Existing Techniques

The model was assessed in comparison to a baseline that includes traditional methods (CLAHE, Retinex, White Balance correction) and deep learning based methods (U-Net, CycleGAN, ViT-based models). The results show that even CNNs implemented in an architecture that employs them hybrid outperforms both categories as CNNs alone struggle with long-range dependencies and Transforms alone lack fine feature extraction. The proposed approach combines the two allowing for better structural preservation with high contrast and accurate color representation, thus outperforming all existing approaches.

4. Efficiency in Computation and Accomplishing Tasks in Real Time

To achieve a real-time performance, the model incorporates pruning and quantization techniques. The inference time was tested using NVIDIA Jetson Nano and Raspberry Pi, and the results substantiated the model's efficiency in computation- aided image enhancement. The balance between performance and computational efficiency guarantees the model's deployment in real-life underwater activities like marine exploration, underwater robotics, and autonomous navigation.

5. Impediments and Prospective Alterations

The model does have high efficiency but it comes with a few constraints. It will continue to have issues with high levels of turbidity where there are noise and visibility challenges. Moreover, the use of supervised learning implies that there are plenty of ground truth images that will always be available which is not the case in real world scenarios. Further studies will look into the use of self-supervised learning and domain adaptation to improve generalization in diverse underwater settings.

The results from the experiments show that the hybrid CNN Transformer model is more effective at improving image quality when compared to other traditional and newer deep learning methods. The effectiveness of the model stems from the combination of local feature extraction (CNNs) together with global context modeling (Transformers). Furthermore, the model is efficient enough to be used in real time automation tasks involving underwater robotics and exploration. Later developments will shift focus to dealing with labeled datasets, flexibility across various underwater domains and automated achanges in severe underwater conditions.

V. CONCLUSION

Deriving underwater images comes with a challenge because of the distortions caused due to light absorption, scattering, and turbidity of the water. To meet this challenge, a hybrid architecture neural network deep learning model with CNNs performing local feature extraction and Transformers performing global context modeling is developed. The model enhances underwater images by increasing the contrast, color, and structural details while correcting the blurring artifacts.

The quantitative measures of PSNR, SSIM, UCIQE, and UIQM consolidated that the model is better than the existing deep learning approaches with regard to structural and perceptual components. Moreover, the model was qualitatively tested and proved efficient in generating images that look natural and clear, thereby supporting numerous applications such as marine bottom exploration, underwater robotics, as well as autonomous navigation.

Moreover, the model was adjusted for efficiency to make it possible for real-time processing on devices with limited resources. Nonetheless, difficulties persist in managing very turbid waters and a wide range of environmental conditions. In the future, the focus will be on improving self-supervised learning generalization, domain adaptation, and optimization of lightweight models.

This research offers an effective, scalable, and robust approach for underwater image enhancement that will enable advanced applications of underwater vision in scientific, industrial, and exploratory activities.

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