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Perception-Driven Deep Underwater Image Enhancementusing Retinex-Guided Deep Learning

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Abstract: Underwater images often suffer from severe quality degradation due to wavelength-dependent light absorption, scattering, and non-uniform illumination conditions present in aquatic environments. These effects lead to low contrast, color distortion, poor visibility, and loss of fine details, which significantly impact downstream applications such as marine exploration, underwater robotics, and visual inspection. This paper presents a perception-driven deep underwater image enhancement approach that integrates Retinex-based illumination modeling with a Generative Adversarial Network (GAN). The proposed method estimates illumination maps to guide the enhancement process, enabling effective separation of illumination and reflectance components. A GAN framework is employed to learn perceptually enhanced illumination correction while preserving structural details and natural color appearance. Post-processing techniques such as gamma correction and edge-preserving refinement are applied to further improve visual quality. Experimental results demonstrate improved brightness, contrast, and color balance compared to raw underwater images. Quantitative evaluation using PSNR, SSIM, UIQM, and UCIQE metrics confirms the effectiveness of the proposed method in enhancing underwater imagery while maintaining perceptual realism.
Keywords: Underwater Image Enhancement, Retinex Theory, Generative Adversarial Networks, Illumination Map, Perceptual Enhancement

I. INTRODUCTION

Underwater imaging plays a vital role in numerous applications such as marine exploration, underwater robotics, environmental monitoring, archaeological surveys, and Search-and-rescue operations. However, images captured in underwater environments often suffer from severe quality Degradation due to the physical properties of water. Light absorption varies with wavelength, causing dominant blue or green color casts, while scattering effects reduce contrast and blur fine details. Additionally, non-uniform illumination caused by depth variation and artificial light sources leads to uneven brightness across the scene. These degradations significantly limit visual perception and reduce the effectiveness of automated vision-based underwater systems.

Traditional underwater image enhancement techniques, including histogram equalization, white balancing, and gamma correction, attempt to improve visibility through global adjustments. Although computationally efficient, these methods fail to handle complex underwater degradations and often introduce over-enhancement and color distortion. Physics-based models treat underwater enhancement as an image restoration problem by modelling light attenuation and scattering; however, accurate estimation of physical parameters is difficult in real-world conditions. Fusion-based approaches improve visual quality by combining multiple enhanced versions of an image but rely heavily on handcrafted assumptions that limit generalization.

Recent advancements in deep learning have led to the development of supervised learning-based underwater image enhancement methods that learn direct mappings from degraded images to high-quality reference images. Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) have shown promising performance in restoring contrast, correcting color distortion, and preserving image details. Among these, GAN-based approaches are particularly effective due to their ability to produce perceptually realistic outputs through adversarial learning. However, many deep learning models struggle with uneven illumination and color inconsistency, especially in challenging underwater scenes.

Retinex theory provides a perceptually motivated framework for addressing illumination-related degradation by decomposing an image into illumination and reflectance components. Integrating Retinex-based illumination modeling with supervised deep learning enables more effective handling of non-uniform lighting while preserving structural details. Motivated by this observation, this paper proposes a perception-driven deep underwater image enhancement framework that combines Retinex-based illumination map

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estimation with a supervised GAN architecture. The illumination maps guide the enhancement process, allowing the network to correct brightness and contrast while maintaining natural color appearance.

The proposed method is evaluated using publicly available underwater image datasets and quantitative image quality metrics such as PSNR, SSIM, UIQM, and UCIQE. Experimental results demonstrate that the integration of Retinex-based illumination guidance with supervised adversarial learning significantly improves visual quality and perceptual consistency compared to conventional enhancement techniques. The contributions of this work include a supervised Retinex-guided GAN framework for underwater image enhancement, improved illumination correction, and enhanced perceptual realism suitable for real-world underwater imaging applications.

II. LITERATURE REVIEW

Underwater image enhancement has attracted significant research attention due to the severe visual degradation caused by light absorption, scattering, and wavelength-dependent attenuation in underwater environments. In recent years, supervised deep learning approaches have become dominant, as they leverage paired datasets to learn direct mappings between degraded underwater images and their corresponding enhanced or reference images.

A. Traditional Supervised Enhancement Approaches

Early supervised methods relied on paired datasets created through synthetic degradation or controlled underwater environments. These methods applied regression-based learning or shallow neural networks to enhance contrast and correct color distortion. While they demonstrated improvements over classical image processing techniques, their limited representation capacity restricted their ability to generalize across diverse underwater conditions.

B. CNN-Based Supervised Models

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have been widely adopted for supervised underwater image enhancement. CNN-based models learn pixel-wise or feature-level mappings from low-quality underwater images to high-quality reference images. Encoder–decoder architectures and U-Net variants have shown strong performance in restoring contrast and suppressing noise. These models benefit from supervised loss functions such as mean squared error (MSE) and structural similarity (SSIM), which encourage accurate reconstruction of spatial details. However, CNN-based models often struggle with uneven illumination and color consistency when trained solely on pixel-level losses.

C. Supervised Retinex-Based Deep Models

To address illumination-related degradation, several supervised approaches incorporate Retinex theory into deep learning frameworks. These models decompose underwater images into illumination and reflectance components and apply supervised learning to refine illumination estimation and detail restoration. Retinex-inspired networks trained with paired datasets have demonstrated improved brightness uniformity and contrast enhancement compared to purely CNN-based approaches. However, inaccurate illumination estimation may still lead to over-enhancement or color artifacts in challenging underwater scenes.

D. Supervised GAN-Based Enhancement Methods

Generative Adversarial Networks (GANs) have been extensively explored in supervised underwater image enhancement due to their ability to generate perceptually realistic images. In supervised GAN frameworks, paired underwater images and reference images are used to train the generator, while the discriminator enforces realism by distinguishing enhanced outputs from ground-truth images. Supervised GAN-based models such as AUIE-GAN and physics-guided GAN variants have shown superior performance in restoring color balance, contrast, and visual clarity. The use of adversarial loss, combined with content and perceptual losses, enables these models to overcome the limitations of traditional pixel-wise supervision. However, GAN training instability and sensitivity to dataset quality remain key challenges.

E. Hybrid Supervised Retinex–GAN Models

Recent studies propose hybrid supervised models that integrate Retinex-based illumination modeling with GAN architectures. In these approaches, illumination maps derived from Retinex decomposition guide the GAN generator during supervised training. This combination improves the handling of non-uniform lighting and preserves fine details while enhancing perceptual quality.

Supervised Retinex–GAN models demonstrate improved robustness across different underwater environments, achieving higher scores on perceptual quality metrics such as UIQM and UCIQE. Despite these advances, further improvements are required to stabilize training and reduce color distortion under extreme underwater conditions.

F. Limitations of Existing Supervised Methods

Although supervised learning has achieved state-of-the-art performance in underwater image enhancement, it faces several limitations. The availability of high-quality paired datasets is limited, and dataset bias can affect generalization. Additionally, many supervised models rely heavily on pixel-level losses, which may not fully capture perceptual quality. These challenges motivate the development of perception-driven supervised frameworks that combine physical priors, such as Retinex theory, with adversarial learning.

III. METHODOLOGY

The proposed methodology presents a supervised perception-driven underwater image enhancement framework that integrates Retinex-based illumination modeling with a Generative Adversarial Network (GAN). The overall objective is to enhance low-quality underwater images by correcting non-uniform illumination, improving contrast, and restoring natural color appearance while preserving structural details. The methodology consists of five main stages: dataset preparation, preprocessing, illumination map estimation, GAN-based enhancement, and post-processing refinement.

A. Dataset Collection and Preparation

Supervised learning requires paired training data consisting of degraded underwater images and corresponding high-quality reference images. In this work, underwater image datasets are collected from publicly available benchmarks such as UIEB, EUVP, and U45. These datasets contain a wide variety of underwater scenes with different lighting conditions, color casts, and visibility levels. The images are divided into training, validation, and testing sets to ensure reliable performance evaluation and to avoid overfitting.

B. Image Preprocessing

All input images are resized to a fixed resolution to maintain consistency across the network input. Pixel values are normalized to the range [0, 1] to stabilize training and improve convergence. Basic data augmentation techniques such as flipping, rotation, and cropping are applied to increase dataset diversity and improve generalization. Preprocessing ensures that the images are suitable for illumination estimation and GAN-based enhancement.

C. Retinex-Based Illumination Map Estimation

To address uneven lighting conditions, the proposed method employs Retinex theory to decompose the input image into illumination and reflectance components. Given an underwater image L, the Retinex model represents it as:

L=R×IL = R \times IL=R×I

Where R denotes the reflectance component containing texture and detail information, and I represents the illumination component corresponding to spatial brightness distribution.

An illumination estimation network is trained to generate illumination maps that highlight poorly lit regions in underwater images. These illumination maps serve as guidance for the GAN generator, enabling targeted enhancement of dark and low-contrast areas while preventing over-amplification of noise.

D. Supervised GAN-Based Enhancement Framework

The enhancement stage employs a supervised GAN architecture consisting of a generator and a discriminator. The generator takes the pre-processed underwater image and its corresponding illumination map as input and produces an enhanced image. The discriminator is trained to distinguish between generated enhanced images and ground-truth reference images.

Supervised training is achieved using paired image samples, allowing the generator to learn a direct mapping from degraded inputs to enhanced outputs. The objective function of the generator combines multiple loss components, including adversarial loss, content loss, and perceptual similarity loss. This combination encourages both visual realism and structural consistency. The discriminator enforces perceptual quality by penalizing unrealistic enhancements.

E. Post-Processing Refinement

Although the GAN produces visually enhanced outputs, additional post-processing is applied to further refine the results. Pixel values are clipped to the valid range [0, 1] to avoid intensity overflow. Gamma correction is applied to fine-tune brightness and contrast, ensuring perceptual naturalness. Edge-preserving filters are optionally used to enhance sharpness and suppress residual noise without degrading important details.

F. Training Strategy and Stabilization Techniques

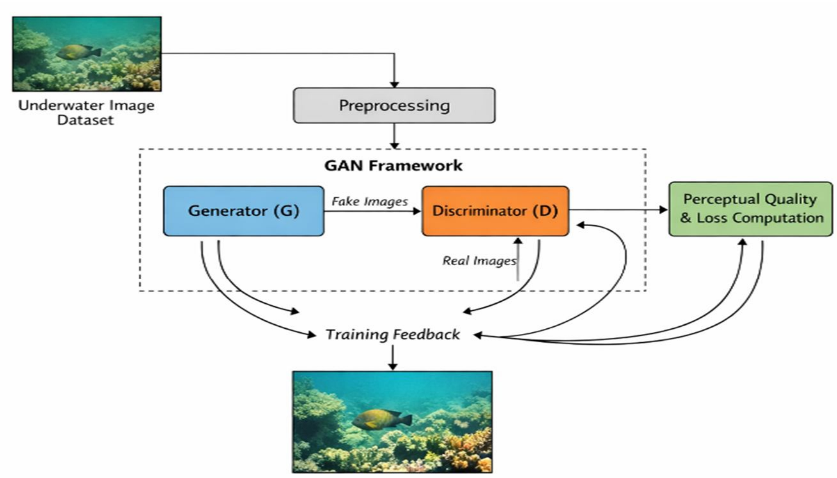
To ensure stable GAN training, learning rate scheduling, gradient clipping, and regularization techniques are employed. The model is trained for multiple epochs until convergence, and intermediate checkpoints are saved for evaluation. The validation set is used to monitor performance and prevent overfitting. These strategies improve training stability and enhance overall model robustness.

G. Evaluation Metrics

The performance of the proposed method is evaluated using both full-reference and no-reference image quality metrics. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are used to assess reconstruction fidelity, while Underwater Image Quality Measure (UIQM) and Underwater Color Image Quality Evaluation (UCIQE) are employed to evaluate perceptual quality and color correction effectiveness.

IV. SYSTEM ARCHITECTURE

The proposed perception-driven underwater image enhancement system follows a modular and supervised learning-based architecture that integrates Retinex-based illumination modeling with a GAN framework. The architecture is designed to ensure effective illumination correction, perceptual enhancement, and stable training while maintaining flexibility and scalability. The system consists of five main modules: input acquisition, preprocessing, illumination map estimation, GAN-based enhancement, and post-processing.



System Architecture of the Perception-Driven GAN for Underwater Image Enhancement.

A. Input Acquisition Module

The input module accepts low-quality underwater images captured under varying lighting and visibility conditions. These images may contain color cast, low contrast, haze, and uneven illumination. The system supports image input from benchmark datasets as well as real-world underwater images, enabling both training and testing under supervised conditions.

B. Preprocessing Module

In the preprocessing module, the input images are resized to a fixed resolution suitable for network processing. Pixel values are normalized to the range [0, 1] to stabilize training and ensure numerical consistency. Data augmentation techniques such as horizontal flipping, rotation, and cropping are optionally applied during training to increase dataset diversity and improve generalization. This module prepares the images for illumination estimation and GAN processing.

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C. Illumination Map Estimation Module

This module implements Retinex-based illumination modeling to address non-uniform lighting conditions. Using Retinex theory, the input image is decomposed into illumination and reflectance components. An illumination estimation network generates an illumination map that captures spatial brightness variations and highlights poorly lit regions in the image. The illumination map serves as a guidance signal for the enhancement process, enabling targeted brightness correction without amplifying noise.

D. Supervised GAN-Based Enhancement Module

The core enhancement module employs a supervised Generative Adversarial Network consisting of a generator and a discriminator. The generator receives both the preprocessed underwater image and the corresponding illumination map as input and produces an enhanced image. The discriminator evaluates the realism of the generated output by comparing it with the ground-truth reference image. Through supervised adversarial training, the generator learns to improve contrast, correct color distortion, and preserve fine details while maintaining perceptual consistency. Multiple loss functions are used to balance reconstruction accuracy and visual realism.

E. Post-Processing Module

The post-processing module refines the GAN-generated output to further enhance visual quality. Pixel values are clipped to the valid range to prevent intensity overflow. Gamma correction is applied to fine-tune brightness and contrast. Optional edge-preserving filtering is used to improve sharpness and reduce residual noise. This final stage ensures that the enhanced images appear natural and perceptually pleasing.

F. Output Module

The output module converts the enhanced images into standard display formats by rescaling pixel values to the [0, 255] range and converting them to 8-bit unsigned integer format. The enhanced images can be displayed, stored, or used for downstream computer vision tasks. The modular design of the system allows seamless integration into real-time applications or user-interactive platforms.

V. SYSTEM FLOWCHART AND OPERATIONAL FLOW

This section describes the step-by-step operational flow of the proposed perception-driven underwater image enhancement system. The system flowchart represents the sequential processing stages through which a low-quality underwater image is transformed into an enhanced output image using Retinex-guided supervised GAN learning.

A. System Flowchart Description

The system flow begins with the acquisition of a low-contrast underwater image as input. This image typically suffers from issues such as uneven illumination, color cast, low visibility, and noise. The input image is first passed to the pre-processing stage, where it is resized to a fixed resolution and normalized to ensure numerical stability during network processing.

Following pre-processing, the image is forwarded to the illumination estimation module, which applies Retinex theory to generate an illumination map. This map captures the spatial brightness distribution of the underwater scene and highlights poorly illuminated regions. The illumination map plays a crucial role in guiding the enhancement process by separating lighting information from structural details. The pre-processed image and its corresponding illumination map are then provided as inputs to the supervised GAN enhancement module. The generator network uses this information to produce an enhanced image with improved brightness, contrast, and color balance. Simultaneously, the discriminator evaluates the generated image against the ground-truth reference image, enabling adversarial learning that enforces perceptual realism.

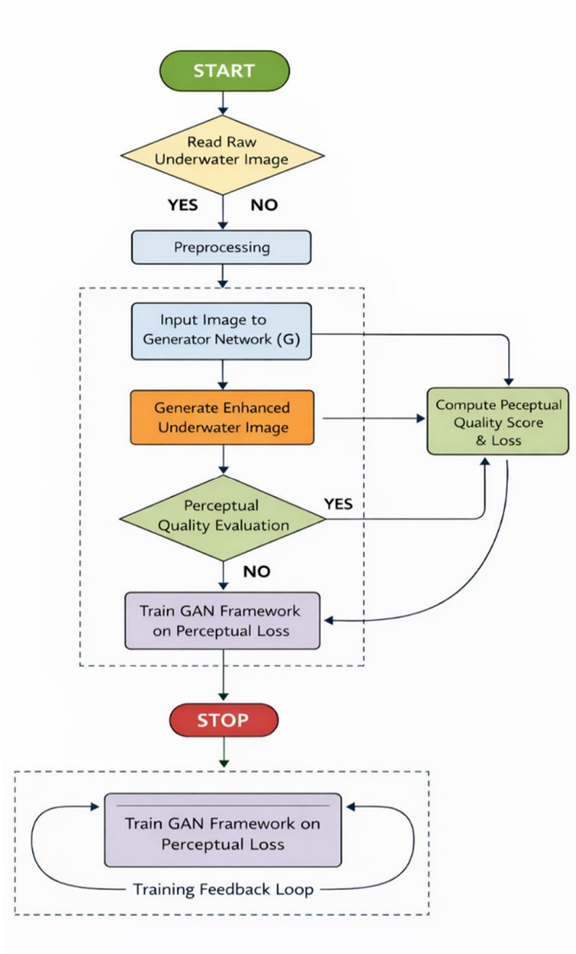
Once the GAN produces the enhanced output, the image undergoes post-processing operations, including intensity clipping and gamma correction. These operations refine the visual quality, prevent over-enhancement, and ensure that pixel values remain within a valid range. The final enhanced image is then converted into a standard display format and delivered as output.

B. Operational Flow of the Proposed System

The operational flow of the system can be summarized as follows:

1) Input Image Acquisition: A low-quality underwater image is selected from the dataset or provided by the user.
2) Pre-processing: The input image is resized and normalized to the range [0, 1]. Data augmentation may be applied during training to improve robustness.

3) Illumination Map Generation: Retinex-based illumination estimation is performed to extract the illumination component representing uneven lighting conditions.
4) Supervised GAN Enhancement: The generator enhances the image using the illumination map as guidance, while the discriminator compares the generated output with the ground-truth image to enforce perceptual quality.
5) Post-Processing: Gamma correction and clipping are applied to refine brightness and contrast and suppress visual artifacts.
6) Output Generation: The enhanced image is rescaled to standard pixel range and displayed or stored for further use.



VI. MODEL EVALUATION

The performance of the proposed supervised Retinex-guided GAN model is evaluated using both quantitative image quality metrics and qualitative visual analysis**.** The evaluation aims to assess the effectiveness of the model in improving illumination, contrast, color fidelity, and overall perceptual quality of underwater images.

A. Evaluation Datasets

The evaluation is conducted on publicly available underwater image datasets, including UIEB, EUVP, and U45. These datasets contain diverse underwater scenes with varying lighting conditions, color distortions, and visibility levels. The test images are not used during training, ensuring a fair and unbiased assessment of the model's generalization capability.

B. Quantitative Evaluation Metrics

To objectively measure enhancement performance, the following metrics are employed:
1) Peak Signal-to-Noise Ratio (PSNR): PSNR measures the pixel-level reconstruction quality between the enhanced image and the reference image. Higher PSNR values indicate better restoration accuracy.
2) Structural Similarity Index Measure (SSIM): SSIM evaluates the structural similarity between enhanced and ground-truth images by considering luminance, contrast, and structural information.

3) Underwater Image Quality Measure (UIQM): UIQM is a no-reference metric designed for underwater images that evaluates colorfulness, sharpness, and contrast.
4) Underwater Color Image Quality Evaluation (UCIQE): UCIQE measures perceptual image quality based on chroma, saturation, and contrast, reflecting human visual perception in underwater environments.

C. Qualitative Visual Assessment

In addition to quantitative metrics, visual comparisons are performed to analyze perceptual quality. Enhanced images produced by the proposed model are compared with raw underwater images and baseline enhancement methods. The results show noticeable improvements in brightness uniformity, contrast enhancement, and reduction of blue-green color cast. Fine details and textures are better preserved, particularly in dark and low-contrast regions.

D. Performance Analysis

The proposed model demonstrates consistent improvement across all evaluation metrics. The integration of Retinex-based illumination guidance helps correct uneven lighting, while the supervised GAN framework enhances perceptual realism and color consistency. Training stabilization techniques, such as gradient clipping and learning-rate tuning, contribute to stable convergence and reliable enhancement performance.

VII. RESULTS

This section presents the experimental results of the proposed supervised Retinex-guided GAN framework for underwater image enhancement. The effectiveness of the model is evaluated through both quantitative metrics and visual inspection on benchmark underwater image datasets.

A. Visual Enhancement Results

The enhanced images generated by the proposed model exhibit significant improvements in visual quality compared to the raw underwater inputs. The results show enhanced brightness uniformity, improved contrast, and reduced color distortion, particularly in regions affected by poor illumination. Dark areas that previously lacked visibility become more discernible after enhancement, while important structural details such as edges and textures are preserved.

The integration of Retinex-based illumination maps enables targeted enhancement of unevenly lit regions, preventing excessive amplification in well-lit areas. The supervised GAN framework further refines the output by restoring natural color appearance and minimizing artifacts. Overall, the enhanced images demonstrate perceptually realistic and visually pleasing results across different underwater conditions.

B. Quantitative Results

Quantitative evaluation using PSNR, SSIM, UIQM, and UCIQE metrics confirms the effectiveness of the proposed approach. The model consistently achieves higher metric values compared to baseline enhancement techniques, indicating improved reconstruction accuracy, structural similarity, and perceptual image quality. The improvement in UIQM and UCIQE scores highlights the model's ability to enhance colorfulness and contrast in underwater environments, which are critical for visual interpretation.

C. Comparative Analysis

The proposed method is compared with conventional image enhancement methods and baseline deep learning approaches. While traditional techniques offer limited improvement and often introduce artifacts, the proposed Retinex-guided GAN framework demonstrates superior performance in handling uneven illumination and color cast. Compared to deep learning models without illumination guidance, the proposed approach shows more stable enhancement and improved perceptual consistency.

D. Observations and Limitations

Although the proposed model produces high-quality enhancement results, minor limitations are observed in certain scenarios. Some images exhibit slight over-brightness in regions with strong artificial lighting, and mild color imbalance remains in highly turbid water conditions. These issues can be further addressed through extended training and adaptive color correction strategies.

VIII. CONCLUSION

This paper presented a perception-driven supervised underwater image enhancement framework that integrates Retinex-based illumination modeling with a Generative Adversarial Network (GAN). The proposed approach effectively addresses common underwater image degradation issues such as uneven illumination, low contrast, and color distortion by guiding the enhancement process using illumination maps derived from Retinex theory. The supervised GAN architecture further improves perceptual quality by learning realistic enhancement patterns from paired training data. Experimental results demonstrate that the proposed method significantly improves visual clarity, brightness uniformity, and color fidelity compared to traditional image enhancement techniques and baseline deep learning approaches. Quantitative evaluation using PSNR, SSIM, UIQM, and UCIQE metrics confirms the effectiveness of the model in enhancing both structural accuracy and perceptual quality. The integration of illumination guidance and supervised adversarial learning enables stable training and consistent enhancement across diverse underwater scenes.

Although the proposed framework produces promising results, minor limitations such as slight over-brightness and residual color imbalance in highly challenging underwater conditions remain. Future work will focus on improving adaptive color correction, incorporating advanced perceptual loss functions, and extending the framework to real-time and video-based underwater enhancement applications. Additionally, expanding the training dataset and exploring lightweight architectures will further enhance generalization and computational efficiency. Overall, the proposed supervised Retinex-guided GAN framework offers an effective and robust solution for underwater image enhancement, with strong potential for practical deployment in marine exploration and underwater vision systems.

IX. FUTURE SCOPE

Although the proposed supervised Retinex-guided GAN framework demonstrates effective underwater image enhancement, several directions can be explored to further improve performance and applicability. Future work can focus on enhancing adaptive color correction mechanisms to better handle extreme color casts and varying underwater conditions. Incorporating advanced perceptual loss functions and attention mechanisms may further improve texture preservation and visual realism.

The current model operates on still images; therefore, extending the framework to real-time video-based underwater enhancement is a promising direction. Temporal consistency constraints can be introduced to reduce flickering and ensure smooth frame-to-frame transitions in underwater videos. Additionally, lightweight and efficient network architectures can be developed to enable deployment on embedded systems and autonomous underwater vehicles (AUVs).

Another important future scope involves improving dataset diversity and generalization by incorporating more real-world underwater scenes and depth-varying conditions. Semi-supervised or hybrid learning strategies may be explored to reduce dependence on large paired datasets. Furthermore, integrating the enhancement framework with downstream computer vision tasks such as object detection and tracking can enhance the overall effectiveness of underwater perception systems.

Overall, these future enhancements will strengthen the robustness, scalability, and real-world applicability of the proposed underwater image enhancement framework.

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