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An Attention-Driven Multi-Scale Ensemble Framework for Underwater Image Enhancement

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Abstract

Underwater image enhancement plays a critical role in improving image quality for applications such as marine exploration, underwater robotics, environmental monitoring, surveillance, and computer vision. However, underwater images often suffer from severe degradation caused by light absorption, scattering, low contrast, color distortion, and reduced visibility. To address these challenges, this study proposes an advanced underwater image enhancement framework that combines hybrid preprocessing techniques with deep learning-based enhancement strategies. Initially, Underwater White Balance (UWB) and Variational Contrast and Saturation Enhancement (VCSE) are applied to restore color balance and improve image contrast. The enhanced images are further processed using ensemble attention-driven convolutional networks, multi-scale feature fusion, and adaptive contrast-saturation optimization. Experimental evaluation using standard image quality metrics demonstrates significant improvement in color restoration, structural detail preservation, visibility, and overall enhancement performance across diverse underwater environments.

Keywords: Underwater Image Enhancement; Deep Learning; Ensemble Attention Networks; Multi-Scale Feature Fusion; Underwater White Balance; Adaptive Contrast–Saturation Optimization.

How to Cite This Article

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Introduction

Underwater imaging has emerged as an important area of research due to its growing applications in marine exploration, environmental monitoring, underwater robotics, archaeology, surveillance, aquaculture, and scientific observation. Capturing and analyzing underwater images enables researchers and industries to investigate underwater environments without direct human intervention [1]. However, obtaining high-quality underwater images remains a major challenge because underwater environments significantly affect the behavior and propagation of light [2].

Unlike terrestrial imaging, underwater imaging is influenced by physical phenomena such as light absorption and scattering [3]. As light travels through water, different wavelengths are absorbed at different rates. Longer wavelengths, particularly red and orange, are absorbed rapidly, whereas shorter wavelengths such as blue and green penetrate deeper into the water. As a result, underwater images typically exhibit dominant bluish or greenish color tones with severe color distortion. In addition, suspended particles such as sand, plankton, and other impurities scatter incoming light, causing reduced visibility, image blur, haze effects, and loss of fine details.

These degradations significantly affect the visual quality of underwater images and limit their usefulness for computer vision and image analysis applications [4]. Tasks such as object detection, image segmentation, underwater navigation, marine species recognition, and scene interpretation rely heavily on accurate visual information. Poor image quality reduces feature extraction capability and decreases the reliability of automated underwater systems. Therefore, underwater image enhancement has become an essential preprocessing step to improve image clarity and restore meaningful visual information.

Traditional underwater image enhancement techniques primarily focus on methods such as histogram equalization, contrast stretching, image filtering, color correction, and dehazing algorithms [5]. Although these approaches improve specific image characteristics, they often fail to address multiple degradation factors simultaneously and may produce over-enhanced outputs or loss of structural information. Recent developments in deep learning have introduced more effective enhancement methods capable of learning complex image representations directly from data.

Among deep learning approaches, convolutional neural network-based architectures such as UResNet have demonstrated promising results in underwater image enhancement due to their strong feature extraction and image reconstruction capabilities [6]. Residual learning and encoder–decoder structures enable these models to preserve image information while restoring degraded regions. However, existing approaches still face challenges related to limited adaptability across different underwater environments, insufficient preservation of fine textures, and dependency on single-model architectures.

To overcome these limitations, this study proposes an advanced underwater image enhancement framework that integrates hybrid preprocessing techniques with deep learning-based enhancement strategies. Initially, Underwater White Balance (UWB) and Variational Contrast and Saturation Enhancement (VCSE) are employed to correct color imbalance and improve image contrast. The enhanced images are further processed using ensemble attention-driven convolutional networks, multi-scale feature fusion, and adaptive contrast-saturation optimization. These components work together to improve feature extraction, preserve structural details, and generate visually realistic outputs.

The proposed framework aims to produce high-quality underwater images with improved visibility, color fidelity, contrast, and sharpness. By enhancing both visual appearance and image structure, the framework supports reliable performance in downstream applications including underwater inspection, marine research, autonomous underwater systems, and intelligent computer vision tasks.

Related Work

Using deep learning, frequency-domain processing, and attention-based architectures, a number of academics have made substantial contributions to the fields of multimodal picture fusion and low-light image enhancement.

Li Zhang et al. proposed an attention-based deep network for underwater image enhancement using an attention-guided convolutional neural network integrated with feature enhancement and color correction techniques [7]. Their framework focused on improving underwater image quality by selectively emphasizing important image regions through attention mechanisms while restoring color consistency and enhancing contrast. The proposed method effectively improved visibility and structural details in degraded underwater scenes. However, the approach required a large training dataset and involved high computational complexity, which limited its efficiency for real-time applications.

Chen Liu et al. introduced a multi-scale feature learning approach for underwater image enhancement using a multi-scale convolutional neural network architecture [8]. Their method extracted image information at different resolutions to simultaneously preserve fine textures and capture global contextual information. The framework demonstrated improved visibility, enhanced edge preservation, and better reconstruction of underwater details under low-light conditions. Although the method achieved superior enhancement performance, the multi-scale architecture increased computational requirements and resulted in longer training time.

Wang Yu et al. proposed a deep residual learning framework for robust underwater image enhancement based on residual convolutional neural networks with feature reconstruction capability [9]. The model focused on learning residual information to recover degraded underwater images while reducing noise and haze effects. The residual connections improved image reconstruction stability and preserved structural details during enhancement. Despite its effectiveness, the method showed limited adaptability when applied to underwater environments with highly varying lighting and water conditions.

Ahmed Khan et al. presented a transformer-based attention network for underwater image enhancement that employed vision transformer architecture combined with attention modules for global feature learning [10]. The proposed framework captured long-range dependencies across image regions and improved global color consistency, structural representation, and overall image quality. The attention mechanism enabled better restoration of underwater distortions and enhanced visual appearance. However, the model required high computational resources and memory consumption, making deployment more challenging.

Liquan Zhao et al. proposed a generative adversarial network with multi-scale and attention mechanisms for underwater image enhancement using adaptive feature fusion and attention-guided learning [11]. Their framework combined multi-scale dilated convolution and attention modules to restore underwater image quality while improving color correction and visual clarity. The proposed method demonstrated effective enhancement of structural details and reduction of underwater degradation effects. However, the model required extensive training and involved increased computational complexity for large-scale image processing.

Mohamed E. Fathy et al. introduced ViTClarityNet, a vision transformer-based convolutional network for underwater image enhancement that integrates transformer learning with CNN feature extraction [12]. Their framework captured both local image information and long-range dependencies to improve color restoration, contrast enhancement, and visibility under underwater conditions. The model achieved superior enhancement performance and preserved structural consistency across different underwater scenes. However, the transformer architecture increased memory consumption and computational requirements.

Yao Haiyang et al. proposed U-TransCNN, a U-shaped Transformer–CNN fusion model for underwater image enhancement that combines global contextual learning with detailed feature extraction [13]. Their framework introduced synchronized global-detail feature fusion and adaptive weighting mechanisms to improve image reconstruction and detail preservation. The model demonstrated strong performance in recovering textures and enhancing underwater image visibility. However, integrating transformer and CNN architectures increased model complexity and training cost.

Existing underwater image enhancement methods have demonstrated notable progress in improving image visibility, color restoration, and structural preservation. Attention-based deep networks improved enhancement performance by focusing on important image regions; however, they require large-scale training datasets and involve high computational complexity. Multi-scale feature learning approaches preserved textures and global information but increased training time due to complex architectures. Residual learning methods achieved stable image reconstruction and reduced haze effects but showed limited adaptability across diverse underwater environments. Transformer-based enhancement networks improved long-range feature representation and global consistency; however, their high memory requirements restrict practical implementation. Ensemble deep learning approaches enhanced robustness and accuracy but increased overall model complexity and computational cost.

Therefore, a research gap exists in developing a unified underwater image enhancement framework that simultaneously achieves effective color correction, structural preservation, multi-scale feature learning, adaptive enhancement capability, and computational efficiency under varying underwater conditions.

Objectives Of the Study

The primary objective of this study is to develop an advanced underwater image enhancement framework capable of improving underwater image quality by overcoming limitations observed in existing enhancement approaches.

The specific objectives of this study are:

- To reduce underwater image degradation caused by light absorption, scattering, color distortion, and low visibility.
- To apply Underwater White Balance (UWB) and Variational Contrast and Saturation Enhancement (VCSE) for effective preprocessing and color restoration.
- To integrate ensemble attention-based convolutional networks for robust feature extraction and improved enhancement accuracy.
- To implement multi-scale feature fusion for preserving both local textures and global structural information.
- To employ adaptive contrast–saturation optimization for dynamically enhancing image quality based on image characteristics.
- To evaluate the effectiveness of the proposed framework using standard underwater image quality metrics and demonstrate improved visibility, contrast, and structural preservation across diverse underwater environments.

System Analysis

Existing System

Traditional underwater image enhancement techniques mainly rely on methods such as histogram equalization, wavelet transform, image filtering, Retinex-based enhancement, dehazing algorithms, and conventional color correction techniques. These approaches improve certain visual characteristics of underwater images but generally operate using predefined enhancement rules and fixed parameter settings. Although computationally efficient, these methods are unable to adapt to varying underwater environments and often produce inconsistent enhancement results.

Recently, deep learning-based underwater image enhancement methods have gained significant attention due to their capability to automatically learn image features from large datasets. Convolutional Neural Network (CNN)-based methods improve local feature extraction, texture preservation, and color restoration compared to traditional enhancement approaches. However, CNN architectures primarily focus on local receptive fields and frequently struggle to capture long-range dependencies and global contextual relationships.

Transformer-based underwater enhancement approaches have been introduced to overcome these limitations through self-attention mechanisms and global feature modeling. Although these approaches improve image consistency and structural preservation, they require high computational resources, increased memory consumption, and longer training durations.

Additionally, existing methods generally depend on single-stage enhancement frameworks and lack adaptive mechanisms capable of balancing color restoration, contrast improvement, texture preservation, and structural consistency simultaneously. Consequently, the enhanced images may still contain residual haze, color distortion, blurred boundaries, and loss of fine details.

Limitations of Existing System

- Dependence on fixed enhancement and preprocessing operations.
- Limited capability to preserve both local textures and global structures simultaneously.
- CNN-based methods have weak long-range contextual understanding.
- Transformer approaches require high computational and memory resources.
- Reduced enhancement performance under highly degraded underwater conditions.
- Difficulty in achieving adaptive contrast and saturation optimization.
- Increased processing complexity and training time.

Proposed System

The proposed underwater image enhancement framework aims to overcome the limitations of existing enhancement approaches by integrating adaptive preprocessing, ensemble deep learning, multi-scale feature extraction, and intelligent optimization mechanisms.

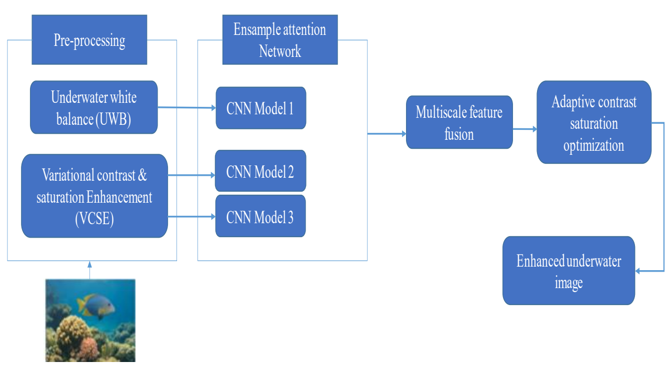

Fig. 1. *Block Diagram of Proposed System*

The proposed framework consists of the following stages:

1. Input Image Acquisition
2. Underwater Image Preprocessing
3. Ensemble Attention Networks
4. Multi-Scale Feature Fusion
5. Adaptive Contrast–Saturation Optimization
6. Enhanced Image Reconstruction
7. Performance Evaluation

The framework processes underwater images to generate visually enhanced outputs with improved color restoration, contrast enhancement, visibility improvement, and structural preservation.

1. Input Image Preprocessing:
The enhancement process begins by collecting degraded underwater images containing distortions caused by water absorption and scattering effects.
The acquired image is represented as:

$$I = \text{Input Underwater Image}$$

This stage serves as the initial input for all subsequent enhancement operations

2. Underwater Image Preprocessing:
The preprocessing stage prepares underwater images for advanced enhancement.
This stage consists of:

- Underwater White Balance (UWB)
- Variational Contrast and Saturation Enhancement (VCSE)

Underwater White Balance restores RGB color balance and reduces blue-green dominance.
VCSE improves image visibility by increasing contrast and saturation while maintaining visual realism.
The preprocessing process is represented as:

$$P = \mathrm{VCSE}(\mathrm{UWB}(I))$$

where:
P = Preprocessed image
I = Original underwater image

3. Ensemble Attention Framework:
The preprocessed image is processed using multiple convolutional networks operating in parallel.
The framework includes:

- AttentionUNet
- ResUNet
- DenseUNet

Attention mechanisms automatically focus on important image regions while preserving textures and structural details.
Feature extraction can be represented as:

$$F = E(P)$$

where:
F = Extracted features
E = Ensemble attention model

4. Multi-Scale Feature Fusion:
This stage extracts image information at different resolutions.
Laplacian decomposition separates:

- Low-frequency structural information
- High-frequency texture information

Feature fusion combines detailed textures and global structural information.
Fusion operation:

$$F_{final} = \mathrm{Fusion}(F_{low}, F_{high})$$

Where:
F_{low} → Structural features
F_{high} → Texture features

5. Adaptive Contrast–Saturation Optimization:
This stage dynamically adjusts enhancement parameters according to image statistics.
Enhancement operations include:

- Gamma Correction
- CLAHE Contrast Enhancement
- Saturation Adjustment
- Image Sharpening

Optimization is represented as:

$$O = Optimize(F\_final)$$

Where:
O → Optimized enhanced image

6. Adaptive Contrast–Saturation Optimization:
The optimized features are reconstructed to generate the final enhanced underwater image.
This stage restores:

- Natural colors
- Improved contrast
- Better visibility
- Enhanced structural details

Output image:

$$I\_out = R(O)$$

Where R represents the Reconstruction function.

7. Performance Evaluation

The final enhanced image is evaluated using underwater image quality metrics.

Performance Metrics:

- UIQM (Underwater Image Quality Measure)
- UCIQE (Underwater Color Image Quality Evaluation)

Higher values indicate improved enhancement performance.

Estimated Comparative Analysis

Table 1. *Estimated Comparative Analysis*

Feature	Traditional Methods	CNN-Based Methods	Transformer Methods	Proposed Framework
Color Restoration	Moderate	Good	Excellent	Excellent
Contrast Enhancement	Medium	Good	Excellent	Excellent
Texture Preservation	Medium	Good	Excellent	Excellent
Global Context Learning	Poor	Limited	Excellent	Excellent
Computational Cost	Low	Medium	Very High	Medium
Adaptive Enhancement	No	Partial	Yes	Yes
Visibility Improvement	Moderate	Good	Very Good	Excellent
Structural Preservation	Moderate	Good	Very Good	Excellent

The comparison demonstrates that the proposed framework achieves superior enhancement performance while maintaining balanced computational efficiency.

Advantages of Proposed System

The proposed underwater image enhancement framework offers several advantages over traditional image enhancement approaches by integrating adaptive preprocessing, ensemble deep learning, multi-scale feature extraction, and intelligent optimization techniques. The framework is designed to effectively address underwater image degradation while preserving visual realism and structural information.

1. Adaptive Preprocessing for Effective Color Restoration: The proposed framework employs Underwater White Balance (UWB) and Variational Contrast and Saturation Enhancement (VCSE) to perform adaptive preprocessing. This stage effectively compensates for wavelength-dependent light absorption and reduces the dominant blue-green color distortion commonly observed in underwater images. As a result, the enhanced output achieves improved color consistency and more natural visual appearance.
2. Improved Feature Extraction through Ensemble Attention Networks: Unlike conventional single-model enhancement methods, the proposed system utilizes multiple deep learning architectures including AttentionUNet, ResUNet, and DenseUNet operating in parallel. The ensemble attention mechanism enables the framework to focus on important image regions and extract complementary features. This improves enhancement accuracy while preserving critical image information.

3. Enhanced Texture and Structural Preservation: The integration of Multi-Scale Feature Fusion enables the framework to simultaneously process low-frequency structural information and high-frequency texture details. This approach ensures effective edge preservation, improved texture reconstruction, and better maintenance of image boundaries during enhancement.
4. Intelligent Adaptive Contrast–Saturation Optimization: The framework dynamically adjusts enhancement parameters based on image characteristics rather than using fixed enhancement values. Techniques such as Gamma Correction, CLAHE, saturation adjustment, and sharpening improve visibility and contrast while preventing excessive enhancement and preserving image realism.
5. Improved Image Visibility and Reduced Underwater Degradation: The proposed system effectively minimizes underwater degradation effects including haze, scattering, low contrast, and poor illumination. This leads to clearer image representation and improved visibility even under challenging underwater conditions.

Results And Discussion

Input Image

The input image represents the original underwater image before enhancement. Underwater images commonly suffer from degradation due to light absorption and scattering effects. Since longer wavelengths such as red are absorbed more rapidly than shorter wavelengths like blue and green, underwater images typically exhibit color distortion with dominant blue-green tones. As shown in Fig. 2, the input image contains low contrast, reduced visibility, haze effects, and loss of fine structural details. These distortions decrease image clarity and make object recognition difficult. The degraded image serves as the initial input for the proposed enhancement framework.

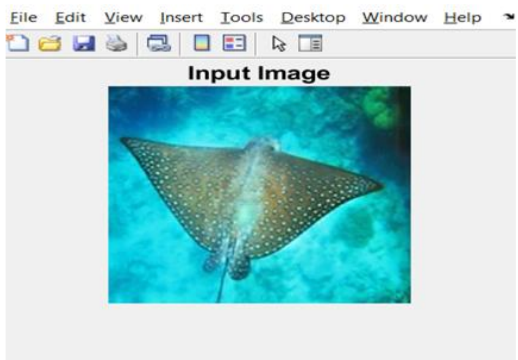

Fig. 2. *Input Image*

Preprocessing

The preprocessing stage corrects major underwater distortions before deep feature extraction. This stage includes Underwater White Balance (UWB) and Variational Contrast and Saturation Enhancement (VCSE). As illustrated in Fig. 3, UWB compensates for wavelength-dependent light absorption and restores balanced color distribution across RGB channels. VCSE further enhances local contrast, brightness, and color intensity while maintaining image realism. The preprocessing output produces a visually balanced image with improved color consistency and enhanced visibility for subsequent enhancement stages.

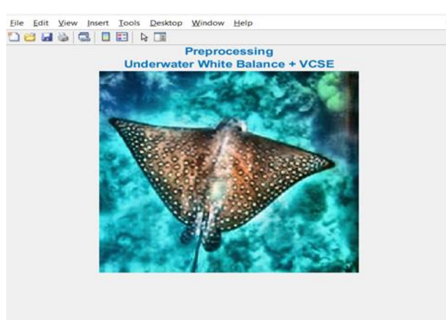

Fig. 3. *Preprocessing*

Ensemble Attention Networks

The Ensemble Attention Networks stage performs feature extraction using multiple convolutional models operating in parallel, including AttentionUNet, ResUNet, and DenseUNet. As shown in Fig. 4, AttentionUNet identifies important image regions, ResUNet preserves structural details using residual learning, and DenseUNet improves feature reuse and representation. The extracted features are fused through attention-based weighting to improve edge preservation, texture recovery, and overall image enhancement while reducing visual artifacts.

Fig. 4. *Ensemble Attention Networks*

Multi-Scale Feature Fusion

Figure 5 presents the Multi-Scale Feature Fusion stage, where image features are extracted and combined at different spatial resolutions. Laplacian pyramid decomposition separates structural and texture information into multiple scales. Lower scales preserve edges and textures, while higher scales maintain global image structure. Edge-guided fusion integrates these features to improve detail reconstruction and preserve structural consistency.

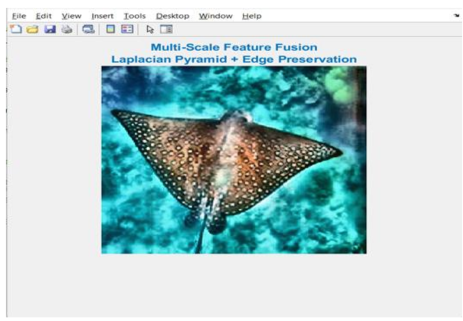

Fig. 5. *Multi-Scale Feature Fusion*

Adaptive Contrast–Saturation Optimization

As illustrated in Fig. 6, this stage dynamically adjusts enhancement parameters based on image statistics such as brightness, contrast, and color distribution. Enhancement operations including Gamma Correction, CLAHE, saturation adjustment, and sharpening are applied adaptively to improve image appearance. This process enhances contrast and visibility while preserving natural visual quality and preventing over-enhancement.

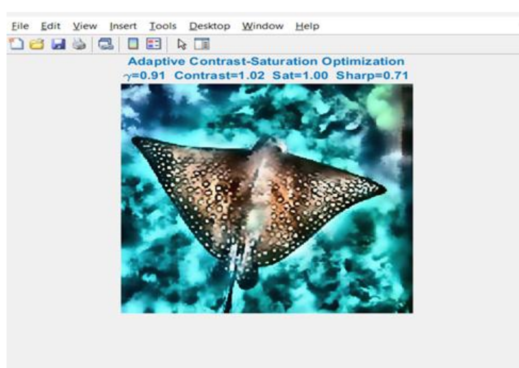

Fig. 6. *Adaptive Contrast–Saturation Optimization*

Output Image

Figure 7 presents the final enhanced underwater image generated by the proposed framework. The output includes both the enhanced image and the difference map, which highlights enhancement regions by calculating absolute pixel differences from the original image. Compared to the input image, the final result demonstrates improved color restoration, reduced haze, better visibility, and clearer structural details, confirming the effectiveness of the proposed enhancement framework.

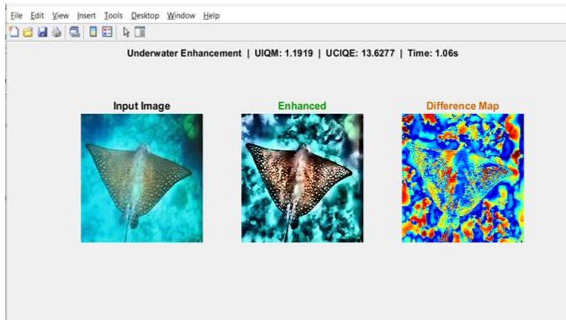

Fig. 7. *Output Image*

Evaluation Metrics

Figure 8 presents the quantitative evaluation results used to validate enhancement performance. Two underwater image quality assessment metrics are employed:

- UIQM (Underwater Image Quality Measure): Measures image quality based on colorfulness, sharpness, and contrast.
- UCIQE (Underwater Color Image Quality Evaluation): Measures underwater image quality using chroma variation, saturation, and contrast.

Higher metric values after enhancement indicate better visual quality and stronger restoration capability. The observed improvement in both evaluation metrics confirms that the proposed framework successfully enhances underwater image quality.

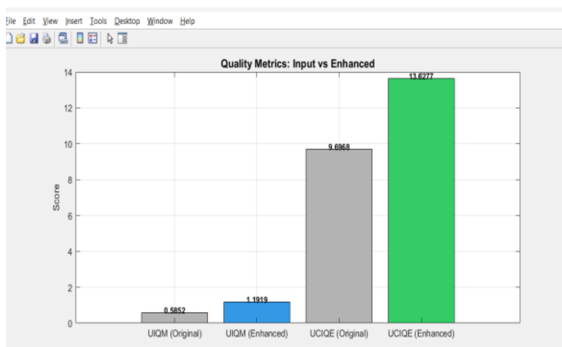

Fig. 8. *Evaluation metrics*

Conclusion

This study presented an advanced underwater image enhancement framework designed to improve the visual quality of degraded underwater images. The proposed approach combined Underwater White Balance (UWB), Variational Contrast and Saturation Enhancement (VCSE), Ensemble Attention Networks, Multi-Scale Feature Fusion, and Adaptive Contrast–Saturation Optimization to address major underwater imaging challenges including color distortion, low contrast, haze, and reduced visibility. The preprocessing stage restored color consistency and improved image appearance, while deep feature extraction and multi-scale fusion preserved structural and texture information. Adaptive optimization further enhanced brightness, contrast, and image clarity based on image characteristics. Experimental evaluation using underwater image quality metrics demonstrated noticeable improvements in enhancement performance. The proposed framework successfully generated visually realistic underwater images and can support applications such as marine exploration, underwater robotics, environmental monitoring, and intelligent vision systems.

Future Work

Although the proposed underwater image enhancement framework achieved significant improvements in color restoration, contrast enhancement, visibility, and structural preservation, there are several opportunities for further development and optimization. Future work may focus on improving the framework's capability to adapt to highly dynamic underwater environments with varying depth, lighting conditions, and water turbidity. More efficient lightweight architectures can be explored to reduce computational complexity and enable real-time deployment on embedded and underwater robotic systems. Advanced attention mechanisms and transformer-based feature learning may be integrated to improve global contextual understanding and enhancement accuracy. In addition, future studies can incorporate self-supervised and unsupervised learning approaches to reduce dependency on large annotated datasets. The framework may also be extended for video-based underwater enhancement to maintain temporal consistency across frames. Further evaluation using larger benchmark datasets and downstream vision tasks can improve robustness and practical applicability.

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