

MASTER OF SCIENCE IN COMPUTER SCIENCE AND ENGINEERING

**Underwater Image Enhancement Based on Adaptive Color Balance and
Contrast Optimization with Minimum Information Loss**

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August, 2025

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The thesis titled, *Underwater Image Enhancement Based on Adaptive Color Balance and Contrast Optimization with Minimum Information Loss* submitted by Tamanna Tajrin with student ID 191041012 of Academic Year 2023–24 has been found as satisfactory and accepted as partial fulfillment of the requirement for the degree Master of Science in Computer Science and Engineering on August 14, 2025.

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This is to certify that the work presented in this thesis is the outcome of the analysis and experiments carried out by Tamanna Tajrin under the supervision of Dr. Md. Hasanul Kabir, Professor, Department of Computer Science and Engineering, Islamic University of Technology (IUT), Dhaka, Bangladesh. It is also declared that neither this thesis nor any part of it has been submitted anywhere else for any degree or diploma. Information derived from the published and unpublished work of others have been acknowledged in the text and a list of references is given.

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Dedicated to my beloved parents for their unwavering support, my supervisor for his invaluable guidance, and all who encouraged me along the way.

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List of Abbreviations

PCQI	Patch-based Contrast Quality Index
UCIQE	Underwater Color Image Quality Evaluation
IE	Image Entropy
UIQM	Underwater Image Quality Measure
AUV	Autonomous Underwater Vehicle
CNN	Convolutional Neural Network
GAN	Generative Adversarial Network
UIEB	Underwater Image Enhancement Benchmark
HFM	Hybrid Fusion Method
PCDE	Piecewise Color Correction and Dual Prior Optimized Contrast Enhancement
NSST	Non-Subsampled Shearlet Transform
AQSCH	Adaptive Quadruple Segmentation and Cropping of Underwater Image
CLAHE	Contrast-Limited Adaptive Histogram Equalization
CDUIE	Challenging Dataset for Underwater Image Enhancement
RUIFM	Revised Underwater Images Formation Model
CCF	Colorfulness, Contrast, and Fog Density
MAP	Maximum A Posteriori
PSNR	Peak-Signal-to-Noise Ratio
SSIM	Structural Similarity Index Measure
UIEB	Underwater Image Enhancement Benchmark
MOS	Mean Opinion Scores
CBLA	Color-Balanced Locally Adjustable
CACR	Color Adaptive Correction and Restoration
IACR	Illumination-Aware Contrast Restoration
UICM	Underwater Image Colorfulness Measure
UIConM	Underwater Image Contrast Measure
HVS	Human Visual System
UIEVUS	Underwater Image Enhancement Method for Various Underwater Scenes
UIEDP	Underwater Image Enhancement with Diffusion Prior
FPS	Frame-Per-Second

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Abstract

Underwater imaging suffers from severe visual degradation as a result of wavelength-dependent light absorption and scattering, resulting in low contrast, color shifts, and loss of fine details. To overcome these challenges, this study presents a multi-modular underwater image enhancement framework. The first module, adaptive color correction, addresses color shift by compensating the RGB channels and adjusting each channel using condition-checked compensation values, effectively removing bluish, greenish, or yellowish casts. The second module, contrast optimization, enhances visibility by employing dark channel prior-based estimation along with a cost function that maximizes contrast while minimizing information loss. The third module focuses on fusion and visual improvement, where gamma correction adjusts luminance levels, unsharp masking improves edge sharpness, image fusion and histogram stretching redistributes pixel intensities across the full range to improve tonal balance and texture clarity. The system was evaluated on multiple underwater image datasets—OccanDark, UIEB, UIEDP, and EUVP—covering diverse degradation conditions. Performance was measured using both subjective visual assessment and objective metrics, including PCQI, UCIQE, IE, and UIQM. Results confirm that the proposed framework comparatively outperforms existing techniques in color fidelity, contrast enhancement, and detail preservation. By addressing color casts, low contrast, and poor brightness with detail representation, the framework delivers high-quality underwater images with minimal information loss, making it suitable for marine engineering, underwater exploration, and scientific research.

Chapter 1

Introduction

As land resources become increasingly scarce, the vast and largely unexplored ocean has drawn significant attention due to its immense potential for valuable oil, mineral and biological resources. Advancements in marine engineering, oceanographic research, and underwater exploration have required the development of high-quality underwater imaging systems. Underwater imagery is not merely a tool for visualization, but a crucial component in applications such as marine biodiversity studies, underwater archaeology, offshore infrastructure inspection, and autonomous underwater vehicle navigation. However, obtaining clear and high-fidelity underwater images remains a significant challenge due to the inherent complexities of the aquatic environment.

One of the primary issues affecting underwater imaging is the significant degradation in image quality caused by light absorption and scattering. As light propagates through water, it undergoes selective absorption, where longer wavelengths (red) are absorbed more rapidly than shorter wavelengths (green and blue). This differential absorption leads to a characteristic blue-green tint in underwater photographs. Furthermore, suspended particles and marine microorganisms scatter light unpredictably, further distorting the captured images. This scattering effect contributes to common visual distortions, such as reduced contrast, color distortions, poor visibility, and a hazy appearance, severely limiting underwater images' usability in scientific and industrial applications. These limitations underscore the urgent need for innovative solutions in underwater imaging. Various underwater image enhancement techniques have been developed to address these challenges, improving image clarity, restoring natural colors, and improving perceptual quality. Broadly, these techniques can be categorized into physical model-based approaches, non-physical model-based

methods, and deep learning-based solutions. Physical model-based techniques attempt to mathematically model underwater light propagation using hand-crafted priors, allowing for the estimation and compensation of distortion parameters to restore a more precise image. In contrast, non-physical model-based methods directly manipulate image pixel values through contrast enhancement, histogram equalization, and filtering techniques to improve visual perception without explicitly modeling the underwater imaging process.

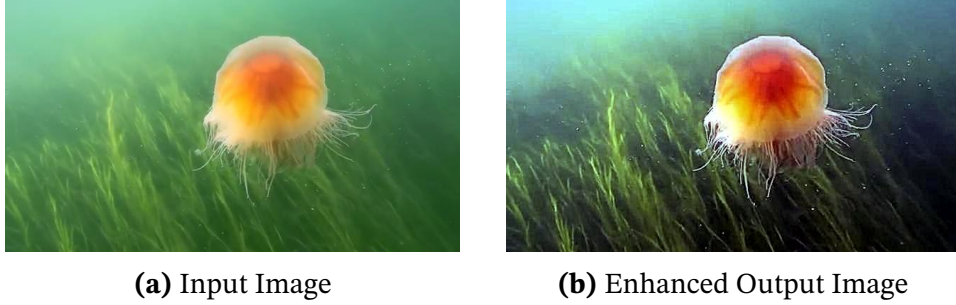


Figure 1: From degraded input image to enhanced output image

Deep learning-based approaches have recently gained significant attention due to their ability to learn complex image enhancement patterns from large datasets. CNNs and GANs have been widely applied to underwater image enhancement, achieving notable improvements in perceptual quality. However, the effectiveness of deep learning methods is often constrained by the limited availability of well annotated high-quality underwater training datasets. The diversity of underwater environments further complicates the generalizability of these models, as different water bodies (e.g., coastal, deep-sea, and turbid waters) present distinct optical characteristics.

As shown in Figure 1, an adaptive system is necessary to automatically transform degraded images into enhanced ones. In this study, we propose an adaptive approach to underwater image enhancement that integrates elements of non-physical model based techniques. This unique blend of traditional modeling and modern learning approach aims to achieve superior visual clarity while minimizing textural information loss, ultimately providing a more robust solution to underwater image degradation. The uniqueness of our approach lies in its adaptability and potential to advance the field of underwater imaging significantly. The proposed approach is evaluated using benchmark datasets and real-world underwater imagery to demonstrate its effectiveness in enhancing visual quality and preserving critical image details.

1.1 Research Challenges

Developing an effective underwater image enhancement system involves addressing several complex challenges stemming from the unique optical characteristics of the underwater environment. Light attenuation, scattering, and wavelength-dependent absorption lead to significant color distortions and reduced visibility. Additionally, underwater scenes vary greatly in turbidity, lighting, and particle concentration, making it challenging as in Figure 2 to design a method that works consistently across all conditions. Ensuring visual improvement without introducing artifacts, while also meeting real-time processing requirements, adds further complexity to the task.

Key challenges faced in this study include:

- Wavelength-dependent color absorption: Rapid loss of red and other longer wavelengths at depth results in severe color shift, making accurate color restoration difficult.
- White balance distortion: Maintaining consistent color tones across varying underwater scenes is challenging due to changes in ambient light and water properties.
- Low visibility: Water turbidity and limited light penetration reduce image clarity, particularly in deep or murky waters.
- Backscatter from suspended particles: Particles in the water scatter light, creating haze and reducing image contrast.
- Lack of reliable reference images: Evaluating enhancement quality is challenging when ground-truth images are unavailable.
- Difficulty in dataset collection: Obtaining high-quality, diverse underwater images for testing requires significant time and resources.
- Balance between enhancement and realism: Excessive color correction or sharpening can produce unnatural-looking results, while insufficient enhancement fails to improve visibility.
- Adaptive processing for real-time use: Achieving both adaptiveness to varying water conditions and computational efficiency for real-time applications remains a major challenge.

These challenges highlight the need for more adaptive, robust, and computationally efficient underwater image enhancement techniques. Overcoming them is essential

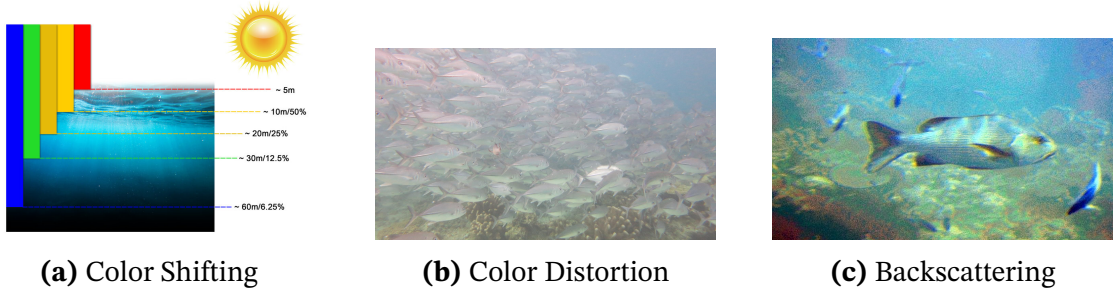


Figure 2: Major challenges for underwater imaging.

for producing visually natural, high-quality images suitable for practical applications such as underwater robotics, exploration, and environmental monitoring.

1.2 Problem statement

Underwater imaging presents significant challenges due to the complex interaction of light with water. Unlike terrestrial photography, where light travels through the air with minimal distortion, underwater images suffer from multiple forms of degradation. These issues arise due to the unique optical properties of water, including selective absorption, scattering, and refraction. Such distortions hinder the visibility, color accuracy, and overall quality of underwater photographs, making enhancement techniques essential for marine research, underwater navigation, and underwater robotics applications.

The target of underwater image enhancement is to develop effective and adaptive methods, incorporating color correction and contrast optimization that restore natural colors and improve visibility in underwater images, overcoming optical distortions and environmental challenges to enable accurate analysis and interpretation with minimum information loss.

1.3 Motivation and Objectives

Underwater imaging is crucial in various scientific, industrial, and military applications, including marine biology, archaeology, ocean exploration, and AUV navigation. However, the quality of underwater images is often severely degraded due to factors such as light absorption, scattering, and backscatter from suspended particles. These distortions lead to significant challenges in extracting meaningful information from underwater imagery. Several questions have motivated this research:

- How can a color correction method improve the visual quality of underwa-

ter images across different conditions? Underwater environments vary significantly based on depth, water turbidity, and light availability. Developing a robust color correction technique that dynamically adapts to these variations is essential for enhancing visual quality.

- What techniques can enhance image contrast while preserving textural details and reducing artifacts? Many existing contrast enhancement methods introduce artifacts, noise, or loss of fine details. This study introduced contrast enhancement techniques that maintain image integrity while improving visibility.
- How does the proposed method compare to state-of-the-art techniques using standard metrics and benchmark datasets? Evaluating the effectiveness of the proposed enhancement method against established techniques using standardized evaluation metrics and publicly available benchmark datasets ensures its validity and practical applicability.

The primary goal of this research is to develop an underwater image enhancement approach that improves visual quality while preserving essential details. The objectives of the study are as follows.

- To develop an adaptive method for color correction that dynamically adjusts to varying underwater conditions. The method should effectively compensate for color distortions caused by selective absorption and scattering, ensuring natural-looking colors across different underwater environments.
- To design a contrast enhancement and edge sharpening mechanism that improves image visibility, edge clarity, and overall contrast, while preserving fine textural details and avoiding excessive noise or artifacts.
- To optimize the computational pipeline for real-time processing, enabling practical deployment in underwater robotics, exploration, and environmental monitoring applications.
- To evaluate the performance of the proposed method using benchmark datasets and standard evaluation metrics, comparing it to state-of-the-art techniques. A rigorous evaluation to validate the effectiveness of the proposed approach in real-world scenarios and ensure its competitive performance relative to existing methods.

This research aims to enhance underwater images by addressing existing limitations and providing a more adaptive and effective solution for improving image quality in challenging underwater environments.

1.4 Contributions

This work presents an underwater image enhancement system with several key contributions. First, it introduces an adaptive color correction method that dynamically adjusts to varying underwater optical properties, effectively mitigating color distortions caused by light absorption and scattering while optimizing contrast to improve scene visibility and maintain a natural appearance. Second, the system integrates multiple advanced image processing techniques, including contrast enhancement for haze reduction, gamma correction for brightness balance, sharpening filters for clearer edges, and histogram stretching to expand dynamic range, resulting in enhanced images with balanced brightness, sharper edges, and richer contrast without losing fine details. Third, the approach has been rigorously evaluated on standard underwater benchmark datasets and compared with state-of-the-art methods using objective metrics such as PCQI, UCIQE, IE, and UIQM, demonstrating high-quality results with minimal information loss. Finally, the enhancement pipeline is designed to be computationally efficient, enabling real-time processing suitable for practical applications including underwater robotics, exploration, and environmental monitoring.

1.5 Thesis Book Structure

This book is organized into five chapters. chapter 1 introduces the research background, motivation, objectives, contribution, and scope. chapter 2 reviews existing underwater image enhancement techniques, identifying gaps the proposed system addresses. chapter 3 details the methodology, including color correction, contrast optimization, brightness adjustment, sharpening, and histogram stretching. chapter 4 presents experimental results, comparing the proposed system with existing methods using subjective and objective evaluations. Finally, chapter 5 summarizes key findings, acknowledges limitations, and provides future research directions.

Chapter 2

Related Works

In recent years, underwater image enhancement has witnessed an increasing need for improved visual clarity in underwater imagery. High-quality underwater images are essential for various applications, including marine life research, archaeology, ocean engineering, and AUV navigation. However, the quality of underwater images is often compromised due to factors such as light absorption, scattering, low contrast, and color distortions. These challenges necessitate the development of effective enhancement techniques to restore visual information and improve image interpretability. Underwater image enhancement techniques can be broadly divided into two main categories:

Non-physical model-based methods: These approaches enhance images by direct pixel-wise operations without explicitly modeling the underwater light propagation process. Techniques such as contrast stretching, histogram equalization, and other image processing operations fall into this category. They offer straightforward and computationally efficient solutions but may lack adaptability to varying underwater conditions.

Deep learning-based methods: These methods utilize neural networks trained on large datasets to learn complex enhancement mappings directly from data. Deep learning approaches can effectively model nonlinear relationships and adapt to diverse underwater scenarios, often achieving superior results compared to traditional methods. However, they require extensive labeled data and significant computational resources for training [1].

This chapter reviews the existing literature on underwater image enhancement, highlighting key methodologies, their strengths, and limitations. A critical analysis of these techniques provides the foundation for the research presented in this study, leading to the identification of gaps that the proposed approach aims to address.

2.1 Non-Physical Model-Based Methods

2.1.1 Fusion-Based Approaches

A hybrid fusion method (HFM) was proposed for underwater image enhancement, integrating color correction, contrast adjustment, and multi-scale fusion. The method in Figure 3 combines complementary information from multiple enhanced images to improve visibility and color consistency, demonstrating superior performance compared to traditional fusion and Retinex-based methods [1]. The approach contributes by effectively integrating hybrid fusion with adaptive preprocessing, but it has higher computational cost due to multiple image fusion stages.

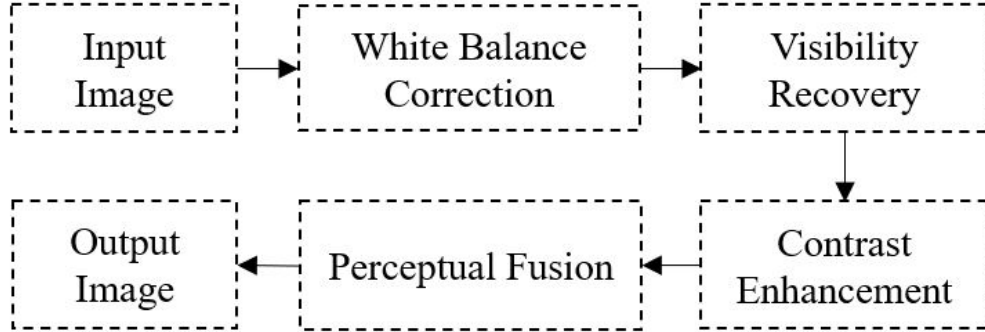


Figure 3: Framework of Hybrid Fusion Method [1].

A color balance and fusion framework enhanced underwater images by combining multiple pre-processed images into a single output [2]. Evaluated using UIQM and UCIQE, it produced natural-looking results, although it is computationally intensive and may introduce artifacts in high-detail regions.

Multi-scale fusion using a multi-layer perceptron was applied to underwater images to integrate complementary features. This approach showed improved visibility, but it is training-dependent and may overfit to specific datasets [3].

Multi-task fusion combined color correction, contrast enhancement, and structural refinement in a unified framework, achieving balanced enhancement [4]. However, model complexity and inference time are higher than single-task methods.

2.1.2 Retinex-Based Approaches

An adaptive color correction method combined with an improved Retinex algorithm to enhance underwater images [5]. The process in Figure 4 involves illumination estimation, color compensation, and contrast enhancement, effectively addressing color

cast and low contrast, though it may struggle in highly turbid water conditions.

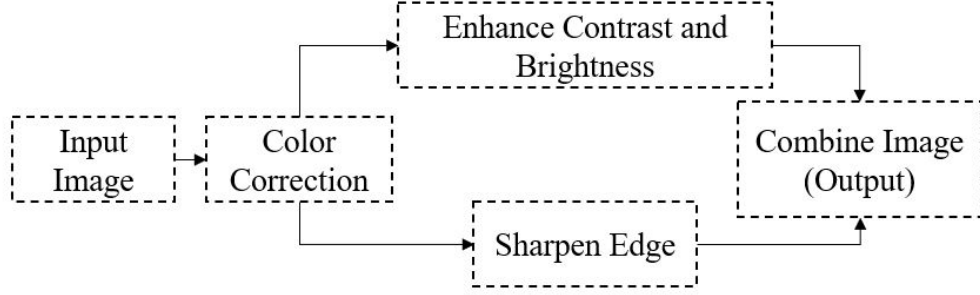


Figure 4: Framework of Improved Retinex Algorithm [5].

A Bayesian Retinex-based method was developed for underwater image enhancement, applying probabilistic modeling to Retinex decomposition for improved illumination correction and color restoration [6]. This approach provides more balanced color correction while reducing over-enhancement artifacts near edges.

A Retinex-based method with multiorder gradient priors was proposed to preserve high-frequency details while correcting illumination, effective in detail preservation but sensitive to noise under extremely low-light conditions [7].

Multi-scale Retinex-based adaptive grayscale transformation improved dynamic range and contrast, though computational cost is higher due to multi-scale processing [8]. Extended multi-scale Retinex was applied to enhance underwater images by combining illumination correction with multi-scale detail extraction, showing improved visibility and contrast, although halo artifacts near edges may appear.

An improved adaptive MSRCR method [9] combined with gamma correction was used to enhance underwater images, demonstrating enhanced brightness and color balance, but sensitive to parameter selection in diverse environments.

An edge-preserving filtering Retinex algorithm enhanced contrast while avoiding halo artifacts and retaining details, but is less effective for heavy color casts [10].

2.1.3 Color Correction and Contrast Enhancement Methods

An underwater image restoration and enhancement method based on a fusion algorithm with color balance, contrast optimization, and histogram stretching was proposed [11]. This method in Figure 5 integrates multiple enhancement steps to simultaneously correct color, optimize contrast, and stretch histograms, effectively improving overall visibility and color fidelity in diverse underwater scenes.

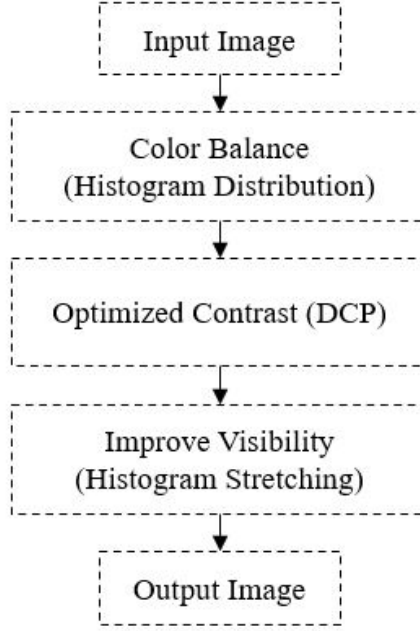


Figure 5: Framework of Fusion Algorithm [11].

Piecewise color correction combined with dual-prior optimized contrast enhancement was introduced, correcting color via channel-specific mapping and enhancing contrast using luminance and gradient priors [12]. Minor artifacts may appear in high-frequency regions.

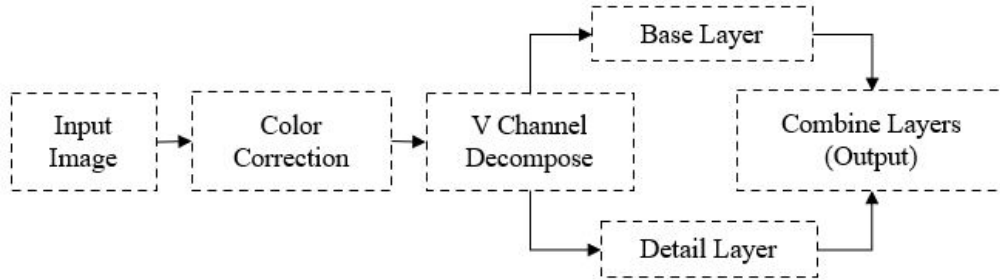


Figure 6: Framework of Piecewise Method [12].

An optimized histogram equalization approach (AQSCHE) [13] partitions images into segments and applies adaptive equalization while preventing over-enhancement, improving local contrast and naturalness, but with higher computational cost and potential color distortion.

The red channel prior combined with the haze-lines prior has been applied to underwater image restoration to address wavelength-dependent attenuation and scattering [14]. The red channel prior enhances recovery of attenuated red components, while

the haze-lines prior provides a statistical constraint for accurate transmission estimation. This integration improves color balance, visibility, and contrast across diverse underwater conditions. The approach is more physically grounded than simple enhancement techniques, though it may face limitations under extreme turbidity and increased computational demands.

A color-balanced locally adjustable enhancement (CBLA) method [15] performed local contrast and color adjustment with adaptive weighting, improving local color consistency but computationally expensive for high-resolution images.

A method for various underwater scenes (UIEVUS) [16] combined dynamic color correction, contrast enhancement, and detail recovery, achieving balanced enhancement across diverse environments, though it may introduce color artifacts in highly scattering water.

A variable contrast and saturation enhancement model adapted adjustments based on local image statistics, enhancing color fidelity and dynamic range, but less effective in low-light or extremely turbid water [17].

Local contrast correction combined with multi-scale fusion improved visibility in underwater images, but may produce unnatural colors in certain scenes [18].

An adaptive dynamic range adjustment method [19] optimized luminance distribution to enhance underwater image visibility, demonstrating improved contrast and brightness uniformity, Figure 7 though local detail may be reduced in highly textured areas.

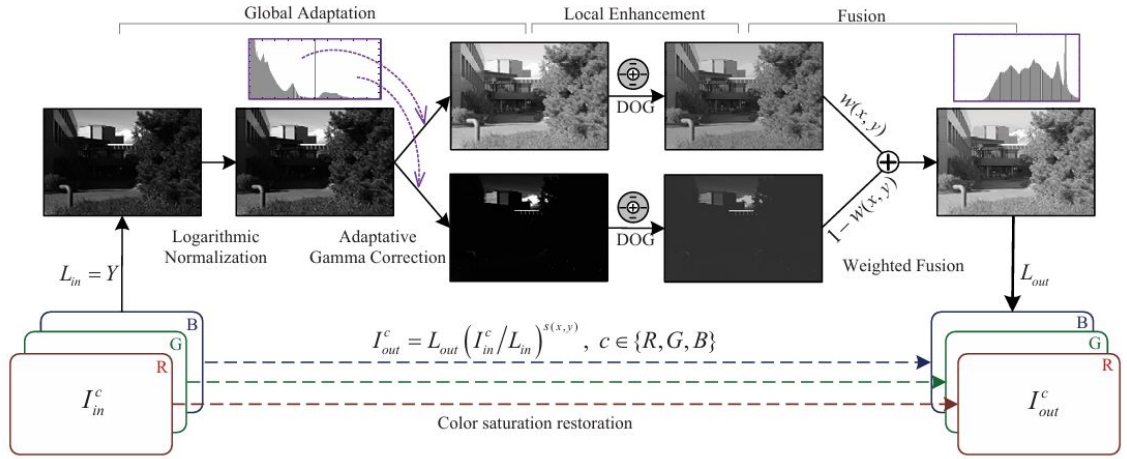


Figure 7: An Adaptive Dynamic Range Adjustment Method [19].

Attenuated color channel correction with detail-preserving contrast enhancement improved image quality while maintaining structural details, but can be sensitive to noise in low-light conditions [20].

Color, detail, and contrast restoration were combined with adaptive processing [21] for each component, demonstrating balanced enhancement, although computationally intensive and may introduce minor artifacts.

Adaptive stretching for color correction normalized intensity distributions across channels, improving color balance, but does not explicitly enhance contrast or structural details [22].

2.1.4 Low-Light and Multi-Scale Enhancement Methods

A framework for low-light underwater image enhancement [23] utilized local contrast improvement combined with multi-scale fusion, efficiently improving low-light images but less effective for strongly color-distorted inputs.

A multi-scale denoising and enhancement method based on Laplacian Pyramid decomposition demonstrated effective multi-scale contrast enhancement and denoising, but was primarily designed for sonar imagery with limited validation on natural underwater images [24].

Non-uniform illumination restoration via illumination channel sparsity prior corrected uneven lighting while preserving color, though it may fail under severe scattering conditions [25].

2.1.5 Evaluation and Benchmarking Methods

A non-reference evaluation framework [26] compared various enhancement methods using UIQM, UCIQE, and NIQE, providing a standardized benchmark, though relying on a single dataset.

A benchmark dataset was created for underwater image enhancement along with evaluation metrics, enabling quantitative comparisons, but with limited coverage of extreme lighting and turbidity conditions [27].

A patch-structure representation method [28] quantified local and global contrast changes for robust assessment of enhancement effects, but focuses on contrast rather than color fidelity.

An underwater color image quality metric considering colorfulness, sharpness, and naturalness aided objective assessment, though it may not fully capture complex scene distortions [29].

Human-visual-system-inspired quality measures [30] emphasized edge preservation,

contrast, and color perception, facilitating perceptually relevant enhancement evaluation, but may not fully predict performance under severe degradation.

A survey [31] on underwater contrast enhancement analyzed challenges, methods, and evaluation metrics, providing insights into algorithm selection, but was primarily theoretical with limited practical experiments.

A comprehensive review [32] summarized underwater image enhancement techniques, recent trends, challenges, and applications, highlighting gaps and future directions, but did not propose new algorithms.

A survey on GAN-based underwater image enhancement reviewed architectures, loss functions, and evaluation metrics, but lacked experimental validation [33].

2.2 Physical Model-Based Methods

2.2.1 Scene Radiance and Transmission Estimation

An imaging information estimation network was designed to restore underwater image color by estimating scene radiance and transmission maps, showing improved color fidelity [34]. However, it requires paired training data and may struggle with unstructured scenes.

A restoration method [35] based on the red channel and haze-lines prior estimated depth and transmission maps for image recovery, effectively enhancing color and contrast in hazy underwater images, though it struggles in highly turbid water or images with strong backscatter.

The Sea-Thru water-removal method reconstructed underwater images by estimating water attenuation and depth maps, achieving clear color recovery, but it requires accurate depth estimation, which may not always be available [36].

2.2.2 Structure and Detail Decomposition Methods

A two-stage enhancement network [37] decomposed images into structure and detail layers for targeted enhancement, improving detail preservation and color restoration, though it requires large training datasets and significant computational resources.

2.3 Deep Learning-Based Methods

2.3.1 CNN-Based Methods

A recurrent neural network-based method [38] combined white balancing and color correction for enhanced underwater images, demonstrating improved color uniformity, but requires large training data and may generalize poorly to unseen environments.

A deep residual framework [39] incorporated multi-level residual learning for detail preservation, showing robust enhancement across scenes, although it demands high computational resources and training.

The UIECs-Net CNN processed two color spaces for enhanced underwater image restoration, achieving improved color fidelity, but the model complexity is high and requires substantial training data [40].

2.3.2 GAN-Based Methods

A physical model-guided GAN [41] with dual discriminators enhanced underwater images while respecting physical image formation, producing realistic results, though GAN training can be unstable and dependent on the dataset.

FE-GAN [42], a fast and efficient GAN model with conditional GAN and lightweight architecture, achieved fast processing and good visual quality, but may produce minor color inconsistencies.

A generative adversarial framework [43] integrated denoising and color correction for fast underwater image enhancement, showing significant quality improvement, although training may be unstable and dataset-specific.

2.3.3 Transformer-Based Methods

Dual attention transformer-based enhancement (UDAformer) used spatial and channel attention to improve underwater images, achieving state-of-the-art results, but is computationally expensive for high-resolution images [44].

A U-Shape transformer architecture [45] captured multi-scale dependencies for better contrast and color restoration, showing effective global and local enhancement, though it requires large datasets and high computational resources.

Depth-aware U-shape transformer [46] incorporated depth information to guide image enhancement, improving structural preservation, but depth maps may not be available for all scenes.

2.3.4 Advanced Deep Learning Approaches

Cascaded contrastive learning was applied to enhance underwater images while preserving structure and color consistency, demonstrating balanced improvements, though it requires large training data and significant computational resources [47].

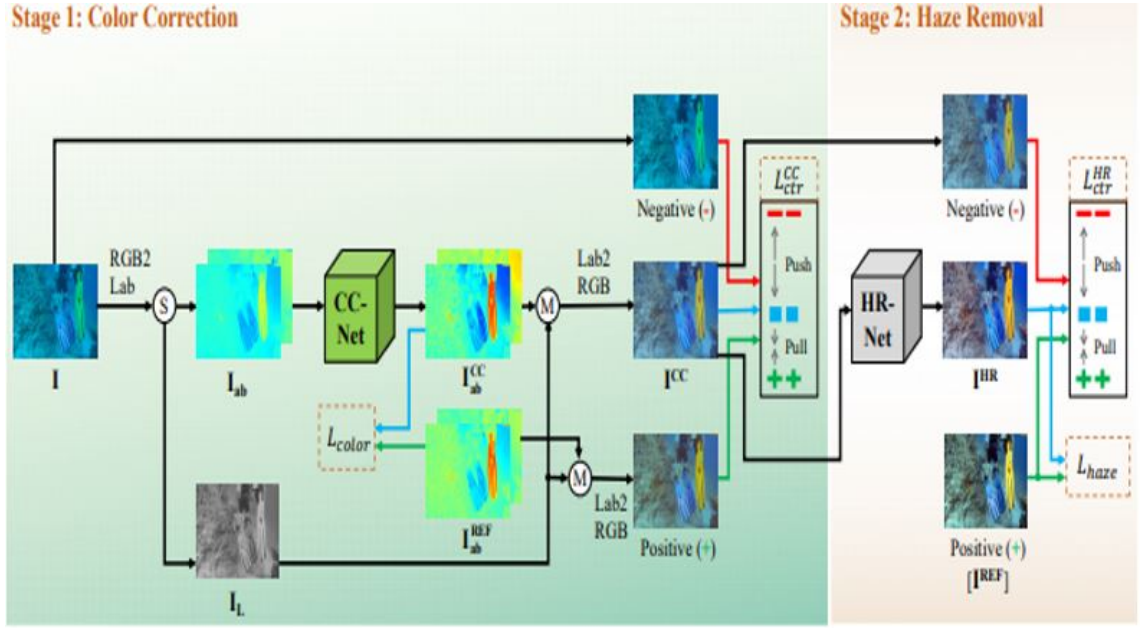


Figure 8: Framework of Cascaded Contrastive Learning Method [47].

Domain adaptation [48] was used to enhance underwater images by transferring knowledge from source domains to target scenes, improving generalization, though adaptation may fail under highly diverse target conditions.

A Dual Information Modulation Network was proposed to address non-homogeneous degradation in underwater imagery. It introduces a Multi-Information Enhancement Module that combines spatial-aware attention with multi-scale Transformer blocks, restoring color consistency while preserving fine details. This method outperforms many state-of-the-art techniques in adapting to diverse degradations across color channels and spatial regions [49].

A hybrid underwater image enhancement framework [50] integrates CNNs, Transformers, Particle Swarm Optimization, and data augmentation. By leveraging evolutionary optimization, the model achieves high performance on NIQE, BRISQUE, and UIQM benchmarks while demonstrating strong generalization across diverse scenes.

The approach highlights the benefits of combining deep learning with heuristic optimization.

To tackle challenges of limited training data and computational resources, a Zero-Reference Parameter Estimation Network [51] was introduced. It employs a lightweight parameter estimation architecture guided by non-reference loss functions and an underwater adaptive curve model. With about 17K parameters, the model delivers adaptive, real-time enhancement at minimal computational cost.

These comprehensive studies illustrate considerable progress in underwater image enhancement and quality evaluation. Although deep learning and fusion-based approaches have pushed forward performance, persistent issues such as backscatter artifacts, insufficient imaging models, and the need for effective no-reference metrics remain. Future directions involve expanding datasets, refining physics-based models, and developing fast, reliable quality assessment tools to meet practical underwater imaging needs.

2.4 Limitations of Existing Methods

Despite significant advancements in underwater image enhancement, each existing method has limitations that impact its effectiveness in real-world applications:

- **Limited Adaptability:** Non-Physical based methods perform well under specific conditions but struggle to generalize across underwater environments with varying turbidity and lighting conditions.
- **Loss of Detail:** Some enhancement techniques, particularly those based on histogram equalization, sacrifice fine details for better contrast.
- **Processing Speed:** Model-based and deep-learning approaches require high computational power, making them unsuitable for real-time applications.
- **Ineffective in Low-Light Conditions:** The existing algorithm [1] fails to restore images effectively in extremely low-light environments, such as deep-sea explorations.
- **Color Distortion:** Non-Physical approaches improve contrast, they still struggle to maintain accurate color representation, particularly with red tones.

2.5 Scopes of the Research Work

The literature highlights several key scopes for advancing underwater image enhancement within traditional algorithmic frameworks. There is a clear need for more adaptive techniques capable of handling the variability of underwater conditions, including diverse lighting, water types, and turbidity levels, without relying on fixed priors or handcrafted rules. Improving the balance between color correction, contrast enhancement, and texture preservation remains an important research direction to achieve overall better perceptual quality. Enhancing computational efficiency to facilitate near real-time or real-time processing is also a vital area, as many current methods are limited by high computational demands. Furthermore, refining evaluation methodologies by employing diverse and realistic benchmark datasets along with comprehensive image quality metrics can help better guide and validate new enhancement approaches. Exploring advanced fusion strategies, multi-scale processing, and more accurate physical models of underwater light propagation offer promising avenues for future research in improving the robustness and general applicability of underwater image enhancement techniques.

Chapter 3

Proposed Framework

This chapter presents the framework employed for enhancing underwater images. Our approach systematically refines images through color correction, contrast optimization, brightness adjustment, sharpening, and histogram stretching. The proposed system ensures high visual clarity and detailed retention, making the final output more suitable for analysis and interpretation.

To address common limitations, the framework adapts to varying turbidity and lighting by dynamically tuning enhancement parameters. Unlike traditional histogram equalization, it enhances contrast without losing details. Brightness and sharpening steps improve performance in low-light and low-resolution conditions. The color correction module specifically restores red tones to fix color distortion.

Designed for efficiency, the system ensures fast processing with low computational cost, making it suitable for real-time applications. Additionally, evaluation across multiple diverse datasets overcomes the typical limitation of narrow testing, confirming robustness.

3.1 Overview of the Framework

The proposed framework systematically enhances underwater images through adaptive color correction, contrast optimization, brightness adjustment, sharpening, and histogram stretching. Each step builds upon the previous one to produce a visually appealing and highly detailed output image. In Figure 9, the workflow of the proposed method is illustrated with the help of three modules.

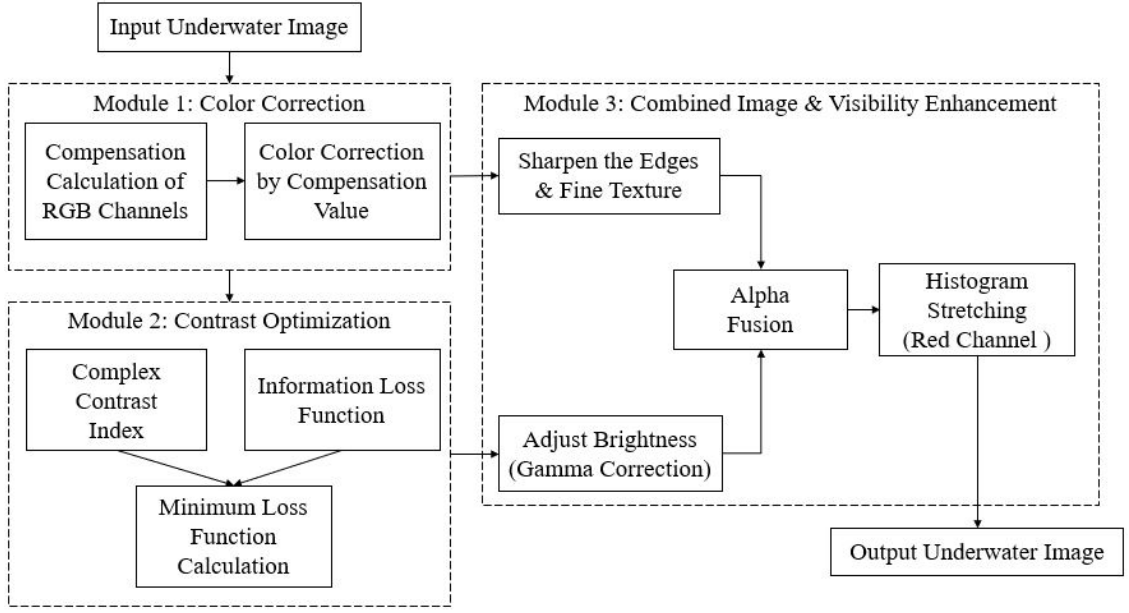


Figure 9: Framework of the proposed system.

3.2 Color Correction

The image enhancement process begins with color correction [11], which aims to remove color casts and restore natural colors. The red channel is compensated using constant coefficients to mitigate distortions caused by underwater environments. Adaptive color correction is applied to adjust and correct color imbalances automatically.

3.2.1 RGB Compensation

A compensation method is applied to each channel to correct the color imbalances. The average pixel values of the RGB color channels are denoted as Im_r , Im_g and, Im_b respectively. The RGB channels are compensated by checking several conditions. By alternatively taking two channels we computing an inequality measure as in equation (1):

$$(Im_r + Im_b)/(Im_r + Im_g + Im_b) < 1/3 \quad (1)$$

Compensation is performed using the following equations (2)-(4):

$$Ir_c(x) = Ir_c(x) + p(Im_g - Im_r)(1 - Ir_c(x))Ig_c(x) \quad (2)$$

$$Ig_c(x) = Ig_c(x) + q(Im_g - Im_b)(1 - Ig_c(x))Ib_c(x) \quad (3)$$

$$Ib_c(x) = Ib_c(x) + r(Im_g - Im_b)(1 - Ib_c(x))Ig_c(x) \quad (4)$$

Ir_c , Ig_c , and Ib_c represent the compensated red, green, and blue channels, respectively, with compensation coefficients p , q , and r . These coefficients must be calculated for four different scenarios. Depending on their values, channel loss levels can result in either over-compensation or under-compensation. To balance this, we used a channel loss level value of 0.5. The output of this initial module is a restored image free from reddish, greenish, or yellowish tone. Figure 10 shows the input underwater images (a–d) in the first row and their corresponding color corrected images (e–h) in the second row.

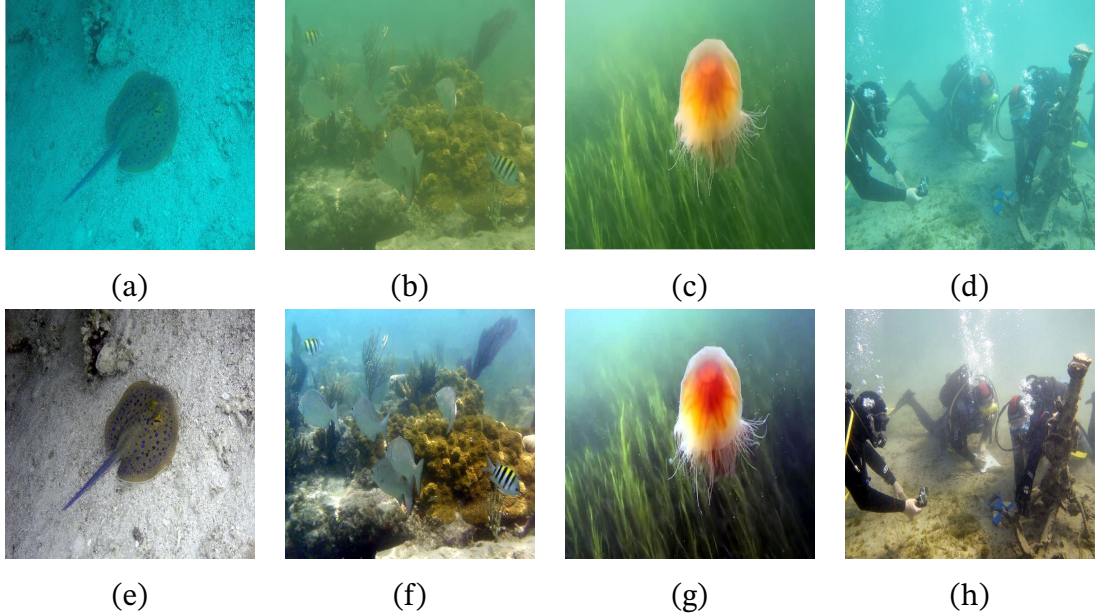


Figure 10: (a–d) Input Images and (e–h) Color Corrected Images.

3.2.2 Compensation Coefficients

Underwater images often suffer from uneven color channel losses due to light absorption and scattering. To restore natural colors, compensation coefficients p , q , and r are applied to the red, green, and blue channels, respectively. The degree of channel loss is determined by the threshold E , which controls when a difference between channels is considered significant [4]. Experimental results indicate that setting $E = 0.5$ provides an optimal balance between overcompensation and under-correction for equation (5)–(9).

Minimal difference between Green and Blue channels: If $(|Im_g - Im_b| \leq E)$, then $q = 0$, $r = 0$. Since the green and blue channels are nearly balanced, only the red channel

requires compensation.

$$p = 1 - \ln(Im_g - Im_r) \quad (5)$$

Strong Blue Channel Presence: If $(Im_b - Im_g > E)$, then $q = 0$, $r = -\ln(Im_b - Im_g)$. A dominant blue tone suggests a significant loss in the red and green channels, so compensation is applied to these two channels.

$$p = 1 - \ln(Im_g - Im_r) \quad (6)$$

Strong Green Channel Presence: If $(Im_b - Im_g > E$ and $Im_r - Im_b \leq E)$, then $r = 0$. When green is dominant, adjustments are made to the red and green channels while ensuring the blue compensation does not exceed red compensation, following established color correction techniques.

$$p = 1 - \ln(Im_g - Im_r) \quad (7)$$

$$q = 1 / (1 - \ln(Im_g - Im_r)) \quad (8)$$

Strong Yellow Tone (Red and Green Dominant, Blue Weak): If $(Im_g - Im_b > E$ and $Im_r - Im_b > E)$, then $p = 0$, $r = 0$.

$$q = 1 - \ln(Im_g - Im_b) \quad (9)$$

In this scenario, the blue channel has suffered significant loss, while the red and green channels are well-preserved. Therefore, compensation is applied only to the blue channel.

3.2.3 Ablation Study of Threshold E in Color Compensation

Underwater images often suffer from uneven color channel losses due to light absorption and scattering. The threshold E determines when a difference between channels is significant enough to apply compensation. Based on experimental results, setting $E = 0.5$ effectively balances the need for correction while avoiding overcompensation.

Setting $E = 0.5$ provides a practical threshold that ensures meaningful channel differences are corrected while avoiding overcompensation due to minor variations. This leads to visually balanced underwater images with accurate color restoration.

The four cases presented in Table 3.1 illustrate the adaptability of Module 1, referred

Table 3.1: Rationale for Choosing $E = 0.5$ and Effects of Other Values

Case		Why $E = 0.5$ is used	Effect of Using $E \neq 0.5$ (0.1–0.9)
Minimal Green-Blue Difference		Green and blue channels are nearly balanced, so only the red channel needs compensation. Choosing $E = 0.5$ prevents unnecessary adjustments due to minor natural variations.	Too small $E = 0.1$ – 0.4 : over-compensation of red channel, causing unnatural reddish tones. Too large $E = 0.6$ – 0.9 : insufficient correction of red channel, resulting in dull or unbalanced colors.
Strong Channel Presence	Blue	Dominant blue tone indicates a significant loss in red and green channels. Compensation is applied to these channels, while $E = 0.5$ ensures small fluctuations are ignored.	Too small $E = 0.1$ – 0.4 : small blue fluctuations trigger unnecessary compensation, producing unnatural magenta tints. Too large $E = 0.6$ – 0.9 : red and green channels are under-compensated, leaving strong blue dominance.
Strong Channel Presence	Green	Green dominates, so adjustments are applied to red and green channels while avoiding excessive blue compensation. Setting $E = 0.5$ balances sensitivity to significant differences and ignores minor variations.	Too small $E = 0.1$ – 0.4 : excessive correction, causing over-saturation in red and green. Too large $E = 0.6$ – 0.9 : green dominance not properly corrected, leaving image slightly yellowish or dull.
Strong Tone	Yellow	The blue channel has suffered significant loss, while red and green are well-preserved. Only the blue channel is compensated. Choosing $e = 0.5$ ensures only meaningful blue loss is corrected.	Too small $E = 0.1$ – 0.4 : over-compensation of blue, causing unnatural cyan tones. Too large $E = 0.6$ – 0.9 : blue channel under-compensated, yellow tones persist and image looks unbalanced.

to as color correction, when using a fixed threshold value of $E = 0.5$. The choice of $E = 0.5$ provides a balanced criterion that effectively distinguishes significant channel differences while ignoring minor natural variations. Specifically, in cases of minimal green–blue differences, it prevents unnecessary red-channel compensation; under strong blue dominance, it avoids triggering excessive corrections that could lead to unnatural magenta tones; in strong green dominance, it balances sensitivity by correcting excess green without oversaturating other channels; and in strong yellow tones, it ensures that only meaningful blue-channel losses are corrected without introducing cyan artifacts. In contrast, deviating from $E = 0.5$ (e.g., using values in the range $0.1 - 0.4$ or $0.6 - 0.9$) either causes overcompensation leading to unnatural color casts or results in insufficient correction, leaving residual distortions in the enhanced image.

The influence of varying the threshold E in the average value of qualitative matrices on the UIEB dataset is presented in Table 3.2. As indicated, lower values of E ($0.1-0.4$) result in overcompensation of color channels, producing slightly unnatural color casts and lower image quality scores. For instance, at $E = 0.1$, the PCQI, UCIQE, UIQM, and IE values are 1.10, 0.65, 4.55, and 7.40, respectively, reflecting reduced perceptual quality compared to higher thresholds.

Table 3.2: Ablation study of different E values on UIEB dataset.

E Values	PCQI	UCIQE	UIQM	IE
0.1	1.10	0.65	4.55	7.40
0.2	1.15	0.67	4.60	7.50
0.3	1.20	0.68	4.65	7.60
0.4	1.24	0.70	4.70	7.72
0.5	1.29	0.72	4.77	7.87
0.6	1.27	0.71	4.73	7.80
0.7	1.24	0.69	4.68	7.70
0.8	1.21	0.67	4.62	7.60
0.9	1.18	0.65	4.55	7.50

Increasing the threshold gradually improves the metrics, with the maximum values achieved at $E = 0.5$ (PCQI = 1.29, UCIQE = 0.72, UIQM = 4.77, IE = 7.87), demonstrating that this setting provides an optimal balance between effective color restoration and avoidance of overcompensation. Conversely, larger values of E ($0.6-0.9$) lead to under compensation, resulting in a gradual decline in perceptual quality. Overall, these findings underscore the sensitivity of the color correction module to the threshold E and confirm that $E = 0.5$ represents the most effective setting for achieving consistent and balanced underwater image enhancement.

3.3 Contrast Optimization

After color correction, the image undergoes contrast and sharpness enhancement to improve visual quality. This module ensures that the image has sufficient brightness and sharp details to be effectively analyzed.

Enhancing underwater images requires improving visibility while preserving scene information [11]. The proposed framework follows a step-wise optimization approach that restores pixel values using a total cost function, ensuring both contrast enhancement and minimal information loss.

3.3.1 Estimating Background Light

The first step is to estimate the background light, which is crucial for color correction. The image is divided into smaller regions using quadtree space partitioning. Within each region, the Dark Channel Prior identifies the brightest pixels as candidates. Finally, the Maximum Intensity Search selects the pixel with the largest intensity among these candidates as the background light L . Accurate estimation of L ensures proper color restoration.

3.3.2 Contrast Performance Index

After color correction, the image undergoes *contrast and sharpness enhancement* to improve visual quality. This step expands the tonal range from dark shadows to bright highlights. Pixel values are restored using the estimated transmittance $v(x)$ and background light B as in equation (10):

$$R(x) = \frac{1}{v(x)}(M(x) - L) + L \quad (10)$$

Where, $R(x)$ – Restored image (after contrast enhancement), $M(x)$ - Input image (color corrected image), $v(x)$ - Transmittance (fraction of scene radiance reaching the camera), and L - Background light (estimated from bright regions).

The contrast performance index D_i is calculated by equation (11):

$$D_i = \frac{1}{N} \sum_{k=1}^N (R_i(x_k) - U_i)^2 \quad (11)$$

Where, N - Number of pixels in the considered block, $R_i(x_k)$ - Restored intensity of

the k th pixel in channel i ($i \in \{r, g, b\}$), U_i - Mean intensity of the block in channel i , and D_i Contrast evaluation index for the block.

For a more comprehensive evaluation, the overall complex contrast performance F_c is computed in equation (12):

$$F_c = - \sum_{i \in \{r, g, b\}} \sum_{k=1}^N \frac{(v_i(x_k) - U_i)^2}{u^2 N} \quad (12)$$

Where, $v_i(x_k)$ - Transmittance value for the k th pixel in channel i , u - Normalization constant, and F_c Overall contrast performance.

3.3.3 Measuring Information Loss

In equation (13) information loss function G_l is defined to keep pixel values within the valid intensity range:

$$G_l = \sum_{i \in \{r, g, b\}} \sum_{k=1}^N (\min(0, R_i(x_k))^2 + \max(0, R_i(x_k) - 255)^2) \quad (13)$$

Where, G_l - Information loss function, and $R_i(x_k)$ - Restored pixel intensity for the k th pixel in channel i .

3.3.4 Total Cost Function Formulation

The contrast performance F_c and information loss G_l are combined into a weighted total cost function as in equation (14):

$$H = F_c + u G_l \quad (14)$$

Where, H - Total cost function, and u Weighting factor balancing contrast enhancement and information preservation .

Minimizing H ensures that the enhanced image achieves high contrast while preserving details.

3.3.5 Restore the Image with Lowest Total Cost

Finally, in equation (15) optimal transmittance $v^*(x)$ is determined by minimizing the total cost function H over multiple candidate transmittance:

$$v(x) = \arg \min_{v(x)} H(v(x)) = \arg \min_{v(x)} (F_c(v(x)) + \lambda G_l(v(x))) \quad (15)$$

Once the optimal transmittance $v(x)$ is found, the final restored image $R(x)$ is obtained through computing equation (16):

$$P(x) = \frac{1}{v(x)} (N(x) - L) + L \quad (16)$$

Here, $P(x)$ represents the enhanced image with balanced contrast and preserved information, $N(x)$ is the input image, L is the estimated background light, F_c is the contrast performance index, G_l is the information loss function, and λ is the weighting factor controlling the trade-off between contrast enhancement and information preservation. This procedure ensures that the enhanced underwater image is visually clear and suitable for subsequent analysis or real-time applications.

The proposed framework systematically enhances underwater images by estimating background light B , improving contrast through F_c , preserving information via G_l , and selecting the optimal transmittance $v(x)$ by minimizing the total cost function H . This approach ensures visually enhanced images suitable for further analysis or real-time underwater applications.

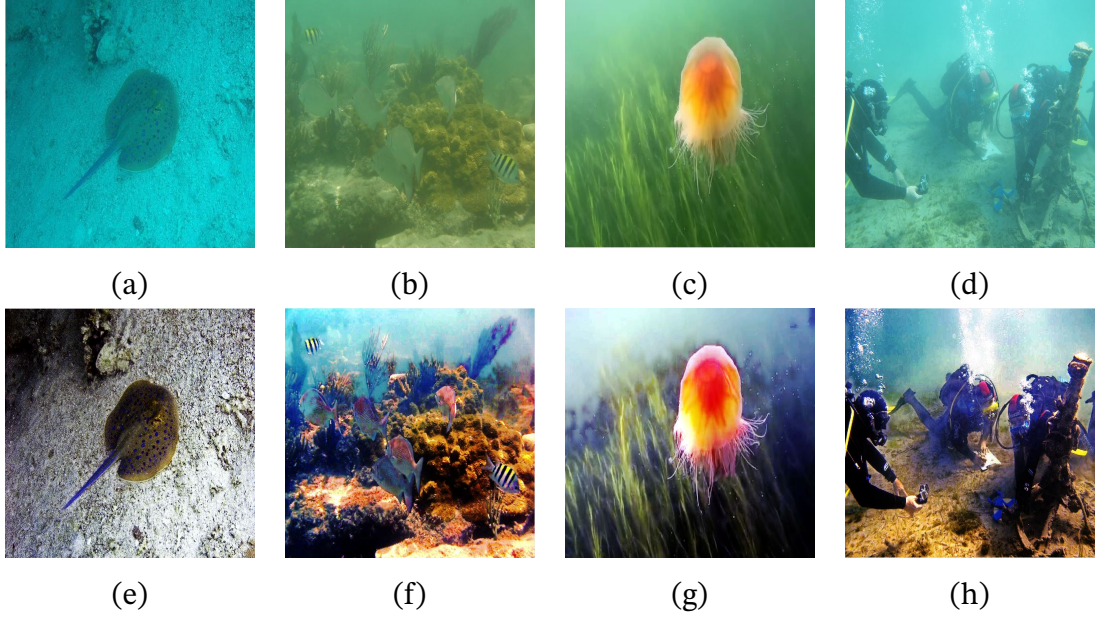


Figure 11: Input Images (a–d) and Color Optimized Images (e–h).

The total cost function guided the optimization process in Figure 11, enhancing image quality while preserving the original data. By minimizing this function, H determined the best transmittance value, with u representing the tradeoff. Next, the image underwent a Brightening process to ensure an appropriate brightness level, preventing underexposure (too dark) or overexposure (too bright). The goal was to achieve balanced luminance that accurately reflected the scene as perceived by the human eye.

3.4 Gamma Correction

Gamma correction is a nonlinear intensity transformation technique that modifies the luminance of an image according to a power-law relationship as in equation (17):

$$I_{\text{out}} = I_{\text{in}}^{\gamma} \quad (17)$$

Here, I_{in} and I_{out} are the normalized pixel intensity values (scaled between 0 and 1), and γ is the gamma coefficient that determines the adjustment curve. The process is performed as follows:

1. Normalization Each pixel value from the original image (0-255 range for 8-bit images) is divided by 255 to convert it into I_{in} within the range $[0, 1]$.

2. Gamma Transformation The normalized value is raised to the power of γ to produce I_{out} .
3. Rescaling The resulting I_{out} values are multiplied by 255 and clipped to the valid intensity range to obtain the enhanced pixel values.

The effect of γ is as follows:

- $\gamma < 1$ Brightens dark regions, revealing shadow details.
- $\gamma = 1$ No change in luminance.
- $\gamma > 1$ Darkens bright regions, increasing contrast.

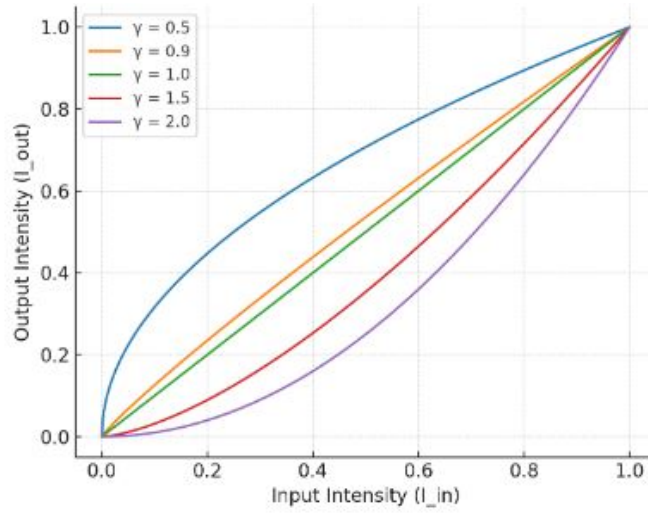


Figure 12: Gamma correction curves for different γ values.

In underwater imaging, light attenuation and scattering cause dark, low-contrast visuals dominated by blue-green tones. In Figure 12 applying gamma correction with $\gamma < 1$ selectively enhances dim regions without linearly boosting noise in already bright areas. Care must be taken to avoid excessive brightening, which may amplify background haze or reduce perceived contrast. clarity.

In this study, a gamma value of $\gamma = 0.9$ was used as it gave the best value of UIQM. This value slightly increases the output luminance for mid- and low-intensity pixels while preserving high-intensity areas, resulting in better visibility of shadowed underwater features without overexposing highlights. In Figure 12 The transformation $I_{out} = I_{in}^{0.9}$ was applied pixel-wise after normalization.

This outcome in Figure 13 aligns with the characteristic attenuation of light in underwater environments, where images often appear darker due to absorption and scattering. The slightly lower-than-1 gamma value effectively compensates for this darkness without introducing excessive brightness, making the details and textures

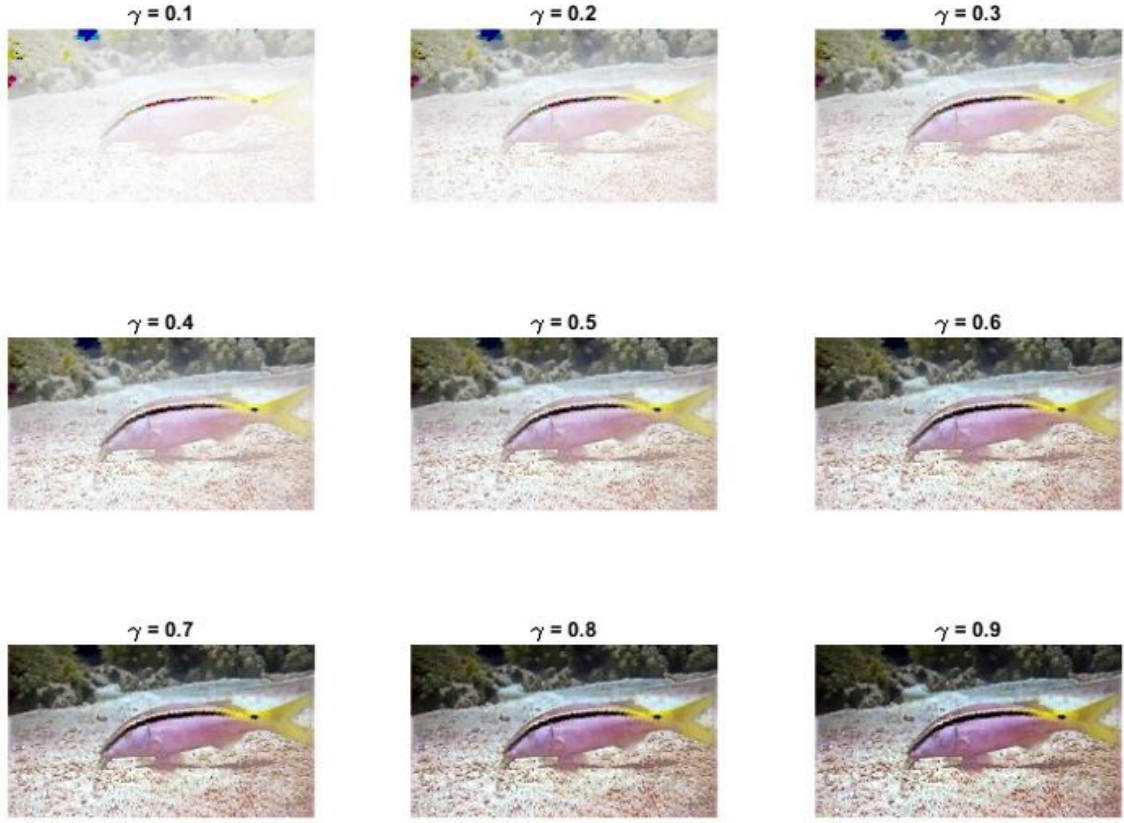


Figure 13: Gamma values and their effect on underwater image.

of underwater objects more distinguishable. Consequently, gamma = 0.9 serves as a well-balanced choice for enhancing visibility and natural appearance in underwater imagery.

3.5 Edge Sharpening

Unsharp masking is a widely utilized image enhancement technique designed to improve perceived image sharpness by selectively amplifying edge structures. This approach is particularly pertinent to underwater image processing, where images are frequently degraded by blurring effects arising from light scattering, diffraction, and wavelength-dependent absorption in the aquatic medium.

Mathematically, the method begins by generating a blurred version of the original image, denoted as I_{blur} , typically obtained through a low-pass filtering operation such as Gaussian smoothing. The high-frequency components, corresponding to edges and fine details, are extracted by subtracting this blurred image from the original image I_{orig} :

$$I_{\text{mask}} = I_{\text{orig}} - I_{\text{blur}} \quad (18)$$

The resultant edge mask I_{mask} is then scaled by a sharpening coefficient k and added back to the original image to yield the sharpened output:

$$I_{\text{sharp}} = I_{\text{orig}} + k I_{\text{mask}} \quad (19)$$

As shown in equations (17) and (18), the method effectively extracts high-frequency components and enhances the image by amplifying these details.

Unsharp masking is preferred over alternative masking-based sharpening methods in underwater image processing for several reasons. It selectively enhances primarily the high-frequency details (edges and fine textures), reducing the risk of amplifying background haze and low-frequency noise that commonly occur in underwater images. Moreover, the blur radius and sharpening coefficient k can be adjusted to finely control the enhancement level, ensuring true structural details are amplified while minimizing noise amplification in smooth regions such as open water. The technique involves simple operations—Gaussian blurring, subtraction, and weighted addition—which are computationally inexpensive and thus suitable for real-time processing on resource-constrained platforms like autonomous underwater vehicles. Finally, when properly tuned, unsharp masking yields more natural-looking images compared to more aggressive methods such as Laplacian sharpening or high-boost filtering, which can create harsh and over-processed appearances in underwater imagery.

3.6 Image Fusion

In the context of underwater image enhancement, the alpha fusion technique serves as an effective approach to merge complementary image attributes such as sharpness and brightness, which are often degraded due to water properties and light scattering. The alpha parameter K , ranging between 0 and 1, controls the blending ratio between the sharpened image and the brightened image according to the equation 20:

$$\text{AlphaFusedImage} = K * \text{SharpImage} + (1 - K) * \text{BrightImage} \quad (20)$$

As shown in equation (20), the fused image is computed by blending the sharpened

and brightened images using the blending factor K .

Selecting the optimal alpha value is crucial to strike a balance between enhancing image clarity and preserving natural brightness. An alpha value closer to 1 places more emphasis on sharpness, potentially amplifying noise and artifacts, while a value nearer to 0 prioritizes brightness, which might reduce detail visibility and result in washed-out images.

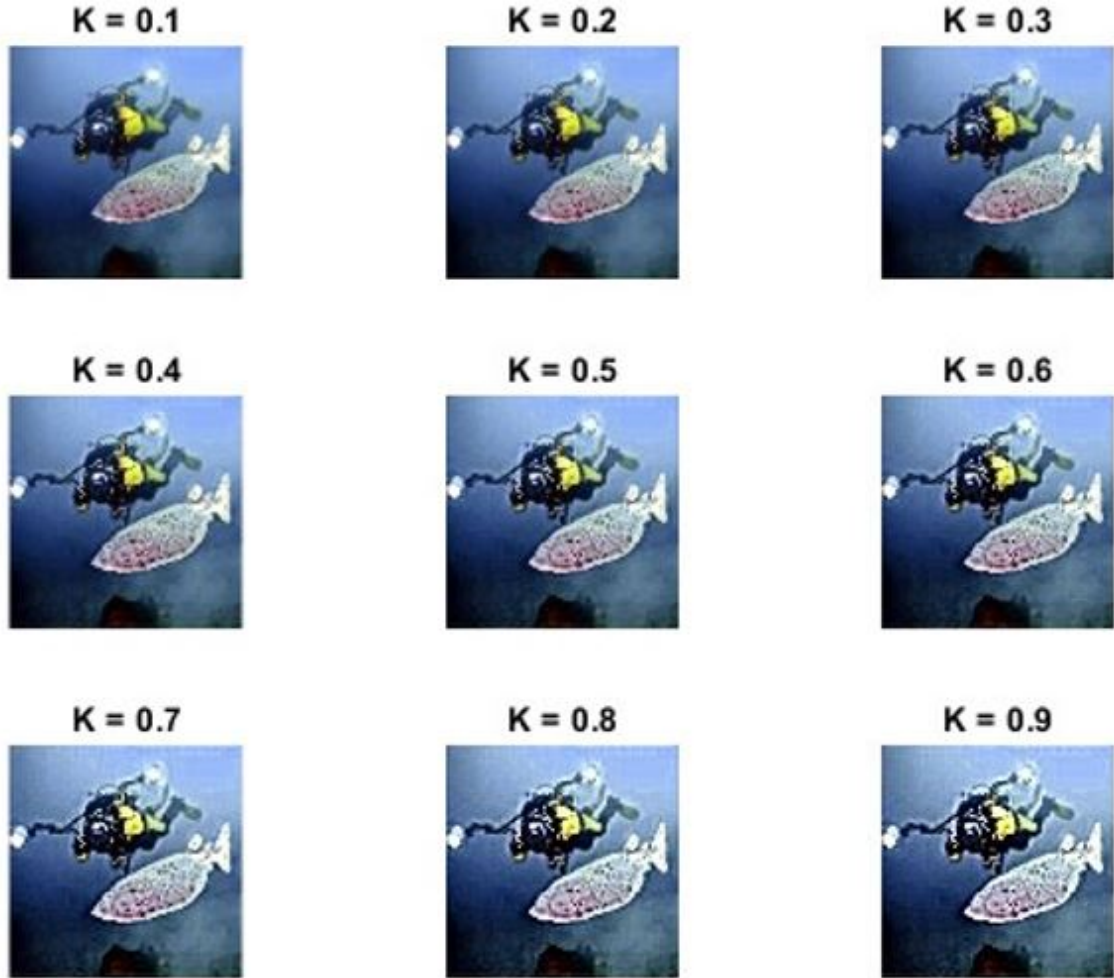


Figure 14: K values and it's effect on underwater image.

Choosing $K = 0.4$ offers a well-balanced fusion between brightness and sharpness, which is vital for underwater images often affected by low light and scattering. This value slightly favors brightness to preserve illumination without amplifying noise, while still enhancing edges effectively. It minimizes artifacts better than higher or lower alpha values, providing smooth, natural results.

Empirical tests such as in Table 3.3 and Figure 14 show that $K = 0.4$ achieves the best trade-off between contrast, clarity, and color fidelity across various underwater datasets. Compared to other fusion methods, alpha fusion is simpler, easier to control

with a single parameter, and reduces unwanted artifacts. Its flexibility allows seamless integration with sharpening and brightening steps, making it especially suitable for underwater image enhancement.

Table 3.3: Effect of Different K Values on Alpha Fusion for Underwater Image Enhancement

K	Observation	Effect of K values
0.1	Bright image dominates	Over-bright, washed-out regions, loss of detail
0.2	Bright image still dominant	Slightly better, but still excessive brightness
0.3	Balanced, but leaning towards brightness	Improved visibility, but some contrast lost
0.4	Optimal fusion	Well-balanced brightness and sharpness, fine details preserved
0.5	Sharper image starts dominating	Increased contrast, brightness reduced slightly
0.6	Sharp image dominates	High contrast, edges emphasized, some unnatural textures
0.7	Strong sharpness emphasis	Over-sharpened, may appear unnatural
0.8	Very sharp image	Details exaggerated, brightness underrepresented
0.9	Sharp image only	High contrast, unnatural appearance, low brightness

3.7 Histogram Stretching

The final step involves histogram stretching to ensure that pixel intensity values. Adjusting the distribution of intensity levels enhances contrast and detail. For optimal histogram stretching, we considered 0.22 percent of the maximum red channel intensity. Histogram stretching is a powerful technique for enhancing an image's dynamic range. It is widely used in underwater research to improve the quality of images used for marine habitat mapping and archaeological site exploration.

The process of histogram stretching follows the equation (21)-(23):

$$V_a(x, y) = 0, \quad \text{when } V_o(x, y) < V_l^b \quad (21)$$

$$V_a(x, y) = 255 * \frac{V_o(x, y) - V_l^b}{V_h^b - V_l^b}, \quad \text{when } V_l^b \leq V_o(x, y) \leq V_h^b \quad (22)$$

$$V_a(x, y) = 255, \quad \text{when } V_o(x, y) > V_h^b \quad (23)$$

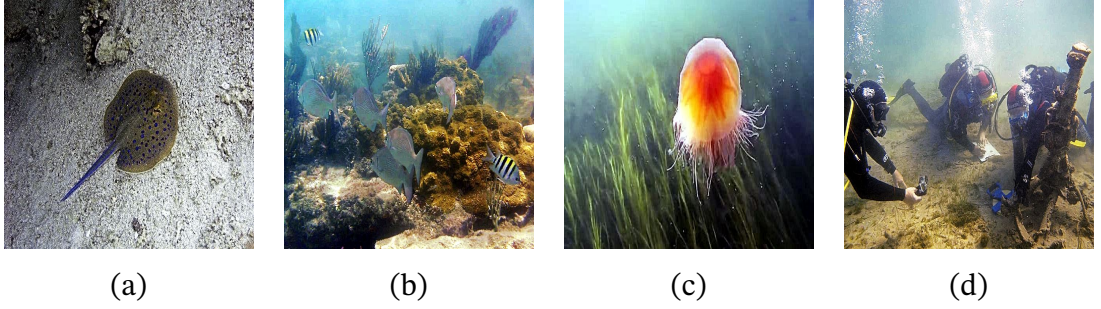


Figure 15: Output Images after Histogram Stretching.

Here, V_l and V_h represent the image's minimum and maximum pixel intensity values. The new pixel intensity at coordinates (x, y) , denoted as $V_a(x, y)$, is computed from the original intensity $V_o(x, y)$ using histogram scaling. Both V_l and V_h are determined based on a threshold T which is calculated as average of red channel multiplied by 0.22 through experimental trials. The output images are shown in Figure 15.

3.8 Algorithmic Distinctions

The proposed method introduces distinct algorithmic approaches compared to existing multi-stage pipelines. Adaptive color correction is achieved through a condition-based compensation calculation, allowing the system to dynamically adjust to varying underwater optical conditions rather than relying on static corrections. In addition, optimized contrast is realized by selecting the minimum cost function value during the tuning of a dehazing technique, ensuring balanced brightness and visibility across diverse scenes. To minimize information loss, the framework employs an optimal contrast enhancement and fusion strategy, whose parameters are determined through repetitive experimentation to achieve the best trade-off between clarity, naturalness, and detail preservation. These design choices distinguish the method from conventional multi-stage approaches by embedding adaptivity, cost-driven optimization, and empirically tuned fusion, while maintaining computational efficiency.

Chapter 4

Experimental Results

The system’s effectiveness is assessed by evaluating its ability to solve common underwater image degradation problems, such as color distortion, contrast loss, and haziness while preserving fine image details. The evaluation consists of subjective and objective comparisons against existing enhancement methods, ensuring that the proposed system provides significant improvements. Various datasets are used to validate the system’s performance, and multiple image quality assessment metrics are applied to measure its effectiveness quantitatively.

4.1 Datasets and Experimental Setup

The experiments were conducted using four underwater image datasets, including OccanDark, UIEB, UIEDP, EUVP which contain diverse underwater images exhibiting various degradation effects. Additionally, the Underwater Image Enhancement Benchmark dataset was used to validate, as it encompasses a wide range of underwater images, including bluish, greenish, yellowish, and hazy. These datasets were chosen to ensure the robustness of the proposed system across different underwater imaging conditions.

4.1.1 Datasets

The four data sets in Table 4.1 were chosen to ensure the robustness of the proposed system under different underwater imaging conditions.

The UIEB dataset [12] contains 950 images. It comprises 890 underwater images paired with high-quality reference images and 60 challenging images without refer-

ence pairs. This data set includes underwater images exhibiting various color casts and degradation levels. It is widely used to evaluate and benchmark underwater image enhancement algorithms.

The UIEDP dataset [52] consists of 195 images. It focuses on underwater images with varying degrees of distortion and degradation under different underwater conditions. This data set aims to evaluate color correction and visibility improvement algorithms, particularly leveraging diffusion priors.

The OceanDark dataset [1] contains 183 images captured under dark, turbid, and low-light underwater conditions. These images feature challenging lighting situations, including dark regions suitable for testing low-light underwater enhancement algorithms. It is commonly used to develop and assess methods tailored to enhance visibility in such difficult scenarios.

The EUVP dataset [13] is composed of 3700 images, including 1270 paired and 2430 unpaired samples with diverse visual impairments captured under different underwater visibility conditions. This large dataset facilitates supervised training and evaluation of underwater image restoration and enhancement models.

Table 4.1: Underwater Image Datasets Used for Evaluation

Dataset	Number of Images
Ocean Dark [1]	183
UIEDP [52]	195
UIEB [12]	950
EUVP [13]	3700

4.1.2 Experimental Setup

The system was implemented and tested on a 64-bit Windows operating system, with all coding conducted in MATLAB-23a, Python- 3.13 and NVIDIA version- 391.35 (GeForce 820M). MATLAB was chosen due to its powerful image processing toolbox, which facilitates efficient implementation and analysis of image enhancement techniques. The input images used for testing are classified based on their dominant degradation characteristics.

4.2 Evaluation Metrics

To assess the performance of the proposed system, both subjective and objective evaluations were carried out. Subjective evaluation relies on visual inspection and qualita-

tive comparison of the enhanced images, focusing on perceived image improvements. On the other hand, objective evaluation employs quantitative metrics to measure image quality improvements numerically.

The following objective metrics were utilized for quantitative evaluation:

Patch-based Contrast Quality Index:

PCQI measures the contrast differences between the reference and enhanced images on a patch basis [28], reflecting improvements in image visibility. It is defined in equation (24):

$$PCQI = \frac{1}{N} \sum_{i=1}^N Q_i \quad (24)$$

Where, Q_i denotes the contrast quality index for the i -th image patch, and N is the total number of patches. A higher PCQI value indicates better contrast enhancement and improved visibility.

Underwater Color Image Quality Evaluation:

UCIQE evaluates underwater image quality based on chroma, contrast, and saturation [29]. It is given by the equation (25):

$$UCIQE = c_1 \sigma_c + c_2 \text{con}_l + c_3 \mu_s \quad (25)$$

Where, σ_c is the standard deviation of chroma, con_l represents luminance contrast, μ_s is the mean saturation, and c_1, c_2, c_3 are empirically determined weights. A higher UCIQE score indicates superior underwater image quality.

Image Entropy (IE):

Entropy quantifies the information content preserved in the enhanced image [1]. It is defined as in equation (26):

$$IE = - \sum_{i=0}^{j-1} p_i \log_2 p_i \quad (26)$$

Where, p_i is the probability of the i -th intensity level and j is the total number of intensity levels. Higher IE values indicate richer details and better feature retention.

Underwater Image Quality Measure:

UIQM is a comprehensive metric [30] that evaluates the quality of underwater image

considering the components of color, sharpness, and contrast as in equation (27):

$$UIQM = c_1 \cdot UICM + c_2 \cdot UISM + c_3 \cdot UIConM \quad (27)$$

Where $UICM$, $UISM$, and $UIConM$ represent the underwater image colorfulness, sharpness, and contrast measures, respectively, with c_1, c_2, c_3 as their corresponding weights. A higher $UIQM$ value indicates better overall image quality and reduced distortions.

4.3 Comparative Result

To demonstrate the effectiveness of the proposed system, a comparative analysis was conducted against four state-of-the-art underwater image enhancement methods: Hybrid Fusion Method [1], Piecewise Color Correction and Dual Prior Optimized Contrast Enhancement [12], Bayesian Retinex Underwater Image Enhancement[6], Underwater Image Restoration and Enhancement Based on a Fusion Algorithm with Color Balance, Contrast Optimization, and Histogram Stretching[11], and the two-stage cascaded contrastive learning framework CCL-Net [47]. The evaluation included both subjective and objective assessments.

4.3.1 Subjective Evaluation Using MOS

To quantitatively assess the perceptual quality of the proposed underwater image enhancement framework, a Mean Opinion Score evaluation was conducted. A total of 40 human participants with normal or corrected-to-normal vision Table 4.2 participated in the study.

Table 4.2: Demographic Distribution of Participants

Characteristic	Distribution
Number of Participants	40
Age Range	20 – 45 years
Mean Age	28 years
Gender Distribution	60% Male, 40% Female
Vision Condition	80% Normal, 20% Corrected-to-Normal
Eye/Color Vision Issues	None Reported

Each rater evaluated a representative set of enhanced images using a 5-point Likert scale ranging from 1 (Poor) to 5 (Excellent).

Questionnaire Setup: Participants were asked the following questions for each enhanced image:

1. How visually pleasing is the image?
2. How natural does the color appear?
3. How well is the contrast enhanced?
4. How satisfied are you with the overall visibility improvement?

Raters provided scores on a 5-point Likert scale as summarized in Table 4.3.

Table 4.3: Likert Scale for Subjective Evaluation

Likert Scale	Description
1	Poor
2	Fair
3	Good
4	Very Good
5	Excellent

Comparison with Existing Methods: The proposed method was compared against five approaches as Hybrid Fusion Method [1], Piecewise Color Correction Method [12], Bayesian Retinex Underwater Image Enhancement System [6], Fusion Algorithm [11], and Cascaded contrastive learning framework CCL-Net [47].

Based on the MOS evaluation, 70% of the participants preferred the proposed framework over the existing methods. Table 4.4 summarizes the preference percentages for proposed framework.

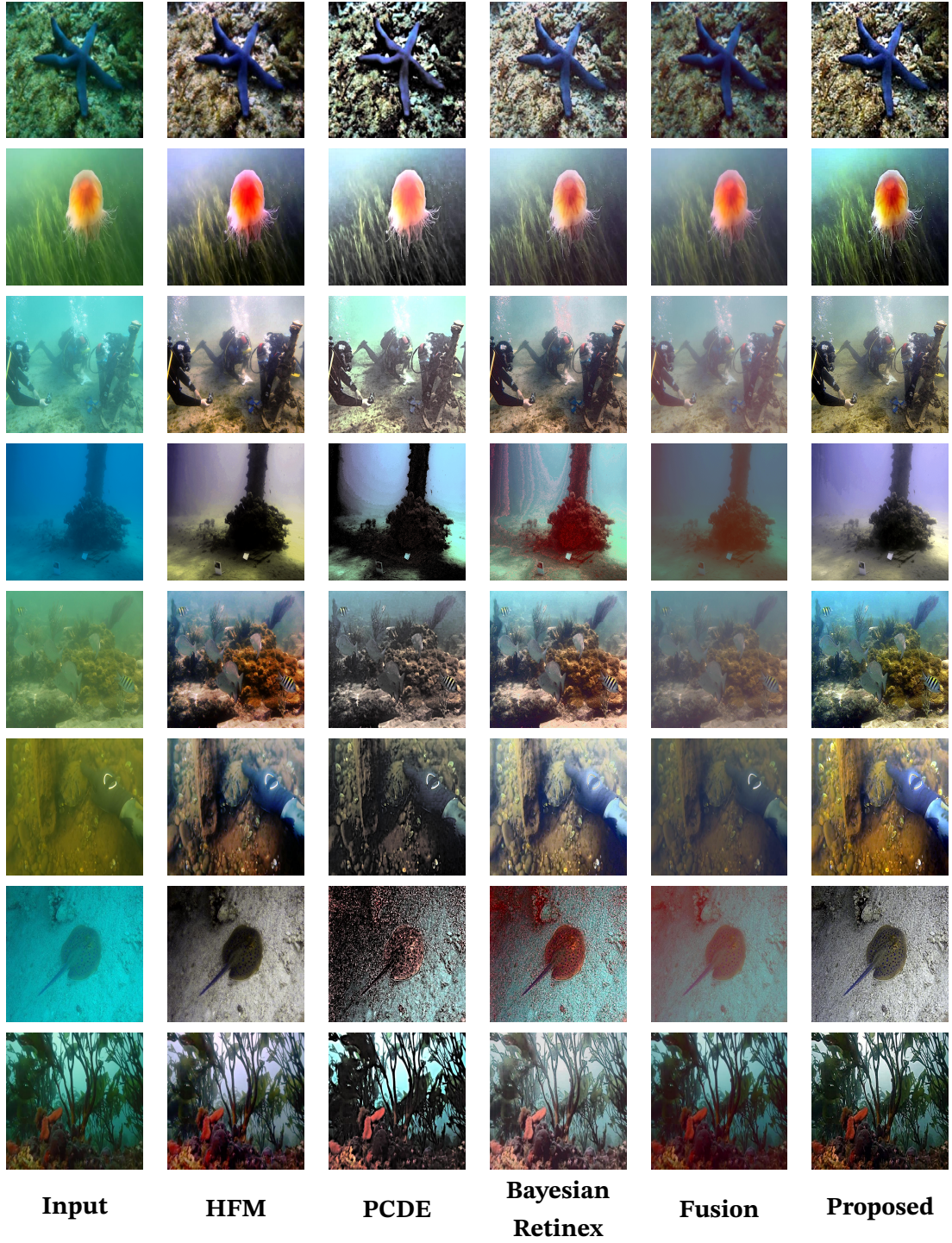
Table 4.4: Distribution of MOS Ratings for Proposed Framework

Likert Scale	Percentage of Raters
1 - Poor	0%
2 - Fair	0%
3 - Good	30%
4 - Very Good	20%
5 - Excellent	20%

These results indicate that the proposed framework achieved superior perceptual quality in terms of visual appeal, color naturalness, contrast enhancement, and overall visibility improvement. The MOS evaluation provides a quantitative validation of the subjective visual improvements compared to existing state-of-the-art methods.

4.3.2 Subjective Comparison

The visual quality of the enhanced images produced by the proposed system was compared with those generated by HFM, PCDE, Bayesian Retinex, Fusion, and CCL-Net. Figure 16 shows the enhancement results of four non-physical based methods applied to eighteen different underwater images.



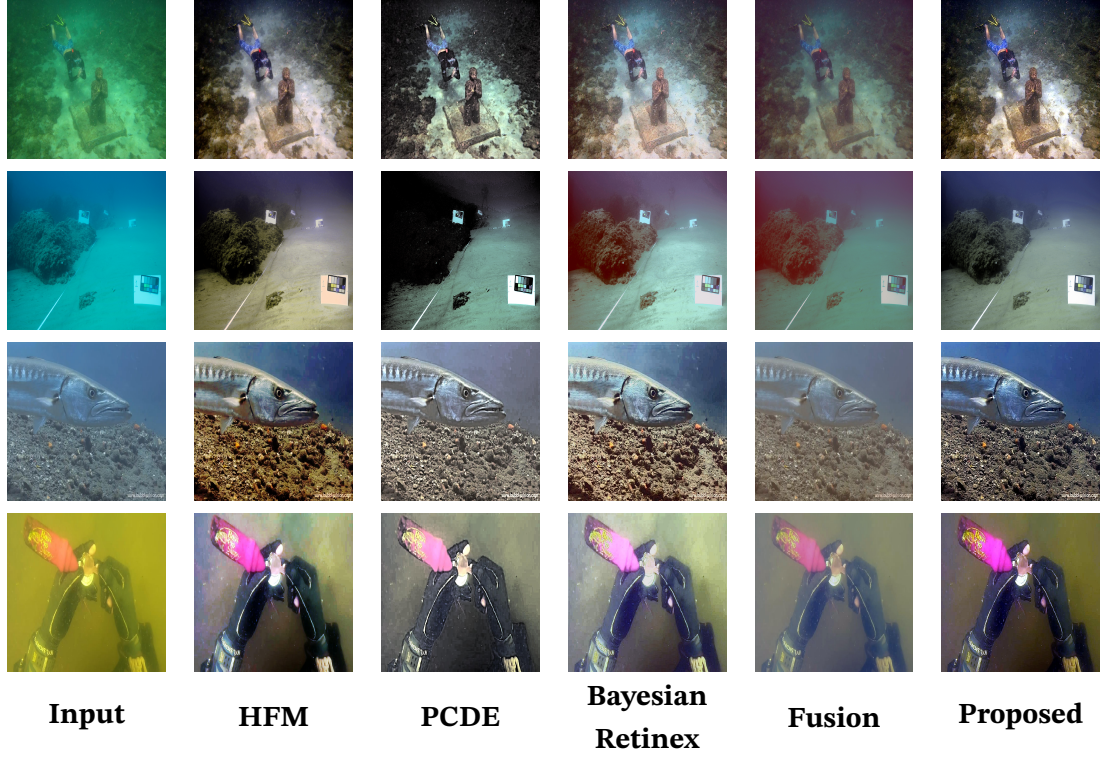


Figure 16: Subjective comparison of enhanced underwater images from Non-physical frameworks.

We have compared the proposed system with HFM, PCDE, Bayesian Retinex and Fusion method as in the Figure 17, with the output image based on databases shown.

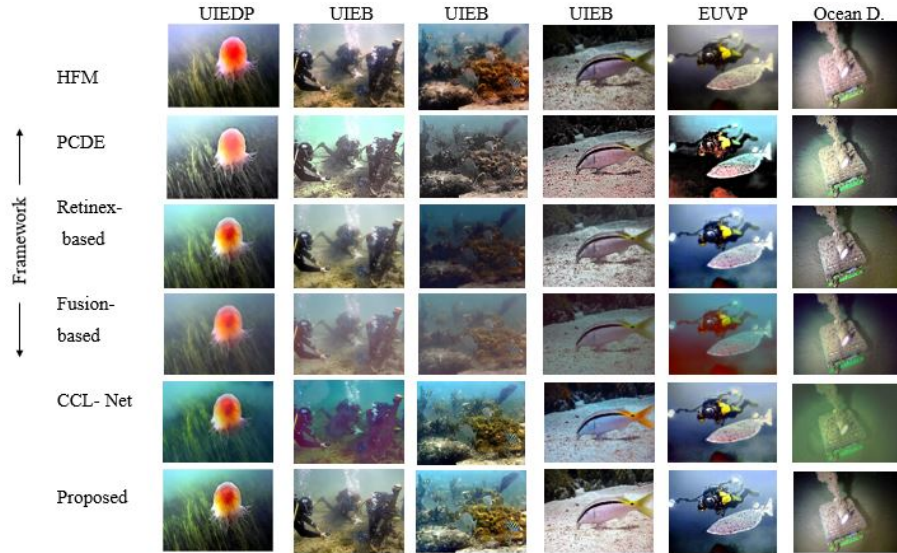


Figure 17: Enhanced images from different dataset.

The output images from the proposed system retained more edge details, aiding in better object identification. This is particularly useful for researchers and marine biologists who rely on enhanced underwater images for further study and analysis.

The subjective evaluation confirms that the proposed system offers superior visual improvements compared to the exist systems.

4.3.3 Objective Comparison

The evaluation was performed on four underwater image datasets with varying numbers of images. The UIEB Dataset contains 950 images featuring diverse underwater scenes and various levels of degradation. The UIEDP Dataset has 195 images that focus on enhanced and preprocessed underwater scenes, useful for testing color and contrast restoration methods. The Ocean Dark Dataset includes 183 images captured in challenging low-light underwater conditions, making it suitable for testing performance in dark environments. Finally, the EUVP Dataset is the largest, with 3700 images covering a wide range of underwater scenarios to evaluate robustness across different conditions.

The objective evaluation results for these datasets are summarized in Tables 4.5, 4.6, 4.7, and 4.8, respectively. These tables present the average values of evaluation metrics including PCQI, UCIQE, UIQM, and IE, reported as mean value and $\text{Mean} \pm \sigma$ for the compared methods.

The quantitative evaluation results in four underwater image datasets (UIEB, UIEDP, Ocean Dark, and EUVP) demonstrate the effectiveness of the proposed enhancement method in balancing key image quality metrics. Collectively, these findings highlight the proposed algorithms balanced improvement in contrast, color fidelity, and image clarity, making it a promising solution for underwater image enhancement tasks.

Table 4.5: UIEB: Average value of Evaluation Metrics and Standard deviation.

Method	PCQI	UCIQE	UIQM	IE
HFM [1]	1.03	0.68	4.63	7.66
PCDE [12]	1.13	0.60	4.50	7.64
Retinex-based [6]	1.19	0.62	4.04	7.59
Fusion-based [11]	1.09	0.58	4.27	6.46
CCL-Net [47]	1.10	0.62	3.75	6.75
Proposed	1.29	0.72	4.77	7.87
Proposed (<i>Mean $\pm \sigma$</i>)	1.29 ± 0.10	0.72 ± 0.15	4.77 ± 0.17	7.87 ± 0.42

The quantitative evaluation across four benchmark underwater image datasets (UIEB, UIEDP, EUVP, and Ocean Dark) demonstrates the robustness and balanced performance of the proposed enhancement method. Compared with classical techniques

Table 4.6: UIEDP : Mean value of Evaluation Metrics and Standard deviation.

Method	PCQI	UCIQE	UIQM	IE
HFM [1]	1.10	1.15	2.96	6.42
PCDE [12]	1.03	1.12	2.98	6.39
Retinex-based [6]	1.26	0.58	4.67	7.62
Fusion-based [11]	1.22	1.14	2.94	6.64
CCL-Net [47]	1.18	1.08	3.50	6.80
Proposed	1.27	1.20	4.73	7.82
Proposed (Mean $\pm \sigma$)	1.27 $\pm$ 0.11	1.20 $\pm$ 0.25	4.73 $\pm$ 0.14	7.82 $\pm$ 0.41

Table 4.7: EUVP: Average value of Evaluation Metrics and Standard deviation.

Method	PCQI	UCIQE	UIQM	IE
HFM [1]	1.12	0.57	3.90	6.43
PCDE [12]	1.11	0.52	4.13	6.22
Retinex-based [6]	1.16	0.62	4.26	6.63
Fusion-based [11]	1.10	0.61	3.71	6.25
CCL-Net [47]	1.13	0.60	3.60	6.42
Proposed	1.25	0.69	4.70	6.85
Proposed (Mean $\pm \sigma$)	1.25 $\pm$ 0.15	0.69 $\pm$ 0.16	4.70 $\pm$ 0.37	6.85 $\pm$ 0.23

Table 4.8: Ocean Dark: Mean value of Evaluation Metrics and Standard deviation.

Method	PCQI	UCIQE	UIQM	IE
HFM [1]	-	0.74	4.34	6.45
PCDE [12]	-	0.72	4.24	6.22
Retinex-based [6]	-	0.72	4.57	6.43
Fusion-based [11]	-	0.64	3.96	6.01
CCL-Net [47]	-	0.70	3.80	6.40
Proposed	-	0.79	4.60	6.75
Proposed (Mean $\pm \sigma$)	-	0.79 $\pm$ 0.15	4.60 $\pm$ 0.27	6.75 $\pm$ 0.26

such as HFM, PCDE, Retinex-based, and Fusion-based approaches, as well as the learning-based CCL-Net, the proposed method consistently outperforms others in terms of PCQI, UCIQE, UIQM, and IE. On the UIEB dataset, it achieves the highest values for all metrics, with particularly strong gains in perceptual quality (UIQM = 4.77) and image clarity (IE = 7.87). These improvements, coupled with relatively low standard deviations, indicate that the method ensures both stability and reliability across diverse underwater conditions. Similar patterns are observed in the UIEDP dataset, where the proposed method achieves a PCQI of 1.27, UCIQE of 1.20, UIQM of 4.73, and IE of 7.82, showing clear advantages in contrast preservation, natural color restoration, and overall visual quality. On the EUVP dataset, the method again demonstrates superior results with PCQI of 1.25, UCIQE of 0.69, UIQM of 4.70, and IE of 6.85, highlighting its ability to maintain perceptual balance and avoid over-enhancement compared to Retinex-based methods. For the most challenging Ocean Dark dataset, the proposed method secures the highest UCIQE (0.79), UIQM (4.60), and IE (6.75), proving its adaptability to extremely degraded low-light conditions where many baseline approaches fail.

4.3.4 Computational Performance

In addition to its improvements in visual quality, the proposed framework is computationally efficient, achieving an average processing time of 5.12 seconds per image as shown in Figure 18, outperforming other competing methods. Collectively, these findings highlight the algorithms consistent and balanced improvements across contrast, color fidelity, and perceptual clarity, while also offering faster processing. This makes the proposed method a promising and practical solution for real-world underwater image enhancement tasks where a quick response is needed.

The average computational time was measured at 5.12 seconds, corresponding to an average processing speed of 16.47 frames per second. In terms of memory usage, the enhanced image required approximately 1.50 MB, while the overall memory consumption of all associated variables was about 15.20 MB. These results highlight that the proposed algorithm is lightweight, both in terms of computational demand and memory requirements. With an average processing speed close to real-time, the method shows strong potential for practical deployment in underwater applications, such as remotely operated vehicles and autonomous underwater vehicles, where efficient image enhancement is critical under limited computational resources. The measured metrics are summarized in Table 4.9.

These results indicate that the proposed algorithm is lightweight and capable of pro-

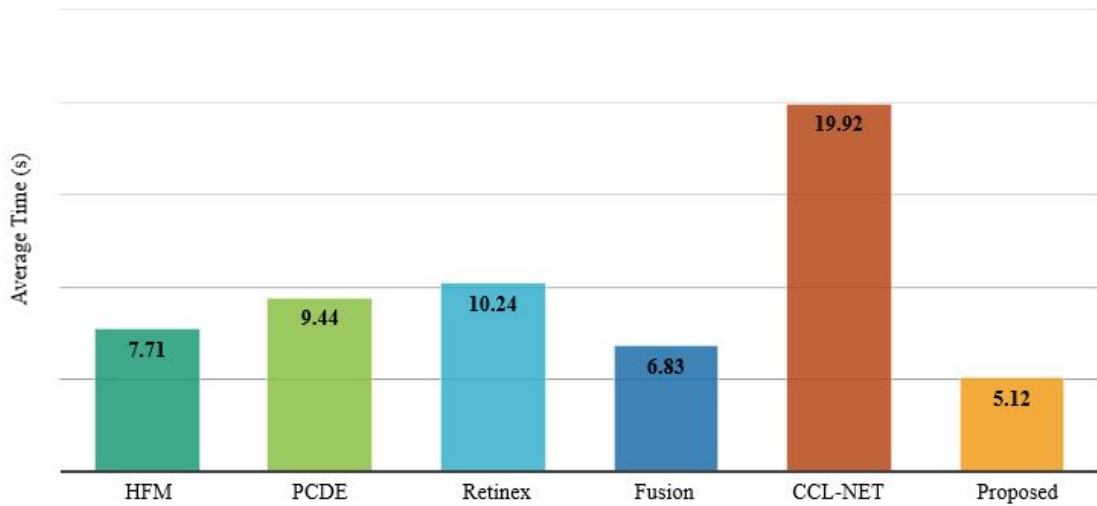


Figure 18: Average computational time.

Table 4.9: Computational Performance Metrics for Output Image

Metric	Value
Average computational time	5.12 s
Average processing speed (FPS)	16.47
Average memory usage of enhanced image	1.50 MB
Average memory usage of all variables	15.20 MB

cessing images in near real-time on a standard desktop environment.

4.3.5 Ablation Study

To evaluate the contribution of individual modules, we conducted ablation experiments under four configurations. Case 1 excludes adaptive color correction, Case 2 excludes contrast optimization, Case 3 excludes sharpening, gamma correction, and histogram stretching, while Case 4 corresponds to the complete proposed framework. The experiments were assessed using the average value of four quantitative metrics—PCQI, UCIQE, UIQM, and IE—on the UIEB [12], UIEDP [52] and EUVP [13] datasets.

Table 4.10: Ablation study results on UIEB dataset

Ablation Cases	PCQI	UCIQE	UIQM	IE
Case 1 (w/o adaptive color correction)	1.11	0.63	4.12	6.98
Case 2 (w/o contrast optimization)	1.18	0.66	4.35	7.25
Case 3 (w/o sharpening, gamma, hist. stretch)	1.22	0.69	4.55	7.53
Case 4 (Proposed framework)	1.29	0.72	4.77	7.87

Table 4.11: Ablation study results on UIEDP dataset

Ablation Cases	PCQI	UCIQE	UIQM	IE
Case 1 (w/o adaptive color correction)	1.13	0.65	4.20	7.05
Case 2 (w/o contrast optimization)	1.19	0.68	4.38	7.30
Case 3 (w/o sharpening, gamma, hist. stretch)	1.23	0.70	4.58	7.55
Case 4 (Proposed framework)	1.27	1.20	4.73	7.82

Table 4.12: Ablation study results on EUVP dataset

Ablation Cases	PCQI	UCIQE	UIQM	IE
Case 1 (w/o adaptive color correction)	1.07	0.60	4.05	6.12
Case 2 (w/o contrast optimization)	1.14	0.64	4.28	6.38
Case 3 (w/o sharpening, gamma, hist. stretch)	1.19	0.66	4.49	6.59
Case 4 (Proposed framework)	1.25	0.69	4.70	6.85

The results in Table 4.10 – Table 4.12 confirms that each module contributes to the effectiveness of the framework. Removing adaptive color correction (Case 1) causes the largest performance drop, highlighting its role in restoring natural colors. Excluding contrast optimization (Case 2) reduces perceptual quality scores, while the removal of sharpening, gamma correction, and histogram stretching (Case 3) leads to moderate declines. The complete framework (Case 4) consistently achieves the best results across all metrics, demonstrating that the integration of all components is essential for robust performance.

Chapter 5

Conclusion

The primary Objective of this research was to develop a robust enhancement system that improves the visibility, contrast, and color accuracy of underwater images while preserving essential details. This chapter summarizes the research’s key findings, contributions, and implications, acknowledges its limitations, and outlines potential directions for future research.

Clear underwater images with minimal information loss are essential for effectively exploring and extracting underwater resources. We proposed an underwater image enhancement method structured into distinct modules. The adaptive color correction module addresses color casts caused by improper lighting or camera settings, resulting in more natural and visually appealing images. Contrast optimization enhances the difference in color, providing a richer range of tones. The brightness adjustment module ensures appropriate brightness levels, avoiding underexposure or overexposure and achieving a balanced luminance that accurately reflects the scene. The sharpening step enhances edges and fine details, making the image more visually pleasant.

5.1 Concluding Remarks and Future Work

This work presents an underwater image enhancement framework that achieves a promising balance between enhancement quality and computational efficiency. Structured into distinct modules, the system applies adaptive color correction to remove color casts, contrast optimization to expand tonal range, brightness adjustment for balanced illumination, and sharpening to refine edges and details. A cost function balances enhancement with information preservation, and final histogram stretching

improves contrast and detail. The methods performance, validated through PCQI, UIQM, UCIQE, and IE metrics, shows superior results compared to existing approaches.

While effective in producing clear underwater images with minimal information loss, further optimization is possible to match or exceed the performance of the current system. Future work will focus on integrating object detection and extending capabilities to video processing for underwater surveillance and monitoring of marine life. The current experiments were conducted using offline MATLAB simulations, and performance benchmarking on embedded platforms such as NVIDIA. As part of future work, the framework will be rewritten in Python to facilitate real-time deployment and evaluation on embedded systems.

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