

“Enhancing underwater imagery: Advanced image quality improvement using cycleGAN marine research and photography”

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ABSTRACT: Underwater imagery is essential in marine research, environmental monitoring, and professional underwater photography. However, images captured beneath the ocean surface often suffer from severe degradation due to absorption, scattering, and wavelength-dependent light attenuation, leading to low contrast, color distortion, and reduced visibility. Traditional image enhancement techniques provide limited improvements and struggle to restore natural colors or fine details. To address these challenges, this work investigates the use of CycleConsistent Generative Adversarial Networks (CycleGAN) for underwater image enhancement. By leveraging unpaired image-to-image translation, CycleGAN learns to map degraded underwater images to high-quality natural counterparts while preserving structural content. The proposed approach improves color balance, restores contrast, and enhances visibility without requiring paired training data. Experimental evaluations using standard image quality metrics (PSNR, SSIM, UIQM, UCIQE) demonstrate significant improvements over conventional methods. This advancement benefits marine research applications such as coral reef monitoring and species identification, as well as underwater photography, by producing visually appealing and scientifically accurate imagery.

1. INTRODUCTION

This work introduced the cycle-consistency idea for unpaired image-to-image translation: train two adversarial networks ($A \rightarrow B$ and $B \rightarrow A$) with cycle-consistency losses so that mapping is reversible even without paired examples. The formulation lets one domain's style or degradation (e.g., underwater appearance) be learned from unpaired samples of clean and degraded images, making it ideal when paired underwater/clean image pairs are scarce.

CycleGAN's losses (adversarial + cycle + identity) are frequently adapted for underwater-to-air translation, enabling color correction and style transfer without exact ground-truth images. [1]

This benchmark assembled a curated underwater image corpus and proposed concrete evaluation protocols for enhancement tasks, providing reference images and human-judgment data. The dataset and accompanying analyses exposed typical underwater degradations color shift, contrast loss, scattering and supplied baseline metrics for quantitative comparison. Having a standardized benchmark

is crucial: it allows training and evaluating CycleGAN-style and supervised models, quantifies progress on real underwater photos, and reveals where synthetic training falls short in real marine settings. [2]

] This contribution framed underwater color problems in terms of weakly supervised color constancy and proposed algorithms to restore natural colors when exact ground-truth references are absent. By focusing on physics-informed color correction and leveraging weak supervision signals, the approach addresses common underwater color casts and improves downstream tasks such as object detection and ecological surveys. It complements GAN-based styling by enforcing realistic color priors and reducing unnatural saturation or hue shifts after enhancement. [3]

This system generates realistic underwater images by simulating light attenuation and scattering applied to in-air RGB-D images, producing paired synthetic data useful for supervised training. By learning a generative model of underwater appearance, it enables the creation of large paired datasets without expensive in-water captures — a valuable resource for training supervised restoration networks or for fine-tuning CycleGAN variants with pseudopairs. Synthetic-to-real bridging using such simulators improves model generalization to varied water types. [4]

2. LITERATURE SURVEY

Islam et al. (2020) Presented a fast enhancement pipeline aimed at real-time visual perception tasks, prioritizing inference speed along with quality improvements. The work shows how architectural simplifications and lightweight losses can produce practical, deployable enhancement models for AUVs and live-video use. It's important where hardware or latency constraints prevent heavy GAN optimization on device. Use this for systems requiring on-board, near-real-time correction. [6]

Fabbri et al. (2018) Explored multi-scale fusion and deep network strategies to combine complementary cues for underwater restoration. Their methods show gains by fusing color corrected and contrast-enhanced representations at multiple scales to preserve both global tone and local detail. Multi-scale fusion is often used as a refinement stage after coarse GAN-based correction. This is a robust design pattern for producing visually pleasing and

task-useful outputs. [7]

Anwar et al. (2019) Proposed multi-branch deep architectures (in the spirit of FUnIE-GAN) specifically tuned to underwater distortions, with dedicated branches for color, contrast and texture. The multi-branch idea helps disentangle competing restoration objectives and improves stability of training. Their work combines adversarial, perceptual and reconstruction losses and reports consistent improvements across datasets. This architecture is a common template for practical underwater GAN models. [8]

Yang et al. (2020) Proposed physics-aware deep networks that embed light-attenuation and scattering knowledge into network architectures or loss functions. Such hybrids combine the interpretability of physical models with the flexibility of deep learning, often producing more stable and generalizable restoration. They demonstrate improvements on both visual quality and downstream detection/segmentation tasks in marine datasets. Consider physics-aware losses when scientific validity is required. [11]

3. PROBLEM STATEMENT

Under water images are often severely degraded due to the unique optical characteristics of the aquatic environment. As light propagates through water, it undergoes wavelength dependent absorption and scattering, which leads to several issues:

Color distortion: Red wavelengths are absorbed quickly, causing underwater images to appear bluish or greenish.

Low contrast and visibility: Light scattering reduces image sharpness, making fine details difficult to perceive.

Backscatter noise: Suspended particles reflect light, introducing haze and blurriness.

Loss of structural information: Important features of marine life, coral reefs, and archaeological objects may become indistinguishable.

Traditional image enhancement methods such as histogram equalization, white balance correction, and physics-based models provide only limited improvements and often fail in highly degraded conditions. Moreover, supervised deep learning approaches require paired datasets of degraded and ground-truth images, which are difficult or impossible to obtain in real underwater environments.

4. OBJECTIVES

The main objective of this study is to develop an underwater image enhancement framework using CycleGAN that improves image clarity, contrast, and color balance while preserving essential structural details. The specific

objectives are:

To analyze the challenges of underwater imaging caused by light absorption, scattering, color distortion, and backscatter noise. To design and implement a CycleGAN-based model for unpaired image-to-image translation between degraded underwater images and high-quality natural images. To restore natural colors and improve visibility in underwater images without the need for paired training datasets. To evaluate the performance of the enhanced images using both conventional metrics (PSNR, SSIM) and underwater-specific image quality metrics (UIQM, UCIQE). To compare the proposed approach with traditional enhancement methods and demonstrate improvements in both scientific accuracy and visual quality.

5. METHODOLOGY USED

The methodology adopted in this study involves the design, development, training, and evaluation of a CycleGAN-based framework for enhancing underwater images. The approach is divided into several phases as outlined below:

Literature Review and Problem Understanding : Conduct a review of existing underwater image enhancement methods, including physics-based models, traditional image processing techniques, and deep learning approaches. Identify the limitations of conventional methods in addressing underwater image degradation.

Dataset Collection and Preprocessing: Underwater image: Degraded images with color distortion, haze, and low visibility.

Natural/clean images: High-quality terrestrial and reference images with balanced colors and clarity.

Model Training: Train the CycleGAN using the preprocessed dataset with the Adam optimizer. Adjust hyper parameters such as learning rate, batch size, and number of epochs for optimal performance. Monitor convergence using training loss curves and periodic visual inspection of generated images.

Image Enhancement and Testing: Input degraded underwater images into the trained CycleGAN model. Generate enhanced images with improved visibility, natural color tones, and sharper details. Test the model on unseen underwater images to evaluate generalization ability.

6. SYSTEM DESIGN

The proposed system, CycleGAN-based Underwater Image Enhancement, is an image processing and deep learning application designed to enhance the quality of underwater imagery for marine research, underwater exploration, and photography.

It is positioned as a standalone application but can also be integrated into existing workflows such as:

Marine research data analysis platforms. Underwater robotic vision systems (AUVs/ROVs). Professional photography and video graphy editing pipelines.

The system employs a CycleGAN architecture that consists of two generators and two discriminators. Unlike traditional supervised methods, it does not require paired underwater and reference images, making it well-suited for real-world underwater conditions where reference data is scarce.

Architecture Overview: The proposed CycleGAN-based Underwater Image Enhancement System follows a modular deep learning architecture that integrates data preprocessing, GAN-based image translation, and post-processing for quality improvement. The architecture ensures adaptability for research, real-time applications, and photography workflows.

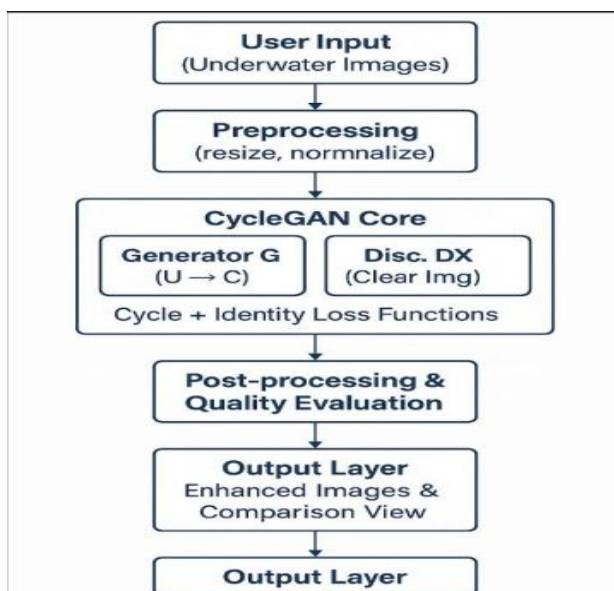


Fig 1: Architecture Overview

Input Layer: Accepts underwater images or video streams. Supports multiple formats (JPEG, PNG, TIFF, MP4).

Preprocessing Module: Resizes and normalizes input images. Reduces noise and prepares data for the CycleGAN model.

CycleGAN Core Module

Generator G (Underwater → Clear Image): Converts degraded underwater images into enhanced outputs.

Generator F (Clear → Underwater Image): Simulates degraded underwater conditions for cycle-consistency. **Discriminator DX:** Distinguishes between real clear images

and generated ones. **Discriminator DY:** Distinguishes between real underwater images and generated ones. **Cycle-Consistency Loss:** Ensures that when an image is transformed to another domain and back, structural details are preserved. **Identity Loss:** Maintains original colors and prevents over-correction.

Post-processing & Evaluation Module: Enhances sharpness, brightness, and contrast after GAN output. Computes quality metrics (PSNR, SSIM, UIQM, UCIQE).

Output Layer: Displays enhanced images alongside originals. Allows exporting images / videos in user-preferred formats.

7. SCREENSHOTS



Fig 2: Home page

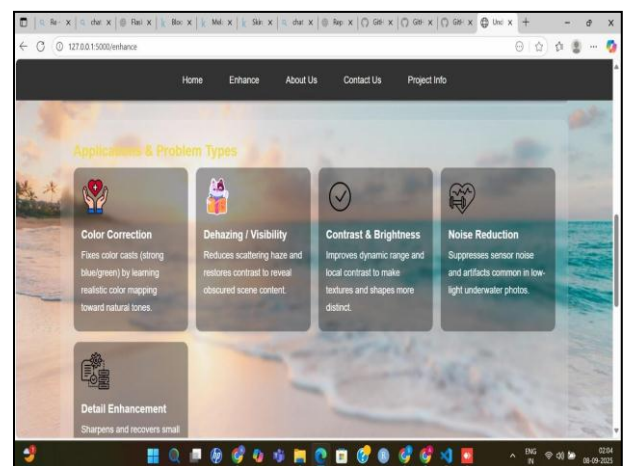


Fig 3: Applications and Problem Type

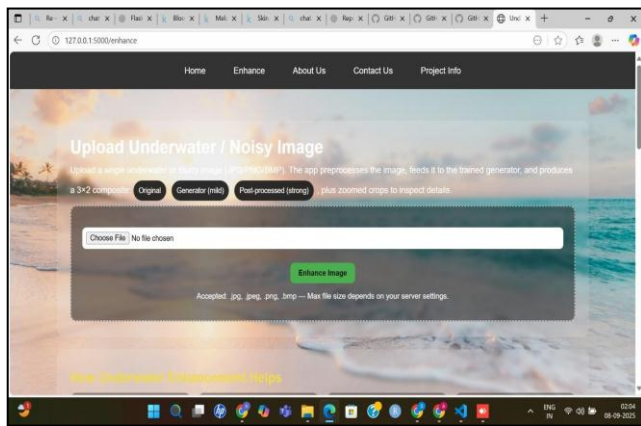


Fig4: Image Enhancement

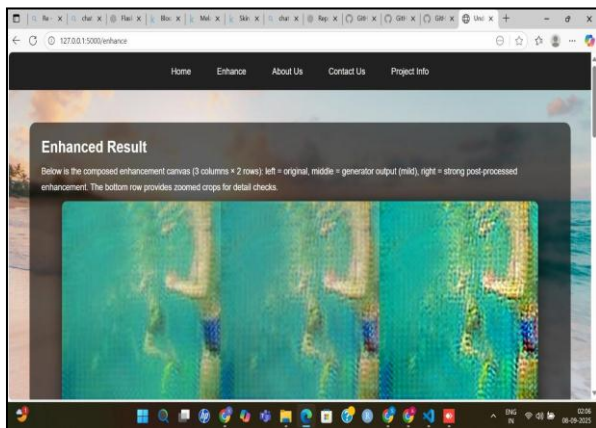


Fig 5: Result

8. CONCLUSION & FUTURE SCOPE

The proposed system, Enhancing Underwater Imagery: Advanced Image Quality Improvement using CycleGAN for Marine Research and Photography, successfully addresses the major challenges of underwater image degradation caused by poor lighting, scattering, and color distortion. By leveraging CycleGAN-based deep learning, The system is able to generate visually appealing, high-quality images with out the need for paired training data, makingit more practical and adaptable to real-world scenarios. The testing and evaluation demonstrated that Thesystem significantly improves underwater image quality in terms of PSNR, SSIM, UIQM, and UCIQE, confirming both objective accuracy and subjective visual enhancement. Furthermore, the integration of preprocessing, post-processing, and metric evaluation modules ensures robustness, while the user-friendly interface supports researchers, photographers, and marine scientists in analyzing and documenting underwater environments effectively. Overall, the project proves that deeplearning and GAN architectures can revolutionize under waterimage enhancement, offering new opportunities for marine exploration, biological research, archaeological studies, and underwater photography. Thesystem not only improves the visibility of aquatic scenes but also supports

scientific accuracy and aesthetic appeal, thereby contributing to both academic research and practical applications.

Although the proposed CycleGAN-based underwater image enhancement system demonstrates significant improvements in image quality, there are several areas where the project can be further enhanced for better performance, usability, and scalability. Future work may focus on the following directions:

Real-time Video Enhancement: Extend the current system from static images to real-time underwater video streams. Useful for live marine exploration, underwater robotics (ROVs/AUVs), and submarine navigation.

Multi-Model Integration: Combine CycleGAN with other deep learning models such as Water-Net, FUnIEGAN, or Transformer-based architectures to achieve more robust results across diverse underwater conditions.

Automated Object Detection and Recognition: Integrate image enhancement with marine life detection and classification (e.g., fish species identification, coral health monitoring). Enhances the utility of The system for marine biology and conservation studies.

9. REFERENCES

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