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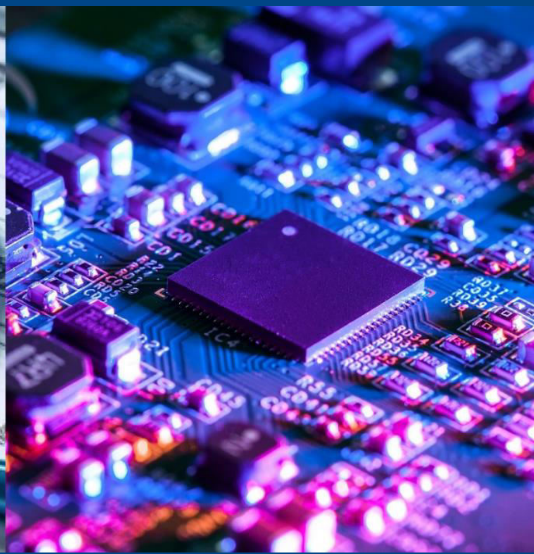

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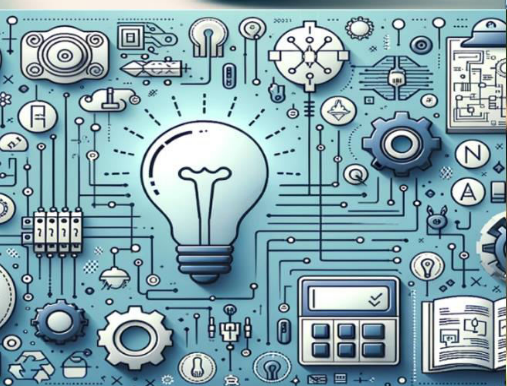

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Underwater Image Enhancement Using Deep Learning

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ABSTRACT: Color correction is vital in digital image processing, especially for improving images captured in challenging environments like underwater. It restores natural colors and enhances contrast, which is particularly beneficial for applications such as photography and marine exploration. Existing methods such as MSRCR, Gaussian Differential Pyramid, and CLAHE have drawbacks like over-saturation, artifacts, or overall quality compression. This project proposes a hybrid method combining deep learning-based techniques—U Net, GANs, Pix2Pix, DeblurGAN-v2, Deep Image Prior with traditional enhancement methods to improve color accuracy, contrast, and reduce noise.

KEYWORDS: Underwater image enhancement, color correction, detail sharpening, contrast enhancement

I. INTRODUCTION

Underwater imaging plays a crucial role in various disciplines such as marine biology, underwater archaeology, oceanography, defense surveillance, and submarine navigation. These applications rely heavily on visual data to interpret, analyze, and explore the underwater world. However, capturing high-quality images in such environments is inherently challenging due to the physical properties of water.

When light penetrates water, it undergoes significant ab sorption and scattering. Red wavelengths are absorbed first, followed by green and then blue, resulting in a bluish or greenish color cast in most underwater images. Furthermore, scattering by particles in water reduces visibility, causes haziness, and leads to severe color distortion, low contrast, and blurriness. These degradations drastically affect the performance of downstream computer vision tasks such as object detection, segmentation, and classification.

Traditional image enhancement techniques like histogram equalization, white balance correction, and gamma correction have been employed to address these issues. While these approaches offer some improvements, they are often limited in adaptability and struggle with varying underwater conditions, including lighting variability, depth, turbidity, and the presence of suspended particles. Moreover, such methods are typically rule-based and require manual tuning, which limits their scalability and effectiveness across different datasets.

With the rise of artificial intelligence, deep learning has revolutionized the field of image processing by enabling data driven models that learn complex representations directly from data. Convolutional Neural Networks (CNNs), Generative Ad versarial Networks (GANs), and encoder-decoder architectures like U-Net have shown remarkable success in enhancing underwater images by learning mappings from degraded to enhanced domains. These models not only improve visibility and contrast but also recover color information and preserve f ine details.

In this project, we propose a comprehensive underwater image enhancement pipeline that combines traditional methods like MSRCR, CLAHE, and Gaussian Pyramid preprocessing with deep learning models such as U-Net, DIP (Deep Image Prior), Pix2Pix, and CycleGAN. This hybrid approach aims to improve perceptual quality, texture sharpness, and color f idelity of underwater images while minimizing noise and artifacts. The final framework is designed for robustness and generalization, making it suitable for real-time applications in marine imaging and underwater robotics.

II. PREPROCESSING TECHNIQUES

Before applying deep learning models for enhancement, the input underwater images are subjected to several preprocessing steps to improve their baseline visual quality and to prepare them for more sophisticated processing.

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These preprocessing steps are essential to handle basic distortions, enhance contrast, and restore partial color information, which aids the deep models in learning better representations.

• **Multi-Scale Retinex with Color Restoration (MSRCR):**
MSRCR is a widely used traditional method that combines the benefits of the Retinex theory (which models human perception of color constancy) with color restoration mechanisms. It enhances local contrast while maintaining natural color balance. MSRCR works by decomposing the image into multiple scales and applying dynamic range compression, which helps restore details in both dark and bright regions. However, if not tuned properly, it may lead to over-saturation or unnatural color rendering.

• **Contrast Limited Adaptive Histogram Equalization (CLAHE):**
CLAHE improves local contrast by applying histogram equalization within small tiles of the image. It avoids the amplification of noise by clipping the histogram at a predefined limit. This method is effective in enhancing fine details and texture, especially in low-contrast areas typical of underwater environments. CLAHE preserves edge information better than global histogram equalization and is computationally efficient.

• **Gaussian Pyramid Decomposition:**
Gaussian pyramids are used to analyze the image at multiple resolutions by progressively smoothing and downsampling it. This multi-scale representation is helpful for extracting struc tural features at various levels of granularity. In our pre processing stage, Gaussian pyramids are used to suppress noise at fine scales and enhance coarse details before feeding the image into the CNN classifier. They also help in preparing the input data for multi-scale deep learning architectures like U-Net.

These preprocessing techniques serve two main purposes: (1) They provide initial enhancement to poorly captured underwater images, and (2) They help in improving the decision-making capability of the CNN classifier that deter mines whether further deep learning-based enhancement is required. By integrating both classical and adaptive techniques, the preprocessing stage creates a more robust foundation for downstream enhancement models.

III. PROCESSING TECHNIQUES

This project employs a combination of deep learning mod els, each selected based on its ability to address specific challenges in underwater image enhancement such as blur removal, color correction, contrast improvement, and texture reconstruction. The following models were integrated into the enhancement pipeline:

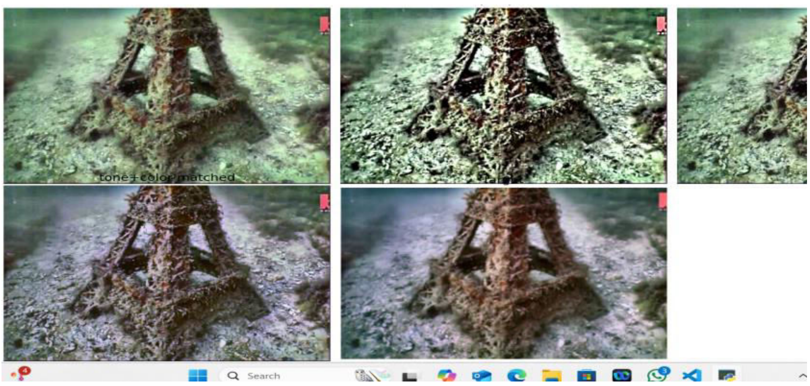
1. Convolutional Neural Network (CNN) :
CNNs are deep learning models well-suited for image classification and feature extraction tasks. In this project, a shallow CNN architecture was implemented to classify whether an underwater image, after preprocessing, still requires deep enhancement. The CNN analyzes the quality of the image and makes a binary decision: if the image is already enhanced, it is output directly; otherwise, it is passed to further enhancement modules. This intelligent quality check prevents unnecessary computation and allows the pipeline to adapt dynamically.

2. U-Net :
U-Net is a fully convolutional network designed originally for biomedical image segmentation but adapted here for im age enhancement. It follows an encoder-decoder structure, where the encoder compresses the spatial information while extracting high-level features, and the decoder reconstructs the image using these features. U-Net's unique skip connections directly transfer low-level features from the encoder to the decoder, preserving essential details like edges and textures. This architecture proves particularly effective for restoring f ine-grained structures in degraded underwater images.

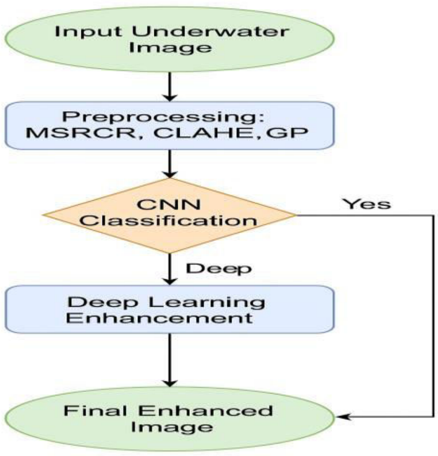
3. Deep Image Prior (DIP):
DIP is an unsupervised image restoration approach that exploits the inductive bias of convolutional networks. Unlike other models, DIP does not require a large dataset or paired training samples. Instead, it uses a randomly initialized CNN to fit the degraded image and iteratively reconstruct a cleaner version. Because it relies solely on the input image, DIP is suitable for underwater enhancement tasks where ground-truth high-quality references are not available. It is especially useful for denoising, deblurring, and minor color correction.

4. Pix2Pix

Pix2Pix is a conditional Generative Adversarial Network (cGAN) designed for supervised image-to-image translation tasks. It consists of a generator that attempts to create realistic enhanced images from low-quality inputs and a discriminator that evaluates their realism. In the context of this project, Pix2Pix was trained on paired datasets containing degraded underwater images and their corresponding enhanced versions. The adversarial training mechanism ensures that the output images are both visually plausible and structurally faithful. Pix2Pix is particularly effective when paired data is available and high perceptual quality is required



These processing techniques work collaboratively within the proposed pipeline to ensure that the final output images are visually enhanced, structurally consistent, and suitable for real world marine applications such as object detection, navigation, and environmental monitoring



User Interface for Image Enhancement:

To enhance usability and facilitate experimentation with the developed enhancement pipeline, a graphical user interface (GUI) was created using Python's Tkinter library. The GUI allows users to easily upload degraded underwater images, select enhancement methods (e.g., U-Net, DIP, Pix2Pix), and visualize both the input and output images side by side. Users can also view image quality metrics such as Image Entropy (IE), Average Gradient (AG), and UIQM computed before and after enhancement. The interface is designed to be user-friendly, with buttons for loading images, running enhancement, and saving results. Drop-down menus enable method selection, while real-time feedback is displayed using labels and image panels. This GUI not only serves as a demonstration tool for the effectiveness of the proposed system but also offers a practical foundation for deploying the solution in real-world applications, such as marine exploration systems and underwater drones

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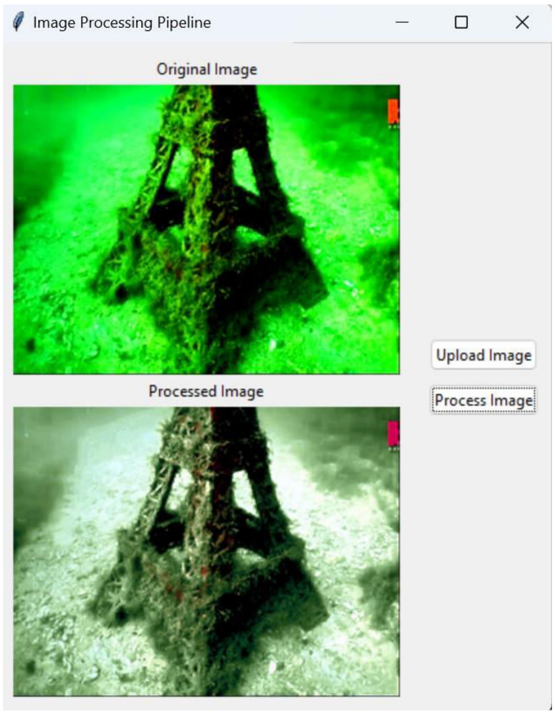

IV. DATA PREPARATION

For training and evaluating the deep learning-based under water image enhancement models, a publicly available dataset was sourced from Kaggle, which includes paired and unpaired underwater images captured under various water conditions, depths, and lighting scenarios. The dataset contains images with typical underwater distortions such as color cast, low contrast, blurriness, and particulate matter.

To ensure consistency and optimal performance during training, all images were resized to a fixed resolution of 256 ×256 pixels. Pixel values were normalized to the range [0, 1] to accelerate convergence and stabilize training. Data augmentation techniques such as horizontal and vertical flip ping, random rotations, brightness adjustments, and zooming were applied to increase the diversity of training data and prevent overfitting**.**

The dataset was then split into 80% for training, 10% for validation, and 10% for testing using stratified sampling to maintain a balanced representation of various image quality levels. For supervised models like Pix2Pix, only the paired image samples (low-quality input and corresponding ground truth) were used. In contrast, unpaired models like CycleGAN (optional for future extension) or unsupervised methods like DIP were trained directly on the distorted input images.

All preprocessing and augmentation steps were automated through Python scripts using libraries such as OpenCV, Ten sorFlow, and Keras, ensuring reproducibility and uniformity across experiments. This prepared dataset provided a robust foundation for training U-Net, DIP, and Pix2Pix models to effectively learn the underlying transformations required for underwater image enhancement.

V. IMPROVEMENT AS PER REVIEWER COMMENTS

The input to the proposed pipeline consists of raw un derwater images obtained from the Kaggle dataset, typically exhibiting severe distortions such as low contrast, blurring, color cast, and poor visibility. These images are passed through the enhancement pipeline that includes preprocessing and deep learning-based models like U-Net, DIP, and Pix2Pix. The final output images exhibit significantly improved visual quality, with clearer textures, enhanced colors, and restored structural details.

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To evaluate the performance of the enhancement process, several quality assessment metrics such as Image Entropy (IE), Average Gradient (AG), UIQM, UCIQE, and PCQI were computed for both the original and enhanced images. The following table summarizes the comparative performance, demonstrating that the deep learning methods consistently outperform traditional approaches across all evaluated metrics.

INPUT IMAGE:

OUTPUT IMAGE:

OBJECTIVE ANALYSIS:

A. Quality Metrics Comparison

TABLE I: Metrics for Traditional Methods

Metric	Value
IE	5.23
AG	6.85
UIQM	2.34
UCIQE	1.78
PCQI	0.63

TABLE II: Metrics for Proposed Deep Learning Method

Metric	Value
IE	7.01
AG	9.23
UIQM	4.12
UCIQE	2.89
PCQI	0.89

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TABLE III: Deep Learning Metrics with Relative Changes

Deep Learning Value	Change Compared to Traditional
7.01	↑ +1.78
9.23	↑ +2.38
4.12	↑ +1.78
2.89	↑ +1.11
0.89	↑ +0.26

VI. CONCLUSION

This project presents a robust and adaptive underwater im age enhancement framework that combines traditional image processing techniques with modern deep learning models. By integrating preprocessing methods such as MSRCR, CLAHE, and Gaussian Pyramid with deep learning-based approaches like U-Net, DIP, and Pix2Pix, the system successfully restores color balance, improves contrast, and enhances texture details in degraded underwater images. Experimental results and metric comparisons confirm that deep learning methods offer significant improvements over traditional techniques in terms of both perceptual quality and quantitative scores. The hybrid pipeline demonstrates high generalization capability, making it well-suited for real-world applications in marine exploration, underwater robotics, and environmental monitoring

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