A Project Report on

"Under Water Image Restoration"

A Project Report Submitted in Partial Fulfillment of the Requirement for the Course of

Minor Project - 2 (23ECSW303)

in

6th Semester of Computer Science and Engineering

by

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June 2024

DECLARATION

We hereby declare that the matter embodied in this report entitled "**Underwater Image Restoration**" submitted to KLE Technological University for the course completion of Minor Project 2 (23ECSW303) in the 6^{th} Semester of Computer Science and Engineering is the result of the work done by us in the Department of Computer Science and Engineering, KLE Technological University's Dr. M. S. Sheshgiri College of Engineering, Belagavi under the guidance of Prof. Savita Bagewadi, Professor, Department of Computer Science and Engineering. We further declare that to the best of our knowledge and belief, the work reported here in doesn't form part of any other project on the basis of which a course or award was conferred on an earlier occasion on this by any other student(s), also the results of the work are not submitted for the award of any course, degree or diploma within this or in any other University or Institute. We hereby also confirm that all of the experimental work in this report has been done by us.

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CERTIFICATE

This is to certify that the project entitled "Underwater Image Restoration" submitted to KLE Technological University's Dr. MSSCET, Belagavi for the partial fulfillment of the requirement for the course – Minor Project 2 (23ECSW303) by Abhishek Ajatdesai , Om Kangralkar and Pratham Shinde students in the Department of Computer Science and Engineering, KLE Technological University's Dr. MSSCET, Belagavi, is a bonafide record of the work carried out by them under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any other course completion.

Belagavi – 590 008
Date :

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(Project Guide)	(Course Coordinator)

Dr. Rajashri Khanai
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Chapter 1

Introduction

1.1 Background

In ocean engineering, Underwater images have large scope in various research work. As we move deeper into the ocean Blurriness gets increased and Colours gets degrade gradually depending on wavelength. Blue and green light reaches depth compared to red and orange. Thus, underwater images have appeared in bluish-green. under water image restoration helps to achieve clear and natural-looking image that reflects the true underwater scene.

1.2 Problem Statement

Underwater images often suffer from blurriness and color degradation (bluish-green) as depth increases. Underwater image restoration aims to produce clear and natural-looking images that accurately reflect the true underwater scene.

1.2.1 Objectives

1. To Reduce haze and scattering effects that obscure details, leading to a clearer image. millets along with their recipes.

2. To Correct the dominant blue/green color cast caused by light scattering and restore a more accurate and balanced color representation of the underwater environment.

Stream : AI/ML
Problem Statement :Underwater images often suffer from blurriness and color degradation (bluish-green) as depth increases. Underwater image restoration aims to produce clear and natural-looking images that accurately reflect the true underwater scene.

Objective	Subject	CO
Restore images such that it accurately reflects the true underwater scene.	ML	Building ML model for Improving Visibility and Enhanced Color Fidelity of greenish-blue image.
Plot graph for restored image metrics - PSNR, SSIM values.	EDA	Analyze the quality of restored image metrics - PSNR, SSIM values.

Figure 1.1: Objectives mapping with subjects

FIGURE 1.1: Caption

Chapter 2

Literature Survey

Peng *et. al.*, [1] Underwater Image Enhancement (UIE) methods are divided into visual prior-based methods, physical models, and data-driven methods. Visual prior-based methods focus on adjusting pixel values to achieve clearer images, using approaches such as contrast adjustment, histogram equalization, and white balance. For example, underwater images can be enhanced by applying contrast adjustment and adaptive histogram equalization in both RGB and HSV color spaces. Fusion-based methods integrate multiple traditional techniques, combining white balance and global contrast adjustments. Retinex-based methods involve color correction and enhancement processes. Utilizing color spaces such as LAB, LCH, and RGB—chosen for their beneficial properties—has proven effective, achieving high PSNR scores.

Chai *et. al.*, [2] propose a method for underwater image restoration in their paper. This method tackles image degradation caused by light behavior in water. It's unique because it doesn't require training data. The approach breaks down an underwater image into key components like scene radiance and light transmission. These components are then reassembled using a self-supervised technique. This eliminates the need for vast datasets typically required for training. However, the paper doesn't discuss potential limitations, which are important for real-world application.

Hao *et. al.*, [3] address color degradation, haze, and blur in underwater images through a "Two-Stage Underwater Image Restoration Algorithm." Their method tackles these issues, caused by light behavior in water, using a two-part approach. First, a model and a special network generate paired training data of degraded and clear underwater images. Second, a detail-preserving restoration network, trained with causal interventions, removes unwanted features for sharper results. While promising for real-time restoration, the paper doesn't discuss potential limitations like computational cost or effectiveness in various underwater environments.

Kuan *et. al.*, [4] offers a significant advancement in underwater image restoration through a novel algorithm that integrates multiple theoretical frameworks. By combining the Jaffe-McGlamery and Lambertian systems into a simplified image formation model, the authors employ Retinex theory to compensate for light source attenuation. The methodology includes an improved scene depth estimation technique for better background extraction and an ensemble color gain to correct color deviations. This integrative approach demonstrates qualitative and quantitative superiority over existing methods across diverse datasets, enhancing the visual quality of underwater images significantly. However, the paper does not discuss potential limitations, such as varying underwater conditions, computational complexity, and real-time application robustness. Addressing these limitations is crucial for future research and practical implementation. Overall, Kuan et al.'s study contributes a promising framework for underwater image processing, providing a foundation for further exploration and improvement in the field.

Shuai *et. al.*, [5] This paper introduces a new image restoration technique specifically designed for underwater robotics, aimed at improving image quality by tackling common underwater imaging challenges. The technique leverages a combination of well-established algorithms and advanced color correction methods to yield clearer and more accurate visual data, which is crucial for marine exploration and research. Demonstrating its practical application in real-world scenarios, this methodology highlights significant potential benefits. However, it is important to note that a thorough evaluation of the system's limitations is still needed and should be the focus of future research.

Kis *et. al.*, [6] This paper presents an innovative approach to underwater image restoration that enhances local feature matching, a key component for computer vision tasks such as SLAM. The proposed method builds on the dark channel prior (DCP) and incorporates a simple yet effective color correction, followed by the estimation of transmission and backscattering light using a simplified optical model. The technique offers notable improvements in contrast and color fidelity, which are critical for the performance of underwater applications. Despite its promising results, the paper does not address the limitations of the approach, suggesting an area for future research. Extensive experiments, particularly in local feature matching with the ORB operator, demonstrate the method's competitive performance

Liu *et. al.*, [7] aims tointroduce a parallel computing approach that adapts the traditional serial model of underwater image restoration to be compatible with CUDA, resulting in a 14-fold speed increase. This technique enables real-time image restoration with effects comparable to existing algorithms. While the method shows significant performance improvements, the paper does not address its specific limitations, which would be beneficial for future research and practical applications in underwater imaging.

Gong *et. al.*, [8]The paper tackles the challenges of color distortion and blurred details in underwater images caused by light attenuation in different bands. The authors propose a novel method that leverages Monte Carlo simulations and experimental measurements to analyze the polarization characteristics of light transmission across various wavelength bands. This methodology involves fusing polarization images with intensity images to improve exposure in low-brightness areas and correct color distortion. Additionally, the approach employs the dark channel prior principle to deblur and enhance the images. While this method effectively compensates for color distortion and enhances the visibility of underwater targets, the paper does not address its limitations, which would be important for future research and applications in underwater imaging technology.

Lu *et. al.*, [9] explores the challenges and solutions in underwater image processing, crucial for resource exploration and environmental studies. The authors survey state-of-the-art deep learning methods for image enhancement, focusing on issues such as absorption, scattering, and color distortion. These advanced techniques for dehazing and color correction are essential for achieving clear and accurate underwater imagery. The methodologies discussed show significant promise for practical applications, including microscopic detection and autonomous vehicles, by improving image clarity and color accuracy. However, the paper does not explicitly state the limitations of these methods. Potential challenges include the complexity of the algorithms and the requirement for large datasets to train the deep learning models. Despite these limitations, the paper underscores the transformative potential of deep learning in underwater image processing, offering valuable insights for future research and technological development in this field.

Dudhane *et, al.,* [10] tackles the intricate challenge of underwater image restoration by introducing a novel end-to-end deep network aimed at correcting distortions from light scattering, color attenuation, and object blurriness. The methodology includes a channel-wise color feature extraction module and a dense-residual feature extraction module, complemented by a custom loss function that preserves structural details and enhances edge information. This approach provides substantial benefits, such as the ability to produce high-quality restorations of real-world underwater images, surpassing current state-of-the-art methods. Nevertheless, the paper does not address the network's performance under varying underwater conditions, which could be a potential limitation and warrants further investigation. Despite this, the proposed technique represents a significant advancement in underwater image restoration, offering promising results and paving the way for future research in this field.

Chapter 3

Design Space

BP 1.1 : It is based on the understanding of the problem. The problem space refers to the scope and boundaries of the issue that the project aims to address. Our problem space of our project follows: Data collection, data preprocessing, GAN (Generative Adversarial Network)model training, Underwater Image restoration and evaluation.

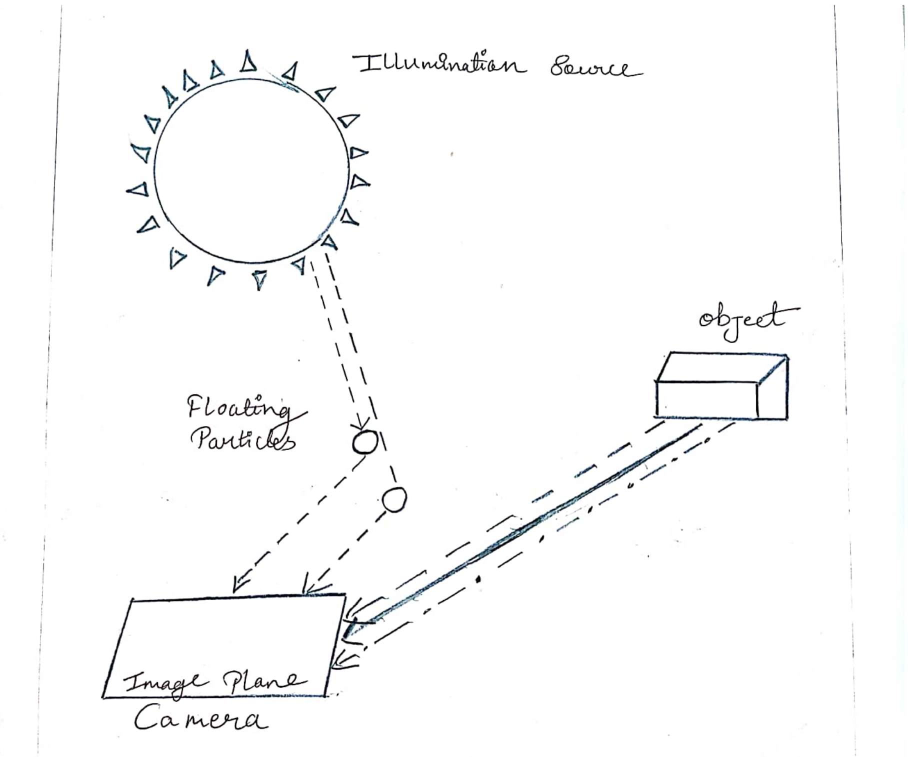

FIGURE 3.1: Understanding the problem

Internal Factors And External Factors

Internal Factors are:

1. Camera settings: Factors like aperture, sheeter speed, Iso can influence the amount of light Captured overall image quality. Underwater, specitic settings might be needed to Compensate for low light color cast.
2. sensor characteristics: The type of camera sensor its sensitivity to different wavelengths of light can impact the final image. Sensor less sensitive to blue light might struggle underwater.

3.Image Noise: Noise introduced during image Captures can furter degrade the quality underwater, making restoration more challenging.

4. White balance: Incorrect white balance settings can read to inaccurate colour representation in the Captured image Underwater. Automatic white balance might struggle with the dominant blue light

External Factors are :

1. water depth: As Depth increases, light gets absorbed and scattered, leading to the bluish - green and loss of color detail. Restoration needs to account for the level attenuation.

2. waver quality: The clarity of the water directly impacts image quality. Turbidity caused by suspended particies can further blur the image and necessitate stronger restoration techniques.

3. Lighting conditions: The type of underwater light Source (natural or Artifical) and its color spectrum influence the captured image. Restoration might need to adjust based on the dominant light source.

4. presence do particles: Microscopic organism or suspended particles in the water can cause scattering and haze, reducing image clarity Restoration algorithms might need to address this scattering effect.

BP 1.2 : This tells flow of the problem. It means that, here it is defined picture of the problem and how solution cam be implemented in different modules with relationship with different features. Modules is shown below

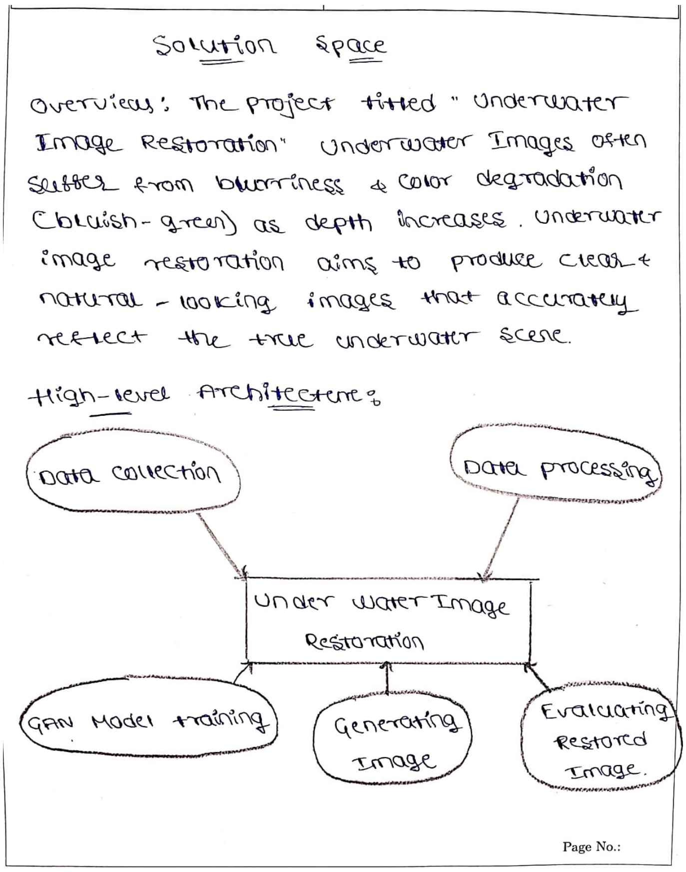

FIGURE 3.2: Solution space

(a) Data Collection: Collecting LSUI (Large Scale Underwater Image) dataset.

(b) Data pre-processing: Standardizing Image Size to 256x256 and Normalization pixel values between 0 and 1.

(c) GAN Model training: GAN (Generative Adversarial Network) model training on LSUI dataset.

(d) Underwater Image restoration : Building Generator model for reconstructing image.

(e) Discriminator: Distinguishing real and fake images using PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index Measure) metric.

Chapter 4

System Modeling

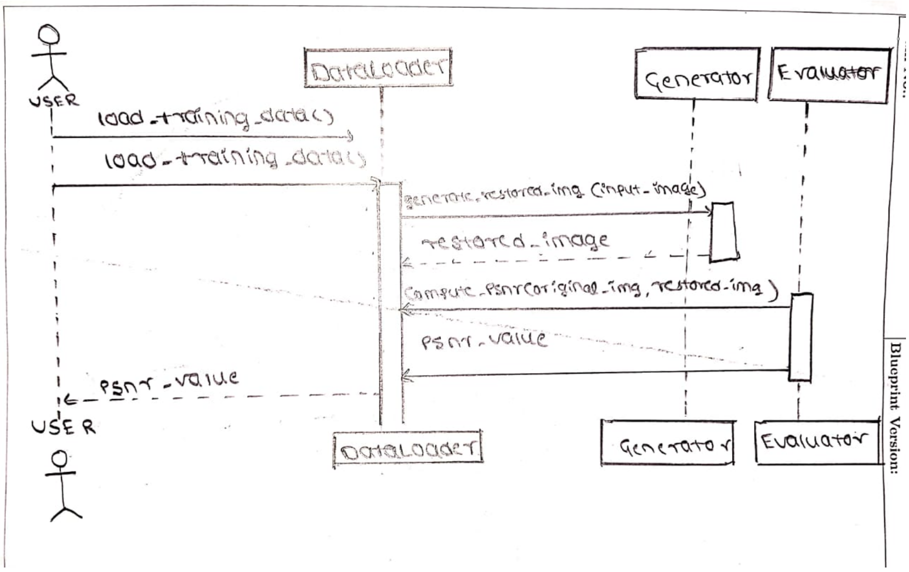

FIGURE 4.1: Sequence diagram

The sequence diagram depicts the interaction between four components:

User: The user is responsible for loading the training and testing data.

Dataloader: The dataloader is responsible for loading the image and feeding it into the model.

Generator: The generator is the deep learning model that is responsible for restoring the underwater images.

Evaluator: Evaluates the performance of the model on the testing data.

 Chapter 4 System Modeling

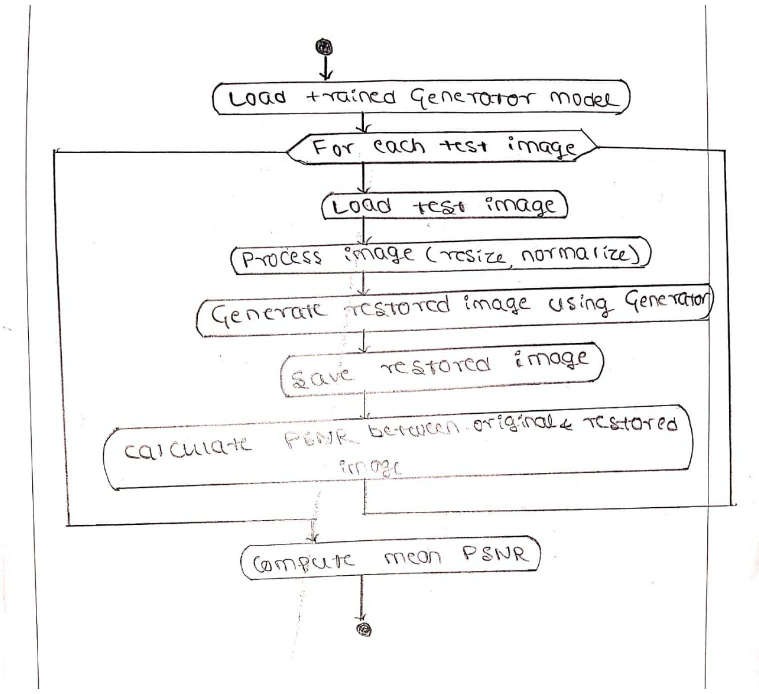

Figure 4.2: Activity diagram

Load Trained Generator Model: In this step, generative model is loaded, which will be used to restore the underwater images.

Preprocess Image (resize, normalize): Standardizing Image Size to 256x256 and Normalization pixel values between 0 and 1

Generate Restored Image using Generator: The preprocessed test image is then fed into the generative model, which generates a restored version of the image.

Calculate PSNR between Original and Restored Images: The PSNR (Peak Signal-to-Noise Ratio) is calculated between the original and restored image. PSNR is a common metric used to assess the quality of the restored image. Higher PSNR values indicate better restoration quality.

Compute Mean PSNR: Once all the test images have been processed, the average PSNR across all the test images is computed.

Chapter 5

Implementation

The implementation of the Underwater Image Restoration system utilizes Python for the backend, Flask for the frontend, and a Generative Adversarial Network (GAN) model for image generation. The GAN model, trained using the LSUI dataset, generates restored images through a generator. The quality of these restored images is then evaluated by a discriminator using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) metrics.

Underwater Image Restoration interface consist of Image Image Upload section where user upload Underwater Image (Bluish-green) to be restored and then model generate restored image with PSNR and SSIM values and plot image similarity graph.

5.1 Output:

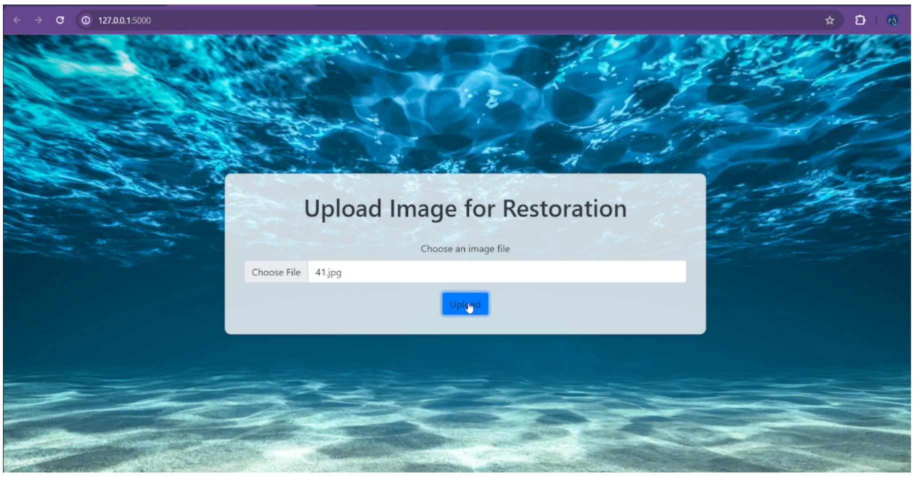

FIGURE 5.1: home page

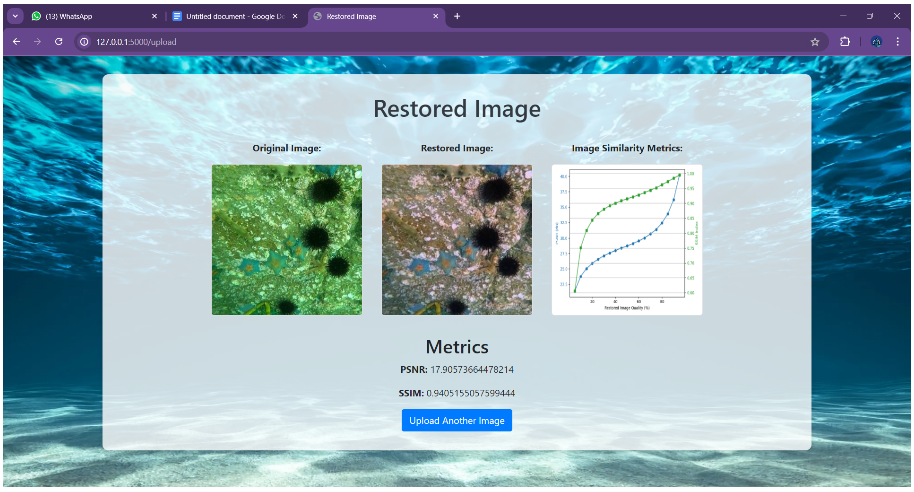

FIGURE 5.2: Result page

5.2 Test cases

Underwater Image Restoration Testcase

ID	Description	Expected Result	Actual Result	Result
TC001	Upload a valid image file and check restoration	Image is uploaded successfully, and restored image is displayed with correct PSNR, SSIM values.	Image uploaded successfully, restored image displayed, and metrics calculated correctly.	Pass
TC002	Upload an invalid file type (e.g., .txt)	Error message indicating invalid file type.	Error message displayed indicating invalid file type.	Pass
TC003	Upload a very large image file	Image is uploaded and processed within reasonable time.	Image uploaded and but not processed within reasonable time.	False
TC004	Upload image with no file selected	Error message indicating no file selected.	Error message displayed indicating no file selected.	Pass
TC005	Refresh page after uploading an image	Page is refreshed and user can upload a new image.	Page refreshed successfully, and user can upload a new image.	Pass
TC006	Upload image when server is down	Error message indicating server is unavailable.	Error message displayed indicating server is unavailable.	Pass

Chapter 6

Conclusion

This project successfully implemented the Underwater Image Restoration system using GAN (Generative Adversarial Network) model architecture. The model was able to generate restored images through a generator model and evaluated the quality of restored images using PSNR (Peak Signal-to-Noise Ratio) and Structural Similarity Index Measure (SSIM) metrics.

The system is built with Python for backend processing and Flask for the frontend interface. It leverages the capabilities of a GAN model trained on the LSUI dataset to produce high-quality restored images from underwater scenes. Ensuring that the images maintain high fidelity and structural integrity. This comprehensive approach highlights the effective integration of advanced machine learning techniques with web-based deployment, making the system robust and user-friendly for underwater image restoration tasks.

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