School

of

Electronics and Communication Engineering

Mini Project Report

on

Underwater Image Enhancement Towards NeRF based 3D Reconstruction

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Semester: V, 2023-2024

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2023-2024

SCHOOL OF ELECTRONICS AND COMMUNICATION ENGINEERING

CERTIFICATE

This is to certify that project entitled **"Underwater Image Enhancement towards NeRF based 3D Reconstruction"** is a bonafide work carried out by the student team of **"Vijeta V Shettar (01FE21BEC156), Anushka Chaurasia (01FE21BEC167), U K Samarth (01FE21BEC126)"**. The project report has been approved as it satisfies the requirements with respect to the mini project work prescribed by the university curriculum for BE (V Semester) in the School of Electronics and Communication Engineering of KLE Technological University for the academic year 2023-2024

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ACKNOWLEDGMENT

The project UNDERWATER IMAGE ENHANCEMENT TOWARDS NeRF-based 3D RECONSTRUCTION has become successful with the kind support and help of many individuals. We the team under the Centre of Excellence in Visual Intelligence[CEVI] extend our sincere thanks to each one respectfully. The team expresses its deepest gratitude to all the people who have assisted us in the process of completion of this project. All their contributions are deeply appreciated and acknowledged. The team would like to place on record our deep sense of respect to Suneeta V Budihal, Head of the Department of the School of Electronics and Communication for allowing extending our skills in the direction of this project. The team expresses heartfelt gratitude to our guides Uma Mudenagudi and Ramesh Ashok Tabib, whose valuable insights proved to be vital in contributing to the success of this project.

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ABSTRACT

In this project, we present a method for the enhancement of images captured underwater. It becomes uneasy for human eye visualization due to various water parameters. When it comes to the real-time application of an underwater image enhancement method, the basic expectations like increased clarity, color correction, reduced backscatter, sharpening of edges, noise reduction, contrast adjustment, visually appealing enhanced image, etc are to be met. The existing methods concentrate on the accuracy of enhancement by using a waternet model which is a pre-trained Convolutional Neural Network(CNN) model used to improve the visibility, and clarity of underwater images It tackles the challenges caused by light scattering, color distortion, and limited visibility, resulting in enhanced images with sharper details, richer colors, and reduced haze.

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Chapter 1

Introduction

Underwater photography is difficult due to water effects such as attenuation and backscattering, which dramatically alter the color and quality of an image.Underwater photos frequently degrade due to the water column's influence on underwater light propagation. In underwater conditions, absorption leads to wavelength-dependent attenuation, which causes color distortion in the image. Backscattering creates a hazy impression throughout the area, similar to fog in the air. Furthermore, there is frequently a lack of ground truth regarding the color and structure of underwater images. These characteristics make underwater image restoration and complex scene reconstruction an ill-posed problem.

In this work, we started by enhancing underwater images with specialized procedures to improve clarity and color accuracy. After being adjusted, these enhanced images were used as input data for a Neural Radiance Fields (NeRF) model. We hoped to achieve a more exact and visually accurate depiction of underwater sceneries in a continuous 5D space by putting enhanced underwater images into the NeRF model. This joint method aimed to improve both the quality of underwater images and the accuracy of 3D scene reconstructions, resulting in a more complete understanding of underwater habitats.

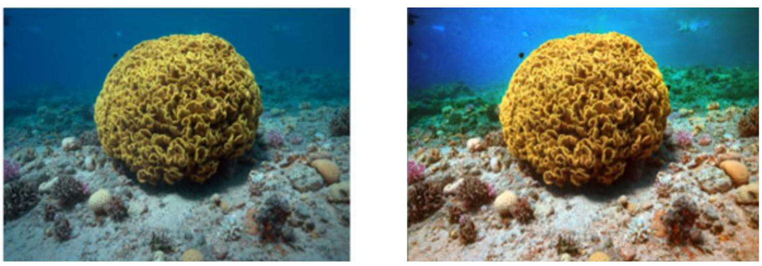


Figure 1.1: a)Original image b)Enhanced image

Nerf uses deep neural networks to create new views of complex scenes. The model takes the 3D position vectors of the objects from different viewpoints and the 2D viewing direction as input. By using a series of images taken from different angles, the neural network can create new views of the scene that look realistic This is an advanced technique which is introduced in 2020 by Ben Mildenhall, (at Google research) which produces better images than classical methods(sparse reconstruction).

Sparse reconstruction is a traditional method that refers to the process of reconstructing a 3D scene or object from a sparse set of input data points, derived from various sources such as 2D images, depth sensors, or other types of sensors. The drawback of sparse reconstruction is that it does not accurately reconstruct the complete 3D structure of an objective scene because it uses only a limited number of input points.

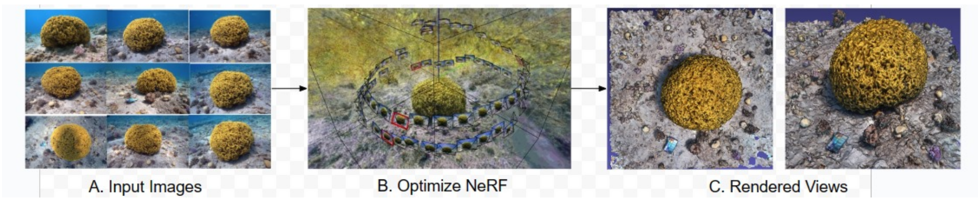


Figure 1.2: Overview of NeRF process

A stationary scene is represented as a continuous 5D function that outputs the radiance emitted in each direction (θ,ϕ) at each point (x, y, z) in space, as well as a density at each point, which acts as a differential opacity controlling how much radiance is accumulated by a ray passing through (x, y, z). Our method optimizes a highly connected neural network without convolutional layers (referred to as a multilayer perceptron or MLP) to represent this function by regressing from a single 5D coordinate (x, y, z, θ, ϕ) to a single volume density and view-dependent RGB color.

1.1 Motivation

The motivation for underwater image enhancement arises from the challenges that are presented by the underwater environment, where images frequently suffer from haze, color distortion, low contrast, and loss of human perception owing to light dispersion and absorption. Light absorption and scattering in water, particularly attenuation of distinct wavelengths, causes color distortions and limited visibility. These limitations not only compromise the integrity of scientific study, but they also have an impact on the use of computer vision in underwater environments.

The goal of underwater image enhancement is to address these challenges and improve the quality of underwater images. By enhancing contrast, removing haze, restoring lost colors, and improving overall visibility and acuity, the enhanced images can provide clearer and more accurate representations of the underwater environment. Overall, the motivation behind underwater image enhancement is to overcome the inherent limitations of underwater imaging and improve the quality and accuracy of visual data captured in underwater environments.

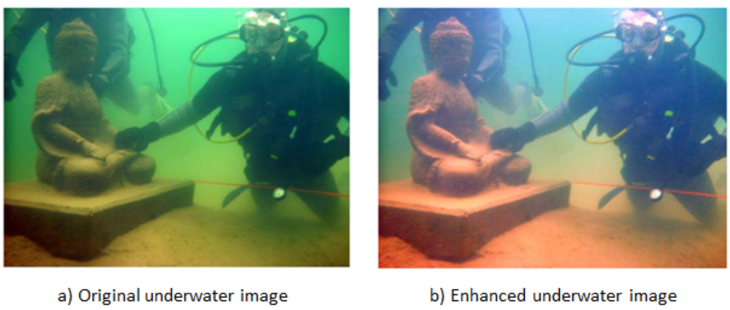


Figure 1.3: Underwater image enhancement

1.2 Objectives

1. To perform enhancement on given underwater images.

2.To use the enhanced images towards 3D reconstruction through NeRF

3.To propose an efficient and effective method for improving underwater photographs. The difficulties encountered by underwater photographs, such as haze, color distortion, low contrast, and loss of human acuity owing to light dispersion and absorption.

4. To improve underwater image visibility, color accuracy, and quality for scientific research and computer vision applications.

5. To validate algorithm effectiveness through experiments and comparisons with existing techniques.

1.3 Literature survey

1.Color Balance and Fusion for Underwater Image Enhancement(CVPR 2017)[1]
The method includes a white-balancing mechanism built specifically for underwater photos, which is critical for obtaining realistic colors.The technique uses a fusion-based boosting method to improve image edges and color contrast.

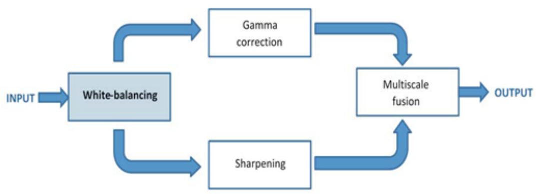


Figure 1.4: Images derived from a white-balancing of the single input, and are merged based on a multiscale fusion algorithm.

2.Underwater Image Restoration Based on Image Blurriness and Light Absorption(CVPR 2017)[2]
A technique for recovering and improving underwater images by precisely calculating scene depth, background light, and transmission maps.

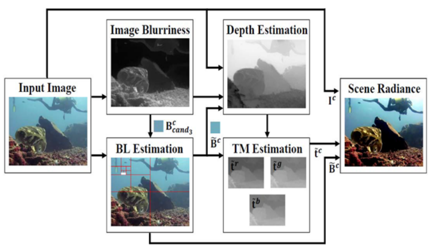


Figure 1.5: Steps of restoration method based on image blurriness and light absorption .

3. An Underwater Image Enhancement Benchmark Dataset and Beyond (CVPR 2020)[3]
The research proposes and demonstrates an underwater image enhancement model (Waternet)

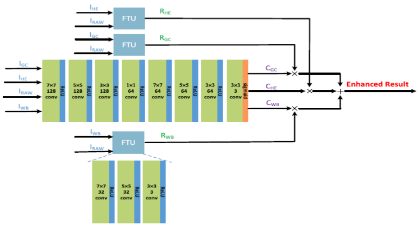


Figure 1.6: Overview of waternet architecture

trained using the constructed UIEB. The dataset can be used to evaluate existing underwater picture improvement approaches as well as train CNNs for underwater image enhancement.

4.Nerf: Representing scenes as neural radiance fields for view synthesis (CVPR 2020)[4]

A continuous scene is represents as a 5D vector- valued function which takes two input:
i) 3D location x=(x,y,z)
ii) 2D viewing direction(θ, ϕ)
The output is an emitted color $c = (r, g, b)$ and volume density σ .
Direction is expressed as 3 D Cartesian unit vector d.We use a multilayer perceptron (MLP) network, denoted as Fθ, to approximate the continuous 5D scene representation.

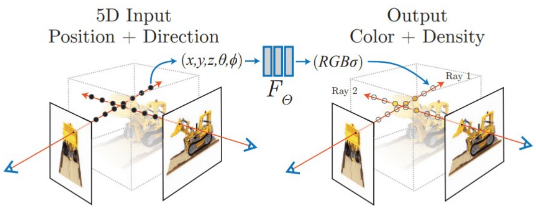


Figure 1.7: NeRF process

5.WaterNeRF:Neural Radiance Fields on Underwater Scenes(CVPR 2023)[5]

WaterNerf is a technique to addressing the issues of underwater image processing, with the authors focusing on image quality, color restoration, and image consistency. It provides a means for creating a unique vision of underwater scenes and includes a color correction capability to counteract the effects of underwater distortion.

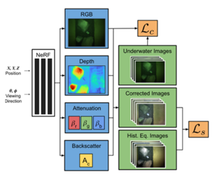


Figure 1.8: Overview of WaterNeRF framework

6.SeaThru-NeRF:Neural Radience Fields in scattering Media (CVPR 2023)[6]

This paper divides the scene into 'clean' and backscatter components, allowing for the restoration of clear views of scenes as well as the reconstruction of the appearance and depth of distant objects badly obscured by the medium.

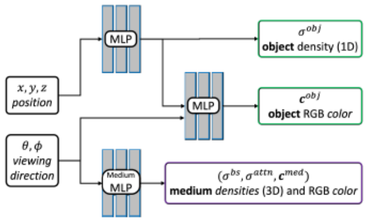


Figure 1.9: SeaThru Architecture

1.4 Problem statement

To demonstrate a learning-based architecture for the enhancement of images captured underwater towards NeRF-based 3D reconstruction.

1.5 Application in Societal Context

Enhancement of images captured underwater is one of the requirements in present societal conditions. If we can achieve a more clear vision of the underwater scenario through such learning-based models, it will be a tribute to many elements/roles of society.

Enhancement of images captured underwater and their reconstruction can have novel societal applications as follows:

1. Marine Conservation and Research.

2.Coral Reef Monitoring.

3.Underwater Surveillance for Protected Areas.

4. Naval Special Operations

a) Reconnaissance missions.

b)Underwater Infiltration.

c)Hydrographic Surveying.

d)Mine Countermeasures.

e)Counter-Terrorism Operations.

5.Scientific Exploration

Chapter 2

System design

In this chapter, we will be looking at the functional block diagram, the design alternatives, and also about the final design that is being implemented.

2.1 Functional Block Diagram

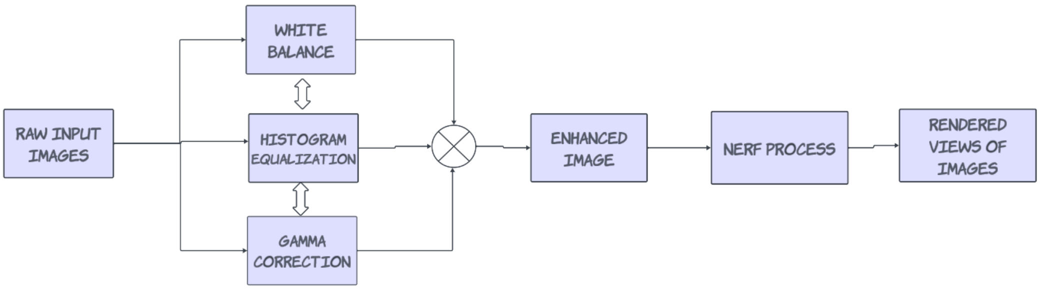


Figure 2.1: Functional block diagram for underwater image enhancement through NeRF based

2.2 Design alternatives

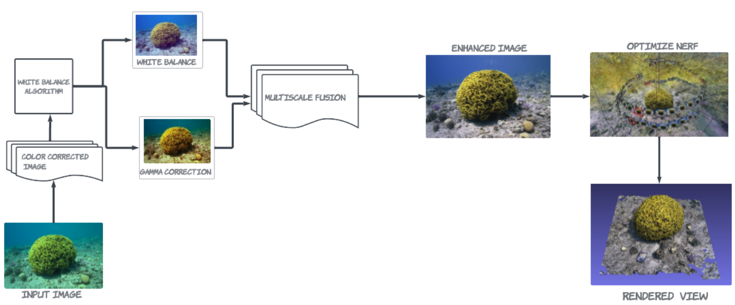


Figure 2.2: Fusion-based image enhancement model

An "Input Image," proceeds through color correction stages including "White Balance Algorithm" and "Gamma Correction," and combines the results through "Multiscale Fusion" to produce an "Enhanced Image". The final step is "Optimize NERF," which creates a detailed 3D "Rendered View" of the scene, indicating a possible application in three-dimensional modeling or visualization. An underwater scene with coral, which goes through "Image Blurriness" and

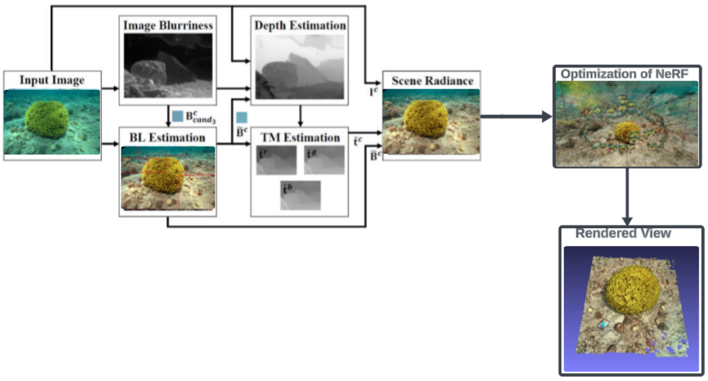


Figure 2.3: BAL-based image enhancement model

"Depth Estimation" processes. These steps lead to "BL Estimation" and "TM Estimation," resulting in a "Scene Radiance" image which appears to have enhanced clarity and detail. The process culminates in "Optimization of NeRF" (Neural Radiance Fields), which seems to refine the image further, and a final "Rendered View" is shown at the bottom right, with improved visibility and detail.

2.3 Final design

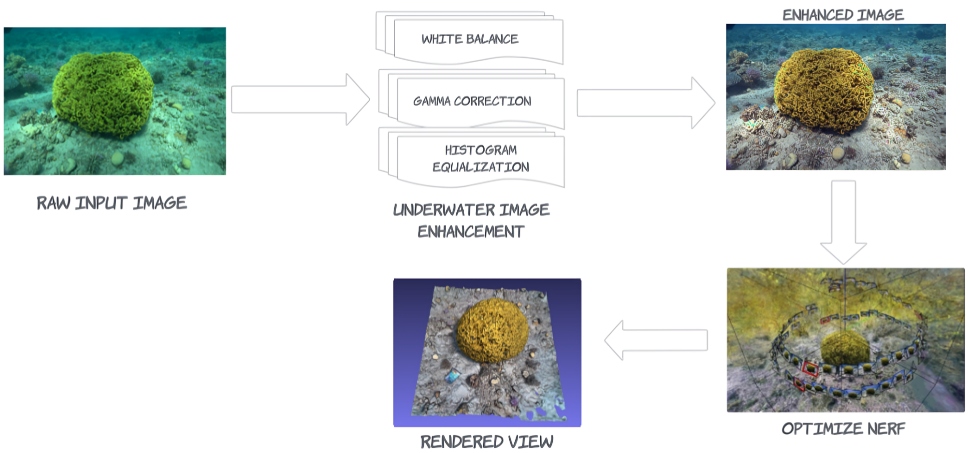


Figure 2.4: Proposed architecture

Chapter 3

Implementation details

3.1 Specifications and final system architecture

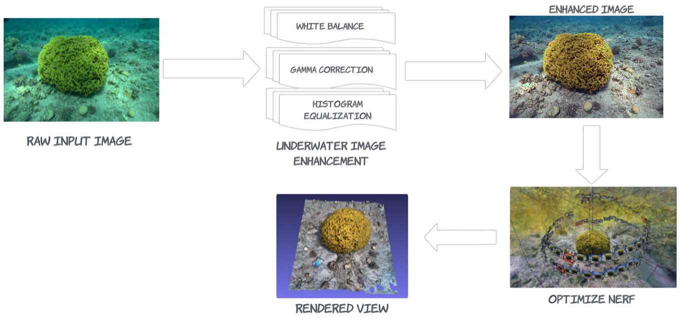


Figure 3.1: Proposed architecture

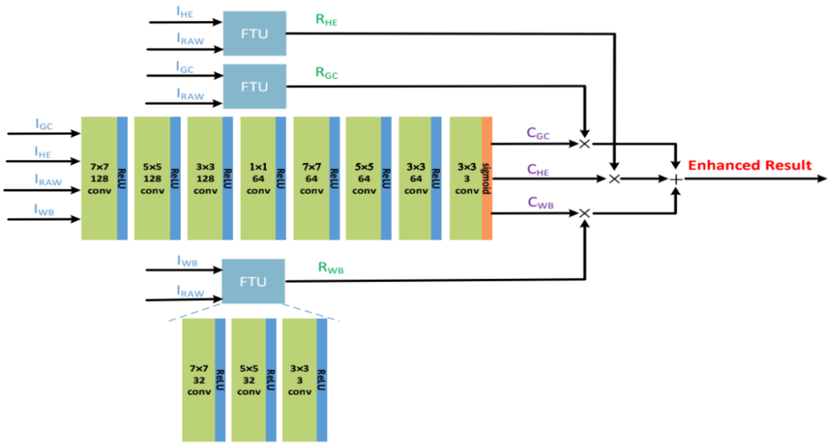
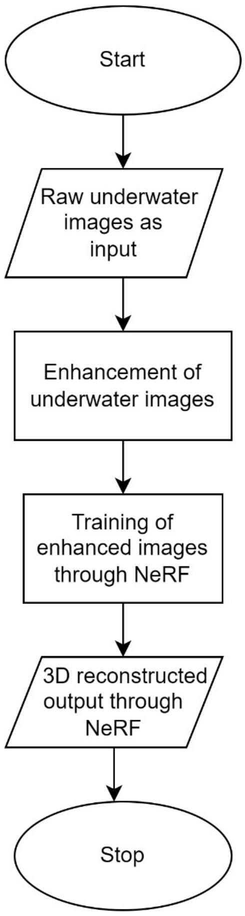


Figure 3.2: Waternet architecture

3.2 Flowchart



Chapter 4

Results and discussions

4.1 Datasets

We apply the pre-trained model for underwater picture enhancement of the dataset, which consists of five subfolders, D1, D2, D3, D4, and D5, each representing a different scene and aspect. D3 is chosen in that subfolder, consisting of 68 photographs of the reef scene, mostly because the images it contains are recorded from all angles, which is essential for the scene's 3D reconstruction.

The collection contains RAW photos (.ARW or.DEF files) and depth maps (.tif files).

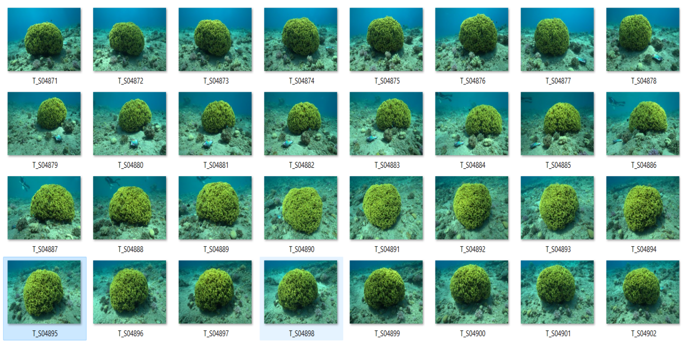


Figure 4.1: Few images from the D3 dataset

http://csms.haifa.ac.il/profiles/tTreibitz/datasets/sea$_t hru/index.html$

4.2 Evaluation metrics

4.2.1 Equations of NeRF: Volume Rendering Equation

$$C(r) = \int_{t_f}^{t_n} T(t)\sigma(r(t))c(r(t), d)\, dt$$

where:

$C(r)$ represents the expected color of the camera ray $r(t)$ passing through the scene.
$T(t)$ denotes the accumulated transmittance along the ray from t_n to t,
$\sigma(r(t))$ is the volume density at the location $r(t)$.
$c(r(t), d)$ is the view-dependent emitted radiance at the spatial location $r(t)$ and viewing direction d.

4.2.2 Loss Function:

$$L = \sum_{r \in R} (\hat{C}_c(r) - C(r))^2 + \sum_{r \in R} (\hat{C}_f(r) - C(r))^2$$

where:

R represents the set of rays in each batch.

$\hat{C}_c(r)$ and $\hat{C}_f(r)$ the ground truth,coarse volume predicted, and fine volume predicted RGB colors for ray r.

4.3 Experimental Setup

Phase I : Underwater image enhancement

We have trained the WaterNet model on an underwater dataset that has the reef scene, which has been taken from all angles. The dataset contains 68 underwater images. We trained the following model on the Google Colab platform, which uses a T4 GPU with 16 GB of VRAM. We are going to get the enhanced image dataset.

Phase II : NeRF Based 3D reconstruction

We have trained the NeRF by giving input as all enhanced 68 images and the camera pose calculation matrix calculated using COLMAP, and we have started the NeRF training using NVIDIA DGX-V100 with 32GB VRAM. The NeRF is trained until it gets overfitted from the input. The evaluation of the following NeRF model can be analyzed using the rendering process.

4.4 Experimental Results

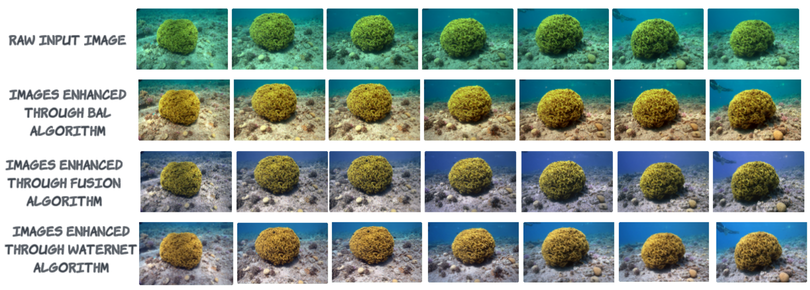


Figure 4.2: Enhanced underwater images

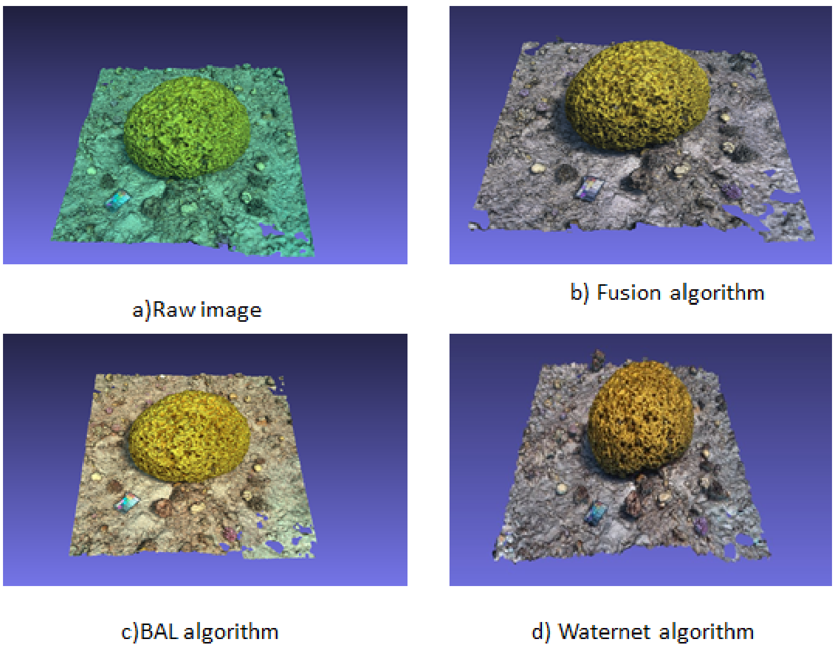


Figure 4.3: NeRF outputs

Chapter 5

Conclusions and future scope

5.1 Conclusion

In conclusion, this study explored the application of Neural Radiance Fields (NeRF) for underwater image enhancement, aiming to address the challenges posed by low contrast, poor visibility, non-uniform illumination, and color distortion in underwater environments. The experimental results demonstrated the effectiveness of NeRF in improving the visual quality of underwater images, particularly in terms of color correction, contrast enhancement, and overall clarity.

5.2 Future scope

Enhancement of images captured underwater and their reconstruction can have many future applications mainly to revolutionize marine research, environmental monitoring, and infrastructure inspection, offering unparalleled insights into underwater ecosystems. The integration of enhanced imagery with NERF's capabilities holds significant potential to reshape how we explore, protect, and harness the vast and intricate landscapes beneath the ocean's surface.

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