Underwater Image Enhancement

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Underwater Image Enhancement

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by

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based on research carried out

under the supervision of

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The undersigned, after checking the thesis mentioned above and the official record book(s) of the student, hereby states approval of the thesis submitted in partial fulfillment of the requirements for the degree of *Bachelor of Technology* in *Computer Science and Engineering* at *National Institute of Technology Rourkela*. I am satisfied with the volume, quality, correctness, and originality of the work.

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Supervisor's Certificate

This is to certify that the work presented in the thesis entitled *Underwater Image Enhancement* submitted by *Shaon Kumer Paul*, Roll Number 120CS0673, is a record of original research carried out by him under my supervision and guidance in partial fulfillment of the requirements of the degree of *Bachelor of Technology* in *Computer Science and Engineering*. Neither this thesis nor any part of it has been submitted earlier for any degree or diploma to any institute or university in India or abroad.

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Declaration of Originality

I, *Shaon Kumer Paul*, Roll Number *120CS0673* hereby declare that this thesis entitled *Underwater Image Enhancement* presents my original work carried out as a undergraduate student of NIT Rourkela and, to the best of my knowledge, contains no material previously published or written by another person, nor any material presented by me for the award of any degree or diploma of NIT Rourkela or any other institution. Any contribution made to this research by others, with whom I have worked at NIT Rourkela or elsewhere, is explicitly acknowledged in the dissertation. Works of other authors cited in this dissertation have been duly acknowledged under the sections “Reference” or “Bibliography”. I have also submitted my original research records to the scrutiny committee for evaluation of my dissertation.

I am fully aware that in case of any non-compliance detected in future, the Senate of NIT Rourkela may withdraw the degree awarded to me on the basis of the present dissertation.

May 12, 2024
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Contents

Abstract

There are numerous difficult aspects of picture improvement, including low-light image enhancement, dehazing, deraining, denoising, and many more. The improvement of underwater images is one of these difficult fields. Underwater image enhancement is a key field of research because it can improve the clarity and quality of underwater image capture. It has several uses, including search and rescue missions, scientific investigation, underwater archaeology, and marine life inspection. Low contrast, light dispersion, low light, and prolonged haziness are just a few of the difficulties this enhancement typefaces, all of which lead to poorer image quality. Recently, several attempts to improve such photos have been proposed by researchers from all over the world, some of which use deep learning techniques while others use more conventional methods. Given all the flaws, our primary contribution will be the creation of a learning-based model to improve underwater image quality and maintain the intrinsic details of the photographs. To demonstrate the effectiveness of our approach, the simulations and experimental findings will also be contrasted to benchmark modern techniques.

Keywords: *Image Enhancement; Underwater Image Enhancement; Deep Learning.*

1 Introduction

Scattering, absorption, and backscattering are common phenomena that degrade underwater photographs and can cause low contrast, color casts, and blurring. This can make extracting important information from the photos challenging, restricting their usage in various fields. The creation of innovative, effective methods for enhancing underwater photos is the main objective of this research. This project will be particularly challenging in terms of developing and putting into practice new underwater picture-enhancing algorithms that consider the underwater environment's unique difficulties.

In this research, we will assess a Deep Learning algorithm against diverse underwater photographs taken in the actual world. The experimental validation will be carried out by using a variety of actual underwater photographs from diverse sources.

1.1 Image Enhancement

Image enhancement is the process used to improve the quality of images. It aims to enhance and produce more valuable images by reducing noise, increasing contrast, and adding detail. This improves visibility, recognizes objects, and finds hidden information. In various applications, such as underwater imaging, medical imaging, and photography, image enhancement is routinely employed to create better-looking and more valuable images.
There are many kinds of image enhancements are there. Such as-
Contrast Enhancement: Makes differences in brightness or color more noticeable, improving image clarity. There are many kinds of contrast enhancement available.Un-sharp masking, contrast limited adaptive histogram equalization (CLAHE), adaptive histogram equalization, etc.
Noise Reduction: Reduces unwanted changes in pixel values, making the image smoother. Noise can caused by different factors such as sensor noise, transmission noise, etc. A few techniques are there to remove noise, like Spatial filtering and frequency domain filtering.
Sharpness Enhancement: Emphasizes edges and fine details, making objects stand out. There are many kinds of Sharpness Enhancement techniques available. Like Unsharp masking, High-pass filtering, and Deconvolution.
Brightness and Color Adjustment: Adjusts overall light, dark, and color balance for better viewing. There are different ways to adjust the brightness and color of an image, such as Using a histogram, curves, sliders, etc.

1.2 Underwater Image Enhancement

Underwater image enhancement is a set of techniques and processes to improve the quality and visibility of underwater images. Water naturally scatters and absorbs light, resulting in diminished contrast, color distortion, and blurriness in underwater photographs. Underwater image enhancement aims to improve the clarity and quality of pictures taken in watery environments.

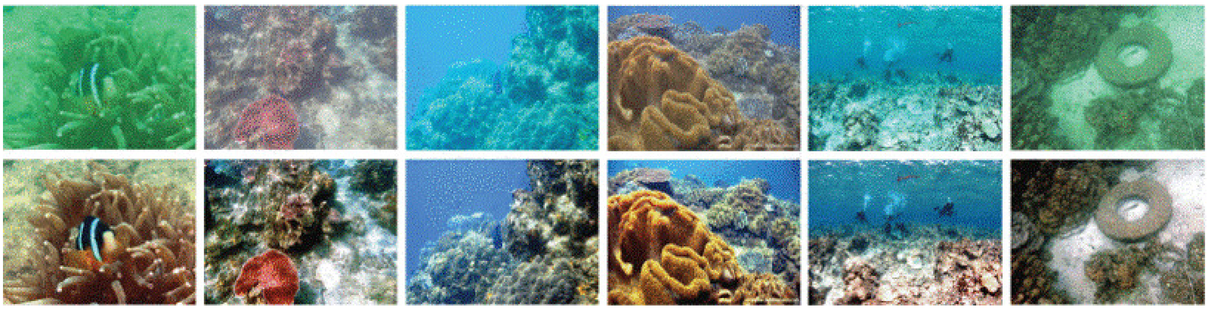


Figure 1: Underwater Image Enhancement

1.3 Application Areas of Underwater Image Enhancement

The significance of underwater image enhancement across various domains is enormous. A few application areas are-

1. Marine Biology and Ecology

2. Underwater Archaeology

3. Oceanography and Environmental Monitoring

4. Underwater Exploration

5. Underwater Robotics and Autonomous Vehicles

6. Underwater Infrastructure Inspection

7. Underwater Search and Rescue Operations, etc.

2 Research Problem

2.1 Dataset Collection Difficulties

One of the most significant challenges is acquiring a dataset of underwater images. Access to underwater environments, especially deep-sea, can be challenging and expensive. Underwater conditions vary significantly based on water type (saltwater, freshwater), depth, and location (ocean, lake, river). Collecting images that cover this wide range of conditions can be logistically complex. The equipment required for underwater photography, such as waterproof cameras and submersibles, can be expensive. Maintaining and operating these equipment in harsh underwater environments can pose technical and financial challenges.

2.2 Color Imbalance

Water absorbs the light. This makes colors less vibrant and the image less clear. So, underwater photos often look blue or green. Sometimes, the water absorbs colors differently, causing color distortion in the image. Fixing this is tricky and needs advanced techniques.

2.3 Low Light

In deeper underwater, there's less sunlight. This makes the images dark, with poor contrast and lots of noise, making it hard to see details. To brighten things up, divers often use unique underwater lights. However, handling these lights in different underwater situations can be tricky and require special skills. The underwater environment's low light levels led to an increase in noise in the underwater photos.

2.4 Diverse Underwater Conditions

Different underwater environments present unique challenges that require specific techniques to handle the situations.

2.5 Underwater Equipment Limitations

Underwater Equipment must be needed to be waterproof and capable of handling underwater pressure. Because of this, there are huge limitations in underwater equipment. And for these factors, the price of the underwater equipment is very high.

2.6 Scattering and Absorption

Water scatters and absorbs light. It causes image degradation and color distortion.

3 Research Objectives

1. to investigate cutting-edge underwater picture-enhancing methods.
2. To create a model that can efficiently improve and address the issue of color inequities and poor contrast.
3. Simulated results to demonstrate the effectiveness of our suggested model.

4 Research Questions

1. How can sight be made better in dim lighting?
2. Can underwater image enhancement techniques leverage deep learning?
3. Can underwater photographs be improved using CNN techniques?

5 Literature Review

Chen et al. proposes [1] a new method for enhancing underwater images using deep learning and an image formation model. The motivation is that images captured by underwater robots tend to have color distortion, low contrast, and blurred details due to the underwater environment. The authors first review existing approaches for underwater image enhancement, including methods based on physical image formation models and methods based on deep learning. They note that methods using physical models are often not generalizable across different underwater conditions, while deep learning methods that ignore the image formation model require complex network structures that are hard to train. Some existing deep learning methods incorporate simplified image formation models, leading to limited enhancement. The paper then discusses the optical principles behind underwater image formation, including light absorption, scattering, and refraction effects. A revised underwater image formation model proposed by Akkaynak et al. (2018) [2] is described mathematically, which accounts for different attenuation coefficients for different color channels. The new method combines this revised image formation model with deep learning for underwater image enhancement. It consists of a backscatter estimation module, a direct-transmission estimation module using dilated convolutions, and a reconstruction module, all implemented as convolutional neural networks using the parametric rectified linear unit activation. Experiments on standard underwater image datasets demonstrate the advantages of the proposed approach over existing methods in terms of visual quality, quantitative metrics like PSNR and SSIM, and computation speed. The authors show that their enhanced images also boost performance on a high-level vision task of feature point matching. In summary, this paper provides a thorough review of prior work on underwater image enhancement and motivates the need for a method combining a revised physics-based model with deep learning. The proposed architecture takes this hybrid model-guided and data-driven approach, demonstrating promising results on real-world underwater imagery.

Li, Chongyi, et al. [3] proposes a new underwater image enhancement technique, Water-Net, trained on the UIEB dataset. Regarding visual and picture quality metrics, The Water-Net operates at a cutting-edge level. The UIEB dataset is useful for developing and testing underwater image enhancement techniques. Modern underwater picture enhancement techniques can considerably improve the visual quality of underwater photographs. However, there is still room for improvement in image quality metrics.

Wheres Liu, Peng, et al. [4] evaluated the Deep Residual Framework approach on the UW-IQA dataset and contrasted it with other cutting-edge techniques. The results showed that the suggested technique delivered the best results in terms of visual quality and picture quality parameters. Images of the ocean can be effectively enhanced using the deep residual framework. The underwater image enhancement procedure performs better thanks to the residual learning module's potential to learn the residual between underwater and clear photos. Modern visual and image quality metrics can produce performance using the suggested technique.

Zhou et al. [5] suggest a multi-feature prior fusion (MFPF) based underwater image enhancement technique. This is accomplished by extracting and combining various underwater photo feature priors, such as global contrast, local contrast, saturation, and exposure. The technique also comprises gamma correction spatial linear adjustment. These methods address underwater image color cast, exposure, low contrast, and detail loss. To provide high-quality enhancements without the use of complicated underwater optical imaging models, several feature priors from a single input image are integrated as the main innovation. The paper uses a qualitative evaluation to compare the suggested MFPF method to 12 existing techniques, including model-free and model-based methods. Using representative underwater photographs that have been degraded from different datasets, the assessment entails visually evaluating the enhancement results. According to the results, the MFPF approach improves both subjective and objective enhancement effects by successfully harmonizing contrast and color while preserving the inherent qualities of the image. However, it points out that the method disregards the connection between scene depth and degradation, allowing room for potential advancements in subsequent studies. In the abstract, no precise quantitative accuracy measurements are given.

Table 1: Underwater Image Enhancement Studies

Title	**Authors**	**Publisher**	**Year**	**Type**	**Method**	**Data**
Deep Underwater Image Enhancement [6]	Saeed Anwar, Chongyi Li, Fatih Porikli	arXiv	2018	DL	CNN	Paired
Underwater image enhancement: A comprehensive review, recent trends, challenges and applications [7]	Smitha Raveendran, Mukesh D. Patil, Gajanan K. Birajdar	Springer	2021	Traditional	Polarization Difference Imaging (PDI)	Paired
Fast Underwater Image Enhancement-GAN with Enhanced Underwater Visual Perception Dataset [8]	Md Jahidul Islam, Youya Xia, Junaed Sattar	IEEE	2020	DL	CNN, GAN	Both Paired and Unpaired

Title	Authors	Publisher	Year	Type	Method	Data
A deep CNN method for underwater image enhancement [9]	Yang Wang, Jing Zhang, Yang Cao, Zengfu Wang	IEEE	2017	DL	CNN	Paired
Underwater Image Enhancement via Minimal Color Loss and Locally Adaptive Contrast Enhancement [10]	Chongyi Li, Xiaojie Guo, Chunle Guo, Xin Liang, Chuan Wang	IEEE	2022	UIE	MLLE	Paired
Underwater Image Enhancement With Hyper-Laplacian Reflectance Priors [11]	Peixian Zhuang, Xinfeng Zhang, Shuyuan Yang, Yanlong Cao, Zhenzhen Zhang, and Jiawan Zhang	IEEE	2022		Hyper Laplacian Reflectance Priors	Paired
Underwater Image Enhancement Quality Evaluation: Benchmark Dataset and Objective Metric [12]	Qiuping Jiang, Yuese Gu, Chongyi Li, Runmin Cong, Feng Shao	IEEE	2022	Traditional	deep neural network	Paired
Underwater Image Enhancement by Attenuated Color Channel Correction and Detail Preserved Contrast Enhancement [13]	Weidong Zhang, Yudong Wang, Chongyi Li	IEEE	2022	Traditional	ACCC, DPCE	Paired

Title	Authors	Publisher	Year	Type	Method	Data
Underwater Image Enhancement Method via Multi-Interval Subhistogram Perspective Equalization [14]	Jingchun Zhou, Lei Pang, Dehuan Zhang, Weishi Zhang	IEEE	2022	Traditional	Multi interval sub histogram perspective equalization (UMSHE)	Paired
Underwater image enhancement method with light scattering characteristics [15]	Jingchun Zhou, Xiaojing Wei, Jinyu Shi, Weishen Chu, Weishi Zhang	Science-Direct	2022	Traditional	LSC	Paired
Underwater Image Enhancement via Medium Transmission-Guided Multi-Color Space Embedding [16]	Chongyi Li, Saeed Anwar, Junhui Hou, Runmin Cong, Chunle Guo, Wenqi Ren	IEEE	2021	DL	Ucolor	Paired
Twin Adversarial Contrastive Learning for Underwater Image Enhancement and Beyond [17]	Risheng Liu, Zhiying Jiang, Shuzhou Yang, Xin Fan	IEEE	2022	DL	Twin adversarial contrastive learning	Unpaired

Title	Authors	Publisher	Year	Type	Method	Data
Underwater Image Enhancement Using a Multiscale Dense Generative Adversarial Network [18]	Yecai Guo, Hanyu Li, Peixian Zhuang	IEEE	2019	DL	Multiscale dense generative adversarial network	Paired
Target Oriented Perceptual Adversarial Fusion Network for Underwater Image Enhancement [19]	Zhiying Jiang, Zhuoxiao Li, Shuzhou Yang, Xin Fan, Risheng Liu	IEEE	2022	DL	Target Oriented Perceptual Adversarial Fusion Network (TOPAL)	Paired
Underwater image enhancement with global–local networks and compressed histogram equalization [20]	Xueyang Fu, Xiangyong Cao	Science-Direct	2020	DL	Global–local networks and compressed histogram equalization for underwater image enhancement	Paired
UW-GAN: Single-Image Depth Estimation and Image Enhancement for Underwater Images [21]	Praful Hambarde, Subrahmanyam Murala, Abhinav Dhall	IEEE	2021	DL	UW-GAN	Paired

Title	Authors	Publisher	Year	Type	Method	Data
LAFFNet: A Lightweight Adaptive Feature Fusion Network for Underwater Image Enhancement [22]	Hao-Hsiang Yang, Kuan-Chih Huang, Wei-Ting Chen	IEEE	2021	DL	Lightweight Adaptive Feature Fusion Network	Paired
Perceptual Underwater Image Enhancement With Deep Learning and Physical Priors [23]	Long Chen, Zheheng Jiang, Lei Tong, Zhihua Liu, Aite Zhao, Qianni Zhang, Junyu Dong, Huiyu Zhou	IEEE	2020	DL	Perceptual Enhance	Paired
UGIF-Net: An Efficient Fully Guided Information Flow Network for Underwater Image Enhancement [24]	Jingchun Zhou, Boshen Li, Dehuan Zhang, Jieyu Yuan, Weishi Zhang, Zhanchuan Cai, Jinyu Shi	IEEE	2023	DL	UGIF-Net	Paired
Benchmarking Underwater Image Enhancement and Restoration, and Beyond [25]	Guojia Hou, Xin Zhao, Zhenkuan Pan, Huan Yang, Lu Tan, Jingming Li	IEEE	2020	DL	GAN	Paired

Title	Authors	Publisher	Year	Type	Method	Data
Underwater Image Enhancement Based on Global and Local Equalization of Histogram and Dual-Image Multi-Scale Fusion [26]	Linfeng Bai, Weidong Zhang, Xipeng Pan, Chenping Zhao	IEEE	2020	Traditional	Dual-image multi-scale fusion.	Paired
An Effectual Underwater Image Enhancement using Deep Learning Algorithm [27]	G. Ramkumar, Anitha. G, Suresh Kumar M, M. Ayyadurai, Senthilkumar C	IEEE	2021	DL	UNET-UIE	Paired
An Experimental Based Review of Image Enhancement and Image Restoration Methods for Underwater Imaging [28]	Yan Wang, Wei Song, Giancarlo Fortino, Li-Zhe Qi, Wenqiang Zhang, Antonio Liotta	IEEE	2019	Experimental based review	IFM free methods, IFM based methods, Deep learning based methods.	Both Paired and Unpaired
Underwater image enhancement based on DCP and depth transmission map [29]	Haifeng Yu, Xinbin Li, Qian Lou, Chengbo Lei, Zhixin Liu	Springer	2020	Traditional	Double transmission map, Dual-image wavelet fusion	Paired

Title	Authors	Publisher	Year	Type	Method	Data
Underwater image enhancement using an edge-preserving filtering Retinex algorithm [30]	Peixian Zhuang, Xinghao Ding	Springer	2020	Traditional	Retinex model with gradient domain guided image filtering (GGF).	Paired
Learning- based approach to underwater image dehazing using CycleGAN [31]	Shima Ramesh Maniyath, K Vijayakumar, Laxman Singh, Sudhir Kumar Sharma, Tunde Olabiyisi	Springer	2021	ML	CycleGAN	Paired

6 Methodology

6.1 Basic Image Processing Tecniques

Fundamental procedures that change digital images to improve their quality, extract valuable information, or get them ready for future analysis are known as basic image processing techniques. There are numerous methods for processing images, including gamma correction, picture segmentation, image restoration, etc. Gamma correction is used to control the overall brightness of images. It is also used with photos that are found to be either bleached out or too dark. The following are some fundamental methods for image processing:

Color Correction: Color correction is an essential step in image processing that modifies an image's colors to make them appear more desired or natural. This procedure entails modifying the image's saturation, contrast, brightness, and color balance. Various methods are employed for color correcting, such as:

White balance: This method corrects an image's color temperature to get rid of unnatural color casts brought on by varying lighting.

Color Curves: By modifying the input-output mapping curves, this technique provides exact control over the tone range of each color channel (red, green, and blue).

Levels Adjustment: Using the black point, white point, and mid-tones for each color channel, this technique modifies the image's tonal range.

White Balancing using the Gray World Algorithm: One well-liked technique for automatically adjusting white balance in picture processing is the Gray World Algorithm. It is predicated on the idea that an impartial image's average color value ought to be gray. The algorithm functions as follows: Determine the mean value of the red, green, and blue color channels for every pixel in the image.

Ascertain which channel best captures the prevailing color cast by looking at its highest average value.

Divide the highest average value by the channel's average value to find the scaling factors for each channel.

To counteract the color cast, multiply each pixel value in the appropriate channel by the scaling factor.

Image Sharpening of White Balanced Image: Image Sharpening of White Balanced Image: The image may seem a little grainy or devoid of detail following white balancing. The sharpness and clarity of an image can be improved by using sharpening procedures. Unsharp masking is a well-liked technique that functions as follows:

Apply a Gaussian blur filter to the source image to make it blurry. To extract the high-frequency information (textures and edges), subtract the blurred image from the original image. Add a sharpening factor to the high-frequency details to make them more amplified. To get a sharper version, add the amplified high-frequency features back into the original picture.

Image Grayscale Conversion: Converting an image to grayscale involves averaging or applying weighted combinations to the color channels of the original color image. Images in grayscale minimize computing complexity and streamline processing.

Image filtration: Apply filters (like Gaussian or median) to minimize noise and blur the image (smoothing).

Image Thresholding: By adjusting a threshold value, a grayscale image can be transformed into a binary image. Pixels are assigned a color depending on whether they are above or below the threshold.

Edge Detection: Edge detection methods, such as the Sobel, Canny, or Prewitt edge detectors, are used to find edges and boundaries inside a picture. Edges frequently represent important characteristics in an image. Use morphological procedures to change the appearance and organization of objects in an image. Examples of these operations include dilatation and erosion. These are frequently employed for activities like object identification and noise reduction.

Image cropping: Cut off any unneeded areas of an image to concentrate on a certain area of interest. Apply filters or other methods to an image to reduce noise.

Image Compression: Use techniques like JPEG or PNG compression to lower the file size of photographs while maintaining an acceptable level of quality.

These fundamental image processing methods provide the foundation for increasingly difficult image analysis and computer vision jobs. By applying these techniques in the given order, the original image undergoes color correction, white balancing, sharpening, and contrast enhancement, resulting in an improved and visually appealing output image.

6.2 CNN Models

Convolutional neural networks (CNNs) have excelled at several image-improving tasks. The goal is to raise the standard of an image by making it more aesthetically pleasing, easier to understand, or more suitable for a given application. Because CNNs are skilled at learning intricate patterns and characteristics from huge datasets, they can be used for image-enhancing applications.

The following are some typical picture-enhancing jobs that utilize CNNs:
Image denoising: A crucial aspect of image enhancement is eliminating noise from images. CNNs can be trained to recognize the features of noise and reduce it effectively while keeping crucial visual details. This has been accomplished using a variety of designs, including U-Net, Deep Residual Networks, and even straightforward autoencoders.
Image deblurring: CNNs can be used to improve blurry photographs. The network gains the ability to restore minute features lost to blur and enhance the image's overall sharpness. CNNs can be used to remedy both defocus and motion blur.
Models like ESRGAN and SRCNN have been utilized for super-resolution tasks.
Image Contrast Enhancement: Increasing contrast can improve an image's details and visual attractiveness. CNNs may be used to manipulate contrast by learning to change pixel intensities.

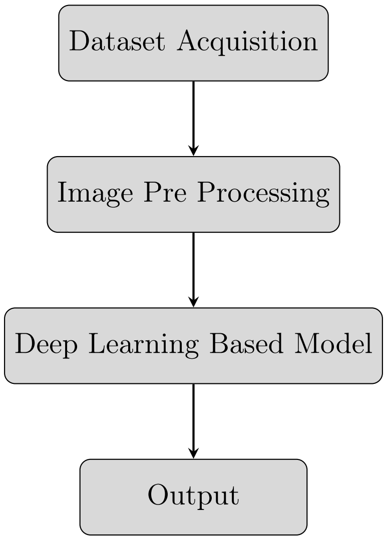
Using CNNs, one may adapt the creative style of one image to another, creating aesthetically pleasing and artistic images, even if this is not exactly a task related to image improvement. The effectiveness of CNNs in image enhancement tasks can also be increased using transfer learning and generative adversarial networks (GANs).

7 Proposed Approach

7.1 Approach

Start by gathering underwater photos. Then, pre-process the images by cleaning up the images, fixing colors, and aligning them. Then, enhance the image quality using the Deep Learning Model to make the pictures look better. Then, Fine-tune the enhanced photos if needed (post-processing). Finally, the output will be clearer and more colorful underwater images for science, research, or other uses.

7.2 Flow Chart



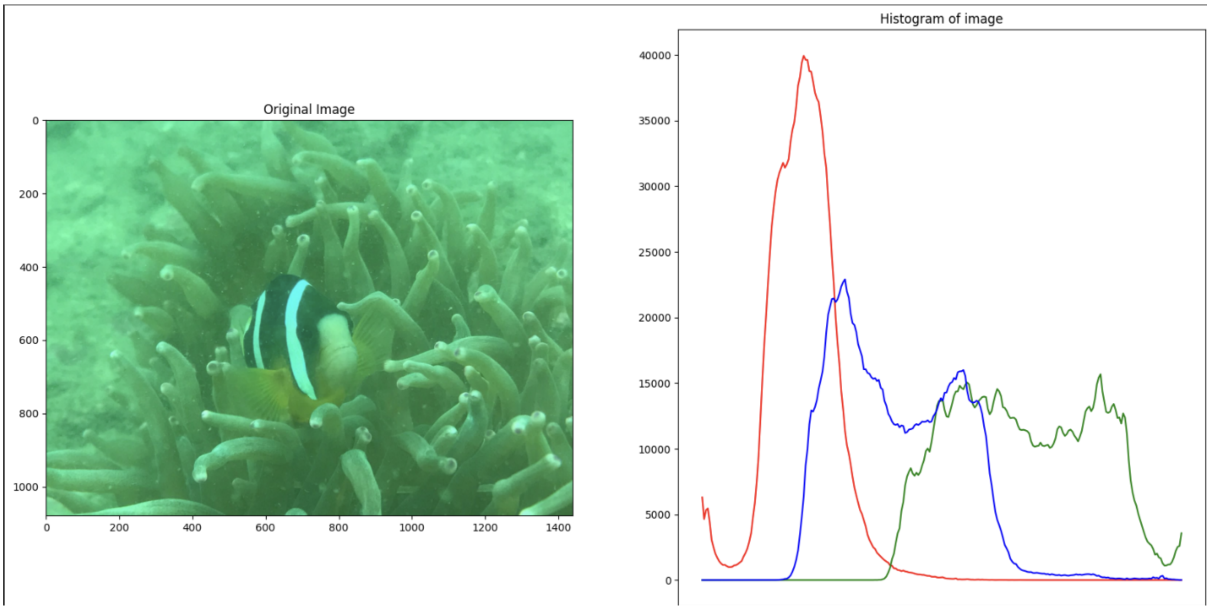
8 Image Pre-Processing

8.1 Image Pre-Processing Approach

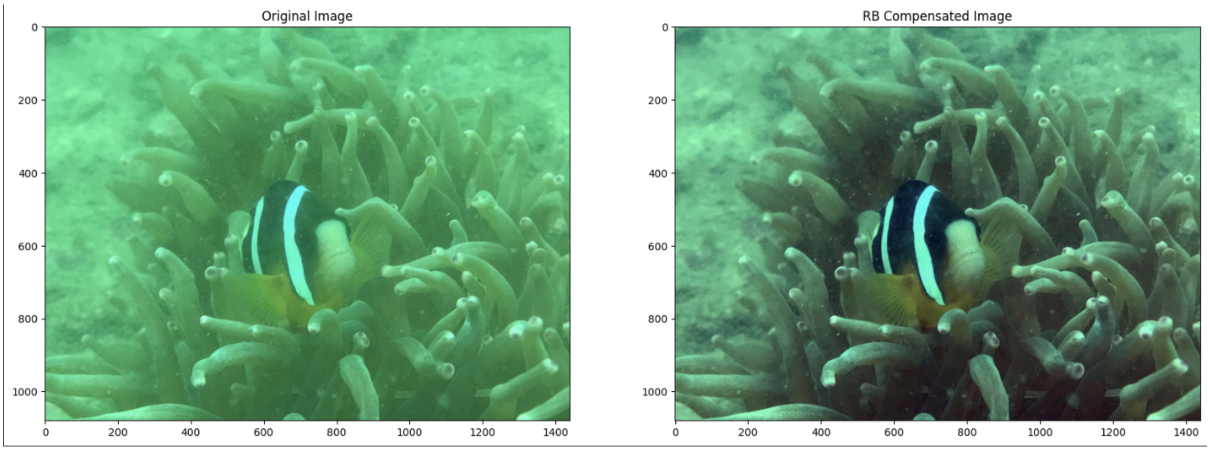
We began our pre-processing journey for underwater image improvement by carefully examining the RGB channel histograms from our large image datasets
From this analysis, we were able to identify a common occurrence in all of the images: red light absorption, especially at longer wavelengths, resulted in a noticeable leftward skew in the red channel.
To correct for color deterioration, we started a compensating process with an emphasis on the red channel. However, we also applied the adjustment to the blue channel in cases when photos had a strong greenish hue. This correction required a calculated move, in which some of the green channel was added to the red and blue channels, respectively, because it suffered from the least amount of deterioration.
Following the compensation stage, we proceeded with the critical task of white balancing, carefully utilizing the Gray World algorithm to guarantee the best possible color balance.
Though we were able to accomplish a commendable reduction in color distortion with our careful color-correction efforts, there was still one significant shortcoming: the resulting photos had a muted contrast and the edges were not well defined.
We were determined to overcome this restriction, so we started working on contrast enhancement using the Global Histogram Equalization method. The first step in this complex operation was to convert the photos into the HSV domain. Next, the Value component had to be carefully equalized. Ultimately, in order to achieve the intended contrast increase, we carefully combined the original Hue and Saturation components with the equalized Value component. This resulted in remarkably improved photos with increased contrast and improved clarity.

8.2 Image Pre-Processing Results

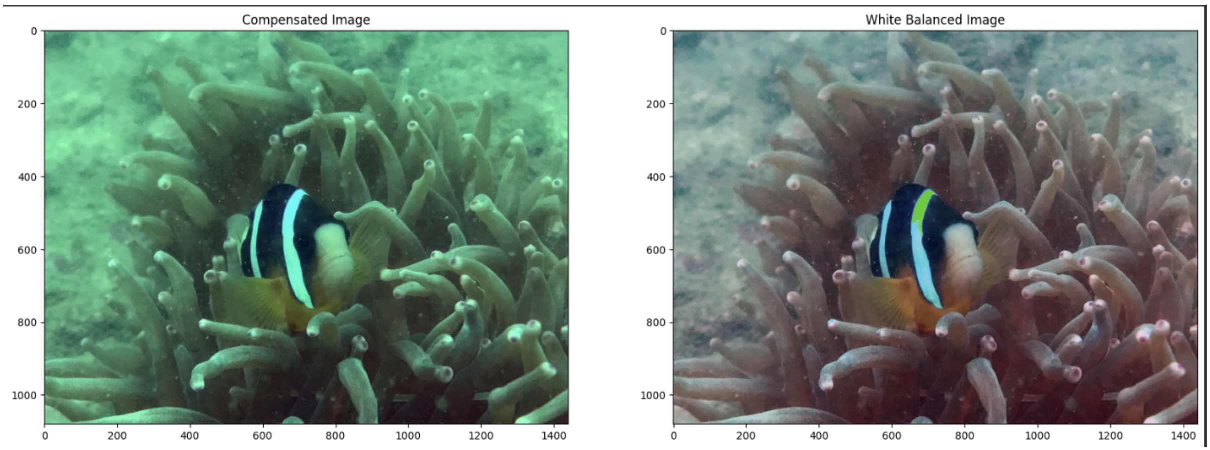
1. Plotting the histograms of each channel of the images.



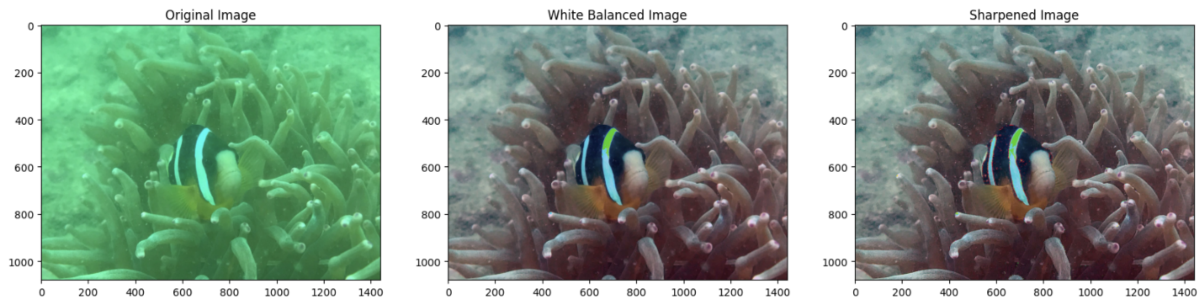
2. Color Correction (Compensating R and B).



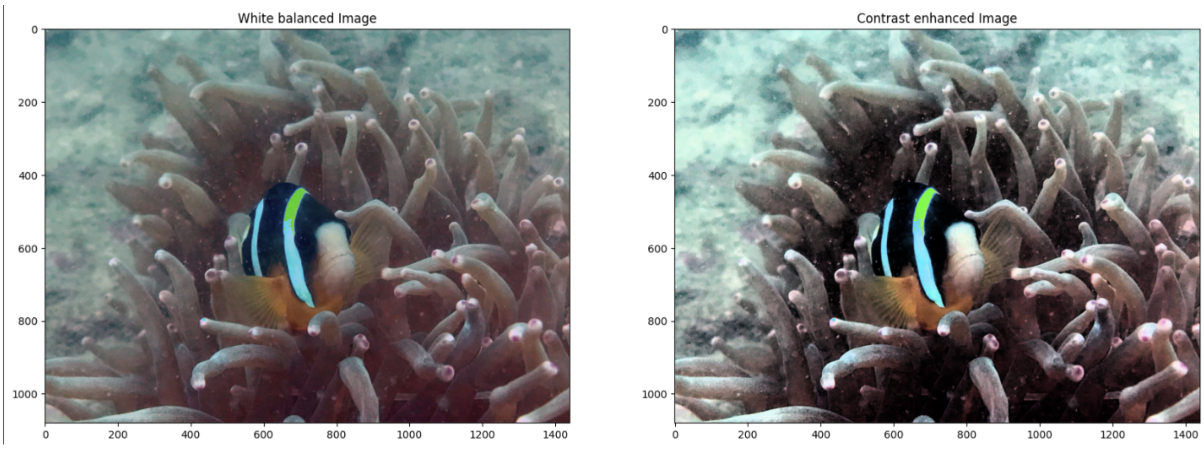
3. White balancing using the Gray World Algorithm.



4. Image Sharpening Of White Balanced Image.



5. Contrast enhancement of white balanced image by Global Histogram Equalization.



9 Deep Learning Based Model

I have implemented the paper of Chen et al. [1]. This paper proposes a new deep-learning model for underwater image enhancement that combines the revised underwater image formation model with convolutional neural networks. The key components of the model are:
Backscatter Estimation Module: This uses global mean pooling, 1x1 convolutions, and convolutional layers with 3x3 kernels to estimate the backscatter component.
Direct-Transmission Estimation Module: To estimate the direct transmission map, this concatenates the backscatter estimate and input picture and passes it through dilated convolution layers with different dilation rates.
Reconstruction Module: Reconstructing the enhanced output image involves combining the backscatter and direct transmission estimations with the input image in accordance with the updated image creation model.

Rather of using the normal ReLU, the model makes use of parametric ReLU (PReLU) activations, which have the ability to acquire negative slopes during training.
To expand the receptive field size without increasing the number of parameters, dilated convolutions are employed.
Using a mean squared error loss between the augmented output and reference ground truth images from the dataset, the model is trained under supervision. PyTorch is used to implement the entire system.

10 Expected Contributions

10.1 Improved Underwater Imaging

The underwater image quality will improve as a result of this research. For marine biologists, underwater explorers, and businesses like robotics and inspections, this is significant since it improves their ability to see and comprehend what is occurring below the surface.

10.2 User-Friendly Algorithm

The goal of this research is to create a user-friendly deep-learning method that will make underwater image enhancement easier. Users of all backgrounds will be able to easily enhance the quality of their underwater visuals thanks to this breakthrough.

10.3 Commercial Opportunities

This endeavor will benefit underwater photography. For companies that use underwater imagery, this may completely alter the playing field. Consider how great-looking underwater images can be created by tourism and entertainment businesses so that more people will be attracted to

their offerings.
Overall, This underwater image enhancement project will improve underwater image quality. This project will also help to improve the deep learning models and computer vision techniques for underwater image improvement, so it will also advance the field of computer science engineering.

11 Conclusion

Enhancing underwater images is difficult for a variety of reasons. The caliber of underwater photos can now be improved thanks to considerable advancements made in recent years and various ways.

There are two varieties of underwater image enhancement. The other is based on deep learning techniques, whereas the first is based on traditional image-processing methods. Deep learning-based algorithms are a potent new tool for underwater image enhancement. Traditional image-processing techniques include color correction, contrast enhancement, and noise reduction. For underwater image improvement, some difficulties must be overcome. The fact that current techniques were created for certain underwater settings is one of the difficulties. As a result, not all underwater photos can be captured effectively using a single technique. Another difficulty is that deep learning-based approaches need a lot of training data, which is very hard to gather.

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