UNDERWATER IMAGE ENHANCEMENT AND RESTORATION USING AI & ML

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of the degree of

Bachelor of Engineering

By

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CERTIFICATE

This project report entitled **“Underwater Image Enhancement and Restoration using AI & ML”** by Ms. Aparna Padmakumar, Ms. Amrutha Padmakumar, Ms. Tejaswini Rasal, Mr. Hitesh Khandelwal is approved for the degree of Bachelor of Engineering in Information Technology for academic year 2022 - 2023.

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LIST OF ABBREVIATIONS

Sr. No.	Symbol	Abbreviation
1	IE	Image Enhancement
2	CLAHE	Contrast Limited Adaptive Histogram Stretching
3	RD	Rayleigh Distribution
4	RGHS	Relative Global Histogram Stretching
5	IR	Image Restoration
6	DCP	Dark Channel Prior
7	MIP	Maximum Intensity Projection
8	ULAP	Underwater Light Attenuation Prior
9	OTF	Optical Transfer Function
10	PSF	Point Spread Function
11	MTF	Modulation Transfer Function
12	IQA	Image Quality Assessment
13	IQE	Image Quality Evaluation

ABSTRACT

A fusion algorithm is proposed for the restoration and enhancement of underwater images. Color balance, contrast optimization and histogram stretching are carried out. To alleviate the effect of color shift in an underwater image, the scalar values of R, G, B channels are renewed so that the distributions of the three channels in histogram are similar. Instead of refining the transmittance in dark channel prior based restoration, an optimized contrast algorithm is employed by which the optimal transmittance is determined. To further improve the brightness and contrast of underwater images, a histogram stretching algorithm based on the red channel is given. To verify the effectiveness of the proposed fusion algorithm, experimental underwater images are treated. Results show that the quality of underwater images is improved significantly, both in term of subjective visual effect and objective evaluation.

The proposed underwater image processing strategy is also compared with some popular techniques. Comparison results indicate the Images taken under water usually suffer from the problems of quality degradation, such as low contrast, blurring details, color deviations, non-uniform illumination, etc. As an important problem in image processing and computer vision, the restoration and enhancement of underwater image are necessary for numerous practical applications. Over the last few decades, underwater image restoration and enhancement have been attracting an increasing amount of research effort. However, a comprehensive and in-depth survey of related achievements and improvements is still missing, especially the survey of underwater image dataset which is a key issue in underwater image processing and intelligent application. In this exposition, we first summarize more than 120 studies about the latest progress in underwater image restoration and enhancement, including the techniques, datasets, available codes, and evaluation metrics. We analyze the contributions and limitations of existing methods to facilitate the comprehensive understanding of underwater image restoration and enhancement advantage of the proposed strategy over others.

Keywords: Enhancement, Restoration, Underwater Image Processing, Colour deviation, Histogram stretching

CHAPTER 1

INTRODUCTION

1. INTRODUCTION

1.1 Introduction

In the human exploration and exploitation of ocean, the underwater mission is challenging. The acquisition and analysis of underwater information is vital to accomplish underwater missions like underwater object localization, marine life recognition, underwater archeology, underwater environment monitoring, underwater search and salvage, underwater maintenance, etc. Underwater optical image provides an important source of underwater information. However, due to the characteristic attenuation and scattering of light in water, underwater images through camera sensors are apt to degrade. Typically, the attenuation results in color shift while scattering of light makes an underwater image blurred and a decrease of contrast. Although the physical characteristics of underwater light emission have a great impact on underwater images, they are not the only phenomena that affect underwater visibility and quality of underwater images. For example, the movement of water or fish shoal can cause so-called motion blur. Dissolved organisms and tiny suspended particles in waters often lead to noises in underwater images and the influence of light backscattering on underwater imaging will be amplified. Representative noises include salt-and-pepper noise, Gaussian noise and marine snow. It is noted that marine snow is a very specific but ubiquitous noise for underwater conditions, caused by biological and mineral particles, or bubbles. Marine snow results in additional light backscattering which manifests in images as white blobs of various size and shape, which negatively affects underwater visibility

To obtain high-quality underwater images, one can resort to an advanced imaging equipment like the divergent-beam underwater Lidar imaging (UWLI) system or multistate underwater laser line scan system. The main obstacle for users is the expensive cost with the equipment. Another alternative to obtain high-quality underwater images is the technique of image processing. It is characterized by high efficiency and low cost. In recent years, underwater image processing has become a hot topic in underwater technology.

Generally, underwater image processing concerns two techniques, i.e. image restoration and enhancement. Image restoration is based on a physical model about original image and recovered image. Degradation of image is focused in a restoration process. For image enhancement, the focus is mainly on the enhancement of pixels of images according to some subjective qualitative criteria, rather than the degradation process and the physical model of imaging for image restoration. From the point of view of calculation burden, image enhancement approaches are usually simpler and faster than image restoration approaches in which convolution and deconvolution operation are conducted. During the last decade, many kinds of underwater image enhancement algorithms have been proposed.

Commonly used methods include histogram equalization, wavelet transform and Retinex algorithm. Over the past decade, these classic algorithms have been applied widely and developed. For example, Iqbal et al. Proposed an enhancement method based on histogram sliding stretching. Henke et al. Proposed a color constancy hypothesis algorithm based on gray world hypothesis to solve the color distortion problem of underwater images. Guraksin et al. addressed the use of a method formed by the wavelet transform and the differential evolution algorithm. Tang et al. presented the underwater image and video enhancement based on Retinex. Although these enhancement algorithms can process underwater images and have been widely used, there exist some inherent shortcomings. For histogram equalization, image enhancement is carried out by obtaining a histogram with approximately uniform distribution. However, some details of the processed image might disappear.

1.2 Objective of the research

- To gather underwater images based datasets from differenrerent sources inorder to train the model.
- We apply supervised and unsupervised learning method to train our model using machine learning algorithms.
- By comparing the datasets the trained model will remove the noise contained in the underwater images.
- Hence the blurness of the image is removed resulting in a clear image as output.
- Various enhancement and restoration techniques are applied like CLAHE, MEP,DCP,etc.
- After appling all these techniques clear and restored images are obtained.

By achieving these objectives, underwater image enhancement and restoration can help to improve the accuracy and reliability of various underwater imaging applications, such as marine biology, oceanography, and underwater exploration.

1.3 Limitation:

- Underwater image enhancement and restoration is a challenging task due to the limitations posed by the underwater imaging environment. Some of the major limitations are:
- Water Turbidity: The presence of suspended particles and organic matter in water results in scattering and absorption of light, which reduces the contrast and color fidelity of underwater images.
- Color Distortion: Water absorbs different wavelengths of light to varying degrees, leading to color distortions in underwater images. The colors shift towards blue and green, and red colors are absorbed more strongly, resulting in a loss of red hues.

- Limited Visibility: The amount of light that penetrates the water surface decreases with depth, leading to reduced visibility in underwater environments. This makes it challenging to capture high-quality images of underwater scenes.
- Motion Blur: Turbulent water flow and camera movement can cause motion blur in underwater images, which reduces image sharpness and detail.

1.4. Image restoration:

Image restoration aims at recovering the original image from the observed image using (if available) explicit knowledge about the degradation function (also called point spread function PSF) and the noise characteristics :where denotes convolution. The degradation function includes the system response from the imaging system itself and the effects of the medium (water in our case). In the frequency domain, we have are spatial frequencies and are Fourier transforms of respectively. The system response function in the frequency domain is referred as the optical transfer function (OTF) and its magnitude is referred as modulation transfer function (MTF). Usually, the system response is expressed as a direct product of the optical system itself and the medium:

The better the knowledge we have about the degradation function, the better are the results of the restoration. However, in practical cases, there is insufficient knowledge about the degradation and it must be estimated and modeled. In our case, the source of degradation in underwater imaging includes turbidity, floating particles and the optical properties of light propagation in water. Therefore, underwater optical properties have to be incorporated into the PSF and MTF. The presence of noise from various sources further complicates these techniques.

Recently, incorporated the underwater optical properties to the traditional image restoration approach. They assume that blurring is caused by strong scattering due to water and its constituents which include various sized particles. To address this issue, they incorporated measured in-water optical properties to the point spread function in the spatial domain and the modulation transfer function in frequency domain. The authors modeled for circular symmetrical response systems (2-dimensional space) as an exponential function. The exponent, , is the decay transfer function obtained by Wells for the seawater within the small angle approximation where is the mean square angle, and are the total scattering and attenuation coefficients, respectively. The system (camera/lens) response was measured directly from calibrated imagery at various spatial frequencies. In water optical properties during the experiment were measured: absorption and attenuation coefficients, particle size distributions and volume scattering functions. The authors implemented an automated framework termed Image Restoration via Denoised Deconvolution. To determine the quality of the restored images, an objective quality metric was implemented. It is a wavelet decomposed and denoised perceptual metric constrained by a power spectrum ratio. Image restoration is carried out and medium optical properties are estimated. Both modeled and measured optical properties are taken into account in the framework.

Image Enhancement:

Image enhancement techniques are used to improve the visual quality of digital images by modifying their brightness, contrast, color balance, sharpness, and other parameters. Some of the commonly used image enhancement techniques are:

Contrast Enhancement: This technique increases the difference between the light and dark areas of an image, resulting in a more vivid and clearer image.

Brightness Adjustment: This technique adjusts the overall brightness of an image, making it brighter or darker as needed.

Color Correction: This technique adjusts the color balance of an image to make it more natural-looking or to create a specific mood.

Sharpness Enhancement: This technique enhances the edges and details in an image, resulting in a crisper and clearer image.

Noise Reduction: This technique reduces the noise in an image, which can be caused by low light conditions, high ISO settings, or other factors.

Deblurring: This technique removes blur from an image, caused by camera shake, motion blur, or other factors.

Super-resolution: This technique enhances the resolution of an image, either by using interpolation techniques or by generating new high-resolution pixels based on existing low-resolution pixels.

These techniques can be applied manually using image editing software, or they can be automated using algorithms based on machine learning, deep learning, or other computational techniques. The choice of technique depends on the specific requirements of the application and the nature of the images being enhanced. Image enhancement techniques are widely used in a variety of applications, including medical imaging, satellite imaging, surveillance, digital photography, and more. In medical imaging, for example, image enhancement can improve the visibility of anatomical structures, making it easier to diagnose diseases and plan treatments. In satellite imaging, image enhancement can reveal details in images that might be difficult to see otherwise, such as changes in vegetation, water bodies, or urban areas. In digital photography, image enhancement can improve the quality of photos taken in low light conditions or with low-end cameras, resulting in more pleasing and attractive images. Overall, image enhancement techniques play a vital role in improving the visual quality and usability of digital images in a wide range of applications.

CHAPTER 2

REVIEW OF LITERATURE

2. REVIEW OF LITERATURE

2.1 Literature Review:

C.S. Tan, et, al [1] says that Underwater images play a key role in ocean exploration, but often suffer from severe quality degradation due to light absorption and scattering in water medium. Although major breakthroughs have been made recently in the general area of image enhancement and restoration, the applicability of new methods for improving the quality of underwater images has not specifically been captured. In this paper, they review the image enhancement and restoration methods that tackle typical underwater image impairments, including some extreme degradations and distortions. Firstly, we introduce the key causes of quality reduction in underwater images, in terms of the underwater image formation model (IFM) in 2005

F. R. Dalgleish et.al, put forward Recursive Adaptive Histogram Modification (RAHIM), which can increase the natural performance of image color by modifying saturation and brightness of the image in the HSV color model through Rayleigh distribution and the human visual system and finally the enhanced image is converted to RGB color model. The Retinex theory simulates the mechanism of the human vision system as it perceives the world. The term of Retinex is created by the combination of the "retina" and "cortex". It attempts to achieve the color constancy when the scene is dominated by a certain illumination, which has a similar situation in the underwater environment in 2009 [2]

M. Boffety et al [3] firstly proposed a simple RGB color cast correction algorithm for underwater images. Then, based on the theory of retina cortex, a new frame was proposed to separate direct light from reflected light in CIE-Lab color model. Finally, different strategies were used to highlight the separated light components to enhance the contrast of underwater images in 2017.

A. Arnold-Bos, et al Through this paper proposed that by improve the above methods and extend the Retinex framework for underwater image enhancement. The brightness L and color a, b components are filtered by bilateral filter and trilateral filter to remove the luminance in Lab color model and suppress the halo artifacts in 2019.[4]

M. Arredondo et al [5], Says that according to this paper adjusting CLAHE and built the mixture contrast limited adaptive histogram equalization (Mix-CLAHE) to improve the visibility of underwater images. The CLAHE was applied to the RGB color model and the HSV color model to generate two images, which are combined by the Euclidean norm. Experimental results show that Mix-CLAHE can significantly improve the visual quality of underwater images by enhancing contrast, reducing noise and artifacts in 2019.

M. Yang, Z. Q.et al [6] proposed through his paper that relative global histogram stretching (RGHS) in RGB and CIE-Lab color models. The pre-processed image based on the theory of Gray-World employed adaptive histogram stretching in the RGB color model according to distribution characteristics of RGB channels and selective attenuation of light propagating under the water. Finally, the brightness a and color b ,components in the CIE-Lab color space are operated as linear and curve adaptive stretching optimization, respectively. RGHS can improve the visual effect of the image and retain available information by avoiding the blind enhancement on account of underwater image characteristics in 2020.

R. Schettini et al, put forth that the visibility range can be increased with artificial lighting but these sources not only suffer from the difficulties described before (scattering and absorption), but in addition tend to illuminate the scene in a non uniform fashion, producing a bright spot in the center of the image with a poorly illuminated area surrounding it. Finally, as the amount of light is reduced when we go deeper, colors drop off one by one depending on their wavelengths. The blue color travels the longest in the water due to its shortest wavelength, making the underwater images to be dominated essentially by blue color in 2020.[7]

F. Galland focus et al, focus on the special transmission properties of the light in the water. Light interacts with the water medium through two processes: absorption and scattering. Absorption is the loss of power as light travels in the medium and it depends on the index of refraction of the medium. Scattering refers to any deflection from a straight-line propagation path. In underwater environment, deflections can be due to particles of size comparable to the wavelengths of travelling light (diffraction), or to particulate matter with refraction index different from that of the water in 2021.[8]

A. Arnold-Bos et al [9], proposed that an image obtained in foggy environment and an image obtained in underwater environment are similar. Therefore, some dehazing algorithms (e.g. DCP) are applied to deal with underwater images. However, the results are not satisfactory. The main reason is that the attenuation of light differs in different environments. In outdoor foggy environments, the attenuations of lights with different wavelengths are almost the same. While in underwater environments, the attenuations of lights vary with wavelengths in 2021.

H. Shen et al, says that Underwater image restoration is of significant importance in unveiling the underwater world. Numerous techniques and algorithms have been developed in the past decades. However, due to fundamental difficulties associated with imaging/sensing, lighting, and refractive geometric distortions, in capturing clear underwater images, no comprehensive evaluations have been conducted of underwater image restoration. To address this gap, we have constructed a large-scale real underwater image dataset, dubbed `HICRD' (Heron Island Coral Reef Dataset), for the purpose of benchmarking existing methods and supporting the development of new deep-learning based methods. [10]

Sr No	Author & Year	Title & Journal name	Research Outcome	Limitation
1	Tan et al 2005 [1]	An indept survey of underwater image enhancement and restoration	Introduced the key causes of quality reduction in underwater images, in terms of the underwater image formation model (IFM).	It does not support advanced image processing techniques.
2	Dalgleish et al 2007 [2]	Underwater image prosessing state of art of restoration of images	The Retinex theory simulates the mechanism of the human vision system as it perceives the world. The term of Retinex is created by the combination of the “retina” and “cortex”.	It attempts to achieve the color constancy when the scene is dominated by a certain illumination.
3	Boffety et al 2017 [3]	Underwater image adjustment and colour equalization.	Proposed a simple RGB color cast correction algorithm for underwater images.	RGB color correction algorithm does not justify enhancement
4	Arnold-Bos et al 2018 [4]	Two step approach for single underwater image and enhancemenet.	The brightness L and color a, b components are filtered by bilateral filter and trilateral filter.	Methods doesnot extend the Retinex framework for underwater image enhancement
5	Yang et al 2019 [5]	Deep supervised residual underwater image system.	Proposed relative global histogram stretching (RGHS) in RGB and CIE-Lab color models.	RGHS doesnot improve the visual effect of the image not available.

Sr No	Author & Year	Title & Journal name	Research Outcome	Limitation
6	Yang et al 2020 [6]	Single Underwater Image Restoration by Contrastive Learning	This paper elaborates on a novel method that achieves state-of-the-art results for underwater image restoration based on the unsupervised learning.	It doesnot support Dark Channel Prior
7	Schettini et al 2020 [7]	Fast Underwater Image Enhancement for Improved Visual Perception	In this paper, we present a conditional generative adversarial network-based model for real-time underwater image enhancement.	Network based model does not allow single method to get applied.
8	Galland et al 2021 [8]	U-shape Transformer for Underwater Image Enhancement	The light absorption and scattering of underwater impurities lead to poor underwater imaging quality.	The existing data-driven based underwater image enhancement (UIE) techniques suffer from the lack of a large-scale dataset.
9	Arnold-Bos et al 2021 [9]	An Underwater Image Enhancement Benchmark Dataset and Beyond	Underwater image enhancement has been attracting much attention due to its significance in marine engineering	Lack of restoration process may cause insignificance
10	Shen et al 2021 [10]	Single Underwater Image Restoration by Contrastive Learning	This paper elaborates on a novel method that achieves state-of-the-art results.	CLAHE is not included.

Table 2.1: Review of Literature

CHAPTER 3

RESEARCH METHODOLOGIES

3. RESEARCH METHODOLOGIES

3.1 Existing System:

Existing systems for underwater image enhancement and restoration can be broadly categorized into two types: traditional image processing methods and deep learning-based methods. Traditional methods include techniques such as color correction, contrast enhancement, dehazing, image deblurring, and denoising.

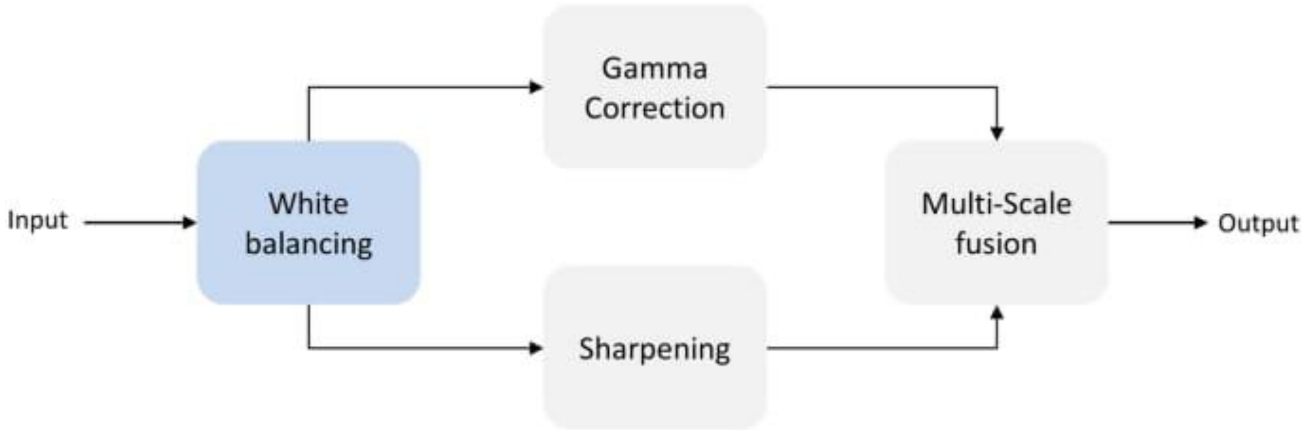

Fig 3.1: Existing System

These techniques use mathematical models and algorithms to modify the pixel values of underwater images to improve their quality. Some of the commonly used traditional methods for underwater image enhancement and restoration include the dark channel prior, the adaptive histogram equalization, and the wavelet transform. Deep learning-based methods, on the other hand, use convolutional neural networks (CNNs) and other deep learning architectures to learn features from large amounts of training data and apply these learned features to enhance and restore underwater images. These methods have shown promising results in improving the visual quality of underwater images and are becoming increasingly popular in underwater imaging research. Some of the existing systems for underwater image enhancement and restoration include commercial software packages such as Adobe Photoshop and specialized software packages such as Sea-Thru and SeaRaptor. In addition, there are several open-source software packages and libraries available for underwater image processing, including the OpenCV library, the DOLPHIN toolbox, and the UWGAN software package. Overall, the existing systems for underwater image enhancement and restoration provide a range of tools and techniques for improving the visual quality of underwater images, and ongoing research in this field is leading to further improvements and advancements.

Image quality assessment (IQA) plays a very important role in the adaptive optimization design of an optical imaging system, image transmission, image enhancement restoration, image retrieval and classification. Objective image quality evaluation (IQE) methods can be classified by whether a reference image exists or not. For underwater images where a reference image cannot be obtained, a no-reference image quality metric is needed to measure the perceptual image quality. The traditional objective evaluation methods evaluate the distortion (such as Gaussian noise) of an image taken in air, rather than the authentic mixed degradation caused by water body, so they often fail to evaluate the quality of an underwater image.

Several quantitative metrics have been used to evaluate enhancement and restoration performance for grayscale underwater images. For instance, Schechner and Karpel applied global contrast as a measure of underwater grayscale image quality. Hou et al. measured the quality of a restored image by a metric based on the weighted gray scale angle (WGSA) for scattering blurred underwater images. Arnold-Bos et al. defined a robustness index to measure the closeness of the grayscale histogram to the exponential distribution. This index was also applied by Bazeille et al. Arredondo and Lebart proposed a methodology to assess the robustness of underwater image noise removing quantitatively.

Seemingly, an image obtained in foggy environment and an image obtained in underwater environment are similar. Therefore, some dehazing algorithms (e.g. DCP) are applied to deal with underwater images. However, the results are not satisfactory. The main reason is that the attenuation of light differs in different environments. In outdoor foggy environments, the attenuations of lights with different wavelengths are almost the same. While in underwater environments, the attenuations of lights vary with wavelengths. displays three randomly selected foggy images and their corresponding histograms. It can be seen that the histograms of different channels (three channels for a RGB image) are very similar, including the peaks, troughs, and grayscales. As a contrast, presents three randomly selected underwater images and corresponding histograms. As can be seen, the color deviation of the underwater images is severe and the contrast is seriously degraded. The peaks and troughs of the different channels of the first two underwater images are similar, except that the single channel values corresponding to the peaks and troughs are different.

It is noted that the third picture is taken in the deep sea without light illumination. In this case, the red light with a longer wavelength is absorbed. Correspondingly, the component of red channel in the histogram vanishes. Sea-Thru: Sea-Thru is a specialized software package developed by the University of California, San Diego, for enhancing underwater images. The software uses a combination of color correction, contrast enhancement, and dehazing techniques to improve the quality of underwater images.

SeaRaptor: SeaRaptor is another specialized software package developed by the University.

OpenCV: OpenCV is an open-source computer vision library that includes several image processing functions and algorithms for underwater image enhancement and restoration. The library provides tools for color correction, contrast enhancement, dehazing, and image denoising, among other techniques.

DOLPHIN: DOLPHIN is an open-source toolbox developed by the Massachusetts Institute of Technology for processing underwater images. The toolbox includes several algorithms for color correction, contrast enhancement, and dehazing, as well as tools for image segmentation and object detection.

UWGAN: UWGAN is an open-source software package developed by the University of Haifa for underwater image enhancement and restoration. The software uses a deep learning-based approach, specifically a generative adversarial network (GAN), to learn features from large amounts of training data and apply these learned features to enhance and restore underwater images.

These existing systems provide a range of tools and techniques for improving the visual quality of underwater images. However, there are still challenges associated with underwater imaging, such as water turbidity and limited visibility, that make image enhancement and restoration a challenging task. Ongoing research in this field is focused on developing new and more effective techniques for underwater image enhancement and restoration.

3.2 Methodology:

The methodology for underwater image enhancement and restoration depends on the specific technique or approach being used. However, there are some general steps that are commonly followed in the process: Image Acquisition: The first step is to acquire the underwater image, which may be captured using specialized cameras or equipment designed for underwater imaging.

Preprocessing: Preprocessing techniques may be used to remove artifacts or noise from the image, or to correct for color balance or other issues. Enhancement or Restoration: The main step is to apply enhancement or restoration techniques to the image. This may involve applying traditional image processing techniques such as color correction, contrast enhancement, and dehazing, or using deep learning-based approaches such as convolutional neural networks (CNNs) or generative adversarial networks (GANs) to learn features from large amounts of training data and apply them to the image.

Postprocessing: Postprocessing techniques may be applied to further refine the enhanced or restored image, such as sharpening edges or removing artifacts.

Evaluation: The final step is to evaluate the quality of the enhanced or restored image using objective or subjective metrics. Objective metrics may include measures such as peak signal-to-noise ratio

(PSNR) or structural similarity index (SSIM), while subjective metrics may involve human evaluation of the image quality. The specific methodology used may vary depending on the technique being applied, and may involve additional steps or modifications to the general process outlined above. For example, some approaches may involve multiple stages of enhancement or restoration, or may incorporate data fusion techniques to combine information from multiple sensors or modalities.

A set of ablation experiments are conducted to verify the effectiveness of each module (i.e. algorithm). As required, each module is gradually removed. Results are presented in Fig. The images in left column labeled with A3) are processed by proposed fusion algorithm in which color balance, optimized contrast and histogram stretching based on red channel are combined. By ablation operation, for the images in the second column labeled with A2, color balance and optimized contrast remain. For the images in the third column labeled with A1, color balance is only kept.

Since the evaluation of visual effect is influenced by human subjective consciousness, objective evaluation is necessary to verify the enhancement measures adopted in image processing. In the study, some classic objective evaluation indicators are used, i.e. contrast, UCIQE (underwater color image quality evaluation), PSNR (peak signal-to-noise ratio) and SSIM (structural similarity).

Generally speaking, the higher the contrast is, the better quality an image has. RMS (root mean square) contrast , Weber contrast and Michelson contrast are commonly used indices. In the study, the RMS contrast is employed, with the form as:

σIw×h=1w×h∑(I(x,y)−1w×h∑I(x,y))2

where σIw×h represents the RMS contrast of an image with the dimension of w×h ; I(x,y) is the pixel value at the point (x , y).

UCIQE is a comprehensive evaluation index that can reflect the overall quality of an image, referring to chroma, luminance contrast and saturation. Generally, a higher UCIQE value represents the better quality of an image. UCIQE index can be described .

UCIQE=c1×σc+c2×Cl+c3×μs,(20)

where σc represents the deviation of chroma; Cl is the luminance contrast; μs is the average saturation; ci(i=1,2,3) the weighted coefficients. In the study, the coefficients are selected as:

c1=0.4680,c2=0.2745,c3=0.2576.

PSNR is a widely used objective metric for image evaluation. It is based on pixel error. A corresponding error sensitivity can be defined to measure whether the processing results are satisfactory. The larger the PSNR value is, the less distortion happens. PSNR can be described .

MSE=PSNR=1w×h∑i=0w−1∑j=0h−1[I(i,j)−K(i,j)]210×log10((2n−1)2MSE)(21)(22)

SSIM is an index to measure the similarity of two digital images, by taking an initial uncompressed or distortion-free image as reference. Usually the larger the value is, the less distortion the image is and the more similar the two images are. It is based on three comparison measurements between images x and y : luminance l , contrast c and structure.

SSIM(x,y)=l(x,y)c(x,y)s(x,y)

View SourceRight-click on figure for MathML and additional features. The results of evaluation metric by RMS contrast, with respect to the eighteen images used in analysis of visual effect.

Underwater Imaging The propagation of light differs in water and air. In the light propagation in water, there are several important factors that result in attenuation and scattering of light. The density of water is greater than air, which causes the attenuation of light. Water selectively scatters and absorbs certain wavelengths of visible light. Suspended particles in water affect the light transmission and produce scattering of light. Various types of noise occur for example marine snow that causes additional light backscattering. Temperature and salinity also cause the light scattering. To summarize, the light attenuation and scattering are more serious in water than air. As a result, underwater optical images are apt to blur along with lower contrast

3.3 Proposed System:

Data Collection: The first step would be to collect a large dataset of underwater images to use for training and testing the proposed system. This might involve using specialized cameras or equipment designed for underwater imaging, and would require careful consideration of factors such as lighting conditions, water turbidity, and camera settings. Training and Validation: Once the dataset has been collected, the proposed system would need to be trained and validated using the data. This would typically involve using a deep learning-based approach such as a convolutional neural network (CNN) or generative adversarial network (GAN) to learn features from the data and apply them to the task of underwater image enhancement and restoration.

Implementation: After the proposed system has been trained and validated, it would need to be implemented in a software package or framework that can be used to apply the system to new images. This might involve developing a new software package or integrating the proposed system into an existing image processing or computer vision framework.

Evaluation: Finally, the proposed system would need to be evaluated using objective or subjective metrics to determine its effectiveness in enhancing and restoring underwater images. This might involve using standard evaluation metrics such as peak signal-to-noise ratio (PSNR) or structural similarity index (SSIM), or using human evaluation of the visual quality of the enhanced or restored images .Six methods including MSRCR, RCP, UDCP, GAN, RAHIM and the proposed method in the study are compared. Table presents the results by UCIQE metric. The results by PSNR metric and

Table presents the results by SSIM metric. From the comparison results, it can be seen that among four methods to be compared, i.e., MSRCR, RCP, UDCP, and GAN, MSRCR gains over the others generally. In fact, MSRCR is preferred for many researchers to conduct image enhancement. Nevertheless, it should be noted that in general the proposed algorithm in the study presents a better performance than MSRCR, so than RCP, UDCP, and GAN, no matter which metric is employed to evaluate the image enhancement algorithms. Minor exceptions include, RMS value of image processed by GAN is larger than the proposed algorithm the UCIQE value of image processed by UDCP is slightly greater than the proposed algorithm. In table, the PSNR values of three images by MSRCR are slightly smaller than the proposed algorithm, while the PSNR values of three images by MSRCR are smaller than the proposed algorithm to some extent. In fact, from the view point of visual effect with respect to these six images, the proposed algorithm outperforms MSRCR. Moreover, it should be noted that PSNR ignores the visual characteristics of human eyes.

As a result, the evaluation results are sometimes inconsistent with human subjective perception. Different from the absolute-error based PSNR, SSIM is a perception-based method for predicting the perceived quality of images. By comparing the visual effects of the six images the proposed algorithm in the study outperforms MSRCR. This can also be confirmed by SSIM metric listed. Obviously, the SSIM values in the last column are the smallest among all values with MSRCR, RCP, UDCP, and GAN. Overall, our proposed system for underwater image enhancement and restoration would involve the development and implementation of a new or improved approach for improving the visual quality of underwater images, and would require careful consideration of factors such as data collection, training and validation, implementation, and evaluation.

3.3.1 System Architecture:

To summarize the theory aspect of this project, the diagram below resumes all the steps described to achieve the original colors of a degraded underwater image. First, we input the degraded underwater image taken by the camera. Second, we extract the bright channel and the maximum color difference versions of the image. Third, we use both of these pictures to rectify the bright channel image.

Fourth, we use the bright channel image to estimate the value of the atmospheric light and then use both the bright channel image and the atmospheric light to obtain the initial transmittance image and to refine it. Fifth, we extract the restored image using all of the rectified bright channel image, the atmospheric light, and the refined transmittance image.

And last, we apply the histogram equalization method on the restored image to obtain the final result.

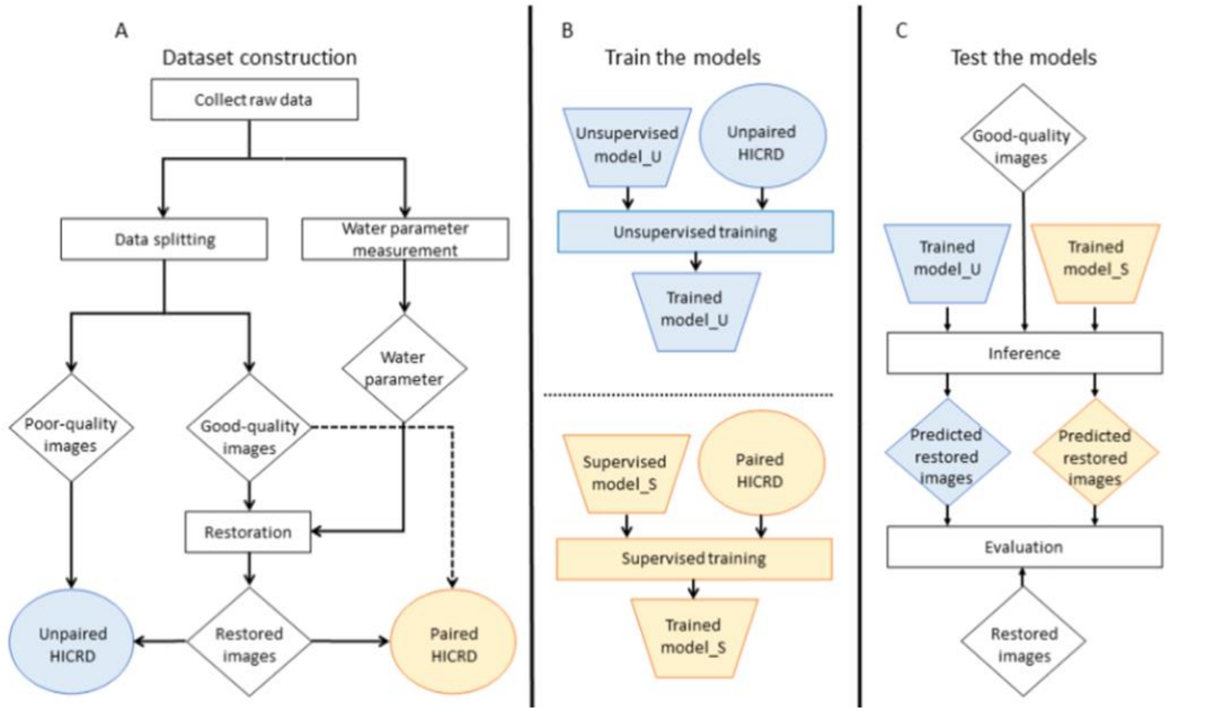

Fig.3.3.1: System Architecture

The system architecture of underwater image enhancement and restoration involves a combination of image processing techniques and deep learning-based methods to overcome the challenges posed by underwater imaging conditions and improve the quality of underwater images.

3.3.2 List of underwater image datasets:

Underwater image datasets are significant in the development of underwater image processing technology. This section summarizes the underwater image datasets, which were used by scholars in the underwater image restoration and enhancement processes, as listed. Examples of the images of these datasets. However, there is no relatively complete underwater image dataset due to difficulty in collecting underwater images. The current underwater image datasets face a series of problems, such as single target object, little category and imperfect labeling information. These problems severely restrict the development of intelligent underwater image processing technology. Several quantitative metrics have been used to evaluate enhancement and restoration performance for grayscale underwater images. For instance, Schechner and Karpel applied global contrast as a measure of underwater grayscale image quality.

Hou et al. measured the quality of a restored image by a metric based on the weighted gray scale angle (WGSA) for scattering blurred underwater images. Arnold-Bos et al. defined a robustness index to measure the closeness of the grayscale histogram to the exponential distribution. This index was also applied by Bazeille et al. Arredondo and Lebart proposed a methodology to assess the robustness of underwater image noise removing quantitatively. The true motion of a sequence of the underwater video was supposed to be known, and the angular deviation between the estimated velocity and the actual one was measured. As for underwater color images, two prominent no-reference underwater image quality evaluation metrics were proposed. Panetta et al. proposed an underwater image quality measure (UIQM) method, in which underwater image colorfulness measurement (UICM), underwater image sharpness measurement (UISM) and underwater image contrast measurement (UIConM) were combined to evaluate the underwater image quality. The choice of weighted coefficients depends on the application purpose. For instance, when evaluating the correction result of the color deviation of an underwater image, a larger weight value of UICM should be allocated. The training data set used in contained 30 randomly selected underwater images captured with different devices and under a different water depth. The mean opinion scores (MOS) of the tested underwater images were gathered from 10 researchers on image processing.

In addition, the subjective evaluations and methods designed for natural image quality evaluations, such as structural similarity index measure (SSIM), patch-based contrast quality index (PCQI) mean square error (MSE), PSNR, average E, contrast to noise ratio (CNR), entropy, discrete entropy and contrast measure (DECM), gradient ratio at visible edges (GAVE), global contrast factor (GCF), and visibility metric based on contrast-to-noise ratio (VM), were commonly adopted. Also, the effectiveness of the improvement for some specific processing such as SLAM and feature point matching of underwater images was also considered. Underwater images are all dominated by the integtation.

Quantitative analysis of restored and enhanced results based on different methods

- IFM free underwater image enhancement

Methods	ENTROPY	BRISQUE	NIQE	UIQM	UCIQUE
HE	7.8139	28.6079	3.9654	4.0399	0.6818
CLAHE	7.1132	27.3445	3.6338	2.0644	0.6567
ICM	6.9117	33.1758	3.4253	2.2999	0.5872
UCM	7.2643	28.2424	3.6339	3.3228	0.6131
FB	7.5269	32.9730	3.9176	2.7567	0.6684
RD	7.7487	29.0286	3.7631	3.2654	0.6721

Table: 3.3.2 Enhancement Methods

Table 2 shows the values of the five quantitative evaluations of the restored and enhanced images, highlighting the best results in bold. Entropy values of the IFM-free results are generally higher than those of the restored images by IFM-based methods. This suggests that image enhancement algorithms can improve the information abundance contained in the image. Yet, image enhancement algorithms blindly amplify the useless information, especially the noises. Although the entropy values of the enhanced images obtained by HE is the highest, it can be seen that enhanced images appear unnatural.

- IFM based underwater image restoration

Methods	ENTROPY	BRISQUE	NIQE	UIQM	UCIQUE
SIR	6.3973	33.5067	3.3175	0.1605	0.5054
IUID	6.5484	29.6948	3.3645	0.7895	0.5270
RIR	6.4863	27.5484	4.2616	2.5178	0.5578
NOM	7.3464	33.2872	4.3518	4.1640	0.5937
TEoUI	6.9915	23.7730	3.4819	2.8488	0.5820
IBLA	66.8470	31.4013	3.5331	1.4764	0.5918
ULAP	6.7583	29.57113	3.4304	3.7060	0.5872

Table. 3.3.3 Image Enhancement

In Table 3 both BRISQUE and NIQE models are built using outdoor images as evaluation criteria. TEoUI results are obviously unnatural, perceptually, but obtain the best naturalness (the lowest BRISQUE score). By contrast, FB, IBLA and ULAP obtain relatively higher BRISQUE score. SIR gains the best assessment according to NIQE, but it gives almost no improvement to the original underwater images. Therefore, it is problematic to directly use the quality assessment metrics based on outdoor images to evaluate underwater images.

UCIQE and UIQM were developed to reflect the quality of underwater color images. According to these two metrics, overall IFM-free methods perform significantly better than IFM-based methods. But these underwater image quality assessment metrics favor the images with high contrast and extreme chroma, such as the images produced by HE and NOM. Both UCIQE and UIQM metrics focus on the intensities of low level features such as contrast, chroma and saturation but ignore higher semantic or prior knowledge from human perception.

Background and Theory : The absorption and scattering process [9]is leads to the attenuation of light. The light particles are considered several hundreds of times denser in sea water than in normal atmosphere. As a consequence,the sub-sea water absorbs gradually different wavelength of light. The absorption capability of colors can be expressed in terms of the longest wavelength color red, orange and yellow. The corresponding wavelengths are mentioned as (10 - 15 ft), (20 -25 ft), and (35 - 45 ft) respectively. The works of authors McGlamery[10]and Jaffe [11] proved that the illumination of light when falls on the image scene splits into three main components ie, direct component, forward scattering and back scattering in underwater medium. The direct component is the component of light reflectedirectly by the target object onto the image plane.

expressed as: $E_D(x) = J(x)e^{-\eta d(x)} = J(x)t(x)$ (1) where, $J(x)$ is considered as object radiance, $d(x)$ is the observer-object, distance η is the attenuation coefficient. Scattering of the light is due to the presence of particles in underwater medium. Scattering consists of forward scattering and back scattering. Random deviation of the light ray from the camera lens is termed as forward scattering. The artificial light hits the particles present in water and is reflected back to the sensor camera. This process is called back scattering. The forward scattering component EBS is a part of deflection of light. It has only a little part in image degradation process and so it can be ignored. The back scattering component is the main reason for loss of color contrast. The back scattering component is expressed as: $E_{BS}(x) = B_\infty(x)(1 - e^{-\eta d(x)})$ (2) where $B_\infty(x)$ is a color vector known as the back-scattered light. Thus the simplified underwater optical model is formed by the combination of direct component and back scattering component; ignoring the forward scattering component as, $I(x) = J(x)e^{-\eta d(x)} + B_\infty(x)(1 - e^{-\eta d(x)})$ The attenuation coefficient strongly depends on the wavelength of light and also the color in underwater environ-ment. This is not reflected in the light model. Therefore the explicit inversion of the light model does not produce the required results and it is not used.

Luminance Enhancement : In this work, enhancement is done parallelly as a two step process. In the first step, the gamma corrected output undergoes a luminance enhancement in LAB color space.In the second step, histogram linearization is applied to the sharpened image. 2.3.1. Luminance Enhancement using CLAHE One of the challenging factors in an underwater image is non-uniform illumination. In order to overcome this limitation, luminance enhancement of the image is performed. The gamma-corrected output of the white balanced image is subjected to luminance enhancement in L*a*b* color space. The L*a*b* is a device-independent Color space. Here L* denotes luminance and a* and b* denotes the chromaticity coordinates. The L* component is separated and CLAHE is applied on it. 2.3.2 Contrast Enhancement using Histogram Linearization The sharpened output obtained after applying unsharp masking is subjected to Histogram Linearization .As a result, an output image is obtained which has a higher contrast than the input

CHAPTER 4

SYSTEM DESIGN

4. SYSTEM DESIGN

4.1 DFD : Data Flow Diagram

Level 0: Data Flow Diagram

Level 0 Data flow diagram for underwater image enhancement and restoration would provide a high-level overview of the system's main components and how they interact with each other. At this level, there are typically only two types of entities: external entities and the system under consideration. The external entities represent the sources and destinations of data and are usually represented by rectangles, while the system under consideration is represented by a single square. The diagram would show the system under consideration receiving input data from an external entity, such as an underwater camera.

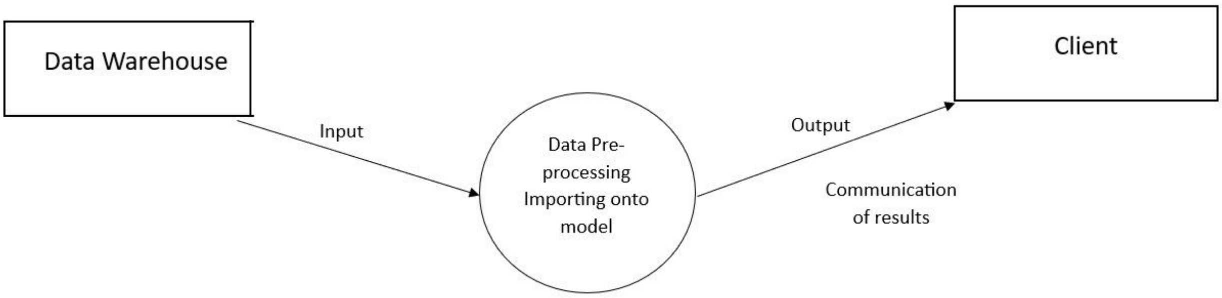

Fig 4.1: Level 0 DFD for image enhancement and restoration

The system would then perform various image enhancement and restoration operations, such as color correction, noise reduction, and contrast enhancement, to improve the quality of the image. Finally, the system would output the processed image data to an external entity, such as a display screen or a storage device. The level 0 data flow diagram would provide a high-level view of the overall data flow within the system, but it would not provide any detailed information about how each component operates.

Level 1: Data Flow Diagram

A level 1 data flow diagram for underwater image enhancement and restoration would provide a more detailed view of the system's internal components and their interactions. At this level, the system under consideration would be decomposed into a number of subprocesses, each of which would be represented by a rectangle. The data flows between the subprocesses would be represented by arrows, and data stores, such as databases or files, would be represented by parallel lines.

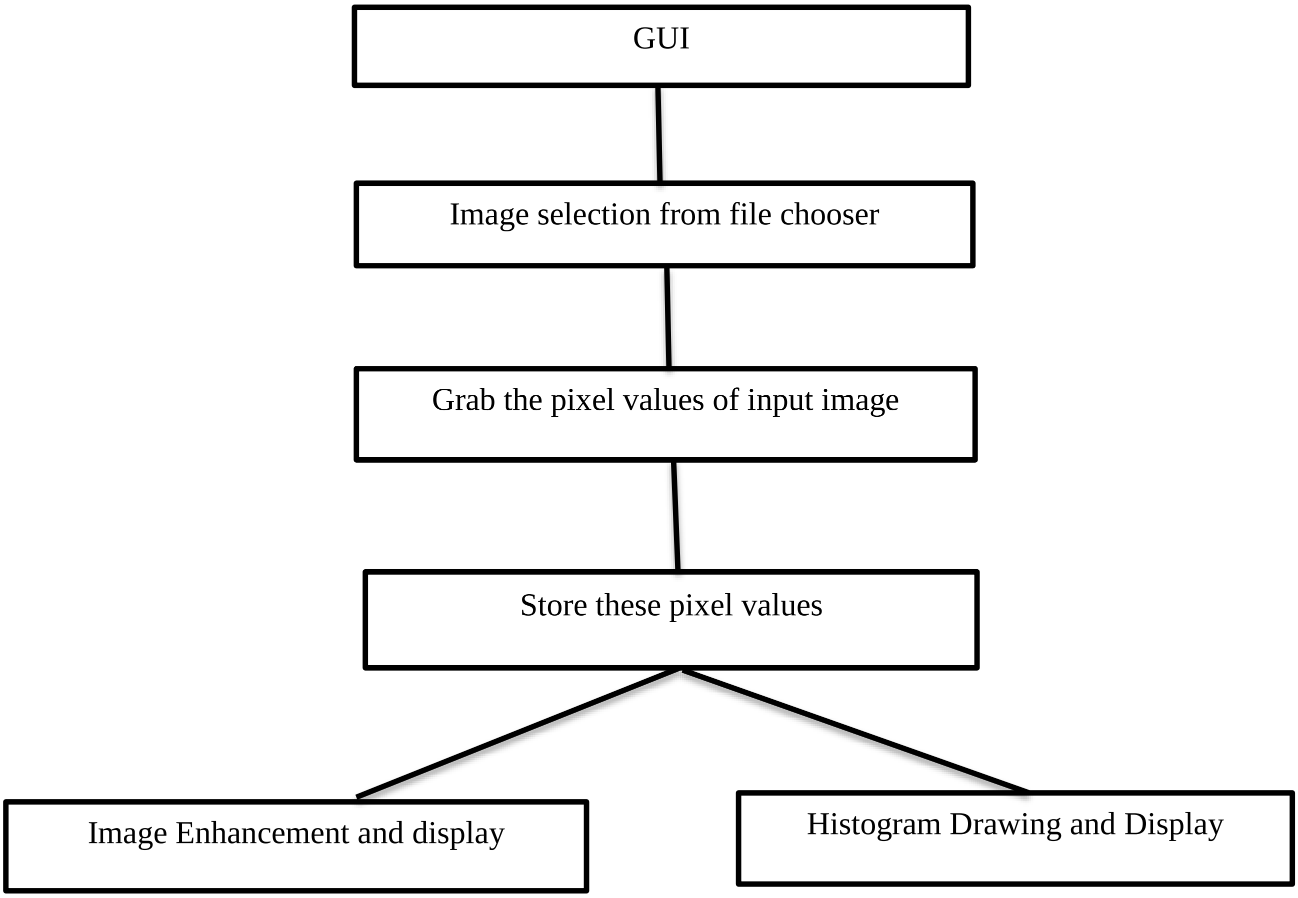

Fig 4.2: Level 1 DFD for underwater image enhancement and restoration

The diagram would show the input data from the external entity, such as an underwater camera, being received by the system's input subprocess. The input subprocess would perform basic validation and error checking on the data before passing it to the image enhancement subproces .The image enhancement subprocess would perform various operations, such as color correction, noise reduction, and contrast enhancement, to improve the quality of the image. The processed image data would then be stored in a data store before being passed to the image restoration subprocess.

Level 2: Data Flow Diagram

A Data Flow Diagram (DFD) level 2 for underwater image enhancement and restoration system would typically show more detail than a level 1 DFD, focusing on the processes that take place within the system. Assuming a level 1 DFD that shows the main inputs, processes, and outputs of the system, a level 2 DFD could include the following:

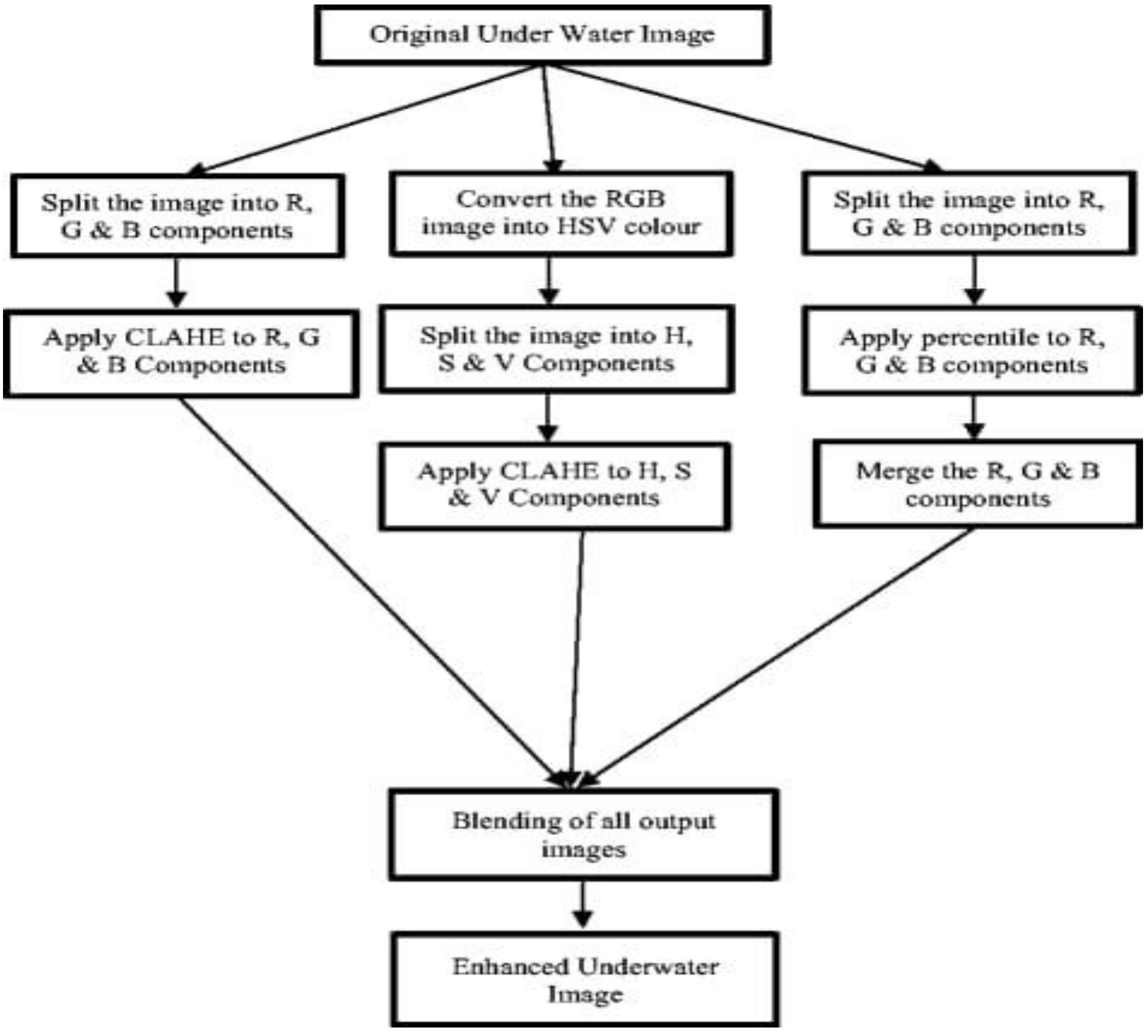

Fig 4.3: Level 2 DFD for underwater image enhancement and restoration

Input Process: The system would receive the raw underwater image data as input. The input process would validate the input data and then forward it to the next process.

Preprocessing Process: This process would involve various techniques such as noise removal, color correction, and contrast adjustment. This process is used to improve the quality of the input data before restoration is applied. Restoration Process: The restoration process is where advanced algorithms would be applied to restore the image quality. Techniques such as dehazing, image fusion, and wavelet transforms can be used here.

4.2 UML : Unified Modelling Language

4.2.1 Use Case Diagram

Capture Underwater Image: The diver captures an underwater image using a camera.

Upload Image: The diver uploads the captured image to the system.

Apply Filters: The system applies various filters such as noise reduction, color correction, and contrast enhancement to the uploaded image.

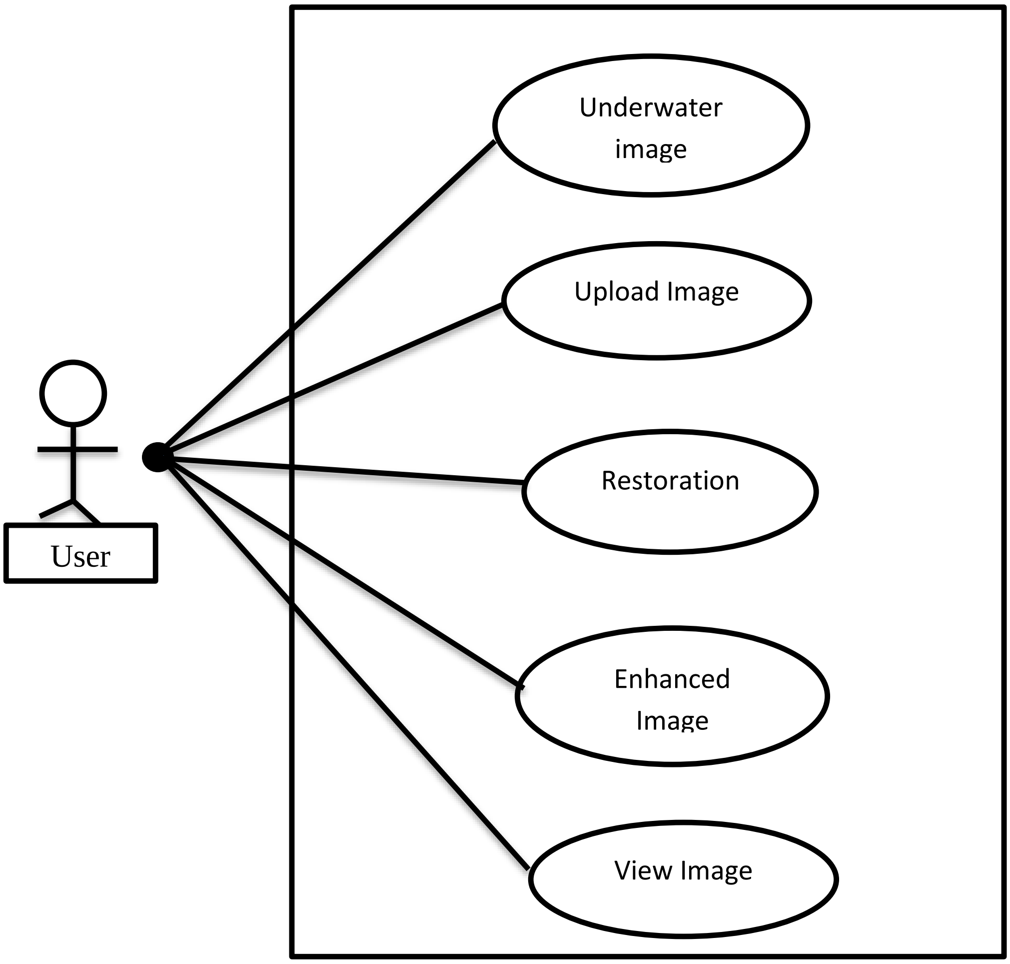

Fig 4.2.1: Use Case Diagram

Apply Restoration Techniques: The system applies various image restoration techniques such as deblurring and denoising to the image.

Save Enhanced Image: The system saves the enhanced image back to the user's device or in the cloud.

View Enhanced Image: The diver can view the enhanced image on their device or computer.

These use cases represent the basic functionalities of an underwater image enhancement and restoration system. They can be further refined or elaborated upon based on the specific requirements of the system.

4.2.2 Activity Diagram

Start: The process of image enhancement and restoration starts.

Upload Image: The user uploads an underwater image to the system.

Pre-processing: The system performs pre-processing activities such as noise reduction, color correction, and contrast enhancement on the uploaded image.

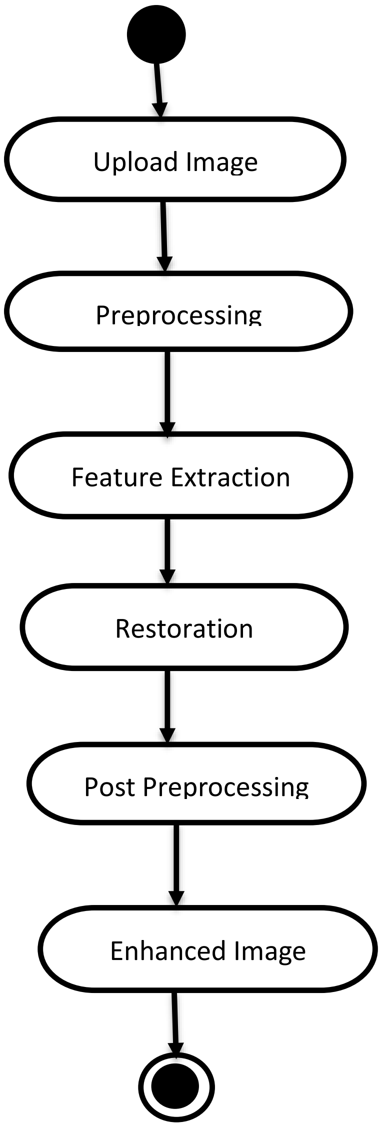

Fig 4.2.2: Activity Diagram

Feature Extraction: The system extracts features such as edges, corners, and textures from the pre-processed image.

Apply Restoration Techniques: The system applies various image restoration techniques such as deblurring and denoising to the image.

Post-processing: The system performs post-processing activities such as smoothing and sharpening on the restored image.

4.2.3 Sequence Diagram

The user captures an underwater image with a camera.

The camera sends the image data to the image enhancement system.

The image enhancement system processes the image data and applies various enhancement algorithms such as color correction, contrast enhancement, noise reduction, and dehazing. The enhanced image data is sent back to the camera. The camera displays the enhanced image on its screen.

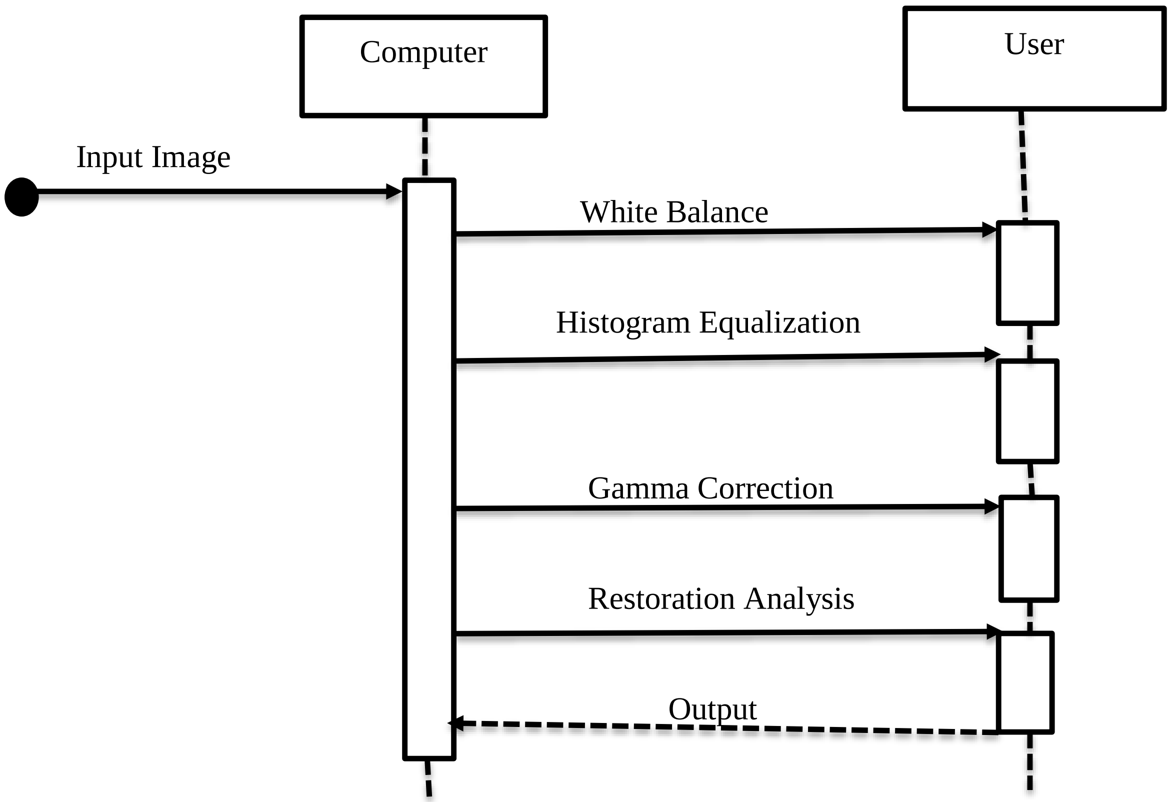

Fig 4.2.3: Sequence Diagram

The user reviews the enhanced image and may choose to capture another image or exit the application. The sequence diagram could also include interactions between different components of the image enhancement system, such as the color correction module communicating with the contrast enhancement module, or the noise reduction module communicating with the dehazing module. Additionally, it could show the user making adjustments to the enhancement settings, which would result in the system reprocessing the image data.

4.2.4 Composite Structure Diagram

The diagram show the different processing stages involved in underwater image processing, such as image preprocessing, segmentation, feature extraction, and classification. Each stage may involve different algorithms and techniques for processing the images.

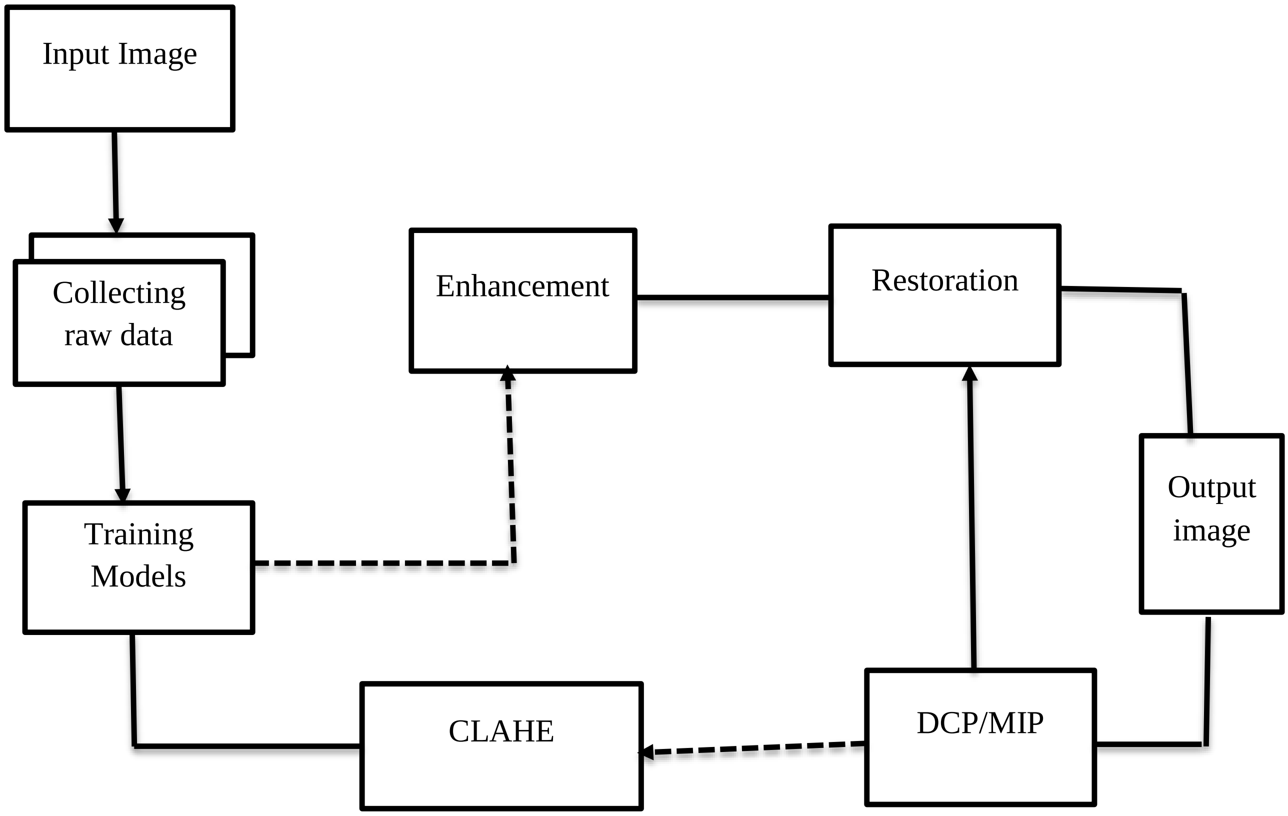

Fig 4.2.4 Compostite Structure Diagram

Additionally, the diagram include components for storing and retrieving image data, as well as components for displaying and visualizing the processed images and data. Overall, the composite structure diagram of underwater image processing provide a high-level view of the system's internal structure, including the components and their interactions, and how they work together to process underwater images.

4.2.5 State Machine Diagram

A state machine diagram, also known as a state diagram, is a graphical representation of a system or software that shows the various states that the system or software can be in, as well as the events and transitions that cause the system to move from one state to another

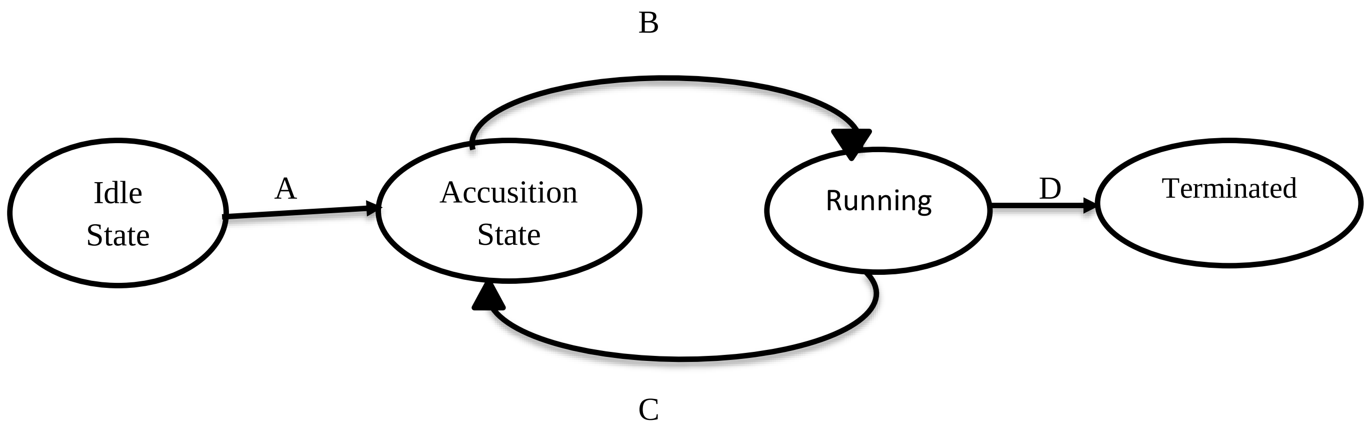

Fig 4.2.5: State Machine Learning

Idle state: In this state, the system is not actively processing any data and is waiting for input.

Data acquisition state: In this state, the system is actively collecting data from sensors and other sources.

Data processing state: In this state, the system is processing the data it has collected and generating output.

Data transmission state: In this state, the system is transmitting the output data to a remote location or device.

Error state: In this state, the system has encountered an error or exception and is waiting for corrective action

4.2.6 State Chart Diagram

In the context of underwater image enhancement and restoration, a state chart diagram could be used to model the different states and transitions of the image processing pipeline.

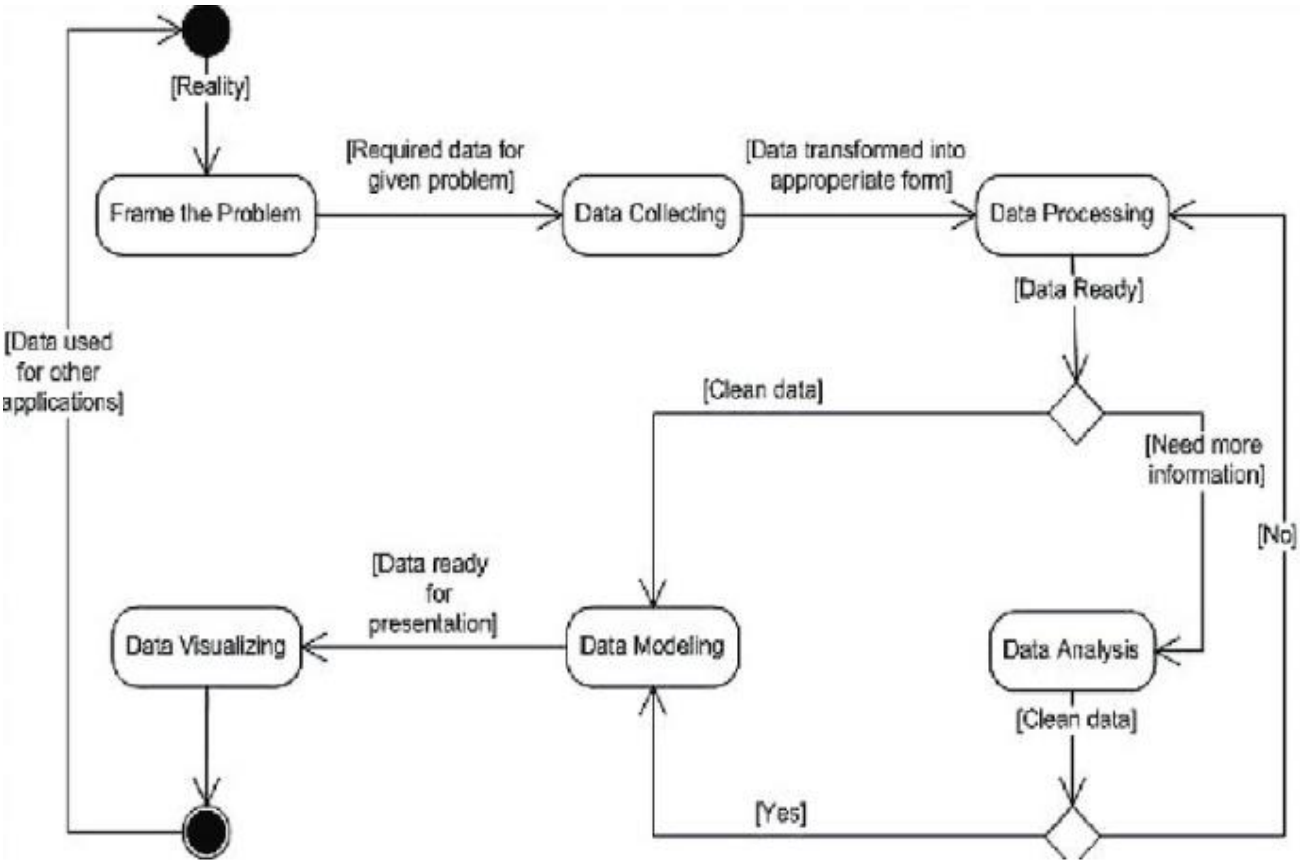

Fig 4.2.6: State Chart Diagram

For example, the initial state could be "Raw Underwater Image," and the system could transition to "Preprocessing" state when the image is being preprocessed to remove noise, distortion, and other artifacts. From there, the system could transition to the "Enhancement" state where the image is being enhanced to improve its visual quality. Finally, the system could transition to the "Restoration" state where the image is restored to its original quality, or even improved beyond its original quality.

CHAPTER 5

SYSTEM REQUIREMENTS AND SPECIFICATIONS

5. SYSTEM REQUIREMENTS AND SPECIFICATIONS

5.1 Hardware Requirement

- Processor : i3
- RAM : 8 GB
- Hard Disk : 250 GB
- Input devices : Standard Keyboard and Mouse
- Output devices : High Resolution Monitor

5.2 Sofrware Requirement

- Operating System : Windows 10/11
- Language : Python 3.11
- Libraries : Tensorflow, Matplotlib, Pillow, Tkinter, CV2

5.3 Technology Used

5.3.1 Artificial Intelligence

Artificial intelligence (AI) is intelligence demonstrated by machines, as opposed to the natural intelligence displayed by animals and humans. AI research has been defined as the field of study of intelligent agents, which refers to any system that perceives its environment and takes actions that maximize its chance of achieving its goals. The term "artificial intelligence" had previously been used to describe machines that mimic and display "human" cognitive skills that are associated with the human mind, such as "learning" and "problem-solving". This definition has since been rejected by major AI researchers who now describe AI in terms of rationality and acting rationally, which does not limit how intelligence can be articulated .AI applications include advanced web search engines (e.g., Google), recommendation systems (used by YouTube, Amazon and Netflix), understanding human speech (such as Siri and Alexa), self-driving cars (e.g., Tesla), automated decision-making and competing at the highest level in strategic game systems (such as chess and Go). As machines become increasingly capable, tasks considered to require "intelligence" are often removed from the definition of AI, a phenomenon known as the AI effect. For instance, optical character recognition is frequently excluded from things considered to be AI, having become a routine technology.

5.3.2 Machine Learning :

A computer “learns” when its software is able to successfully predict and react to unfolding scenarios based on previous outcomes. Machine learning refers to the process by which computers develop pattern recognition, or the ability to continuously learn from and make predictions based on data, and can make adjustments without being specifically programmed to do so. A form of artificial intelligence, machine learning effectively automates the process of analytical model-building and allows machines to adapt to new scenarios independently.

The four steps for building a machine learning model are:

1. Select and prepare a training data set necessary to solving the problem. This data can be labeled or unlabeled.
2. Choose an algorithm to run on the training data.

If the data is labeled, the algorithm could be regression, decision trees, or instance-based.

If the data is unlabeled, the algorithm could be a clustering algorithm, an association algorithm, or a neural network.

3. Train the algorithm to create the model.
4. Use and improve the model.

5.3.3 Image Processing:

Image processing is a field of study that involves the use of mathematical algorithms and techniques to manipulate, analyze, and enhance digital images. This process involves converting an image into digital form and performing various operations on it to obtain a desired result. The goals of image processing can vary widely depending on the application, and can include tasks such as enhancing image quality, removing noise or artifacts, extracting useful information from images, or detecting and recognizing objects within an image. Image processing techniques can be classified into two main categories: spatial and frequency domain methods. Spatial domain methods operate directly on the pixels of an image, while frequency domain methods transform an image into a different representation that emphasizes different features of the image. Common image processing techniques include image filtering, edge detection, image segmentation, object recognition, and image compression. These techniques are used in a wide range of fields, including medical imaging, remote sensing, computer vision, and digital art. Image processing techniques can be divided into two main categories: digital image processing and analog image processing. Digital image processing involves the use of digital computers to manipulate digital images, while analog image processing involves the use of analog devices such as filters and lenses to modify the properties of an image. Some common techniques used in digital image processing include image filtering, image segmentation, feature extraction, and image recognition. These techniques are used in a variety of applications such as medical imaging, surveillance, remote sensing, and digital photography.

Image processing is a rapidly growing field with new techniques and algorithms being developed all the time. It has applications in many different fields and is used in industries such as entertainment, automotive, healthcare, and robotics .

5.4 Techniques Applied:

5.4.1 CLAHE -Constrat limited adaptive histogram equalization:

Contrast limited adaptive histogram equalization (CLAHE) is used for improve the visibility level of foggy image or video. In this paper we used CLAHE enhancement method for improving the video quality in real time system. Adaptive histogram equalization (AHE) is different from normal histogram equalization because AHE use several methods each corresponding to different parts of image and used them to redistribute the lightness value of the image and in case of CLAHE `Distribution' parameter are used to define the shape of histogram which produce the better quality result compare then adaptive histogram equalization (AHE). In this algorithm rayleigh distribution parameter are used which create bell shaped histogram. The drawback of AHE is work over homogeneous fog but CLAHE applied over both homogeneous and heterogeneous fog and single image and video system. And the second drawback of AHE is used `cumulation function' which applied over only gray level image but CLAHE used both images colored and graylevel.

5.4.2. Rayleigh distribution:

Rayleigh distribution is a continuous probability distribution for positive-valued random variables. The data can be given by the mean value and a lower bound, or by a parameter and a lower bound. These are interconnected by a well-documented relationship given in the literature.

The distribution with probability density function and distribution function

5.4.3. RGHS (Relative global histogram stretching)

The blind global histogram stretching usually uses the same parameters for all R-G-B channels of the images, ignoring the histogram distribution characteristics of different channels and in different images;

5.4.4. Image Restoration:

Image restoration is the operation of taking a corrupt/noisy image and estimating the clean, original image. Corruption may come in many forms such as motion blur, noise and camera mis-focus. Image restoration is performed by reversing the process that blurred the image and such is performed by imaging a point source and use the point source image, which is called the Point Spread Function (PSF) to restore the image information lost to the blurring process.

Image restoration is different from image enhancement in that the latter is designed to emphasize features of the image that make the image more pleasing to the observer, but not necessarily to produce In order to deal with underwater image processing, we have to consider first of all the basic physics of the light propagation in the water medium. Physical properties of the medium cause degradation effects not present in normal images taken in air. Underwater images are essentially characterized by their poor visibility because light is exponentially attenuated as it travels in the water and the scenes result poorly contrasted and hazy. Light attenuation limits the visibility distance at about twenty meters in clear water and five meters or less in turbid water. The light attenuation process is caused by absorption (which removes light energy) and scattering (which changes the direction of light path). The absorption and scattering processes of the light in water influence the overall performance of underwater imaging systems. Forward scattering (randomly deviated light on its way from an object to the camera) generally leads to blurring of the image features. On the other hand, backward scattering (the fraction of the light reflected by the water towards the camera before it actually reaches the objects in the scene) generally limits the contrast of the images, generating a characteristic veil that superimposes itself on the image and hides the scene. Absorption and scattering effects are due not only to the water itself but also to other components such as dissolved organic matter or small observable floating particles. The presence of the floating particles known as "marine snow" (highly variable in kind and concentration) increase absorption and scattering effects. The visibility range can be increased with artificial lighting but these sources not only suffer from the difficulties described before (scattering and absorption), but in addition tend to illuminate the scene in a non uniform fashion, producing a bright spot in the center of the image with a poorly illuminated area surrounding it. Finally, as the amount of light is reduced when we go deeper, colors drop off one by one depending on their wavelengths. The blue color travels the longest in the water due to its shortest wavelength, making the underwater images to be dominated essentially by blue color. In summary, the images we are interested on can suffer of one or more of the following problems: limited range visibility, low contrast, non uniform lighting, blurring, bright artifacts, color diminished (bluish appearance) and noise. Therefore, application of standard computer vision techniques to underwater imaging requires dealing first with these added problems.

The image processing can be addressed from two different points of view: as an image restoration technique or as an image enhancement method:

The image restoration aims to recover a degraded image using a model of the degradation and of the original image formation; it is essentially an inverse problem. These methods are rigorous but they require many model parameters (like attenuation and diffusion coefficients that characterize the water turbidity) which are only scarcely known in tables and can be extremely variable. Another important parameter required is the depth estimation of a given object in the scene.

Image enhancement uses qualitative subjective criteria to produce a more visually pleasing image and they do not rely on any physical model for the image formation. These kinds of approaches are usually simpler and faster than deconvolution methods.

In what follows we give a general view of some of the most recent methods that address the topic of underwater image processing providing an introduction of the problem and enumerating the difficulties found. Our scope is to give the reader, in particular who is not an specialist in the field and who has a specific problem to address and solve, the indications of the available methods focusing on the imaging conditions for which they were developed (lighting conditions, depth, environment where the approach was tested, quality evaluation of the results) and considering the model characteristics and assumptions of the approach itself. In this way we wish to guide the reader so as to find the technique that better suits his problem or application we briefly review the optical properties of the light propagation in water and the image formation model of Jaffe-McGlamery.

In this section we focus on the special transmission properties of the light in the water. Light interacts with the water medium through two processes: absorption and scattering. Absorption is the loss of power as light travels in the medium and it depends on the index of refraction of the medium. Scattering refers to any deflection from a straight-line propagation path. In underwater environment, deflections can be due to particles of size comparable to the wavelengths of travelling light (diffraction), or to particulate matter with refraction index different from that of the water (refraction). According to the Lambert-Beer empirical law, the decay of light intensity is related to the properties of the material (through which the light is travelling) via an exponential dependence. The irradiance *E* at position *r* can be modeled as:

where c is the total attenuation coefficient of the medium. This coefficient is a measure of the light loss from the combined effects of scattering and absorption over a unit length of travel in an attenuation medium. Typical attenuation coefficients for deep ocean water, coastal water and bay water are 0.05 m^{-1}, 0.2 m^{-1}, and 0.33 m^{-1}, respectively .Assuming an isotropic, homogeneous medium, the total attenuation coefficient c can be further decomposed as a sum of two quantities a and b, the absorption and scattering coefficients of the medium, respectively:

$$E(r) = E(0)e^{-ar}e^{-br} .$$

The total scattering coefficient b is the superposition of all scattering events at all angles through the volume scattering function $\beta(\theta)$ (this function gives the probability for a ray of light to be deviated of an angle θ from its direction of propagation)

$$b = 2\pi\int_0^{\pi}\beta(\theta)\sin\theta\, d\theta .$$

The parameters a, b, c, and $\beta(\theta)$ represent the inherent properties of the medium and their knowledge should theoretically permit us to predict the propagation of light in the water. However, all these

parameters depend on the location r (in a three dimensional space) and also on time. Therefore, the corresponding measurements are a complex task and computational modeling is needed.
McGlamery [1] laid out the theoretical foundations of the optical image formation model while Jaffe [2] extended the model and applied it to design different subsea image acquisition systems. Modeling of underwater imaging has also been carried out by Monte Carlo techniques [3].
In this section we follow the image formation model of Jaffe-McGlamery. According to this model, the underwater image can be represented as the linear superposition of three components. An underwater image experiment consists of tracing the progression of light from a light source to a camera. The light received by the camera is composed by three components: The direct component E_d (light reflected directly by the object that has not been scattered in the water, The forward-scattered component E_f (light reflected by the object that has been scattered at a small angle) and The backscatter component E_b (light reflected by objects not on the target scene but that enters the camera, for example due to floating particles). Therefore, the total irradiance E_T reads:

$$E_T = E_d + E_f + E_b .$$

Spherical spreading and attenuation of the source light beam is assumed in order to model the illumination incident upon the target pane. The reflected illumination is then computed as the product of the incident illumination and the reflectance map. Assuming a Lambertian reflector, geometric optics is used to compute the image of the direct component in the camera plane. The reflected light is also small scattered on its way to the camera. A fraction of the resultant blurred image is then added to the direct component. The backscatter component is the most computationally demanding to calculate. The model partitions 3-dimensional space into planes parallel to the camera plane, and the radiation scattered toward the camera is computed superposing small volume elements weighted by an appropriate volume scattering function. The detail derivation of each of the components of can be found in [2]. We report here the final results, as they appear in Jaffe's article. The direct component results.

$$E_d(x,y) = E_I(x',y')\exp(-cR_c)\frac{M(x',y')}{4F}T_l\cos^4\theta\left[\frac{R_c-F_l}{R_c}\right]^2,$$

where E_I is the irradiance on the scene surface at point (x',y'), R_c is the distance from (x',y') to the camera and the function $M(x',y')$ represents the surface reflectance map. We note that $M(x',y') < 1$ and typical values for objects of oceanographic interest are $0.02 < M(x',y') < 0.1$. The camera system is characterized by F (F-number of the lens), T_l (lens transmittance) and F_l (focal length). The angle θ is the angle between the reflectance map and a line between the position (x', y') and the camera. The forward scatter component is calculated from the direct component via the convolution operator with a point spread function g; and its derivation is valid under the small angle scattering approximation

$$E_f(x, y) = E_d(x, y) * g(x, y, R_c, G, c, B),$$

where the function g is given by

$$g(x, y, R_c, G, c, B) \\ = [\exp(-GR_c) - \exp(-cR_c)]\mathcal{F}^{-1}\{\exp(-BR_c w)\}$$

with G an empirical factor such that $|G| < |c|$ and B a damping function determined empirically. $\mathcal{F}^{-1}$ indicates the inverse Fourier transform and w is the radial frequency. Experimental measurements of the point spread function validate the use of the small angle scattering theory [5, 6]. For the calculation of the backscatter component the small angle approximation is no longer valid as the backscattered light enters the camera from a large distribution of angles. The model takes into account the light contributions from the volume of water between the scene and the camera. The three dimensional space is divided into a large number N of differential volumes ΔV. The backscatter component is a linear superposition of these illuminated volumes of water, weighted by the volume scattering function realistic data from a scientific point of view. Image enhancement techniques (like contrast stretching or de-blurring by a nearest neighbor procedure) provided by imaging packages use no a priori model of the process that created the image.

5.4.5. DCP (Dark channel prior):

Dark Channel Prior (DCP) is one of the significant dehazing methods based upon the observation of the key features of the haze-free images. But it has disadvantages; high computational complexity, over-enhancement in the sky region, flickering artefacts in video processing, and poor dehazing.

The presence of haze in the atmosphere degrades the quality of images captured by visible camera sensors. The removal of haze, called dehazing, is typically performed under the physical degradation model, which necessitates a solution of an ill-posed inverse problem. To relieve the difficulty of the inverse problem, a novel prior called dark channel prior (DCP) was recently proposed and has received a great deal of attention. The DCP is derived from the characteristic of natural outdoor images that the intensity value of at least one color channel within a local window is close to zero. Based on the DCP, the dehazing is accomplished through four major steps: atmospheric light estimation, transmission map estimation, transmission map refinement, and image reconstruction. This four-step dehazing process makes it possible to provide a step-by-step approach to the complex solution of the ill-posed inverse problem. This also enables us to shed light on the systematic contributions of recent researches related to the DCP for each step of the dehazing process. Our detailed survey and experimental analysis on DCP-based methods will help readers understand the effectiveness of the individual step of the dehazing process and will facilitate development of advanced dehazing algorithms.

5.4.6. MIP (Maximum intensity projection):

Maximum intensity projection (MIP) is a simple three-dimensional visualization tool that can be used to display computed tomographic angiography data sets. MIP images are not threshold dependent and preserve attenuation information. Thus, they often yield acceptable results even in cases in which shaded surface display images fail because of threshold problems. MIP is particularly useful for depicting small vessels. Because MIP does not allow for differentiation between foreground and background, MIP images are best suited for displaying relatively simple anatomic situations in which superimposition of structures does not occur (eg, the abdominal aorta.)

The main limitation of MIP is that it cannot adequately depict the spatial relationships of overlapping tissues. Context-preserving illustrative volume rendering model is an extension to direct volume rendering (DVR). In volume rendering this model can simultaneously visualize interior and exterior structures while preserving clear shape cues using a function of shading intensity, gradient magnitude, distance to the eye point, and previously accumulated opacity to selectively reduce the opacity in less important data regions. It is controlled by two user-specified parameters. In this paper, we advance MIP based on this model. On one hand, we improve the opacity computation method correspond with the Context-preserving illustrative volume rendering model. On the other hand, for lighting of the objects the Phong-shading is employed in the new algorithm. Through shading and combining MIP with the Context-preserving illustrative volume rendering, the new MIP images greatly communicate 3D shape, depth information.

5.2.7. ULAP (Underwarter light attenuation prior)

Underwater images present blur and color cast, caused by light absorption and scattering in water medium. To restore underwater images through image formation model (IFM), the scene depth map is very important for the estimation of the transmission map and background light intensity. In this paper, we propose a rapid and effective scene depth estimation model based on underwater light attenuation prior (ULAP) for underwater images and train the model coefficients with learning-based supervised linear regression. With the correct depth map, the background light (BL) and transmission maps (TMs) for R-G-B light are easily estimated to recover the true scene radiance under the water. In order to evaluate the superiority of underwater image restoration using our estimated depth map, three assessment metrics demonstrate that our proposed method can enhance perceptual effect.

Underwater images often have severe quality degradation and distortion due to light absorption and scattering in the water medium. A hazy image formation model is widely used to restore the image quality. It depends on two optical parameters: the background light (BL) and the transmission (TM). Underwater images can also be enhanced by color and contrast correction from the perspective of image processing. In this paper, we propose an effective underwater image enhancement method for underwater images in composition of underwater image restoration and color correction. Firstly, a manually annotated background lights (MABLs) database is developed. With reference to the relationship between MABLs and the histogram distributions of various underwater images, robust statistical models of BLs estimation are provided. Next, the TM of R channel is roughly estimate based on the new underwater dark channel prior (NUDCP) via the statics.

CHAPTER 6

IMPLEMENTATION AND RESULT

6. IMPLEMENTATION AND RESULT

6.1 Implementation

We propose an underwater image enhancement method for different illumination conditions based on a new model of underwater image degradation. In the new model, illumination is included in the modeling of the single-pixel intensity, so its influences to local regions as well as the whole image range are covered in this model. The proposed method is composed of two components: color-tone correction and fusion-based descattering. The first component is based on a frequency-based color-tone estimation strategy. By changing its application range and using necessary modification filters, it can be used to correct the global color cast in uniformly-illuminated images and regional color cast in non-uniformly-illuminated images. The second component is used to solve the residual degradation problems that are related to the scene-camera distance. This component adopts a fusion strategy to enhance images under different states. Experiments on laboratory and open-water images of different depths and lighting conditions prove the effectiveness of the proposed method. According to qualitative and quantitative evaluation results, the proposed method can improve the color balance and contrast of underwater images, and restore the color accuracy and visibility of images.

Underwater image enhancement and restoration are important tasks in computer vision and image processing. Images captured in underwater environments are often degraded due to various factors such as absorption, scattering, and color cast, which result in poor visibility and reduced image quality. To improve the quality of underwater images, several enhancement and restoration techniques have been proposed. In this answer, I will discuss the implementation of an underwater image enhancement and restoration model. The first step in the implementation of an underwater image enhancement and restoration model is to acquire the data. For this task, a dataset of underwater images is required. There are several publicly available datasets for underwater images, such as the UCSD Underwater Dataset, the Kongsberg Maritime Image Dataset, and the C-DiverNet Dataset. The selected dataset should be diverse and representative of different underwater environments. Once the dataset is acquired, the next step is to preprocess the images. This involves correcting the color cast, removing noise, and enhancing contrast. There are several techniques available for preprocessing underwater images, such as the white balance algorithm, the dark channel prior method, and the adaptive histogram equalization technique. The chosen preprocessing method should be suitable for the dataset and the specific underwater environment.

After the preprocessing step, the image enhancement and restoration model can be implemented. The model can be divided into two stages: enhancement and restoration. In the enhancement stage, the goal is to improve the contrast and visibility of the image. Several enhancement techniques can be used, such as the multiscale retinex algorithm, the histogram equalization method, and the adaptive gamma correction technique. The chosen enhancement technique should be robust to the variations in the dataset and the specific underwater environment. In the restoration stage, the goal is to remove the blur and noise from the image. Several restoration techniques can be used, such as the wavelet denoising method, the non-local means algorithm, and the bilateral filter. The chosen restoration technique should be able to preserve the details in the image while removing the noise and blur.

Finally, the performance of the implemented model can be evaluated. This can be done by comparing the results of the model with the ground truth images in the dataset. Several evaluation metrics can be used, such as the peak signal-to-noise ratio (PSNR), the structural similarity index (SSIM), and the visual information fidelity (VIF). The chosen evaluation metric should be suitable for the specific application.In conclusion, the implementation of an underwater image enhancement and restoration model involves acquiring a diverse dataset of underwater images, preprocessing the images to correct color cast and enhance contrast, implementing an enhancement and restoration model, and evaluating the performance of the model using appropriate evaluation metrics. The success of the model depends on the choice of the preprocessing, enhancement, and restoration techniques, which should be suitable for the dataset and the specific underwater environment.

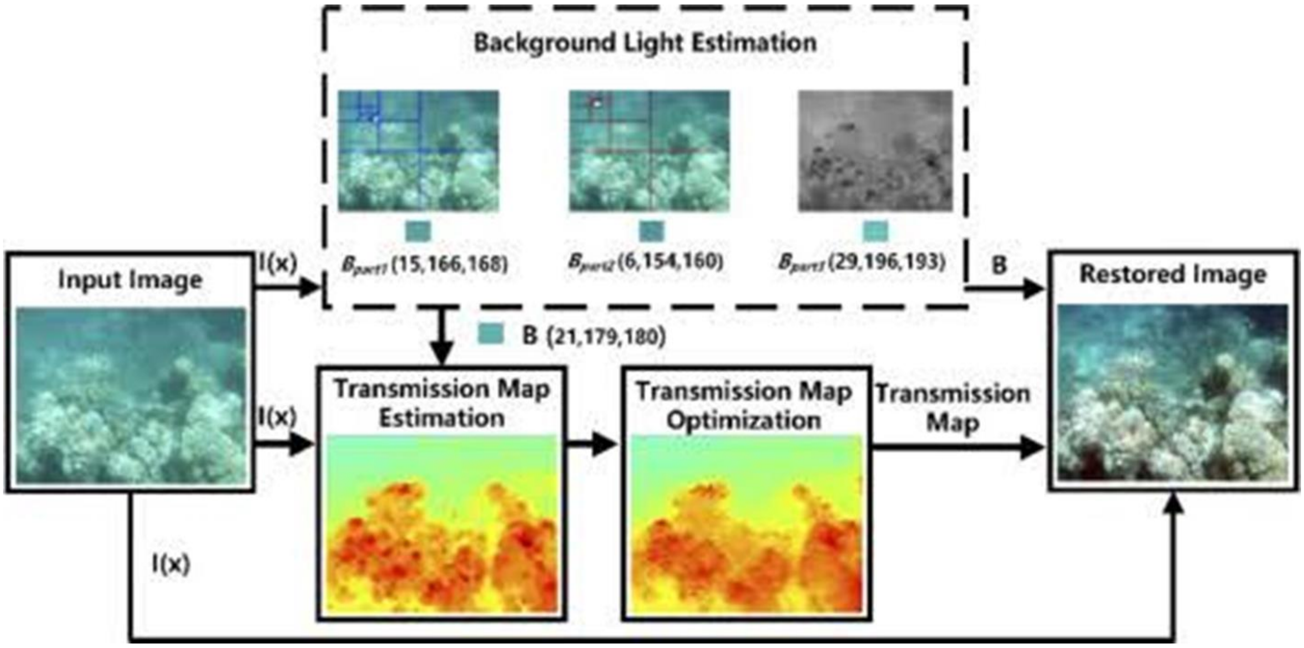

Fig 6.1: Implementation

The image restoration aims to recover a degraded image using a model of the degradation and of the original image formation; it is essentially an inverse problem. These methods are rigorous but they require many model parameters (like attenuation and diffusion coefficients that characterize the water turbidity) which are only scarcely known in tables and can be extremely variable. Another important parameter required is the depth estimation of a given object in the scene. Image enhancement uses qualitative subjective criteria to produce a more visually pleasing image and they do not rely on any physical model for the image formation. These kinds of approaches are usually simpler and faster than deconvolution method. Get the distorted underwater as our input image.

Determine the size of the image. Calculate the enhancement variable. Normalize the image using k, and finally we will get the enhanced output. For the past several years, the attention of more and more scholars was drawn to the field of underwater images enhancement and restoration. As a result of scattering and absorption, underwater images always suffer from the problems of low contrast, blur, and color distortion. So, underwater image restoration and enhancement has been a challenging field. some pictures captured in underwater environment and we can see the quality decline obviously. High quality images are needed in many fields which use the underwater images to achieve some specific goals.

Tracking of underwater objects, 3D reconstruction of underwater objects, underwater archaeology, underwater biological research, and sea floor exploration. In order to obtain high quality images, scholars proposed different approaches which could be sorted into two categories. One is image restoration and the other one is image enhancement. The image enhancement technology does not consider the physics model and it can improve the image quality by image processing methods simply. The image restoration technology is based on the physics model of image formation. But this technology is not good at dealing with the color distortion. Because the two technologies have their own advantages and disadvantages, in this paper, we combined the two technologies and obtained satisfying results. For the image dehazing questions in air, some scholars proposed the method which needed several pictures obtained under different weathers to get the image without fog. Recently more and more researchers have begun to focus on single image dehazing. Tan in [3] dehazed images by maximizing the local contrast of restoration images. The result of this method was satisfying, but the saturation suffered from over enhancement. Fattal in [4] used one single image to obtain a transmittance image and used this transmittance image to dehaze the image. He et al. in [5] proposed the dark channel prior to acquire the transmittance image. He found that one of the three channels (R/G/B) of images without fog and sky areas normally had low intensity. Once sky or foggy areas existed in images, this phenomenon would be invalid. He found this statistics phenomenon and then proposed the dark channel prior. Ge et al. in [6] proposed one single image dehazing method by linear transformation. one single image dehazing method which utilized the detailed prior information. For underwater environment, by observing the relationship between the blurring degree and the imaging distance, Peng et al. [8] applied the blurring method to the imaging formation model and estimated the distance between the scene and the camera and then removed the fog. Ancuti et al. [9] utilized the image fusion method to remove the fog; up to now this method may be the best method on visual perception. Considering the features of underwater environment, Carlevaris-Bianco et al. in [10] used the notable differences of attenuation among different channels to estimate the depth of the scene. input forward an automatic red channel underwater image restoration method, and this method could be regarded as the deformation of the dark channel prior method. The blue and green channel without the red channel to redefine a new dark channel that fitted the underwater image. This slightly modified dark channel prior based method was successfully applied to underwater images. In this paper, we proposed one new restoration and enhancement method for underwater images: underwater image restoration and enhancement based on bright channel prior. Our method could be regarded as the improved version

This method consists of first extracting the bright channel image from the input, which is the degraded underwater image.

6.2 Test Cases:

6.2.1 Unit testing:

Unit testing is a software testing technique where individual units or components of the software are tested in isolation to ensure that they are functioning as intended. A unit can be a function, method, or class, and it is tested in isolation from the rest of the software system. The purpose of unit testing is to identify and fix bugs early in the development process before the software is integrated. This saves time and effort in the long run, as it is easier and less expensive to fix a bug in the early stages of development than later on. Unit tests are typically automated, which means that they are executed automatically by a testing framework. The framework provides tools for creating and running tests, as well as for reporting test results. Unit tests are designed to test the functionality of a unit in isolation, which means that they do not test the interactions between units or the software system as a whole. This is the job of integration testing and system testing.

Integration testing is a software testing technique that tests how different components or subsystems of the software work together as a whole. It verifies the interactions between components to ensure that they work seamlessly when integrated.

6.2.2 Integration Testing:

The purpose of integration testing is to identify defects in the interaction between software components, which are not detectable by unit testing. Integration testing is performed after unit testing, where individual units or components are tested in isolation.

Integration testing is essential for identifying defects in the interaction between software components. It helps to ensure that the integrated system meets the requirements and specifications and behaves as expected. By catching defects early in development, integration testing helps to ensure that the final product is of high quality and meets the customer's expectations.

6.2.3 System Testing:

System testing is a software testing technique that tests the entire software system as a whole. It is performed after integration testing and involves testing the system's behavior and performance to ensure that it meets all functional and non-functional requirements. The purpose of system testing is to verify that the software system is complete, functions as expected, and meets all the specified requirements. System testing can be performed in different ways, such as:

Functional testing: This involves testing the functionality of the software system to ensure that it meets the specified requirements.

Performance testing: This involves testing the software system's performance under various workloads to ensure that it meets the specified performance requirements.

Security testing: This involves testing the software system's security features to ensure that they meet the specified security requirements.

Compatibility testing: This involves testing the software system's compatibility with different hardware, software, and network configurations.

6.2.4 Regression Testing:

Regression testing is a software testing technique that verifies that changes made to the software do not unintentionally impact previously working functionality. It is performed after modifications or updates are made to the software to ensure that they do not introduce new bugs or cause previously fixed bugs to reappear. The purpose of regression testing is to ensure that the software system continues to function as intended after changes are made to it. Regression testing is essential for detecting and fixing defects that might have been introduced during development, such as bugs that were not caught during unit testing or integration testing. Regression testing can be performed manually or through automated testing tools, depending on the complexity of the software system and the testing requirements.

6.2.5 Acceptance Testing:

Acceptance testing is a software testing technique that verifies whether a software system meets the customer's requirements and expectations. It is the final stage of testing before the software system is released to the end-users or customers. The purpose of acceptance testing is to ensure that the software system is ready for deployment and meets the customer's expectations. Acceptance testing is typically performed by the end-users or customers or their representatives to ensure that the software system meets their needs and performs as expected. Acceptance testing is essential for ensuring that the software system meets the customer's requirements and expectations. By performing acceptance testing, software developers can ensure that the software system is ready for deployment and that it meets the needs of the end-users. Acceptance testing helps to ensure customer satisfaction and reduces the risk of potential issues after the software system is released.

6.3 Result:

The graphical user interface (GUI) for underwater image enhancement typically consists of a set of controls and displays that allow the user to adjust the various parameters of the image enhancement process and view the results in real time. The GUI can be designed using a variety of software tools and frameworks, depending on the specific requirements and constraints of the system.

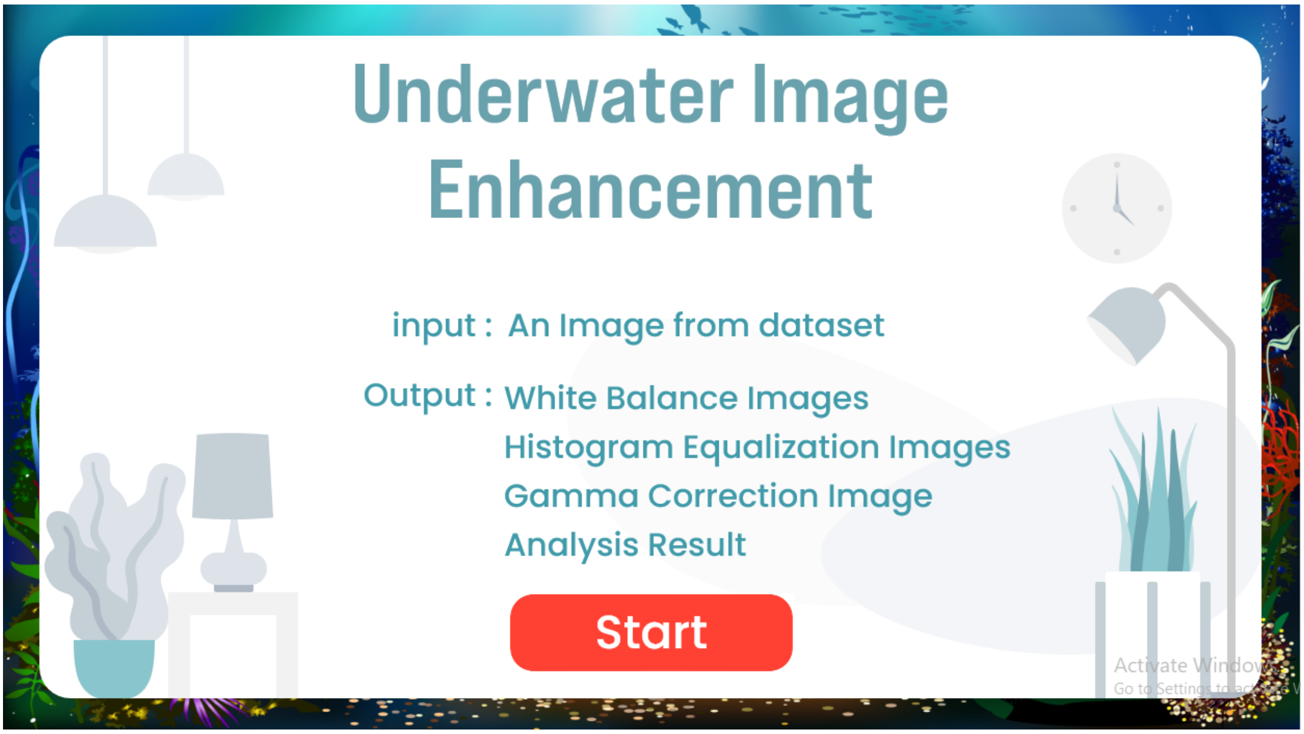

Fig 6.3.1: Dashboard

This is the Graphical User Interface of our model. After clicking the start icon we will be redirected to page were the image processing will take place. Further we can continue with enhancement and restoration process. The graphical user interface will allow user to interact with the model and perform various operations. Typically includes several components that provides information and tols for the user.

The process of improving the visual quality of an image by adjusting its various attributes such as brightness, contrast, sharpness, color balance, and noise reduction. There are various methods and techniques for image enhancement, ranging from traditional methods based on image processing techniques to more advanced methods based on machine learning algorithms.

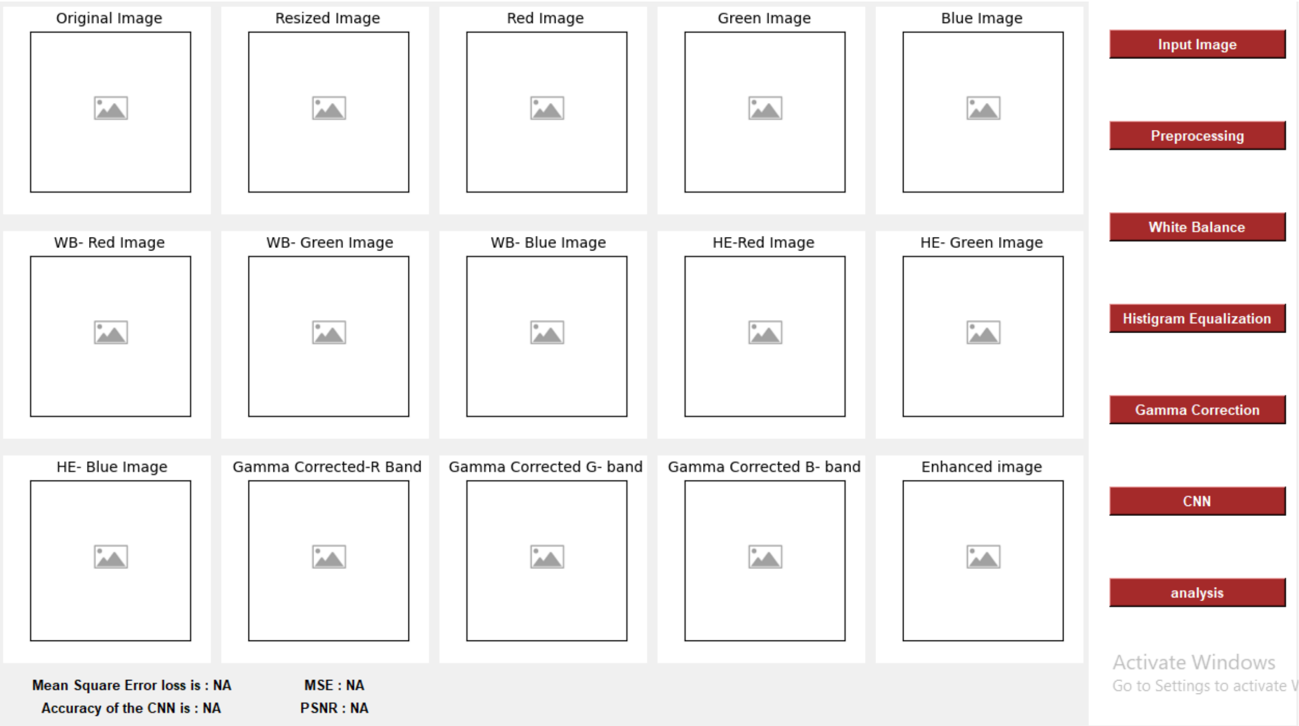

Fig 6.3.2: Enhancement and restoration process

The underwater image enhancement process involves a combination of pre-processing, enhancement techniques, post-processing, and evaluation to improve the visual quality of an underwater image. The specific techniques used may vary depending on the imaging conditions and the requirements of the image.

This component allows users to load and view underwater images that they want to enhance or restore. Users can select from a range of enhancement options based on the specific model, such as brightness adjustment, contrast enhancement, noise reduction, color correction, and sharpening.

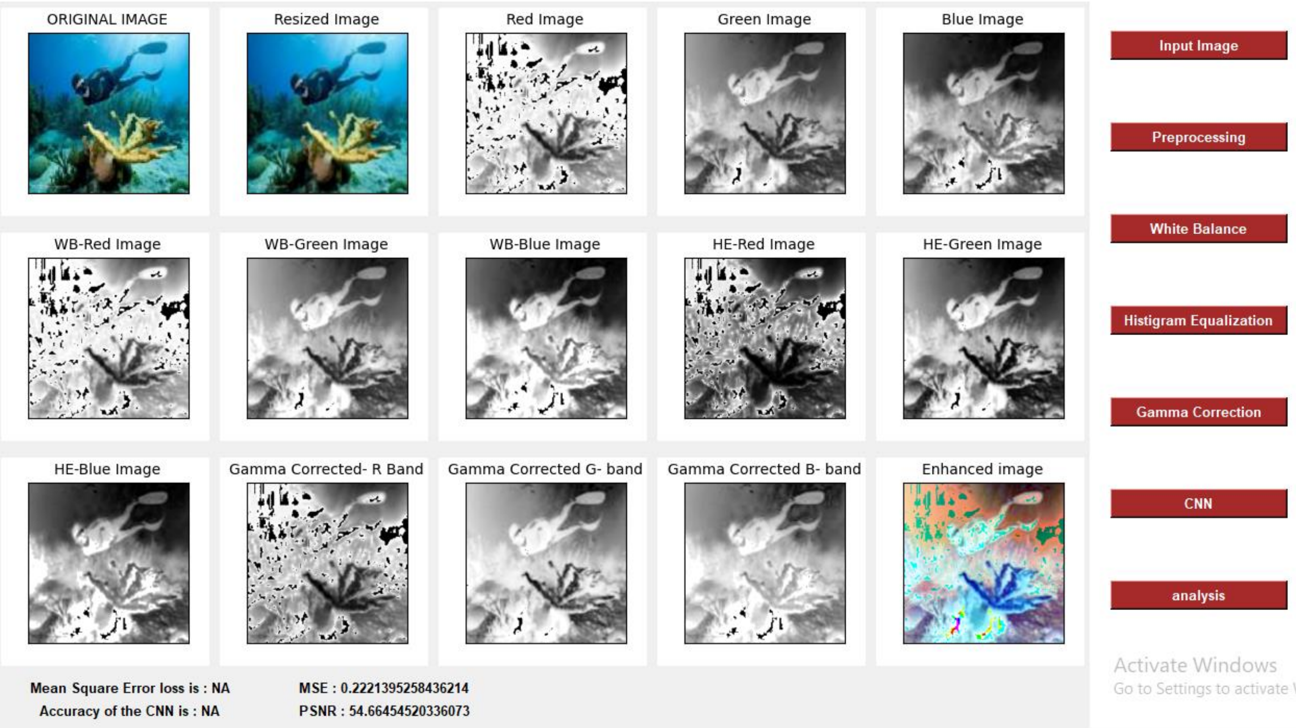

Fig 6.3.3: Output

Restoration options may include methods for removing or reducing distortions, such as blurring, haze, or color casts, and for correcting image alignment. Once the user has selected the desired enhancement and restoration options, the dashboard displays the output image so the user can compare it with the original.

A restored image is an image that has been processed using techniques to improve its visual quality and restore some of its original details. Image restoration techniques aim to remove or reduce distortions that have been introduced to the image during acquisition or transmission, such as blur, noise, or compression artifacts.

Fig 6.3.4: Restored Image

An underwater enhanced image is an image that has been processed to improve its visual quality and clarity, usually by correcting for color and contrast issues caused by the way light behave underwater. An enhanced underwater image will typically have more accurate colors, better contrast, and fewer artifacts or visual distortions.

Underwater image enhancement and restoration techniques generally fall into two categories: global and local. Global techniques, such as color correction and contrast enhancement, adjust the overall appearance of the image, and can improve the visibility of the subject and the overall clarity of the image. These techniques are applied uniformly across the entire image and can help to correct for the color and contrast issues caused by the way light behaves underwater. Local techniques, such as noise reduction and image restoration, target specific areas of the image and attempt to correct for visual distortions or damage in those areas. These techniques can be more targeted and precise than global techniques, and can help to improve the sharpness and quality of the image in specific areas.

Both global and local techniques can be used in combination to achieve the best possible results in underwater image enhancement and restoration. The specific techniques used and the order in which they are applied will depend on the characteristics of the image and the desired outcome.

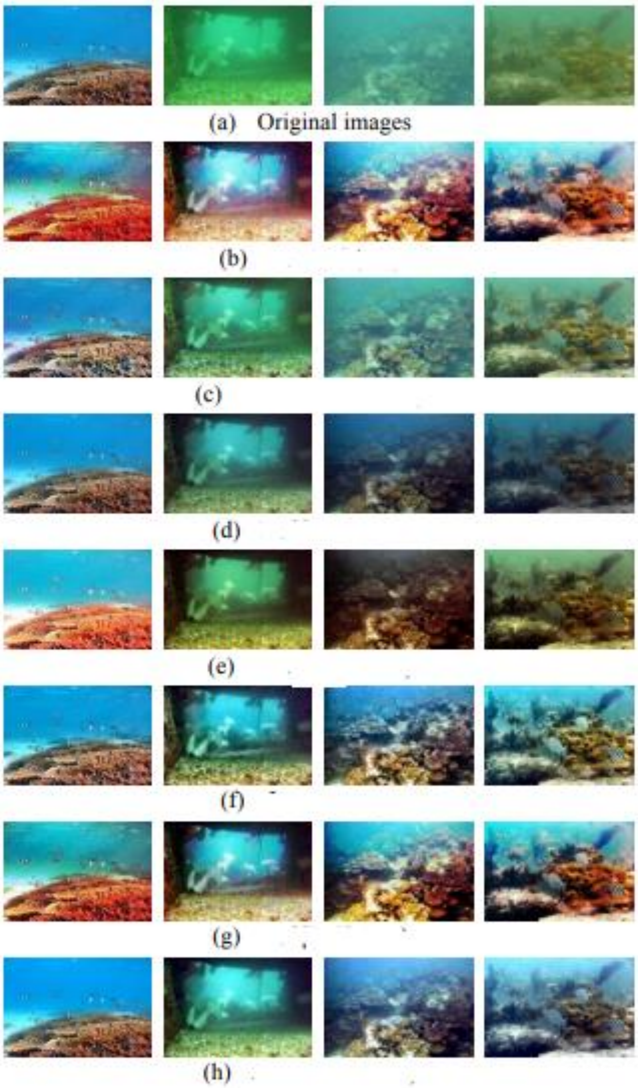

Fig 6.3.5: Enhanced images

(a) Shows the original image, (b) shows image enhancement, (c) shows the image after CLAHE, (d) Shows image after MIP (e) Shows image after UCM, (f) Shows image after ULAP, (g) shows image after Rayleigh Distribution, (h) shows image after RGHS.

The main difference is that image enhancement aims to improve the visual quality of an image by increasing its contrast, brightness, or sharpness while image restoration aims to remove or reduce the degradation or distortion that an image may have suffered during acquisition, transmission, or storage.

CONCLUSION

CONCLUSION

We proposed an enhancement method for underwater images with uniform or non-uniform illumination conditions. In practical operations, these conditions usually correspond to the shallow-water environment and the deep-sea environment, respectively. The proposed method is composed of two modules: color-tone correction and fusion-based descattering. The first module reduces the regional or full-extent color-tone deviation that is caused by different types of incident light. And the second module solves the problems of low contrast and pixel-wise color deviation that are left after applying the first module. The proposed method is experimented on laboratory and open-water images under different depths and illumination states. Qualitative and quantitative evaluations show that the proposed method outperforms many other methods in improving the color balance and contrast of underwater images with different illumination conditions, and is especially effective in improving the color accuracy and information content in badly-illuminated regions of underwater images with non-uniform illumination, which are commonly seen in deep-sea researches and operations. Going through all the steps of research, implementation, and testing allowed me to achieve a visually acceptable result following the underwater image restoration using the bright channel method. What can still be improved by future work is applying other types of testing on different inputs to leave no doubts about the accuracy of the program. Nevertheless, the field of underwater image restoration knows different solutions that are all valid despite the differences of the color, saturation, and contrast intensities between the applied methods.

This field is still under development and research, and until now there is no absolute ground truth standard to go back to.

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We are graceful to all staff members, non-teaching staff and all our friends us the helping hand.

ANNEXTURE –I

RESEARCH PAPER AND CERTIFICATES