CHAPTER 1

INTRODUCTION

1.1 Background of the Work

The exploration and study of underwater environments have become increasingly significant due to their vast potential in fields such as marine biology, resource discovery, industrial inspection, environmental protection, and defense operations. Oceans, covering over 70% of the Earth's surface, hold invaluable resources such as mineral deposits, oil reserves, and countless undiscovered species. They also play a critical role in regulating the Earth's climate and supporting diverse ecosystems. However, obtaining clear and high-quality underwater images remains a substantial challenge due to the optical complexities of water as a medium. Unlike air, water causes rapid absorption, scattering, and refraction of light, which severely impacts image clarity and color fidelity.

Light absorption in water is wavelength-dependent, where longer wavelengths, such as red, are absorbed first, followed by green and blue, leaving a dominant bluish-green hue in underwater images. Additionally, suspended particles and organic matter scatter light, leading to blurred, hazy, and low-contrast visuals. These challenges are exacerbated by non-uniform illumination, where the center of the image often appears brighter due to artificial lighting, while the edges remain dark and shadowed. This makes conventional imaging techniques[12] inadequate, as they fail to address all degradations comprehensively.

Over the years, several image enhancement and restoration methods[9] have been developed to address these challenges. Techniques such as histogram equalization, color correction, and dehazing methods have shown partial success in improving underwater images. However, these methods are often task-specific, focusing on resolving one aspect of image degradation while leaving others unresolved. Recent advancements in image fusion strategies have opened new possibilities by combining multiple enhancement techniques to tackle various challenges simultaneously. This motivates the exploration of multi-fusion techniques for underwater image enhancement, which can produce high-quality visuals by addressing color distortion, low contrast, noise, and non-uniform illumination in a unified framework.

1.2. Motivation

The demand for clear and high-quality underwater images stems from their importance in a wide range of critical applications. Marine biologists rely on enhanced images to monitor marine ecosystems, identify species, and analyze biodiversity patterns. Underwater robotics and autonomous underwater vehicles (AUVs) require real-time, sharp visuals for navigation, mapping, and performing search-and-rescue missions in complex marine environments. Industrial sectors depend on underwater imaging for inspecting pipelines, shipwrecks, and submerged structures, ensuring safety and efficiency in operations.Despite the advancements in camera technologies and imaging devices, the underwater environment poses significant hurdles that hinder the quality of captured images.

1.3. Scope of the proposed work

The scope of this project focuses on enhancing underwater images to improve their visual quality and usability across various applications. Underwater images often face challenges such as color distortion, low contrast, haziness, and poor sharpness due to the absorption and scattering of light in water. This project addresses these challenges through a structured approach involving color correction, contrast enhancement, and sharpening techniques. The enhanced images can be used in fields like underwater robotics, naval surveillance, object detection, and entertainment, where clear and accurate visuals are critical.

The proposed method, including advanced fusion techniques, ensure that the images not only appear visually appealing but also retain important details for analysis. By creating images with improved clarity and balance, the project contributes to better functionality in automated systems and human-centered applications. For example, in robotics, the improved visuals can help with navigation and object detection, while in surveillance, they can aid in identifying crucial details in underwater environments.

This project also opens possibilities for further research in real-time image enhancement and the application of more sophisticated algorithms to handle diverse underwater conditions. The methods developed here provide a strong foundation for future innovations and applications, making the project relevant for both research and practical implementations in underwater imaging.

1.4. Research Significance and Applications

The significance of the proposed multi-fusion underwater image enhancement technique lies in its ability to produce high-quality visuals across a wide range of underwater conditions. Enhanced underwater images play a crucial role in the following applications:

1. Marine Life Monitoring:

   Clear and detailed underwater images enable marine biologists to observe marine species, track their movements, and assess ecosystem health. High-quality visuals aid in biodiversity studies and the discovery of new underwater species.

2. Underwater Robotics and Navigation:

   In underwater robotics, autonomous vehicles rely on real-time visuals for navigation, obstacle avoidance, and task execution. Enhanced images improve the accuracy and reliability of robotic operations in complex underwater environments.

3. Search and Rescue Operations:

   During search-and-rescue missions, clear underwater images help identify objects, people, or structures submerged in water, improving the efficiency and success rate of rescue operations.

4. Industrial Inspections:

   High-quality visuals are essential for inspecting underwater pipelines, oil rigs, shipwrecks, and other infrastructure. Enhanced images facilitate accurate defect detection and structural analysis.

5. Scientific Research and Exploration:

   Researchers rely on clear underwater images to study marine habitats, analyze oceanic conditions, and explore underwater geological formations. Enhanced visuals support advanced scientific discoveries and monitoring.

6. Defense and Surveillance:

   Underwater imaging plays a vital role in defense operations, including surveillance, reconnaissance, and monitoring submerged threats. Enhanced visuals provide clearer insights for decision-making.

CHAPTER 2

LITERATURE SURVEY

2.1. A Novel Two-Step Strategy Based on White-Balancing and Fusion for Underwater Image Enhancement

The paper "A Novel Two-Step Strategy Based on White-Balancing and Fusion for Underwater Image Enhancement" by Ye Tao, et al.[1] deals with the challenges faced in underwater imaging,which includes color distortion, detail loss, and contrast reduction due to scattering of light and absorption . Due to these issues the visual quality of underwater images becomes difficult to obtain clear and accurate representations required for scientific analysis and underwater exploration. The two-step strategy for enhancing underwater images proposed by the authors are an improved white-balancing technique, where the optimal color compensation is determined using the Underwater Color Image Quality Evaluation (UCIQE) and Underwater Image Quality Measure (UIQM) which ensures minimized color distortion,and the second step is the artificial multiple under exposure image fusion strategy. To generate multiple under-exposure versions of the image , gamma-correction is applied. By blending three weights i.e, contrast, saturation, and well-exposedness into a multi-scale fusing scheme the final image is enhanced.

The effectiveness of the proposed method is measured using UCIQE, UIQM, and PCQI (Patch-based Contrast Quality Index). The strategy produces superior visual quality in enhanced underwater images which significantly outperforms existing techniques . Measurably, the proposed method shows higher UCIQE and UIQM values compared to traditional methods, indicating better color correction, contrast enhancement, and detail preservation.

2.2. An Underwater Image Enhancement Method Based on Balanced Adaption Compensation

The paper titled 'An Underwater Image Enhancement Method Based on Balanced Adaption Compensation' by Wenjia Ouyang,et al.[2] is intended to improve underwater images through the BAC method. The proposed method integrates a learning based and a physical based approach in order to address some of the weaknesses such as color distortions, Artificial look and poor robustness to different underwater environments. Balanced Adoption Compensation (BAC) is a method that comprises two major modules, Semantic Transfer (ST) and Scene-Relevant Reconstruction (SR).The division of work between the two modules is in the form dynamic balance factor (μ) that is aimed at balancing through the scene attenuation levelsAlternatively switching the contributions of both approaches based on the scene conditions through the balancing factor μ derived from image color channels correlation and attenuation levels.

The method was evaluated using the Test-R and Test-U datasets, with two metrics: Two models have to do with the quality of underwater image namely UIQM (Underwater Image Quality Measure) and UCIQE (Underwater Color Image Quality Evaluation). The method was evaluated using the Test-R and Test-U datasets, with two metrics: UIQM (Underwater Image Quality Measure) and UCIQE (Underwater Color Image Quality Evaluation).

2.3. HIFI-Net: A Novel Network for Enhancement to Underwater Optical Images

"A Novel Network for Enhancement to Underwater Optical Images " by Jiajia Zhou, Junbin Zhuang, et al.[3] has the objective of presenting HIFI-Net as the new approach towards improving underwater optical images. The network integrates a Reinforcement Fusion Module that utilizes Haar wavelet images; to enhance the quality of blurry underwater images because of degradation through underwater light absorption and scattering that leads to color casts and haze effects.

The method Reinforcement Fusion Module for Haar (RFM-Haar) is a core component of HIFI-Net, which fuses Haar wavelet transformed images with the original underwater images. The wavelet-transformed images provide additional high-frequency information that, when fused with the original image, helps in enhancing the fine details.The network employs Convolutional Neural Networks (CNN) and combines spatial information processing with frequency domain processing. The Reinforcement Fusion Unit, RFU, extracts and fuses base image information and reinforcement information, Haar wavelet-transformed images, in high-dimensional space. This enhances the amount of information that is contained in each pixel hence enhancing the quality of the images.

2.4. Self-Adversarial Generative Adversarial Network for Underwater Image Enhancement

The paper titled "Self-Adversarial Generative Adversarial Network for Underwater Image Enhancement" by Haiwen Wang, et al.[4], aims to address the challenges in underwater image quality such as blur, low contrast, noise, and color distortions. The network focuses on improving underwater images by transferring quality from high-quality natural images to distorted underwater images.The method SA-GAN (Self-Adversarial GAN) introduces a self-adversarial model that enhances images in two stages:1.Generate a high-quality image from a low-quality underwater image.2.Forward the generated image back into the generator for further improvement. A dual pairwise discriminator compares the quality of the generated images with high-quality reference images, improving the decision boundary for image quality.Two discriminators are employed—one evaluates the quality of the generated image by comparing it with the natural high-quality image, and the second compares two stages of generated images (first and second enhancement) to ensure continuous improvement.

The evaluation was made by means of certain criteria including Underwater Color Image Quality Evaluation (UCIQ) and Underwater Image Quality Measure (UIQM) that determine color, contrast and clarity.Hence, the proposed SA-GAN proved a superior method to other existing methods such as UWCNN, FUnIE-GAN, and LA-Net in terms of UCIQE and UIQM scores of the real-world and benchmark underwater image dataset. The network was particularly effective in correcting colour and improving the aesthetic quality of under-water pictures.

2.5. Underwater Image Enhancement Based on Zero-Reference Deep Network

The research study titled "Underwater Image Enhancement Based on Zero-Reference Deep Network" by Yifan Huang,et al.[5] offers an improved Zero-UIE technique for improving the quality of underwater images. The proposed aim is to improve underwater images with no need of paired or unpaired reference data in training.The network estimates dynamic adjustment parameters using a curve model based on the principles of haze image formation, improving the visual quality of underwater images affected by color distortion and contrast reduction.The proposed network, called Zero-UIE (Zero-Reference Underwater Image Enhancement), is based on a novel underwater curve model. This model calculates certain parameters to improve underwater images, problems such as color distortion and contrast loss are fixed. The method includes adaptive color compensation as a preliminary step for image improvement to enhance the result of the images, especially those captured underwater which are highly prone to be deteriorated.

The network works as it accepts an underwater image as input and utilizes the curve adjustment approach employed to address haze formation in order to improve image quality. The method includes the estimation of the parameter map for the underwater curve model, and pixel-wise modification of the image in order to correct its color and contrast. A set of non-reference loss functions is designed to drive the training process, ensuring that the model learns to enhance the image without paired training data.

2.6. Color Correction and Local Contrast Enhancement for Underwater Image Enhancement

The paper of Songlin Jin, Peixin Qu titled “Color Correction and Local Contrast Enhancement for Underwater Image Enhancement “ [6] is a paper that aims at addressing the issue of enhancing underwater images through a series of multi- step processes of color correction, detail sharpening, and contrast enhancement. In particular, it tries to solve problems related to color distortion, low contrast in underwater images and blurring of details.The method makes use of Retinex theory as well as Gaussian pyramid decomposition and Contrast Limited Adaptive Histogram Equalization in producing more enhanced underwater image clarity. The multi-channel color compensation enables correction of color as it also compensates for light attenuation. GDPIR enhances details better than the Gaussian pyramid and the CLAHE equalizes the intensities of different parts of the image and avoids the amplification of noise. The method was compared against several state-of-the-art underwater enhancement techniques including UDER, MILHD, IBLA and UICR and observed improvements in terms of brightness, color fidelity and contrast.Since the paper compares results with underwater images, it employs UCIQE and UIQM, and other metrics such as information entropy (IE), average gradient (AG), and patch-based contrast quality index (PCQI).

2.7. Underwater Image Enhancement Method Based on Dynamic Heterogeneous Feature Fusion Neural Network

The paper “Underwater Image Enhancement Method Based on Dynamic Heterogeneous Feature Fusion Neural Network” by Xuejun Zhou,et al.[7] presents a novel method for underwater image enhancement using a dynamic heterogeneous feature fusion neural network. The goal is to solve the problems of gray-scale loss, noise amplification, and color distortion in underwater images by proposing a neural network model that improves image clarity and color fidelity while maintaining computational efficiency.The approach uses a Dynamic Heterogeneous Feature Fusion Neural Network. It combines bit-depth quantization, convolutional neural networks (CNN), and pseudo-color enhancement to restore details and enhance underwater images.The Key Components are Global Background Light Estimation using convolution kernels to extract feature maps from multi-scale images, Multi-scale Image Feature Extraction to restore low-light images using a fusion of different levels of image features, Noise Reduction to suppress noise introduced during brightness and detail enhancement stages.The model consists of two modules:Image Brightness Enhancement Module and an Image Denoising Module.It is then compared with other methods such as Retinex based methods, CLAHE, Dehaze, and modern CNN methods including LL-CNN and MSRNet. By applying the proposed method, it has been revealed that color fidelity is maintained much better and noise and detail information in images are also improved than other methods.

The paper evaluates performance using the following metrics: PSNR (Peak Signal-to-Noise Ratio): This rate the signal and the higher the value the better the enhancement. SSIM (Structural Similarity Index): Implies the level of ‘blurry’ of the image before and after the improvement has been made. NIQE (Natural Image Quality Evaluator): The scores represent deviations from the natural appearance; therefore the lower the score, the better the image quality. BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator): It evaluates spatial quality, by providing lower value that shows better performance.

CHAPTER 3

OBJECTIVES AND METHODOLOGY

This chapter outlines the specific objectives of the proposed work, which are formulated based on the challenges identified during the literature survey and analysis of underwater images. The primary goal is to address the limitations posed by underwater environments, such as color distortion, low contrast, and poor image sharpness, by developing a comprehensive methodology for underwater image enhancement. These objectives form the foundation for the systematic steps adopted to improve image quality and ensure the effectiveness of the proposed enhancement techniques.

3.1. Objectives of the proposed work

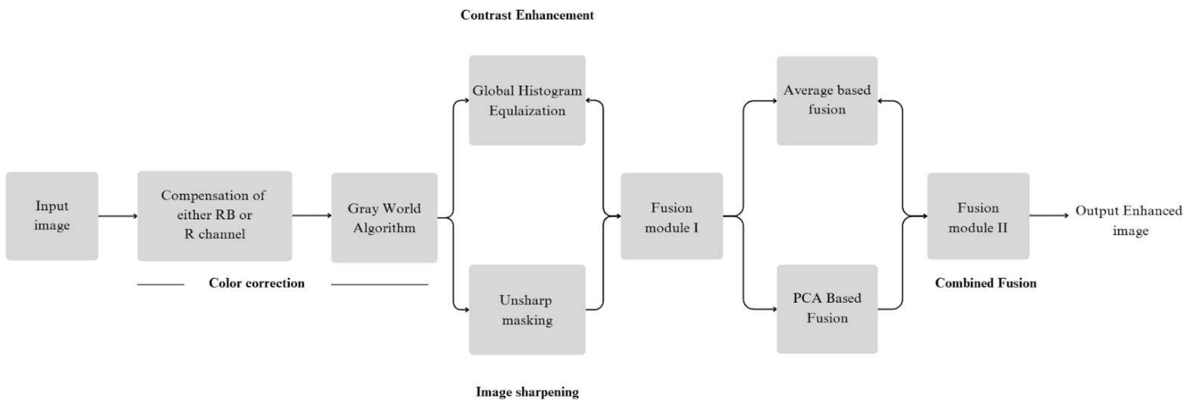
The primary aim of this project is to enhance underwater images to make them suitable for a range of practical applications, such as entertainment, underwater robotics, surveillance for naval operations, and object detection. Underwater images often suffer from significant challenges, including poor color accuracy, haziness, and low visibility, which hinder their usability. By addressing these issues through advanced image enhancement techniques, this work aspires to improve the visual quality of underwater images and make them more functional for critical and diverse applications.

1. To enhance the clarity, sharpness, and overall visual appeal of underwater images, making them suitable for applications such as entertainment media, underwater robotics, and naval surveillance. Improved image quality ensures better usability in scenarios requiring high visual fidelity and precision.

2. To achieve accurate color correction by addressing distortions caused by the absorption and scattering of light in underwater environments, while also removing haziness to restore image clarity. This objective aims to make underwater images more realistic and visually interpretable.

3. To prepare underwater images for use in automated systems like underwater robots, object detection algorithms, and navigation tools. Enhanced images will support improved machine vision, enabling accurate object recognition, tracking, and analysis in underwater environments.

3.2. Work-flow of the proposed work



The proposed work begins with an input image, which may exhibit distortions such as poor color balance, low contrast, or reduced sharpness. To correct the color imbalance, the image undergoes compensation of either the RB or R channel, where adjustments are made to reduce dominant color casts and bring the color channels to a more neutral state. This step ensures a more accurate representation of colors in the image. Following this, the Gray World Algorithm[8] is applied, a color correction technique based on the assumption that the average reflectance of the world is gray. It works by normalizing the RGB channels such that their means are approximately equal, leading to a natural-looking color balance.

Once the color correction is complete, the process focuses on contrast enhancement through Global Histogram Equalization (GHE)[13]. GHE redistributes the pixel intensity values across the full dynamic range, which improves the visibility of details in regions that might appear too dark or too bright, thereby enhancing the overall contrast of the image. Simultaneously, image sharpening is performed using Unsharp Masking, which improves the clarity of the image by enhancing edges. This method works by creating a blurred version of the input image, subtracting it from the original, and adding the result back to emphasize fine details and edges. The results of Global Histogram Equalization (contrast enhancement) and Unsharp Masking (image sharpening) are then combined in the fusion stage to further refine the image. Two fusion techniques are employed: Averaging-Based Fusion and PCA-Based Fusion[16]. Averaging-Based Fusion blends the outputs smoothly by averaging the pixel intensities, producing a balanced enhancement without harsh transitions. On the other hand, PCA-Based Fusion applies Principal Component Analysis, a statistical method[20] that reduces data redundancy by extracting the most significant features from the processed images, leading to an optimal fusion output. Finally, the enhanced image is generated with significant improvements in color correction, contrast, and sharpness. The resulting image is visually appealing, with clearer details and balanced colors, making it suitable for applications requiring high-quality image enhancement.

3.3. Data collection

The underwater image data is collected from various web sources. These images depict common challenges like color distortion, haziness, and reduced visibility, making them ideal for testing enhancement techniques. The dataset includes images captured in different environments, such as shallow and deep waters, and varying lighting conditions. Figure 1.1 shows sample sets of underwater images and its enhanced version as references. The reference images are used to compare with the resultant images that are enhanced using our method. [19]

Figure 1.1.sample underwater images and their corresponding references

CHAPTER 4

PROPOSED WORK

4.1. LIMITATIONS OF PREVIOUS METHODS

The primary goal of our work is to make a better algorithm to the previous work done by Pranjali Bajpai and Yogesh Vaidhya[19] in the name of "Implementation of Underwater Image enhancement". Their image enhancement process has several challenges and limitations.Firstly, it is not automated, meaning we must make manual decisions to fix color issues. Specifically, the process involves identifying the type of image and deciding which color channels need compensation. To do this, a variable flag is provided to the algorithm that takes values 0 or 1.When the flag is set to 0, it indicates that the image has a greenish tint. In this case, we need to compensate for both the R (Red) and B (Blue) channels to fix the color imbalance.When the flag is set to 1, the image has a bluish tint. For bluish images, only the R channel needs compensation because the B channel is not much degraded.This manual approach makes the process inefficient and time-consuming. It also requires expertise to decide the correct flag value for each image. If the wrong decision is made, it may lead to poor results.

Another major issue is the presence of bluish artifacts[17]. While compensating for bluish images, the process often fails to address this problem effectively. These artifacts degrade the image quality, making the enhancement less reliable.To improve this situation, the process needs to be automated.The goal is to make the process efficient, robust, and capable of handling all types of images. It is important to eliminate the bluish artifacts and enhance the image without manual intervention.

We have proposed a solution that overcomes these challenges and addresses the problems discussed above.

4.2. APPROACH

Step-1: Initial Image Analysis

Underwater images typically exhibit a bluish or greenish tint because of the absorption and scattering of light. Longer wavelengths (red) are absorbed more rapidly in water compared to shorter wavelengths (blue and green). As a result, the red and blue channels in the image suffer degradation, leading to a loss of color accuracy and balance. We begin our enhancement process by analyzing the histograms of the Red, Green, and Blue channels. This analysis reveals that the Red channel is typically concentrated toward the left side of the histogram, indicating a significant reduction in its intensity due to light absorption. Similarly, the Blue channel often shows a similar concentration in images with a greenish tint. These initial observations help guide the subsequent color correction process, where the goal is to compensate for this degradation and restore a more natural color balance.

Step-2: Compensation for Degraded Color Channels

The next key step is compensating for the degradation of the Red and Blue channels, which are most affected by underwater conditions. The Green channel, being less degraded, serves as a reference for restoring the color balance in the image. By adding a fraction of the Green channel to the Red and Blue channels, we effectively compensate for the loss of color in these channels. The formula for this compensation takes into account the mean value of each channel and uses the difference between the current value and the reference Green channel to determine the necessary adjustment. This compensation helps bring the image closer to its natural appearance by reducing the dominance of the bluish or greenish tint caused by underwater conditions.

The formula for the compensated red channel Irc at every pixel location (x)

$$Irc(x) = Ir(x) + (g - r) * (1 - Ir(x)) * Ig\ I\ I\ (x)$$

The formula for the compensated blue channel Ibc at every pixel location (x)

$$Ibc(x) = Ib(x) + (g - b) * (1 - Ib(x)) * Ig\ I\ I\ (x)$$

Ir, Ig represent the red and green color channels of the image I, *I*r, *I*g, *I*b denote the mean value of Ir , Ig , and Ib respectively.

Step-3: White Balancing using the Gray World Algorithm

After compensating for color degradation, the next step is white balancing, which ensures that the image's overall color tone is corrected for any color cast. The Gray World algorithm is employed to perform this correction, based on the assumption that the average color of the image should be achromatic (gray). The algorithm works by adjusting the RGB channels to ensure that the average color of the scene appears neutral. While the compensation step restores the individual channels, the Gray World algorithm ensures that the overall color balance is improved. After applying this algorithm, the image undergoes significant color correction, resulting in an image with more accurate and visually appealing color representation. However, while color balance is achieved, the image still suffers from low contrast, and fine details remain hard to discern.

For an image with color channels R, G, and B, the Gray World Algorithm formula is:

$$R_{\text{new}}(x,y) = \frac{R(x,y) \cdot M_G}{M_R}, \quad G_{\text{new}}(x,y) = G(x,y), \quad B_{\text{new}}(x,y) = \frac{B(x,y) \cdot M_G}{M_B}$$

Where,

R(x,y) ,G(x,y) ,B(x,y): Pixel values of the red, green, and blue channels at position (x,y)(x, y)(x,y).

Mr,Mg,Mb: Mean values of the red, green, and blue channels across the entire image.

Rnew(x,y) ,Gnew(x,y), Bnew(x,y): New white-balanced pixel values for the red, green, and blue channels.

The green channel G(x,y) is often chosen as the reference because it is less prone to absorption in natural scenes.

Step-4: Contrast Enhancement through Global Histogram Equalization

One of the most common issues in underwater images is poor contrast, especially in darker regions. To address this, we apply Global Histogram Equalization (GHE), which is a technique that redistributes the intensity values of the image to enhance the contrast across the entire image. GHE operates by first converting the image from the RGB color space to the HSV (Hue, Saturation, Value) color space. The Value component of the image corresponds to the brightness of the image, and by equalizing this component, we can enhance the contrast. Once the Value component is equalized, the original Hue and Saturation components are retained, and the new enhanced Value component is concatenated with them. This process results in a contrast-enhanced image where details in darker regions are made more visible, and the overall dynamic range of the image is improved.

Histogram Equalization is a technique to redistribute the pixel intensities of an image such that the histogram becomes uniform. For an image with L intensity levels (0 to L−1), the GHE formula is:

$$s_k = \text{round}\left((L-1)\frac{\sum_{j=0}^{k} p_j}{N}\right)$$

Where:

Sk: New intensity value for level k.

Pj: The number of pixels at intensity level j.

N: Total number of pixels in the image.

L: Total number of intensity levels (e.g., 256 for an 8-bit image).

k: Current intensity level ranging from 0 to L−1.

Step-5: Edge Sharpening with Unsharp Masking

While GHE enhances the contrast, it often introduces a soft or blurry appearance to the image, which reduces the clarity of fine details. To counter this, we apply unsharp masking to sharpen the edges and restore detail in the image. Unsharp masking involves subtracting a blurred version of the image from the original, emphasizing the high-frequency components[14] of the image, such as edges. A Gaussian blur is first applied to the image, and the difference between the original and the blurred image is calculated to create the unsharp mask. This mask is then added back to the original image to sharpen it. The result is a crisper image with more clearly defined edges, which is especially important for applications requiring precise detail, such as underwater object detection or marine biology studies.

$$gMASK(x, y) = f(x, y) - Gaussian\_Blur(f(x, y))$$

$$g(x, y) = f(x, y) + gMASK(x, y)$$

$$g(x, y) = 2*f(x, y) - Gaussian\_Blur(f(x, y))$$

Here, f(x, y) is the image on which we want to perform unsharp masking

Step-6: Fusion of Contrast-Enhanced and Sharpened Images

At this stage, we have two enhanced versions of the image: one with improved contrast (via GHE) and one with enhanced sharpness (via unsharp masking). To combine the strengths of both images, we use image fusion techniques. The goal is to integrate the contrast-enhanced and sharpened images into a single image that retains the high contrast and sharp details from both versions.

In Averaging-based Fusion, the resultant fused image is obtained by taking the average intensity of corresponding pixels from both the input image.

$$F(i,j) = A(i,j) + B(i,j) /2$$

A(i,j), B(i,j) are input images and F(i,j) is a fused image.

Step-7: Final Image of Combined fusion

The Combined Fusion approach creates the final enhanced underwater image by blending the results of PCA Fusion and Average Fusion using a weighted formula

Combined = weight_pca * PCA + (1 - weight_pca) * Average

This method integrates the sharpness and detail emphasis of PCA Fusion with the smooth transitions and uniform color blending of Average Fusion. By adjusting the fusion weight, the user can prioritize either sharper details or natural color blending, making the approach adaptable to various underwater conditions. The final image exhibits improved color balance, enhanced contrast, and sharp details while maintaining a natural and realistic appearance, effectively minimizing artifacts and providing a visually appealing result.

4.3. ALGORITHM OF THE PROPOSED METHOD

Step 1: Plot Histogram of an Image

1. Function plot_histogram(image)
2. $[R, G, B] \leftarrow$ image.split()
3. Plot:

    Subplot 1: Original Image.

    Subplot 2: Histograms of R, G, B.
4. Output: Display image + histogram.

Step 2: Split RGB Channels

1. Function channel_split(image)
2. $[R, G, B] \leftarrow$ image.split()
3. Rchan,Gchan,Bchan $\leftarrow$ zeros$(x, y, 3)$

4. Fill channels:

$$\text{Rchan}[:,:,0] \leftarrow R$$

$$\text{Gchan}[:,:,1] \leftarrow G$$

$$\text{Bchan}[:,:,2] \leftarrow B$$

5. Plot: Original, R, G, B components.
6. Output: Visualize RGB channels.

Step 3: Compensate R/B Channels

1. Function compensate_RB(image, flag)
2. $[R, G, B] \leftarrow$ image.split()
3. Normalize: $R, G, B \rightarrow [0,1]$
4. meanR,meanG,meanB $\leftarrow$ mean(R, G, B)
5. If flag = 0:

   Adjust R, B using meanG.

   Scale back G.
6. If flag = 1:

   Adjust R using meanG.

   Scale back G, B.
7. Combine R, G, B.
8. Plot: Original, Compensated Image.
9. Output: Compensated image.

Step 4: Gray World Step

1. Function gray_world(image)
2. $[R, G, B] \leftarrow$ image.split()
3. Gray $\leftarrow$ image.convert$('L')$
4. meanR,meanG,meanB,meanGray $\leftarrow$ mean$(R, G, B, Gray)$
5. Adjust R, G, B:
   i. $R[i,j] \leftarrow R[i,j] \cdot$ (meanGray/meanR)
   ii. $G[i,j] \leftarrow G[i,j] \cdot$ (meanGray/meanG)
   iii. $B[i,j] \leftarrow B[i,j] \cdot$ (meanGray/meanB)

6. Combine R, G, B.
7. Plot: Original, White Balanced Image.
8. Output: White Balanced Image.

Step 5: Sharpen Image

1. Function sharpen(wbimage, original)
2. smoothed ← wbimage.filter(GaussianBlur)
3. Split channels:
    iv. $[R, G, B] \leftarrow$ wbimage.split()
    v. $[R_s, G_s, B_s] \leftarrow$ smoothed.split()
4. Convert to arrays: $R, G, B, R_s, G_s, B_s \rightarrow$ np.array
5. For i, j:
    vi. $R[i][j] \leftarrow 2 \cdot R[i][j] - R_s[i][j]$
    vii. $G[i][j] \leftarrow 2 \cdot G[i][j] - G_s[i][j]$
    viii. $B[i][j] \leftarrow 2 \cdot B[i][j] - B_s[i][j]$
6. Create sharpenedIm ← $[R, G, B]$.
7. Plot: Original, White Balanced, Sharpened Images.
8. Output: Sharpened Image.

Step 6: Average Fusion

1. Function average_fusion(image1, image2)
2. Split channels:

$$[R_1, G_1, B_1] \leftarrow \text{image1.split()}$$

$$[R_2, G_2, B_2] \leftarrow \text{image2.split()}$$

3. Convert to arrays: $R_1, G_1, B_1, R_2, G_2, B_2 \rightarrow$ np.array.

4. For i, j:

$$R[i][j] \leftarrow \frac{R_1[i][j] + R_2[i][j]}{2}$$

$$G[i][j] \leftarrow \frac{G_1[i][j] + G_2[i][j]}{2}$$

$$B[i][j] \leftarrow \frac{B_1[i][j] + B_2[i][j]}{2}$$

5. Create fusedIm $\leftarrow [R, G, B]$.
6. Plot: Sharpened, Contrast Enhanced, Fused Images.
7. Output: Average Fused Image.

Step 7: PCA Fusion

1. Function pca_fusion(image1, image2)
2. Split channels:

$$[R_1, G_1, B_1] \leftarrow \text{image1.split()}$$

$$[R_2, G_2, B_2] \leftarrow \text{image2.split()}$$

3. Flatten channels and calculate mean:

   $R_1, R_2 \rightarrow$ flatten(), $\text{meanR}_1, \text{meanR}_2$.

   Similarly for G, B.
4. Create arrays: imageR,imageG,imageB $\leftarrow [[R_1, R_2], [G_1, G_2], [B_1, B_2]]$
5. Subtract mean from each column.
6. Compute covariance matrices: covR,covG,covB.
7. Find eigenvalues and eigenvectors.
8. Calculate coefficients: coefR,coefG,coefB.
9. For i, j:

   $R[i][j] \leftarrow \text{coefR}_1 \cdot R_1[i][j] + \text{coefR}_2 \cdot R_2[i][j]$.

   Similarly for G, B.
10. Create fusedIm $\leftarrow [R, G, B]$.
11. Plot: Sharpened, Contrast Enhanced, PCA Fused Images.
12. Output: PCA Fused Image.

Step 8: PSNR Calculation

1. Function psnr(reference, fused, original)
2. Calculate R^2:

$$R^2 \leftarrow \max(reference)^2$$

3. Compute MSE for Reference vs Original:

$$MSE_{original} \leftarrow \frac{\sum(reference - original)^2}{reference.size}$$

4. Compute PSNR for Reference vs Original:

$$PSNR_{original} \leftarrow 10 \cdot \log_{10}\left(\frac{R^2}{MSE_{original}}\right)$$

5. Compute MSE for Reference vs Fused:

$$MSE_{fused} \leftarrow \frac{\sum(reference - fused)^2}{reference.size}$$

6. Compute PSNR for Reference vs Fused:

$$PSNR_{fused} \leftarrow 10 \cdot \log_{10}\left(\frac{R^2}{MSE_{fused}}\right)$$

CHAPTER 5

RESULT AND DISCUSSIONS

5.1. Metrics Explanation

In the evaluation of underwater image enhancement techniques, metrics play a crucial role in quantitatively assessing the effectiveness of the applied methods. These metrics help measure improvements in visual quality and ensure that the enhanced images meet the desired standards for usability and clarity. Underwater images pose unique challenges such as color distortion, low contrast, and haziness, making it essential to use appropriate metrics that can capture these deficiencies and evaluate their correction accurately.

The metrics can broadly be classified into objective and subjective categories. Objective metrics rely on mathematical computations to evaluate specific aspects of the image, such as sharpness, color accuracy, and contrast. These include metrics like Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Contrast-to-Noise Ratio (CNR), and Colorfulness Index. On the other hand, subjective metrics involve human perception and are often assessed through visual inspection or user studies to evaluate the naturalness and visual appeal of the enhanced images.

5.1.1 Mean Squared Error (MSE)

The Mean Squared Error quantifies the difference between the original and fused image pixels. It is defined as:

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2.$$

Where:

1. m and n are the dimensions of the image.
2. I(i,j)is the pixel value of the original image.
3. K(i,j) is the pixel value of the fused image.

The pseudo code for MSE is given as follows.

```
def calculate_mse(image1, image2):
    # Ensure both images are of the same size
    height, width = image1.shape
    mse = 0
    for i in range(height):
        for j in range(width):
            mse += (image1[i, j] - image2[i, j]) ** 2
    mse /= (height * width)
    return mse
```

Squaring the pixel-wise difference prevents negative errors from canceling each other out. Lower MSE indicates the fused image is closer to the original.

5.1.2 Peak Signal-to-Noise Ratio (PSNR)

PSNR measures the quality of a fused image compared to the original. It is based on the logarithmic scale:

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

Where:

MAXI is the maximum pixel value (255 for an 8-bit image),

MSE is the Mean Squared Error.

The pseudo code for PSNR is given as follows.

```
import math
def calculate_psnr(image1, image2):
```

```
    mse = calculate_mse(image1, image2)
    if mse == 0:  # Prevent divide-by-zero error
        return float('inf')
    max_pixel = 255.0
    psnr = 10 * math.log10((max_pixel ** 2) / mse)
    return psnr
```

PSNR uses MSE as an input but translates it into a more intuitive "quality" scale where higher values mean less distortion. Logarithmic scaling helps interpret large differences easily.

5.1.3 Structural Similarity Index (SSIM)

SSIM assesses the perceptual similarity between two images, considering luminance, contrast, and structure.

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

with:

- μ_x the average of x;
- μ_y the average of y;
- σ_x^2 the variance of x;
- σ_y^2 the variance of y;
- σ_{xy} the covariance of x and y;
- $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$ two variables to stabilize the division with weak denominator;
- L the dynamic range of the pixel-values (typically this is $2^{\#bits\ per\ pixel} - 1$);
- $k_1 = 0.01$ and $k_2 = 0.03$ by default.

The pseudo code for PSNR is given as follows.

```
from skimage.metrics import structural_similarity as ssim
def calculate_ssim(image1, image2):
    ssim_value, _ = ssim(image1, image2, full=True)
```

```
    return ssim_value
```

SSIM breaks the image into regions to compare local structure, brightness (mean), and contrast (variance).

5.1.4 Underwater Image Quality Measure (UIQM)

UIQM evaluates underwater image quality based on three components:

1. UCIQE: Measures colorfulness.
2. UICM: Measures color distortion.
3. UISM: Measures sharpness.

The overall UIQM is:

$$\mathbf{UIQM=c1\cdot UICM+c2\cdot UISM+c3\cdot UCIQE}$$

Where c1,c2,c3 are weights.

The pseudo code for UIQM is given as follows.

```
def calculate_uiqm(image):
    uicm = compute_color_metric(image)
    uism = compute_sharpness(image)
    uciqe = compute_colorfulness(image)
    uiqm = 0.028 * uicm + 0.295 * uism + 3.575 * uciqe
    return uiqm
```

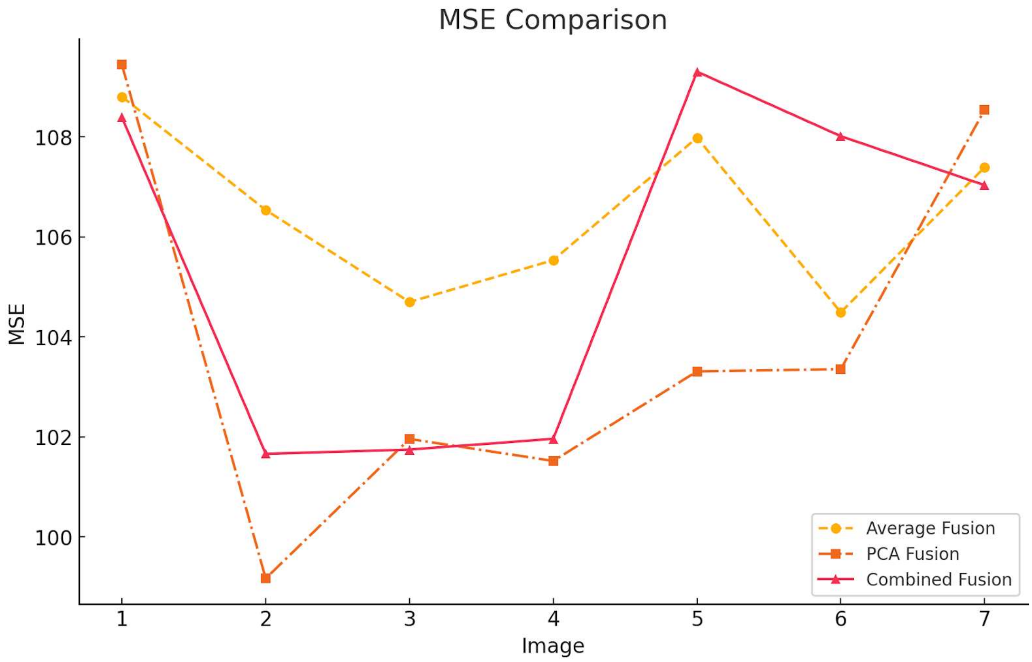
UIQM combines three key underwater image properties: Better color preservation, Clearer details, Improved visibility.

5.2. Analysis of Results

5.2.1 MSE Analysis

1. MSE values vary around 104–108, indicating relatively lower errors on Average based fusion.
2. PCA shows slightly lower MSE on some images, e.g., Image 2 has the lowest value (99.16).
3. Combined Fusion consistently reduces the MSE across most images, maintaining values close to PCA.

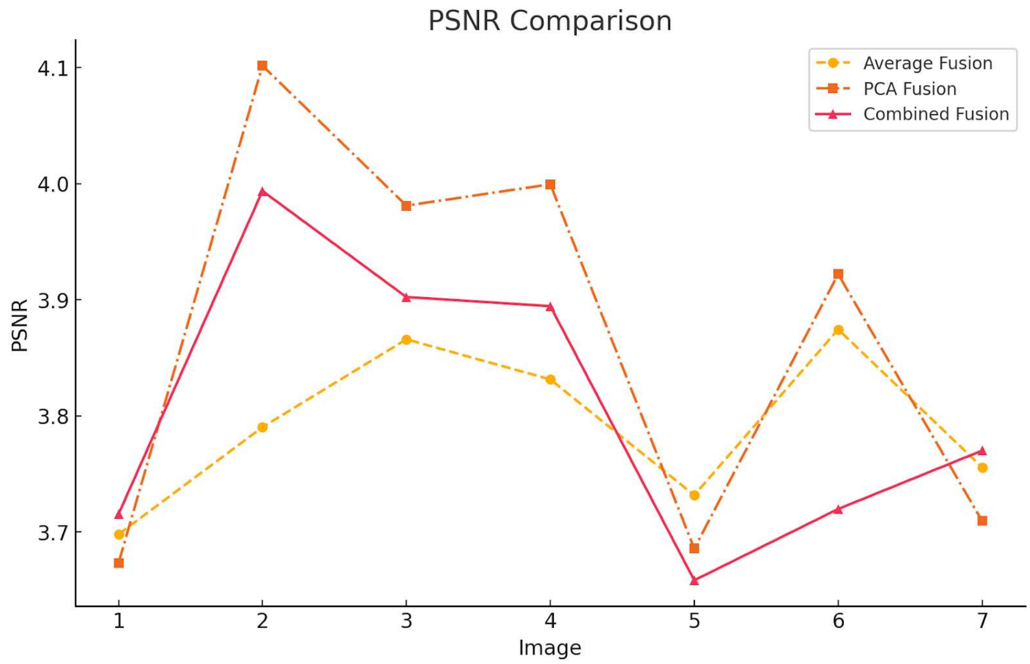
Inference: Combined Fusion achieves lower reconstruction errors compared to Average Fusion, performing slightly better than PCA in several cases.



5.2.2 PSNR Analysis

1. In Average Fusion PSNR remains consistent around 3.7.
2. PCA Fused Image 2 (4.10) stands out as a better PSNR.
3. Combined Fusion maintains higher PSNR values across images.

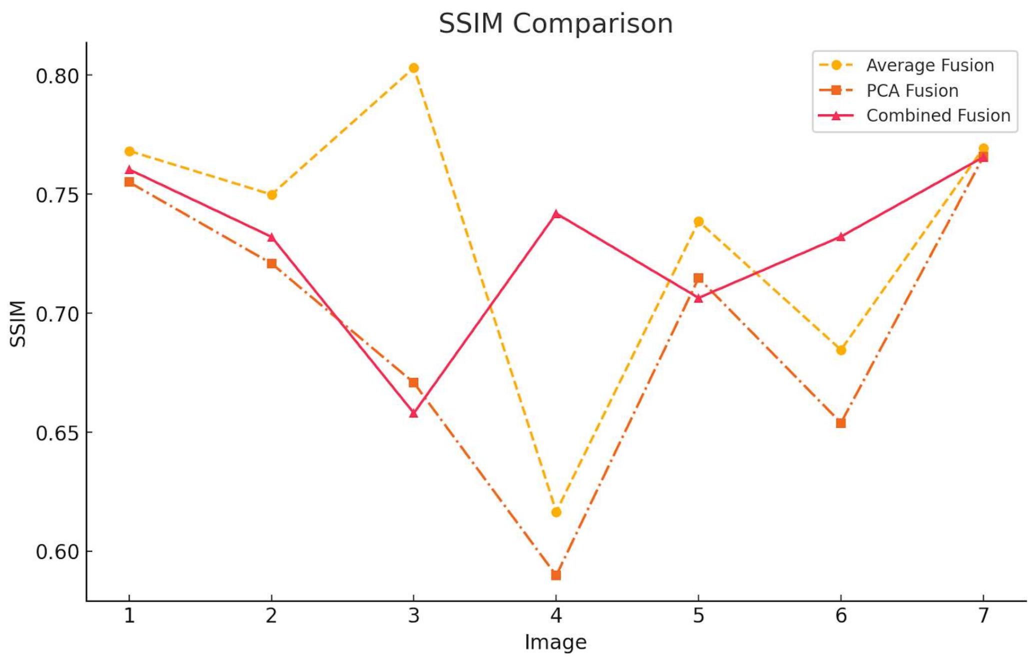
Inference: Combined Fusion consistently enhances image quality with higher PSNR compared to PCA and Average Fusion.



5.2.3 SSIM Analysis

1. In Average Fusion SSIM values fluctuate between 0.6 and 0.8.
2. In PCA Fusion SSIM dips on Image 4 (0.589), indicating lower structural similarity.
3. Combined Fusion shows significant improvement in structural similarity, often exceeding PCA Fusion.

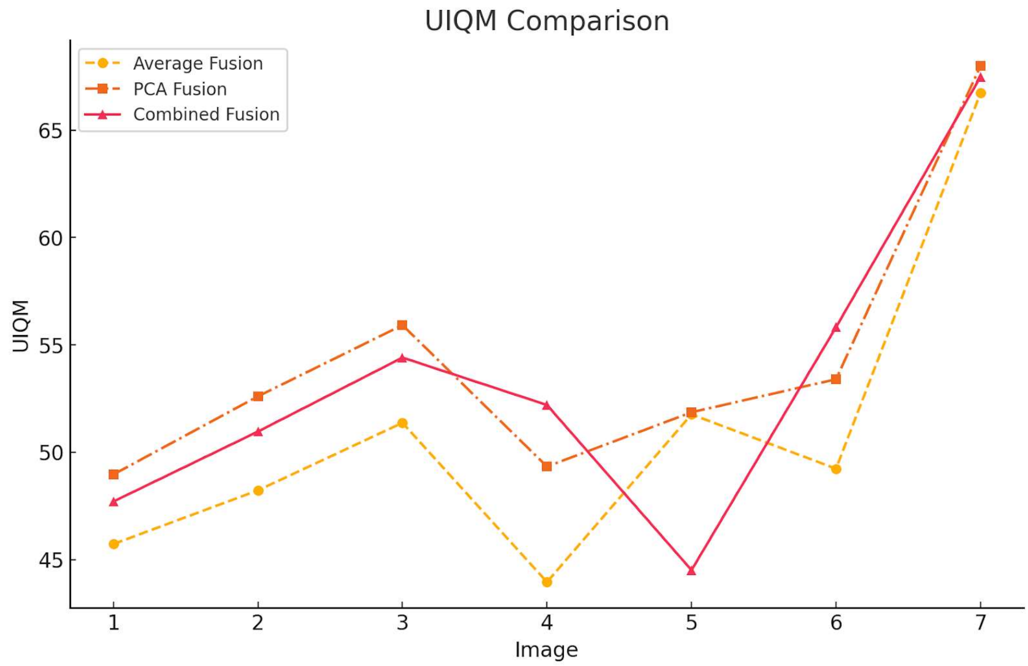
Inference: Combined Fusion preserves structural details better than other methods.



5.2.4 UIQM Analysis

1. In Average Fusion, UIQM values vary but peak at Image 7.
2. In PCA Fusion UIQM consistently improves underwater image quality.
3. Combined Fusion UIQM scores remain the highest overall, e.g., Image 7 (67.47).

Inference: Combined Fusion achieves superior underwater image quality.



	Average Fusion			
IMAGE	MSE	PSNR	SSIM	UIQM
1	108.8051594	3.698906909	0.7682058877	45.72419886
2	106.5381364	3.790350848	0.7498721813	48.42412005
3	104.6986865	3.86598947	0.6810355262	53.92730823
4	105.5345569	3.831454895	0.6165936495	43.95465329
5	107.9850864	3.731764004	0.7385638912	51.76241455
6	104.4918715	3.874576726	0.6846033268	49.22329323
7	107.3906649	3.755736492	0.7693179701	66.72800328

	PCA Fusion			
IMAGE	MSE	PSNR	SSIM	UIQM
1	109.4463567	3.673388713	0.7550533134	48.96404687
2	99.16821289	4.101676935	0.7208291538	52.60367746
3	101.9592205	3.981136737	0.6707786251	55.918894
4	101.5182911	3.99995882	0.589870901	49.33293417
5	109.1350589	3.685758931	0.7146738447	55.42937895
6	103.3539486	3.922131069	0.6539465198	53.39862786
7	108.5374613	3.709605211	0.7650788629	67.98769597

	Combined Fusion			
IMAGE	MSE	PSNR	SSIM	UIQM
1	108.3911558	3.715463333	0.7604018441	47.70519745
2	101.6622175	3.993806021	0.7321010713	50.96214694
3	102.9485996	3.939197371	0.674647346	55.07010452
4	101.7458339	3.990235449	0.6013584084	47.23348512
5	109.9623888	3.652960148	0.7237701404	54.00958518
6	104.0101796	3.894643341	0.6647996194	51.78198955
7	107.035296	3.77013166	0.7658577801	67.4787976

Final Comparison Table

Metric	Average Fusion	PCA Fusion	Combined Fusion
MSE	Moderate	Low	Lowest
PSNR	Moderate	Higher	Highest
SSIM	Moderate	Low	Highest
UIQM	High	Higher	Highest

Combined Fusion outperforms both PCA and Average Fusion across all metrics, making it the most effective method for image fusion.

5.2.5. Color Detection

Color detection in images typically involves analyzing the intensity of the different color channels (red, green, and blue) to determine the dominant color and any possible color casts. The process is based on evaluating the relative strength of each color channel in an image and then deriving equations that describe their contributions to the overall color perception.

When detecting color in an image, the first step is to split the image into its RGB components. Each pixel in the image has values for red, green, and blue channels. The intensity of these channels is measured using statistics like the mean, which gives an average value for each channel across the entire image. The next step is to compute the relative contribution of each color channel to the overall color composition. This is done by dividing the intensity of each channel by the total intensity of all three channels. The relative color intensities (ratios) can be represented as:

$$\textit{Channel Ratio} = \textit{Channel Mean} / \textit{Total Intensity} = \textit{Channel Mean} / \textit{R Mean} + \textit{G Mean} + \textit{B Mean}$$

For detecting color casts, the function compares the relative intensities of the blue and green channels (or red, if necessary) to determine if there's a dominant cast. If the blue channel has a higher intensity than the green channel, the image is considered to have a bluish cast, and the confidence score for the bluishness is calculated based on the difference in intensity. The confidence score equation is:

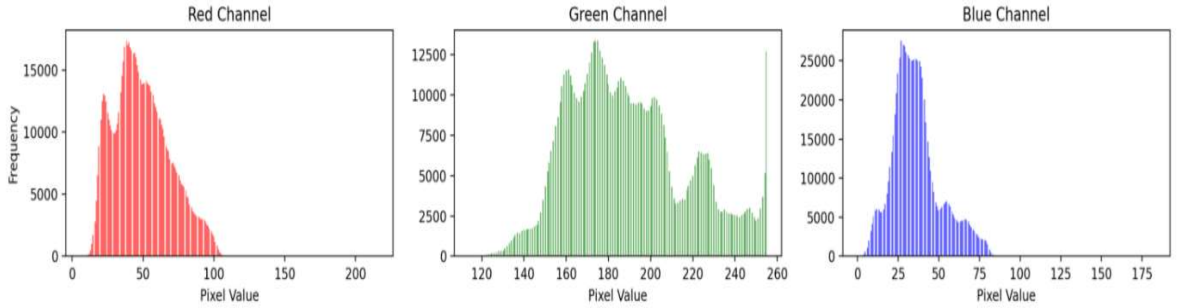
$$\textit{Confidence Score} = |\textit{Blue Ratio} - \textit{Green Ratio}| / \textit{Blue Ratio} \times 100$$

This score gives an indication of how much more dominant the blue channel is compared to the green one. A similar equation can be used for a greenish cast, where the green ratio is compared to the blue ratio.

To compensate for a color cast, especially blue or green, the image's channels can be adjusted by modifying the red and blue channels (or green, depending on the detected cast). The adjustment is based on the difference between the green channel's mean intensity and that of the red or blue channel. The compensation can be calculated as:

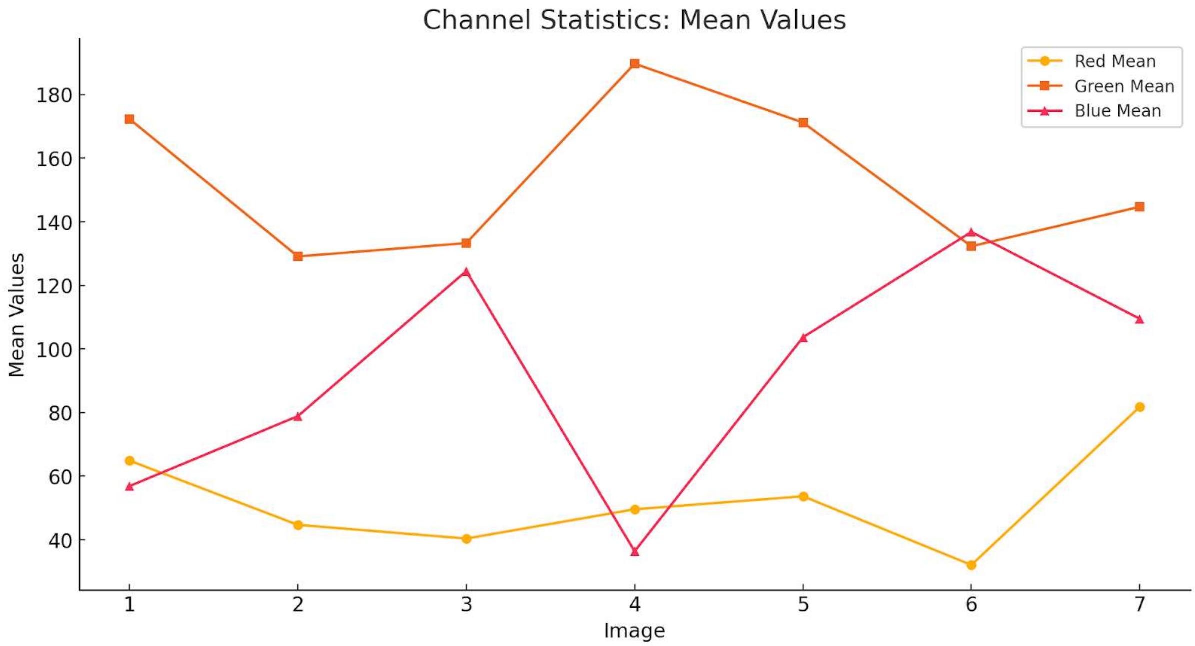
$$New\ Channel\ Value=(Channel\ Value+(Mean\ Green-Mean\ Channel)\times(1-Channel\ Value)\times Mean\ Green)\times Max\ Channel\ Value$$

This equation adjusts the channel to reduce the effect of the color cast by bringing the red and blue (or green) channels closer to the value of the green channel, which is often seen as the neutral reference for compensation.



5.2.6. Channel Statistics

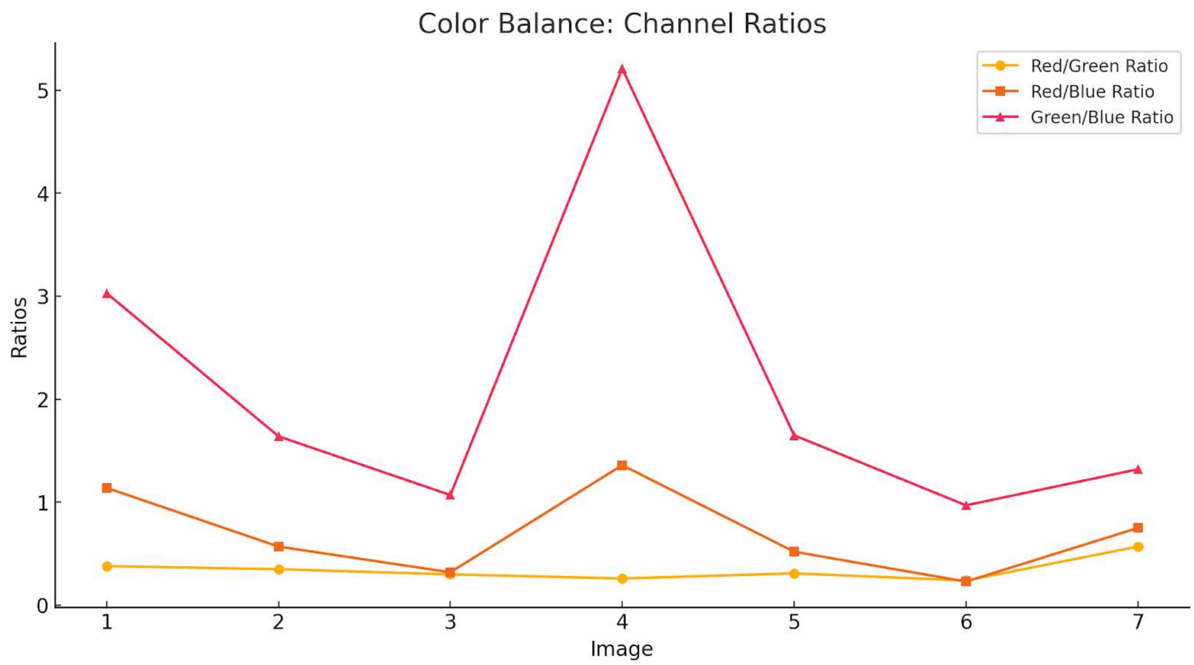
Red, Green, and Blue mean values are calculated for all images. The Green channel consistently has the highest mean values across all images. The Blue channel fluctuates significantly compared to Red and Green.Red remains consistently lower in most images, except Image 7, where it increases.



Channel Statistics							
Mean Values							
Image	1	2	3	4	5	6	7
Red	64.9	44.7	40.4	49.6	53.7	32.1	81.8
Green	172.3	129.1	133.3	189.7	171.2	132.3	144.7
Blue	56.9	78.9	124.5	36.4	103.7	136.8	109.5

5.2.6. Color Ratio Statistics

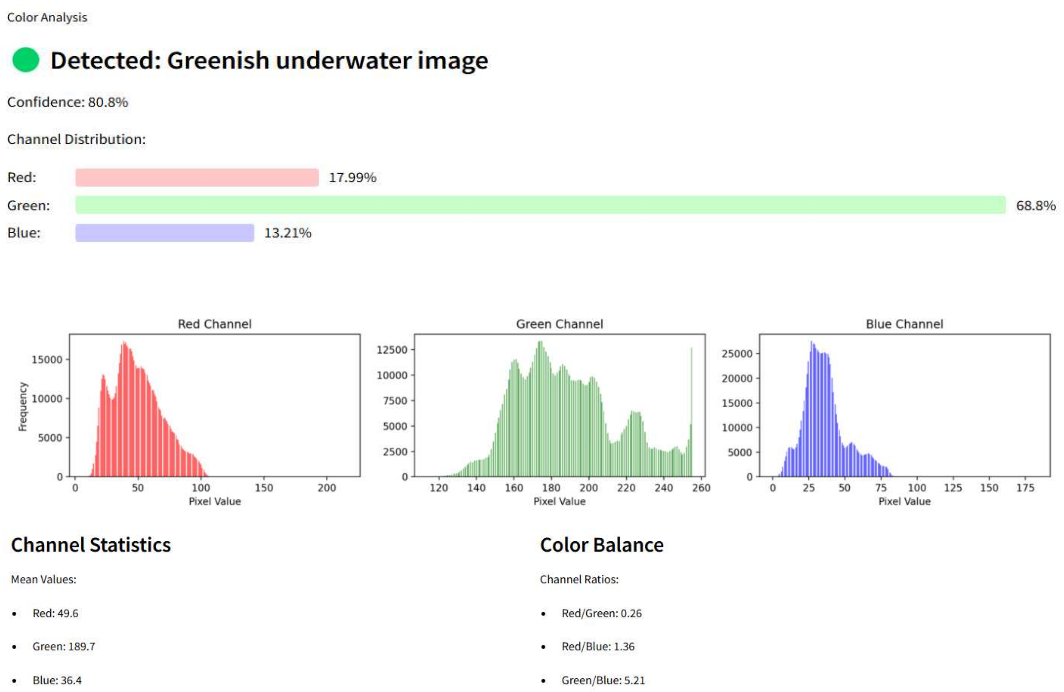
Red/Green, Red/Blue, and Green/Blue ratios are calculated accordingly for all images Green/Blue Ratio dominates in most images, especially in Image 4.Red/Blue Ratio shows notable variability, peaking in Images 1 and 4. Red/Green Ratio stays relatively low but increases in Image 7.



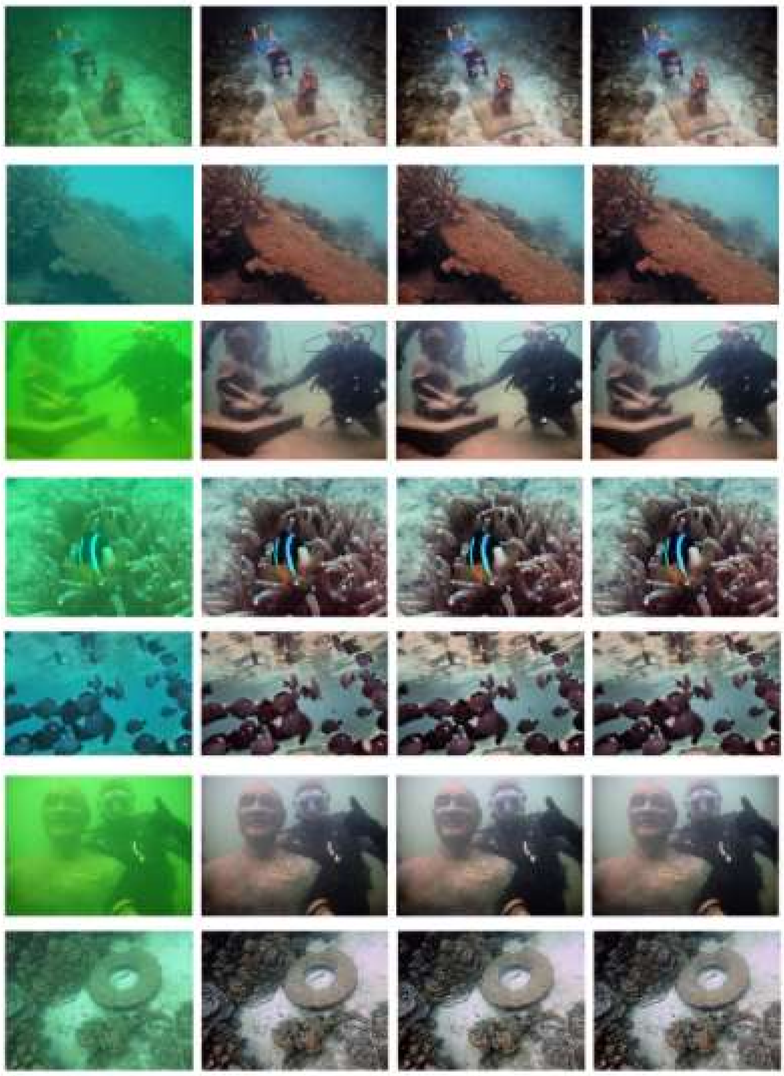
Color Balance							
Channel Ratio							
Image	1	2	3	4	5	6	7
Red/Green	0.38	0.35	0.3	0.26	0.31	0.24	0.57
Red/Blue	1.14	0.57	0.32	1.36	0.52	0.23	0.75
Green/Blue	3.03	1.64	1.07	5.21	1.65	0.97	1.32

5.3. Output discussion

The developed webpage for underwater image enhancement provides a user-friendly interface that enables users to upload underwater images for processing and analysis. Once the user uploads an image, the system performs a comprehensive analysis of the input image and generates useful statistics to highlight the key characteristics and issues associated with the uploaded image. The statistics include channel-wise distributions for red, green, and blue (RGB) color components. As seen in the displayed results, underwater images often have a dominant green or blue channel due to the light absorption properties of water, where red wavelengths are absorbed quickly. The webpage provides visual representations of RGB histograms, mean pixel values, and channel ratios, which help users understand the degree of color imbalance present in the image.

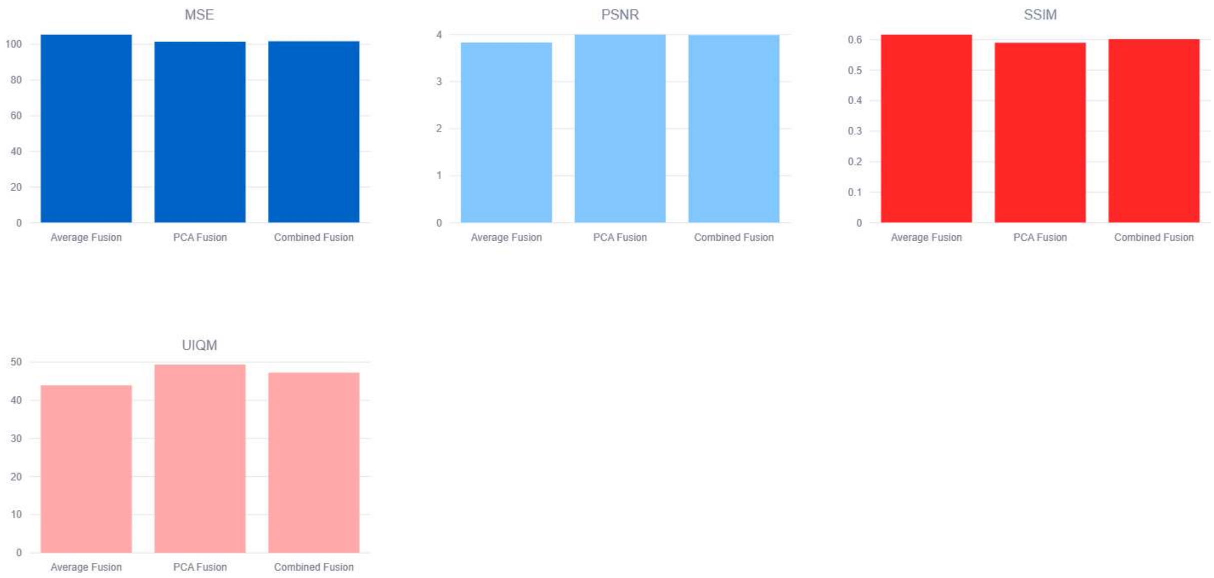


In addition to the statistical analysis, the webpage performs image enhancement through a series of fusion-based techniques. Specifically, three types of enhanced outputs are produced: Average-Based Fusion, PCA-Based Fusion, and Combined Fusion. Each fusion method is designed to address specific deficiencies in the input image, such as color distortions, haziness, and low contrast, while preserving important features like edges and details. The Average-Based Fusion technique generates an enhanced image by computing the average pixel intensity between multiple processed outputs, ensuring a smooth and balanced visual result. The Combined Fusion integrates the benefits of both methods, providing a final output that balances clarity, sharpness, and color correction.



To make the system practical and accessible, the webpage also includes an option to download the enhanced images. Users can download individual enhanced images or all the generated outputs in a single click. This feature allows for convenient use of the enhanced images in further applications, such as underwater surveillance, robotics, object detection, or entertainment purposes. The system is designed to process images efficiently, ensuring a smooth user experience while delivering high-quality results.

Furthermore, the webpage displays metrics comparison tables and graphs to evaluate the performance of the enhancement techniques quantitatively. The graphical representation of these metrics provides a clear understanding of how each fusion method improves the visual quality of the underwater image. This feature ensures that users not only see the enhancements visually but also have measurable evidence of improvement, which is particularly useful for research and analytical purposes.



CHAPTER 6

CONCLUSION & SUGGESTIONS FOR FUTURE WORKS

6.1. Conclusion

The image enhancement project presents a robust pipeline to address challenges like color distortion, poor contrast, and low sharpness in underwater images. Starting with color compensation and using the Gray World Algorithm for natural color balance, the system ensures accurate visual representation. Global Histogram Equalization enhances contrast, making image details more visible, while Unsharp Masking sharpens edges for improved clarity. Fusion techniques, including Averaging-Based and PCA-Based Fusion[18], combine enhancements to produce cohesive, high-quality outputs. The final images are suitable for diverse applications such as underwater robotics, surveillance, and entertainment. While effective, factors like environmental variability and real-time performance were not fully addressed. Future work could focus on advanced algorithms and live processing capabilities. Overall, the project delivers visually appealing and functionally improved images for practical use.

6.2. Future works

While the current image enhancement pipeline demonstrates significant improvements in color balance, contrast, and sharpness, there are several avenues for future work that could further enhance its capabilities, efficiency, and applicability. These improvements could include refining existing algorithms[15], exploring new techniques, and addressing specific limitations of the system. Below are some key areas for potential future development:

1. Real-Time Image Enhancement

Current image enhancement processes, especially techniques like Global Histogram Equalization (GHE) and Unsharp Masking, can be computationally expensive. To make the system more practical for real-time applications, such as live video enhancement, augmented reality, or interactive media, it will be important to explore methods that reduce the computational complexity without sacrificing quality. This could involve utilizing hardware acceleration, such as GPUs or specialized image processing chips, or developing faster algorithms that maintain high performance with low latency.

2. Multi-Modal Enhancement

In many real-world scenarios, images may come from multiple sources or modalities (e.g., optical, infrared, medical imaging). Future work could explore the fusion of multi-modal data to enhance images further. By combining complementary information from different sources, such as combining high-resolution optical images with thermal or depth information, the system could generate more comprehensive and informative outputs. This approach could be particularly useful in fields like remote sensing, medical imaging, or security surveillance.

3.. Application-Specific Optimization

Depending on the intended application, further customization and optimization could improve the system's performance. For instance, medical imaging often requires maintaining fine details in the image, such as tissue boundaries or small lesions, while surveillance systems might prioritize sharpness and clarity in detecting objects or faces. By incorporating application-specific knowledge and optimizing the pipeline for particular domains, the system could be fine-tuned to meet the exact needs of various industries, including healthcare, security, entertainment, and scientific research.

CHAPTER 7

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