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ENHANCING UNDERWATER IMAGE QUALITY: EVALUATING COMBINATIVE APPROACHES FOR EFFECTIVE IN SEAGRASS BED ECOSYSTEM

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Abstract— *The Complex underwater characteristics, challenges for image processing tasks. These images often have poor visibility due to low contrast, light scattering and various types of interference. There is a lack of exploration into the effectiveness of existing underwater image enhancement methods, particularly in the context of seagrass ecosystems, allows for further investigation. This study aims to explore and evaluate the effectiveness of various methods in underwater image enhancement, including Colour Balanced, CLAHE, and Unsharp Masking and their combinations, starting with converting video data from UTS devices into two-dimensional images. Furthermore, the quality of images taken from underwater cameras placed in a complex and wild seagrass meadow environment was improved using the proposed method, and the quality was evaluated by the SSIM value. The results show that the CLAHE method has the highest average SSIM value of 0.898. Meanwhile, the combined Color Balanced-CLAHE method achieved an SSIM value of 0.683 in a separate evaluation. This combination is an innovative approach to address complex underwater image quality problems, providing a more specific and adaptive solution. Overall, the proposed method is able to improve the visual quality of images on aspects such as clarity, color, and visibility of objects in the image.*

Keywords: *CLAHE, color balanced, underwater image, unsharp masking*

Intisari — *Karakteristik bawah air yang kompleks, menjadi tantangan tersendiri bagi tugas pemrosesan gambar. Gambar-gambar ini sering kali memiliki visibilitas yang buruk karena kontras yang rendah, hamburan cahaya, dan berbagai jenis gangguan. Kurangnya eksplorasi terhadap efektivitas metode peningkatan citra bawah air yang ada, terutama dalam konteks ekosistem lamun, memungkinkan untuk dilakukannya investigasi lebih lanjut. Penelitian ini bertujuan untuk mengeksplorasi dan mengevaluasi efektivitas berbagai metode dalam peningkatan citra bawah air, termasuk Colour Balanced, CLAHE, dan Unsharp Masking serta kombinasinya, dimulai dengan mengubah data video dari perangkat UTS menjadi gambar dua dimensi. Selanjutnya, kualitas gambar yang diambil dari kamera bawah air yang ditempatkan di lingkungan padang lamun yang kompleks dan liar ditingkatkan dengan menggunakan metode yang diusulkan, dan kualitasnya dievaluasi dengan nilai SSIM. Hasilnya menunjukkan bahwa metode CLAHE memiliki nilai SSIM rata-rata tertinggi sebesar 0,898. Sementara itu, gabungan metode Color Balanced-CLAHE mencapai nilai SSIM sebesar 0,683 dalam evaluasi terpisah. Kombinasi ini merupakan pendekatan inovatif untuk mengatasi masalah kualitas gambar bawah air yang kompleks, memberikan solusi yang lebih spesifik* *dan adaptif. Secara keseluruhan, metode yang diusulkan mampu meningkatkan kualitas visual gambar pada aspek-aspek seperti kejernihan, warna, dan visibilitas objek dalam gambar.*

***Kata Kunci**: CLAHE, warna seimbang, citra bawah air, unsharp masking.*

INTRODUCTION

Seagrass is a significant coastal habitat. Seagrasses are a functional grouping of vascular flowering plants that grow fully submerged and rooted in soft bottom estuarine and marine environments [1]. Seagrasses are a functional grouping that refers to vascular flowering plants that grow fully submerged and rooted in soft-bottomed estuarine and marine environments [2], [3]. The seagrass ecosystem provides critical services such as coastal protection from erosion, carbon sequestration, and habitat for various commercially valuable fish and invertebrate species.

Seagrass research, particularly seagrass monitoring involving underwater imaging, faces various technological, methodological and environmental challenges. A significant issue is the need for fast, cost-effective and robust imaging techniques that can operate across a wide range of depths, turbidity and weather conditions. In addition, automated seagrass detectors capable of real-time analysis [4]. The main issue is that manual review of seagrass from underwater images is time consuming and expensive [5]. This has driven the development of computer vision solutions, to address this problem. Further refinement is required to ensure higher effectiveness and efficiency [6].

The complexity of the underwater environment in seagrass bed ecosystems causes images taken from digital cameras to often experience a decline in quality due to the absorption and reflection of sunlight by water and other particles [7]. This results in low visibility, such as low contrast, blurriness, and various other types of disturbances. This low visibility complicates image processing tasks such as segmentation, detection, and recognition of seagrass, fish, and other marine life in seagrass bed. These low-visibility images need to be enhanced through underwater image enhancement methods. Additionally, they typically exhibit a green or blue tint, which is reflective of their aquatic surroundings. Moreover, the scarcity of publicly accessible datasets further complicates this task [8][9]. Figure 1 shows an seagrass underwater image taken from a USV device [10] in a seagrass bed environment at Beralas Pasir Island, Riau Islands [5].

Source: (Lestari, 2021)
Figure 1. Seagrass Enhalus acoroides

Techniques to address issues such as low contrast, poor lighting, and blur caused by the underwater environment. One effective method is the use of contrast-limited adaptive histogram equalization (CLAHE), which has been proven to significantly improve contrast and image quality underwater. Additionally, methods employing color balanced techniques, such as those derived from the Grey World algorithm, are utilised to correct colours and enhance the overall appearance of underwater images [11]. Color Balanced (CB) for underwater images is the process of adjusting colours in an image to correct colour deviations caused by the absorption and dispersion of light in an underwater environment. This process is important because underwater images often suffer from decreased contrast, low brightness, and blurred detail owing to poor lighting conditions and varying water quality [12], [13]. Unsharp masking is another technique used to enhance the edges and contrast of underwater images, ensuring that fine details are preserved and highlighted [14].

The research question in this studi is **:** How can underwater image enhancement techniques, including CLAHE, Color Balancing (CB), Unsharp Masking and their combinations, be optimized and standardized to improve the quality and analysis accuracy of images in seagrass bed ecosystems?

Overall, the combination of CLAHE, color balanced, and unsharp masking plays a crucial role in advancing underwater research by providing clearer and more accurate images for analysis. However, it still has limitations, as the outcomes vary depending on different image datasets. Therefore, the standardisation of underwater images is necessary to ensure the compatibility of the applied methods.

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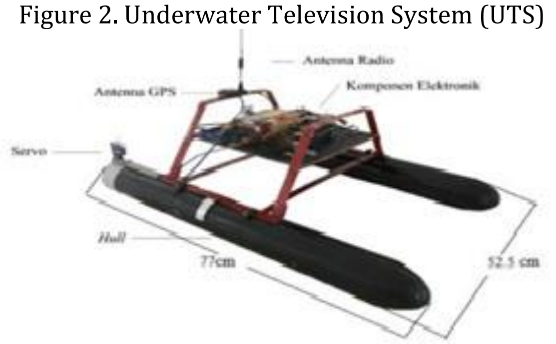
This study aims to establish a benchmark method that can serve as a reference point for future underwater image analysis studies. Additionally, it seeks to determine the most effective method, including CLAHE, CB, and Unsharp Masking, using various experimental setups. Ultimately, this will enhance the accuracy and reliability of image processing techniques in underwater environments.

MATERIALS AND METHODS

This study used secondary data from the Faculty of Fisheries and Marine Science, Bogor Agricultural University. Data were collected using an Underwater Television System (UTS) [15] device placed on the bottom of the water and an Unmanned Surface Vehicle (USV) [10] in the form of a ship-shaped vehicle that moves dynamically equipped with GPS and operates on the surface of the water in the seagrass ecosystem. of Beralas Pasir Island, Bintan Regency, Riau Islands, Indonesia. The UTS and USV data are underwater videos that will later be converted into images for research purposes. Figure 2 shows the UTS device, and Figure 3 shows the USV device.

Source: (Setyadi, 2022)

Figure 2. Underwater Television System (UTS)



Source: (Yashira, 2021)

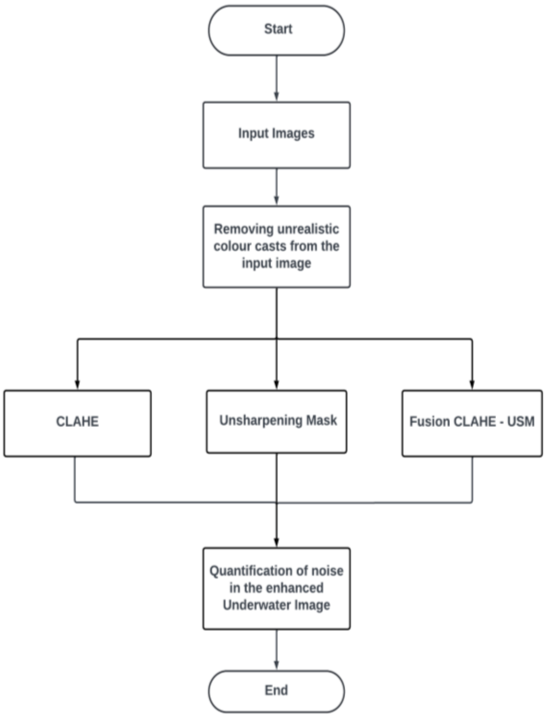
Figure 3. Unmanned Surface Vehicle (USV)

Previous research on underwater seagrass imaging has explored various techniques to enhance image quality and automate detection and classification processes. One common challenge in underwater imaging is the degradation of image quality due to factors such as low contrast, non-uniform lighting, and diminished colour. To address these issues, several studies have proposed the use of contrast limited adaptive histogram equalization (CLAHE) combined with other techniques. For instance, CLAHE has been effectively used to enhance the local contrast in underwater images, ensuring better texture clarity and detail characteristics while suppressing noise [16].

Additionally, the integration of CLAHE with the L*A*B colour space has been shown to significantly improve image quality by addressing uneven illumination and enhancing colour representation [17]. Furthermore, the application of CLAHE in combination with color balancing (CB) and unsharpening mask techniques has been explored to further enhance image clarity and contrast. Color balancing helps correct colour casts caused by the underwater environment, whereas the unsharpening mask technique enhances image edges, making the seagrass features more distinguishable [18]. These preprocessing steps are crucial for improving accuracy in computer vision tasks such as subsequent automated classification and detection. For example, deep convolutional neural networks (CNNs) have been employed to develop multispecies detectors and classifiers for seagrasses to achieve high accuracy [19]. The combination of these image enhancement techniques with advanced machine learning models addresses the limitations of traditional manual and semi-automated methods, offering quicker, cheaper, and more accurate solutions for seagrass monitoring [20], [21].

In this stage, images that are appropriate for the research target are collected and selected, then any unrealistic color casts are removed using color balancing. After that, image enhancement is performed with CLAHE, USM, and a fusion of CLAHE - USM. This research also combines methods used to observe their impact on the quality of underwater images. Overall, the integration of CLAHE, CB, and unsharpening mask techniques in underwater seagrass imaging represents a significant advancement in the field, providing enhanced image quality that facilitates more effective monitoring and conservation efforts [22]. Generally, the evaluation method used for underwater images is the Structural Similarity Index Measure (SSIM), which is a metric used to measure the similarity between two images. The SSIM values range from -1 to 1, where a value of 1 indicates perfect similarity. SSIM considers the changes in luminance, contrast, and structure between two images [23]–[25].

The diagram below depicts the underwater research design.



Source: (Research Results, 2024)
Figure 4. Diagram Framework for Enhanced Underwater Image

Input Images
This step involves inputting the underwater images to be processed. The images used were seagrass datasets obtained from Faculty of Fisheries and Marine Science IPB.

Removing Unrealistic Colour Casts from the Input Image
Description: This step involves the removal of unrealistic colour casts caused by underwater conditions from the images.
Formula: Using color balancing or other colour-correction algorithms.

$$I_{Corrected}(x,y) = I(x,y) \cdot \frac{G_{ref}}{G(x,y)} \quad (1)$$

where $I(x,y)$ is the input image, $G(x,y)$ is the green channel of the image, and G_{ref} is the reference green value used for color correction.

CLAHE (Contrast Limited Adaptive Histogram Equalization)
Description: This method enhances the contrast of an image by applying histogram equalization within small blocks of the image.
Formula: The CLAHE algorithm can be represented as:

$$I_{CLAHE}(x,y) = CLAHE(I_{Corrected}(x,y)) \quad (2)$$

where $I_{CLAHE}(x,y)$ is the intensity value of the pixel in the image enhanced by the CLAHE algorithm. $(I_{Corrected}(x,y))$ is the intensity value of the pixel in the corrected (original) image.

Unsharpening Mask
Description: This technique enhances the details and sharpness of an image by adding a blurred version of the image to the original image.
Formula:

$$I_{USM}(x,y) = I_{Corrected}(x,y) + \alpha(I_{Corrected}(x,y) - I_{Blurred}(x,y)) \quad (3)$$

where $I_{Blurred}(x,y)$ is the blurred image and α is the scaling factor.

Fusion CLAHE - USM
Description: This step involves combining the results of CLAHE and USM to obtain a better-enhanced image.
Formula:

$$I_{Fused}(x,y) = \beta I_{CLAHE}(x,y) + (1-\beta)\, I_{USM}(x,y) \quad (4)$$

where β is the fusion weight.

Quantification of Noise in the Enhanced Underwater Image
Description: In this step, the noise level in the enhanced image was measured to assess the quality of the enhancement.
Formula:

$$SSIM(x,y) = \left[\frac{(2\mu_x\,\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}\right] \quad (5)$$

where:
$\mu_x\ \mu_y$ is the average value (mean) of x and y.
σ_x^2, σ_y^2 is the variance of x and y.
σ_{xy} is the covariance of x and y.
C_1, C_2 is a constant to avoid division by zero.

Noise removal is typically performed using techniques such as a median filter, Gaussian filter, or other de-noising methods before performing quantification. SSIM can be used to quantify the amount of noise in enhanced images, including underwater images that have been through a quality enhancement process.

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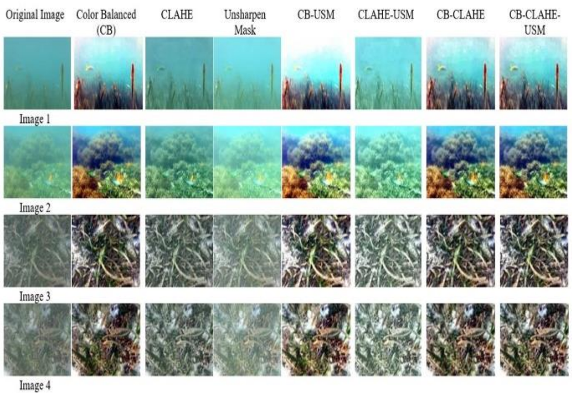
RESULTS AND DISCUSSION

The following section presents the results of the research.



Source: (Research Results, 2024)

Figure 5. Comparative Analysis of Image Processing Effects using CLAHE, Color Balancing, and Unsharp Mask

In our experiments, as shown in Figure 5, the applied enhancement technique significantly improved the clarity and detail in an image that was originally blurry and had low contrast. The original image shows an underwater image dominated by blues and greens, typical colours of the underwater environment where the red light spectrum is quickly dampened, leaving the image with a limited colour range and less prominent details. To overcome this challenge, we apply a series of image quality enhancement techniques which include Colour Balancing (CB), Contrast Limited Adaptive Histogram Equalisation (CLAHE), and Unsharpening Mask (USM), as well as a combination of these three methods.

The results obtained from image processing on Image1, Image2, Image3, and Image4 show a significant improvement in the visual quality of the images. This improvement is obvious in these images, especially after applying various image processing methods. The Color Balancing method is used to improve the colour balance in an image, by correcting colour imbalances caused by uneven lighting or other issues during shooting. This is especially important in underwater images, where lighting conditions often cause unwanted colour shifts. This method helps to restore more natural and balanced colours. The CLAHE (Contrast Limited Adaptive Histogram Equalisation) technique is then applied to increase the contrast in the underexposed or exposed areas of the image, by dividing the image into small sections (tiles) and performing histogram equalisation on each of them. This technique ensures that the overall contrast of the image is increased without making the already bright areas too bright, so that the image still has balanced details between the dark and bright areas.

Next, the Unsharp Mask method is used to enhance the sharpness of the image by accentuating the edges of objects in the image. This process is performed by subtracting the blurred image from the original image and then adding the result back to the original image, which results in a sharp enhancement of the boundaries of the objects in the image. Combination methods such as CB-USM (Color Balancing-Unsharp Mask) first balances the colours of the image with CB, and then enhances the sharpness through Unsharp Mask. Similarly, CB-CLAHE (Color Balancing-CLAHE) combines the two methods by first colour balancing the image and then enhancing the contrast using CLAHE. Other combined methods, such as CB-CLAHE-USM, integrate three techniques-Color Balancing, CLAHE, and Unsharp Mask-where the colours of the image are first balanced, then the contrast is enhanced, and finally, the image is sharpened to improve details. The combination of these methods results in an underwater image that is clearer and more visually appealing than the original, with previously hidden features becoming more prominent, so that important details in the image that were previously invisible can now be identified more easily.

In addition, Figure 5 also shows Image1, which is an underwater image dominated by blue and green colours. These colours are typical of underwater images, where red is often dampened by water, leaving a narrower colour spectrum. Each method applied to Image1 shows how the image details become clearer and sharper after going through the quality enhancement process. For example, methods such as CLAHE increase contrast in areas that previously appeared flat, making details in submerged objects more visible. Likewise, Color Balancing techniques correct natural colour shifts, restoring a more natural colour balance, and Unsharp Mask accentuates the edges of objects, making the overall image sharper and easier to distinguish. With the combination of these methods, Image1 undergoes a significant transformation, where small details that were previously hidden can now be identified more easily.

Image2, which is also an underwater image but with a stronger dominance of green and yellow colours, shows how the application of the same method improves the visibility of objects and colour contrast in the image. The more dominant green colour often masks fine details, but by using techniques such as CLAHE, the contrast can be increased so that objects in the image become more visible and recognisable. The Color Balancing method helps to correct the colour imbalance caused by underwater lighting, restoring a more natural look to the image. Image3 and Image4, which initially appear blurrier and less contrasty compared to Image1 and Image2, show how the techniques applied were able to enhance the details in the blurred images. For example, the Unsharp Mask method is very effective in accentuating the boundaries of objects, while CLAHE works to increase the contrast in the less prominent areas, giving the final image sharper and clearer. The results of this enhancement process show that even in initially sub-optimal images, the application of appropriate image processing methods can significantly improve the visual quality, increase the visibility of objects, and clarify details that were previously difficult to see.

Based on Table 1, which shows the SSIM values given for four images (Image1 to Image4) and four different image processing methods (colour-balanced, Clahe, unsharpened mask (USM), and colour-balanced USM), the Clahe method shows the best results. The average SSIM value for the color balanced method is 0.753, Clahe is 0.898, Unsharpen Mask (USM) is 0.87, and Color Balanced-USM is 0.637. From these average values, it can be concluded that the Clahe method has the highest SSIM value, with an average value of 0.898, which means that it provides the best image quality according to the SSIM evaluation compared to the other methods. Specifically, for each image, Clahe always had the highest SSIM value: 0.973 for Image1, 0.908 for Image2, 0.856 for Image3, and 0.856 for Image4. Therefore, it can be concluded that the Clahe method was the best among the three experiments.

Table 1. Calculation Results Of The Model Comparison Using SSIM

	Color Balanced	Clahe	Unsharpen Mask (USM)	Color Balanced-USM
Image1	0,830	0,973	0,935	0,752
Image2	0,757	0,908	0,883	0,640
Image3	0,699	0,856	0,831	0,559
Image4	0,724	0,856	0,834	0,595
Average	0,753	0,898	0,87	0,637

Source: (Research Results, 2024)

According to the SSIM values presented in Table 2 for four images (Image1 to Image4) and three image processing methods with different combinations (Clahe-USM, Color Balanced-Clahe, and Color Balanced-Clahe-USM), the Color Balanced-Clahe method shows the best results. The average SSIM values for the combination of the three methods are 0.673 for Clahe-USM, 0.683 for Color Balanced-Clahe, and 0.503 for Color Balanced-Clahe-USM. From these average values, it can be concluded that the Color Balanced-Clahe method has the highest SSIM value with an average of 0.683, which means that this combination of methods provides the best image quality according to the SSIM evaluation compared to the other combinations. This method proved to be the most effective in retaining the original structure and details of the image while improving the overall visual quality, especially in terms of colour clarity and contrast.

Table 2. Calculation Results Of The Model Fusion Omparison Using SSIM

	Clahe - USM	Color Balanced-Clahe	Color balanced-Clahe -USM
Image1	0,832	0,794	0,640
Image2	0,704	0,669	0,477
Image3	0,573	0,629	0,443
Image4	0,58	0,643	0,452
Average	0,673	0,683	0,503

Source: (Research Results, 2024)

Specifically, for each image, the method with the highest SSIM value varies. The Clahe-USM method has the highest SSIM values for Image1 (0.832) and Image2 (0.704), indicating that the combination of contrast enhancement and sharpening with USM works very well for these two images. As for Image1 and Image2, the Colour Balanced-Clahe method gave the best results with SSIM values of 0.794 and 0.669 respectively. This shows that for these images, colour balancing followed by contrast enhancement through CLAHE is more effective in producing images with better visual quality. This combination of different methods shows that the effectiveness of image processing techniques can be highly dependent on the characteristics of the image being processed, and the selection of the right method can result in a significant improvement in the quality of the final image.

Based on the analysis of SSIM (Structural Similarity Index) values for various image processing methods on four images (Image1 to Image4), it can be concluded that the Clahe (Contrast Limited Adaptive Histogram Equalisation) and Colour Balanced-Clahe methods show the best results compared to other methods. In the first evaluation (Table 1), the Clahe method achieved the highest average SSIM value of 0.898, which indicates the best image quality compared to the colour balanced, unsharpened mask (USM) and colour balanced-USM methods. This result indicates that Clahe is able to improve image detail and contrast very well, maintaining a visual structure that is close to the original image. In this evaluation, Clahe consistently gave the best results on all tested

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images, demonstrating its superiority in improving overall image quality.

In the second evaluation, as shown in Table 2, the colour balanced-Clahe method resulted in the highest average SSIM value of 0.683, which is superior to the Clahe-USM and colour balanced-Clahe-USM methods. Notably, color balanced-Clahe performed best on two out of the four images, indicating that when Clahe is combined with the colour balancing technique, it is able to significantly improve the image quality in some cases. While there were some cases where the Clahe-USM method showed better results for individual images, overall, the Clahe and Colour Balanced-Clahe methods proved to be the most effective based on the SSIM values. These results confirm that an appropriate combination of image processing techniques, such as those applied in Clahe and Colour Balanced-Clahe, can result in optimal image quality improvement, although it should be noted that the effectiveness of the methods may vary depending on the characteristics of the image being processed.

Therefore, it can be concluded that the color balanced-Clahe method is the best among these three experiments, although there are some cases where the Clahe-USM method has higher SSIM values for individual images.

The SSIM results presented in both tables show that although there is a decrease in value, it opens up opportunities for further research, This provides insight into the challenges of maintaining the structural quality of images generated from images taken in complex and wild seagrass bed ecosystems. Although the combination of different methods in image enhancement may cause distortions that reduce the structural similarity with the reference image, the proposed method is able to visually improve the image quality in aspects such as clarity, color, and visibility of objects in the image.

One alternative solution is to find and use the best parameters for each algorithm before combining them, in order to reduce the negative effects that arise when the methods are combined. Additionally, the use of evaluation metrics based on human vision perception, such as UIQM or UCIQE, can provide judgements that are more relevant to the human visual experience. These metrics focus on aspects that are important to end-users, such as contrast, clarity, and colour naturalness, and can thus complement or even be a more effective alternative to technical metrics such as SSIM. With this strategy, future research is expected to overcome the challenges in method combination and result in improved image quality that is both technical and visual.

Thus, This research provides a deeper understanding of the advantages and disadvantages of various digital image processing methods. Through detailed analyses, this research reveals how each method has unique characteristics that can provide benefits under certain conditions, but also has limitations that need to be considered. These findings can serve as a strong basis for further development in the field of digital image processing, particularly in the quest to optimise the desired results for various applications. In this context, factors such as brightness, contrast and sharpness are important aspects to consider. Understanding how each method affects these factors allows researchers and practitioners to select and customise image processing techniques more effectively according to specific needs.

CONCLUSION

In conclusion, this study successfully enhanced the contrast and brightness of underwater images. It underscores the importance of a combinative approach in image processing through the analysis of SSIM values for various image processing methods. It can be concluded that the Clahe and color balanced-Clahe methods are the most effective in improving underwater image quality. The Clahe method showed the best results with the highest average SSIM value of 0.898, outperforming the color-balanced, unsharpened mask (USM), and color-balanced-USM methods. Meanwhile, the color balanced-Clahe method had the highest average SSIM value of 0.683 in other evaluations, outperforming the Clahe-USM and color balanced-Clahe-USM methods. Although the Clahe-USM method gave better results on some individual images, overall, Clahe and color balanced-Clahe proved to provide the best image quality based on the SSIM evaluation. Future research should focus on further developing the Clahe and color balanced-Clahe methods to ensure higher effectiveness and efficiency and to be more adaptive to changes in underwater environments.

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