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Underwater Image Enhancement Using MIRNet

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ABSTRACT

In recent years, enhancement of underwater images is a challenging task, which is gaining priority since the human eye cannot perceive images under water. The significant details underwater are not clearly captured using the conventional image acquisition techniques, and also they are expensive. Hence, the quality of the image processing algorithms can be enhanced in the absence of costly and reliable acquisition techniques. Traditional algorithms have certain limitations in the case of these images with varying degrees of fuzziness and color deviation. In the proposed model, the authors used a deep learning model for underwater image enhancement. First, the original image is pre-processed by the white balance algorithm for colour correction and the contrast of the image is improved using the contrast enhancement technique. Next, the pre-processed image is given to the MIRNet for enhancement. MIRNet is a deep learning framework that can be used to enhance the low-light level images. The enhanced image quality is measured using peak signal-to-noise ratio (PSNR), root mean square error (RMSE), and structural similarity index (SSIM) parameters.

Keywords: Underwater; Deep learning; MIRNet; Peak signal-to-noise ratio; Structural similarity index

1. Introduction

Image processing can be used to perform some operations on an image to extract some useful information from it. It is one branch of signal processing where the input is a 2-D signal (image) and the output may be an image or an attribute associated with it. Nowadays, image processing is growing rapidly in the core research area within engineering, medicine and other disciplines too [1].

In image processing, underwater image enhancement plays a crucial role and vision applications over the past few years. The images taken underwater

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are affected by various lighting and environmental conditions; hence the quality of the image is degraded. The underwater image suffers from degradation due to scattering and absorption. The scattering and absorption process of light in water influences the overall performance of the systems underwater [2]. Forward scattering leads to blurring of the image features, and backward scattering limits the contrast of the image. Similar is the color fading issue, whereby colors like red and yellow almost disappear with increasing depths, which is the reason for the domination of either the blue or the green color. The underwater images are specified by their poor visibility since light is exponentially attenuated as it travels in water and the scenes result poorly contrasted and hazy as shown in **Figure 1(a-c)**. Hence, it is necessary to enhance the underwater images for analyzing its quality, and to prepare the image for further processing [3].

(a) Underwater Fish image

(b) Coral reef image

(c) Under water image with light scattering

Figure 1. Sample underwater images.

The rest of the paper is organized as follows: Section 2 reviews the literature on image processing underwater. Section 3 presents a new method for enhancing the quality of underwater image. Section 4 discusses the simulation results obtained by using our model and comprehensive analysis of the model by evaluating various metrics. Finally, Section 5 describes the conclusion of the work.

2. Literature survey

Schettini et al. [4] review the enhancement and restoration methods for underwater image processing. They discussed light propagation in water, image color correction, lightning problems, and various quality assessment models.

Boudhane et al. [5] proposed a method for pre-processing and fish localization in underwater images by using a mean-shift algorithm for image segmentation and the Poisson-Gauss mixture algorithm for noise reduction, and tested their model under different underwater conditions.

Ancuti et al. [2] performed a fusion of two images (color compensated and white balance version) and then transforms the edges and color contrast to the output images.

Daway et al. [6] performed underwater image enhancement by changing the color content in the image from RGB to YCbCr space. They used Rayleigh distribution along with an integrated color model and calculated no-reference-image quality metrics.

Li et al. [7] created an underwater image enhancement benchmark with 950 raw images, 890 reference images, and 60 challenging images. They also provided an underwater image enhancement network named Water-Net and made the dataset public.

Han et al. [8] proposed a convolution neural network (CNN) based method by combining the max-RGB method and the shades of grey method for detecting the underwater objects.

Wang et al. [9] proposed an underwater image enhancement CNN using two color spaces that integrate RGB color space and HSV color space and evaluate their method with qualitative and quantitative comparisons on both synthetic and raw images.

Zheng et al. [10] proposed a CNN-based network for enhancing the underwater images using an end-to-end defogging module. They also added a cross-layer connection, and pooling pyramid module to improve the defogging network's ability to extract the required information.

3. Proposed work

This section discusses the proposed methodology for enhancing the quality of underwater images.

3.1 Block diagram

The proposed enhancement process of the model is shown in **Figure 2**. The first step is the acquisition of RGB images from the dataset. The input image is pre-processed by the White-Balance algorithm for colour correction and the contrast of the image is improved using the contrast enhancement technique. White-Balance aims at improving the image aspect, primarily by removing the undesired color castings due to various illumination or medium attenuation properties [11]. White-Balance discusses the visible color white under specific lighting conditions affects the hue of all other colors.

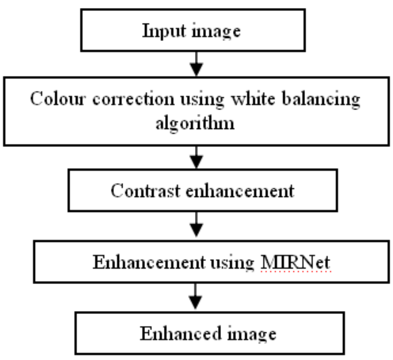


Figure 2. Proposed enhancement process.

White balance algorithm

White-Balance process aims at improving the image aspect, primarily by removing the undesired color castings due to various illumination or medium attenuation properties. White-Balance defines what the color white looks like in specific lighting conditions, which also affects the hue of all other colors. Therefore, when the White-Balance is off, the digital photos and recordings may appear to have a certain hue cast over the image. In underwater the perception of color is highly correlated with the depth, and an important problem is the green-bluish appearance that needs to be rectified. As the light penetrates the water, the attenuation process affects selectively the wavelength spectrum, thus affecting the intensity and the appearance of a colour surface. Since the scattering attenuates more the long wavelengths than the short ones, the color perception is affected down in deeper water. In practice, the attenuation and the loss of color also depend on the total distance between the observer and the scene. Despite white balance being crucial to recover the color, using this correction step is not sufficient to solve the dehazing problem since the edges and details of the scene have been affected by the scattering.

The White-Balance algorithm has three types. They are the White Patch algorithm, Gray World algorithm, and Ground Truth algorithm. From these three algorithms for selecting the best algorithm, we applied the histogram plots on output images of three methods. We found that the Ground Truth algorithm is the best one as compared to the remaining algorithms.

Ground truth algorithm for white-balance

Ground Truth is a term used in statistics and machine learning that means checking the results of machine learning for accuracy against the real world. The term is borrowed from meteorology, where "Ground Truth" refers to information obtained on-site. The term implies a kind of reality checks for machine learning algorithms. The Ground Truth of a satellite image means the collection of information at a particular location. It allows satellite image data to be related to real features and materials on the ground. This information is frequently used for the calibration of remote sensing data and compares the result with Ground Truth. So far, we have made assumptions about how the color spaces behave in our images. Instead of making assumptions for enhancing our images, we select a patch (portion of an image) and use that patch to recreate our desired image. Having selected the patch, we proceed to enhance our image. For this purpose, we can do it two ways: 1) MAX method—normalize each channel of the original image to the maximum value of each channel of the region, 2) MEAN method—normalize each channel of the original image to the mean value of each channel of the region. The output is slightly closer to the white patch output but the latter is brighter. It also emphasized the color of the lily, but instead of highlighting the color of the pads, it only brightened it. For the Ground Truth algorithm, the output image depends greatly on the choice of the patch image. So, the patch is chosen wisely by visualizing the enhanced image based on the type of application.

Next, the colour corrected image can be passed through contrast enhancement. This step aims to increase image perception by the human eye. This technique plays a major role to bring out the existing information within the low dynamic range of that grey level image [12]. It is required to perform the operations like contrast enhancement and reduction or removal of noise to improve the image quality. Adaptive Histogram Equalization is used for contrast enhancement of the image. Adaptive Histogram Equalization is different from Histogram Equalization in that it computes multiple histograms for each individual part of the image and uses them to spread the image's brightness levels. As a result, it is appropriate for enhancing local contrast in images.

Next, the pre-processed image can be passed through the MIRNet for enhancement [13]. MIRNet is a deep learning framework which can be used to enhance the given image at a low light level.

3.2 MIRNet

It is a feature extraction model which calculates a set of features across various spatial scales and maintains the original high-resolution features for preserving the spatial details. In this process, the features across various resolutions are fused together and repeat this mechanism for representation learning. Also, it is a modern approach to fusing the multi-scale features with the help of a selective kernel network which combines variable receptive fields and faithfully preserves the original features at each spatial resolution. This recursive residual design progressively breaks down the input signal to simplify the overall learning process and allows the construction of a deep neural network as shown in **Figure 3**.

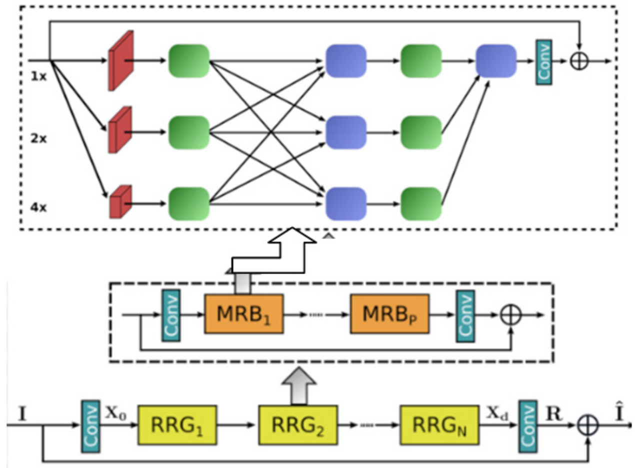


Figure 3. MIRNet architecture.

Selective kernel feature fusion (SKFF)

The SKFF module can perform the dynamic adjustment of receptive fields via i) **Fuse** and ii) **Select** operations. The first operator will generate the global feature descriptors by summing the information from multi-resolution streams. The second operator uses the descriptors for feature maps recalibration followed by aggregation as shown in **Figure 4**.

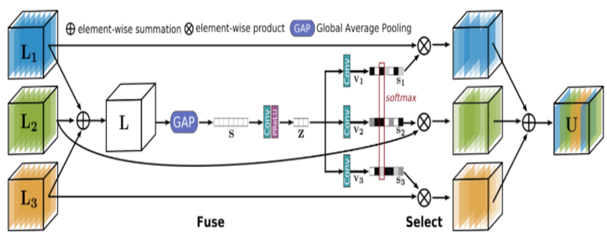


Figure 4. Structure of SKFF.

Dual attention unit (DAU)

The DAU can extract the features from the convolution streams. While the previous block fuses the information across multi-resolution branches, we also need some mechanism to share information within a feature tensor, both along the spatial and the channel dimensions which are done by the DAU block. The DAU reduce less useful features and only allows more informative features to pass further. This process of feature recalibration can be achieved by two mechanisms: **Channel** and **Spatial Attentions** as shown in **Figure 5**.

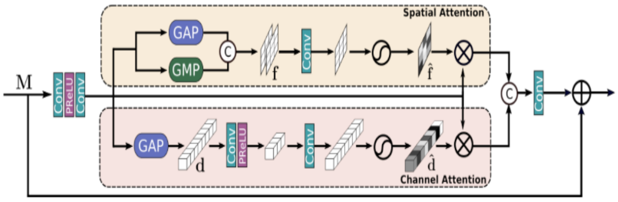
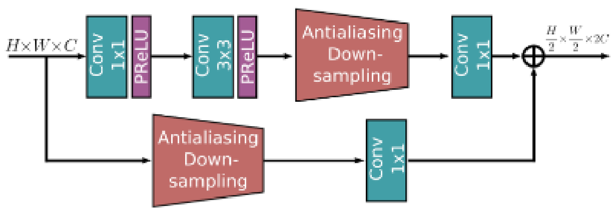


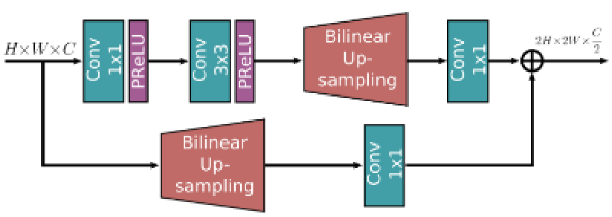
Figure 5. Structure of DAU.

Multi scale residual block (MRB)

The MRB can receive rich contextual information from low-resolutions and generate a spatially-precise output by maintaining high-resolution representations. It consists of multiple (three in this paper) fully-convolution streams which are parallel connected. The MIRNet employs a recursive residual design (with skip connections) to ease the flow of information during the learning process. To maintain the residual nature of our architecture, down sampling and up sampling operations are performed between residual resizing modules as shown in **Figure 6(a-b)**.



(a) Down sampling module in MRB



(b) Up sampling module in MRB

Figure 6. Structure of MRB.

3.3 Software requirements

The software used in our implementation is Python. Python is an object-oriented, high-level language, interpreted, dynamic and multipurpose programming language [14]. The libraries include:

- Numpy
- Keras
- Matplotlib
- Scikit-learn

4. Simulation results

In this section, the simulation results carried out in our work are presented which follows the comparison of results.

4.1 Dataset used

The dataset used in our implementation is the underwater image enhancement benchmark (UIEB) dataset [7], which includes 890 raw underwater images and corresponding reference images.

4.2 Performance metrics

The performance metrics used in our implementation include peak signal-to-noise ratio (PSNR), mean square error (MSE), root mean square error (RMSE), and structural similarity index (SSIM) which are defined as:

$$PSNR = 10.\log_{10}\left(\frac{255^2}{MSE}\right)$$

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[I(i,j) - I'(i,j)]^2$$

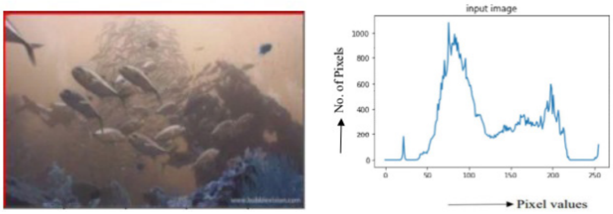
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_1^2 + \mu_2^2 + c_1)(\sigma_1^2 + \sigma_2^2 + c_2)}$$

4.3 Simulation results

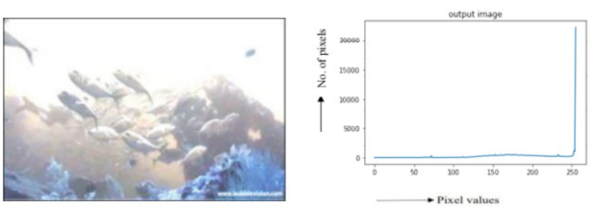
From the UIEB dataset, different raw images are taken as inputs and applied the proposed algorithm and obtained the white balanced image, contrast enhanced image, MIRNet output image, and corresponding histograms for each image. In this paper, the input and output images and corresponding histogram plots for four different raw images are presented and are shown in **Figures 7-10** respectively.

❖ **Raw image-1:** Image size 208 × 319



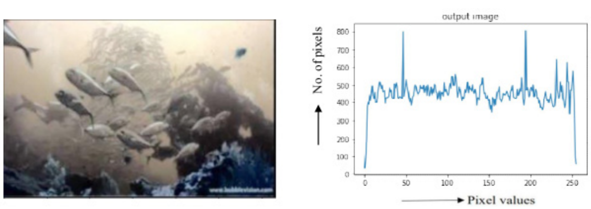
(i) (ii)

Figure 7(a). (i) Input image-1 and (ii) histogram of input image-1.



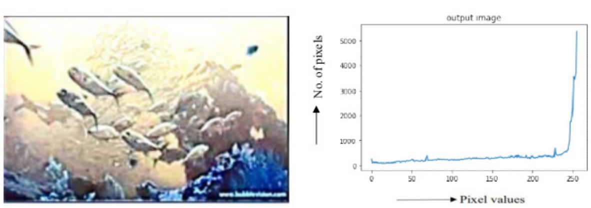
(i) (ii)

Figure 7(b). (i) White balanced output for image-1 and (ii) histogram of white balanced output image-1.



(i) (ii)

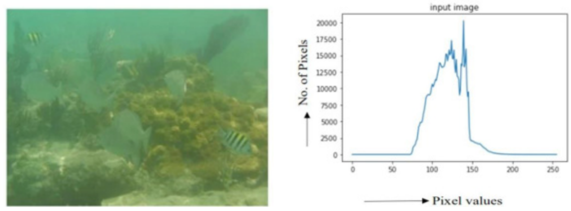
Figure 7(c). (i) Contrast enhanced output for image-1 and (ii) histogram of contrast enhanced output image-1.



(i) (ii)

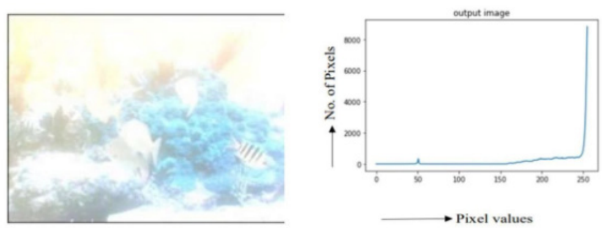
Figure 7(d). (i) Enhanced output for image-1 using MIRNet and (ii) histogram of enhanced output image-1.

❖ **Raw image-2:** Image size 768 × 1024



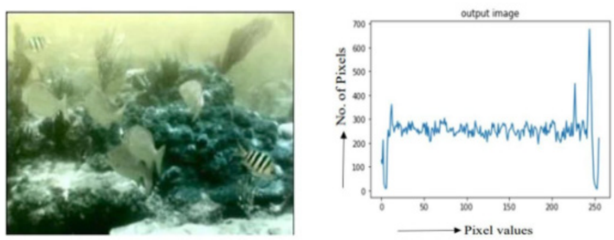
(i) (ii)

Figure 8(a). (i) Input image-2 and (ii) histogram of input image-2.



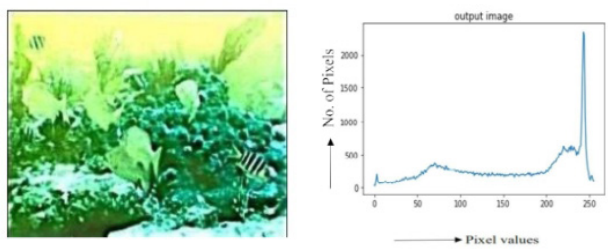
(i) (ii)

Figure 8(b). (i) White balanced output for image-2 and (ii) histogram of white balanced output for image-2.



(i) (ii)

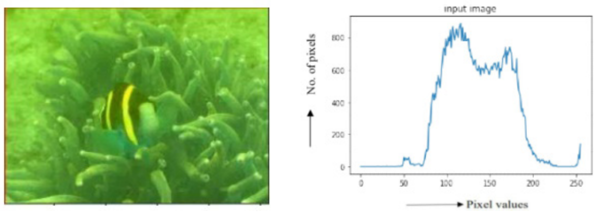
Figure 8(c). (i) Contrast enhanced output for image-2 and (ii) histogram of contrast enhanced output image-2.



(i) (ii)

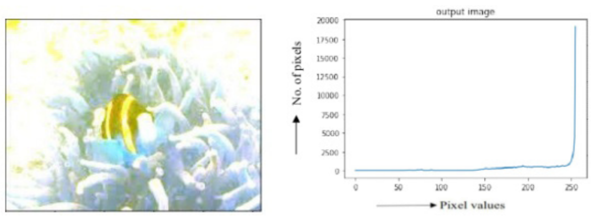
Figure 8(d). (i) Enhanced output for image-2 and (ii) histogram of enhanced output image-2.

❖ **Raw image-3:** Image size 237 × 315



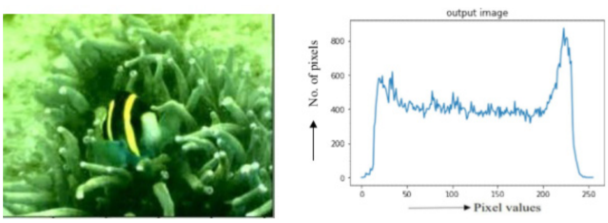
(i) (ii)

Figure 9(a). (i) Input image-3 and (ii) histogram of input image-3.



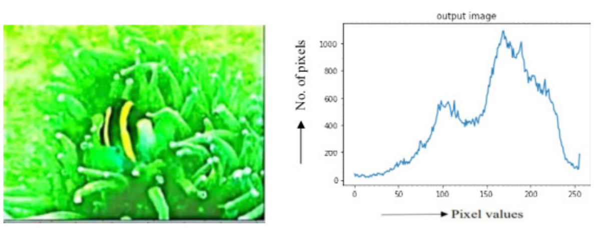
(i) (ii)

Figure 9(b). (i) White balanced output for image-3 and (ii) histogram of white balanced output image-3.



(i) (ii)

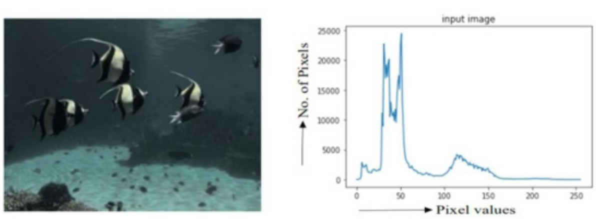
Figure 9(c). (i) Contrast enhanced output for image-3 and (ii) histogram contrast enhanced output image-3.



(i) (ii)

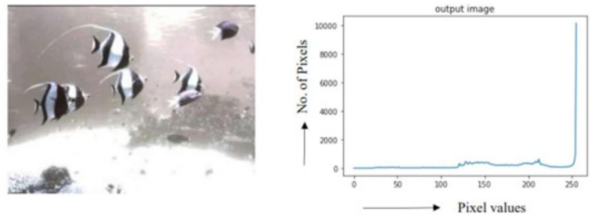
Figure 9(d). (i) Enhanced output for image-3 and (ii) its histogram.

❖ **Raw image-4:** Image size 683 × 910



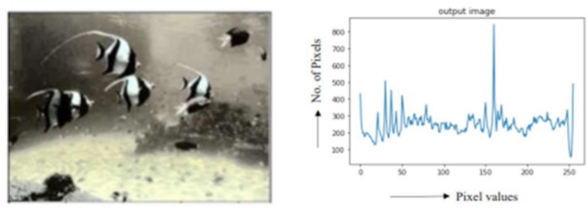
(i) (ii)

Figure 10(a). (i) Input image-3 and (ii) histogram of input image-3.



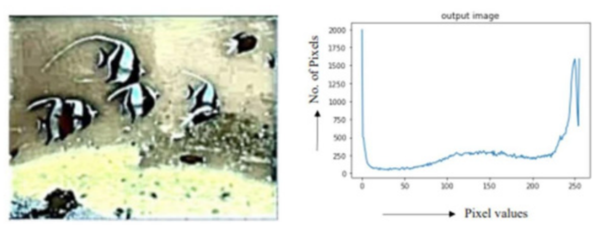
(i) (ii)

Figure 10(b). (i) White balanced output for image-4 and (ii) histogram of white balanced output image-4.



(i) (ii)

Figure 10(c). (i) Contrast enhanced output for image-4 and (ii) histogram of enhanced image-4.



(i) (ii)

Figure 10(d). (i) Enhanced output for image-4 and (ii) histogram of enhanced image-4.

The performance metrics for the above mentioned four images ere calculated and compared with the metrics for the color corrected image and the output enhanced image. The evaluated metrics for the images are represented in **Tables 1-4**.

Table 1. Result comparison for image-1.

Metric	Color corrected image using white balance	Enhanced image using MIRNet
RMSE	73.9	34.7
PSNR	10.7	17.3
SSIM	(0.4, 0.4)	(0.8, 0.8)

Table 2. Result comparison for image-2.

Metric	Color corrected image using white balance	Enhanced image using MIRNet
RMSE	77.3	26.5
PSNR	10.3	19.6
SSIM	(0.3,0.4)	(0.8,0.8)

Table 3. Result comparison for image-3.

Metric	Color corrected image using white balance	Enhanced image using MIRNet
RMSE	53.5	24.5
PSNR	13.5	20.3
SSIM	(0.4, 0.4)	(0.7, 0.7)

Table 4. Result comparison for image-4.

Metric	Color corrected image using white balance	Enhanced image using MIRNet
RMSE	115.8	29.16
PSNR	6.8	18.83
SSIM	(0.2, 0.3)	(0.6, 0.6)

5. Conclusions

A deep learning framework based technique MIRNet is proposed in our paper for underwater image enhancement which transforms images to provide a better representation of the content present in the image. First, the color of the input image is corrected using a technique called the White-Balance algorithm. Next, the contrast of the color corrected images is improved using an adaptive histogram equalization method. Finally, the pre-trained deep learning model MIRNet is used to enhance the image. The quality of the output images is justified in terms of PSNR and SSIM parameters and tabulated. Hence, we conclude that the proposed method can perform underwater image enhancement for low light, low contrast underwater images effectively without any loss of information.

Future Scope

The proposed method can be extended in the future with suitable pre-processing techniques to enhance the blurred underwater images which result from the light scattering problem of the underwater image capturing system.

Conflict of Interest

There is no conflict of interest.

References

[1] Acharya, T., Ray, A.K., 2005. Image processing: Principles and applications. John Wiley & Sons: New York.

[2] Ancuti, C.O., Ancuti, C., De Vleeschouwer, C., et al., 2017. Color balance and fusion for underwater image enhancement. IEEE Transactions on Image Processing. 27(1), 379-393.

[3] Raveendran, S., Patil, M.D., Birajdar, G.K., 2021. Underwater image enhancement: A comprehensive review, recent trends, challenges and applications. Artificial Intelligence Review. 54(7), 5413-5467.

[4] Schettini, R., Corchs, S., 2010. Underwater image processing: State of the art of restoration and image enhancement methods. EURASIP Journal on Advances in Signal Processing. 2010, 1-14.

[5] Boudhane, M., Nsiri, B., 2016. Underwater image processing method for fish localization and detection in submarine environment. Journal of Visual Communication and Image Representation. 39, 226-238.

[6] Daway, H.G., Daway, E.G., 2019. Underwater image enhancement using colour restoration based on YCbCr colour model. IOP Conference Series: Materials Science and Engineering. 571(1), 012125.

[7] Li, C., Guo, C., Ren, W., et al., 2019. An underwater image enhancement benchmark dataset and beyond. IEEE Transactions on Image Processing. 29, 4376-4389.

[8] Han, F., Yao, J., Zhu, H., et al., 2020. Underwater image processing and object detection based on deep CNN method. Journal of Sensors. 2020(9), 1-20.

[9] Wang, Y., Guo, J., Gao, H., et al., 2021. UIEC^2-Net: CNN-based underwater image enhancement using two color space. Signal Processing: Image Communication. 96, 116250.

[10] Zheng, M., Luo, W., 2022. Underwater image enhancement using improved CNN based de-

fogging. Electronics. 11(1), 150.

[11] Thai, B., Deng, G., Ross, R., 2017. A fast white balance algorithm based on pixel greyness. Signal, Image and Video Processing. 11, 525-532.

[12] Hashemi, S., Kiani, S., Noroozi, N., et al., 2010. An image contrast enhancement method based on genetic algorithm. Pattern Recognition Letters. 31(13), 1816-1824.

[13] Zamir, S.W., Arora, A., Khan, S., et al., 2022. Learning enriched features for fast image restoration and enhancement. IEEE Transactions on Pattern Analysis and Machine Intelligence. 45(2), 1934-1948.

[14] Dey, S., 2018. Hands-on image processing with Python: Expert techniques for advanced image analysis and effective interpretation of image data. Packt Publishing Ltd: Birmingham.