International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 5 May 2023, pp: 676-684 www.ijaem.net ISSN: 2395-5252

Enhancing Underwater Photographs with Non-Uniform Lighting and Dehazing

Prachi Verma, Dr. Manish Dixit
(Madhav Institute of Technology and Science Gwalior)
(Madhav Institute of Technology and Science Gwalior)

Date of Submission: 08-05-2023 Date of Acceptance: 20-05-2023

ABSTRACT-
Throughout the last few years, scientists from all across the world have been researching underwater photography and the possibility of obtaining incredibly clear images. Additionally, retrieving all of the gathered photographs requires a lengthy process. The scientific absorbance and scattering processes are to blame for some of the defects in the acquired underwater pictures. These photos are notable for their color distortion, blurriness, and the effects of weak contrast. It is a significant effort for scholars studying image processing to address these issues. When dehazing underwater pictures, the particles present in the water, combined with the uneven absorption of light, create an even more difficult situation. The visibility conditions that affect underwater scenes are described in this paper, as well as contemporary dehazing approaches. This research shows how to use a Neural Network NN-based image-enhancing strategy to improve underwater photographs with non-uniform lighting, low contrast, blurriness, and degraded color. The proposed method is based on the Deep Learning (DL) principle and focuses on the input photos, weight & weight maps, and white balance data from a damaged or noisy underwater image. The Underwater Image(UI) obtained using the aforementioned techniques has lower noise levels and better exposed dark regions, as well as greater global contrast and sharper details and edges. The trials were conducted on the EUVP dataset, and the results show that the suggested method outperforms other current methods in terms of efficiency.

Keywords- Underwater Image Enhancement, Neural Network, Deep Learning, Scattering, Dehazing.

I. INTRODUCTION

Image enhancement is the method of upgrading the current picture content to make it easier for viewers to perceive in the future. Underwater pictures suffer primarily from the difficulties of low color quality and limited clarity. Such issues emerged because of the dispersion of light and light refraction when entering from a rarer to a denser medium. Image enhancement is the rendering method for the input image to allow it more appropriate and recognizable for the task needed. Image enhancement enhances the image's detail quality and modifies the picture's visual effect on the viewer. Image enhancement intensifies camera features[1]. This accentuates picture characteristics such as corners, compared with building views of images that are more suitable for analyzing and learning. The improvement of the vision underwater has immersed a great deal of focus in the production and visual interpretation. Improvementis a concern, as it complicates the underwater environment and lighting conditions. Since water is denser than air, just a limited volume of light hits the target as light enters the water, it falls into reflection phenomena at the surface of thewater[2]. UIE is a set of computer techniques that are applied to degraded photographs to improve image quality, contrast, and detail information acceptable for human and machine interpretation.

Water's physical qualities contribute to the light deterioration effect in underwater images, which is absent in images taken under standard air conditions[3]. Based on the wavelength of the color spectrum, light loses its intensity as it travels through water. Figure 1 illustrates a graphic representation of underwater color fading. The longest wavelengths of light waves are absorbed first in clear open water[4]. The color red, which is the most impacted, is decreased to 1/3 of its original intensity after one meter and completely gone after 4-5-6 meters underwater. Orange, yellow, green, and blue colors appear after absorption. Light attenuation restricts vision distance to roughly 20m in clear water and 5m or less in turbid water[5].

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 5 May 2023, pp: 676-684 www.ijaem.net ISSN: 2395-5252

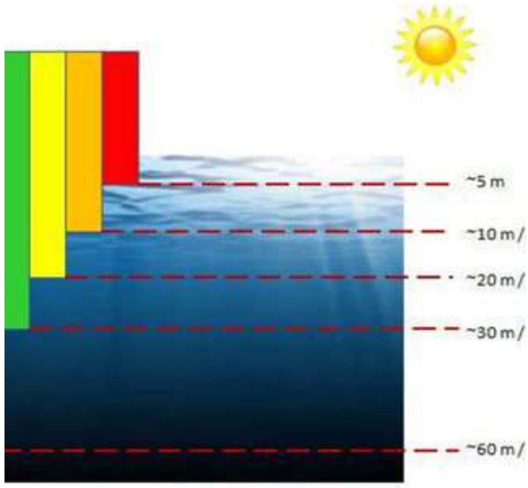


Figure 1- Illustration of diminishing underwater color.

In addition to these elements, the variety of UI distributions presents an additional difficulty for UIE. Figure 1 illustrates how underwater sights photographed in shallow coastal waters, deep oceanic seas, and muddy waters differ from one another in appearance. It is challenging to offer a universal method for UIE since a single model struggles to improve underwater photographs for so many different image distributions. Although the issues of light attenuation and scattering have been addressed in prior work, the issue of picture distribution diversity has not been fully addressed by many.The quality of an image captured in water is constantly diminished since this is a general observation. It loses the true tone quality and contrast required to recognize the image's object of interest. When the pixel intensity levels of adjacent objects change by only a few pixels, the situation gets even more difficult. This scenario makes retrieving fine details from data difficult, and the performance of the approaches employed to extract details from photos suffers. As a result, there is a compelling need for UI to be managed in a way that its real tonal characteristics are preserved[6]. UI has a wide range of uses, including aquatic life inquiry, defense and security, and so on. Therefore, photographs or films attained to achieve these aims must contain perfect information.

To lessen or remove underwater picture difficulties, underwater IP, particularly the contrast enhancement approach, is applied. The focus of this research is on visual contrast in underwater images. Image contrast enhancement has been used in technical instruments such as cameras and video cameras. In a digital camera, for example, the underwater mode is used to take underwater images that are upgraded to generate a higher contrast level than the original image captured in regular mode. In comparison to the subsequent image taken in normal mode, which frequently has issues such as low contrast performance, blue-green lighting, and under- and over-enhanced areas, the resultant image produced in underwater mode has a higher quality[7],[8].Whereas UIP techniques develop over time, a challenging and engaging underwater IP project would be able to tackle UW picture challenges in an efficient, time-saving, and computationally simple manner.

The rest of the paper is organized as follows: The underwater imaging model and the colour model are described in Section 2 and the training dataset and examples of the strategies employed in the proposed algorithm are provided in Section 3. In Section 4 with an explanation, the image processing findings are displayed, and ends with a conclusion is presented.

II. RELATED WORK

DL, a data-driven technique, has gained popularity in image processing during the past few years. DL -based methods are built on learning the relationships between the images, which allows for the avoidance of estimation mistakes brought on by the method's erroneous priors. CNN is a representative method for DL and is frequently used in the evaluation of underwater picture data. In order to effectively handle the diversity of water during improvement, PritishUplavikar[9] suggested a unique model that learns the image's content attributes through adversarial learning by untangling the unwanted annoyances associated with different types of water (viewed as different domains). To create improved underwater photos, they employ the learned domain-neutral features. They use a dataset made up of pictures of 10 different types of Jerlov water to train our model. The suggested model not only performs better than the prior methods in terms of SSIM and PSNR scores for practically all Jerlov water types, but it also generalizes well on datasets from the actual world. Using improved images and our model, the effectiveness of a high-level vision task (object detection) also exhibits improvement. An alternate method to improve underwater photos was proposed by Anushka Yadav et al.[10],the approach is based on histogram equalization and requires only the single original image as additional input. They have demonstrated in their trials the approach is capable of improving a wide range of underwater photographs with excellent precision, being able to recover significant faded features and edges (e.g., different cameras, depths, and light conditions). They provide evidence of the

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 5 May 2023, pp: 676-684 www.ijaem.net ISSN: 2395-5252

usefulness and applicability of the suggested image augmentation method for several difficult underwater computer vision applications. When compared to current ICM techniques, the suggested methods produce lower MSE, better Entropy, and higher PSNR values. A multiscale densely connected deep CNN-based UIE model was suggested by Fucui Li et al.[11] and was influenced by the concept of underwater optical imaging. The most notable aspect of this work is the integration of data-driving DL and expertly created picture enhancement to boost UIE performance. This approach can improve the graphical quality of unprocessed underwater photos while also enhancing how well-upgraded photos perform in vision-related activities. The trials, which included user research, application testing, and qualitative and quantitative comparisons, show that the model outperforms other extant models. For improving UIquality, AnparasySivaanpu et al.[12] presented a unique CNN architecture. To input raw degraded images and the equivalent color-balanced images, it has two identical CNN branches. The suggested network makes use of dense blocks to optimise the model with fewer parameters. In order to maintain the spatial information across the network, skip links are also inserted in between layer blocks. To support the network architecture, a thorough ablation research is carried out. On the UIEB dataset, the suggested model was tested, and the results indicated 28.67 PSNR and 0.89 SSIM index.

III. PROPOSED METHODOLOGY

Neural Network (NN)-

The NN is a collection of linkages that represent brain activity. Each node in an adjacent layer has a weighted association with several other nodes. The node uses the input and weights from individual nodes, as well as the basic capabilities to compute expected output[13]. Neural systems come in many different shapes and sizes. The user must choose the NN design, which includes several hidden layers, the number of nodes, and their connections in particular hidden levels, based on the problem's complexity. It has the ability to learn and model nonlinear and dynamic interactions, which is important because many input-output linkages in real-world settings are nonlinear or difficult. After learning from the fundamental information sources and their linkages, it may infer hidden connections on inconsequential data, affecting the model's ability to summarize and anticipate hidden data[14]. Figure 2 shows the basic NN architecture.

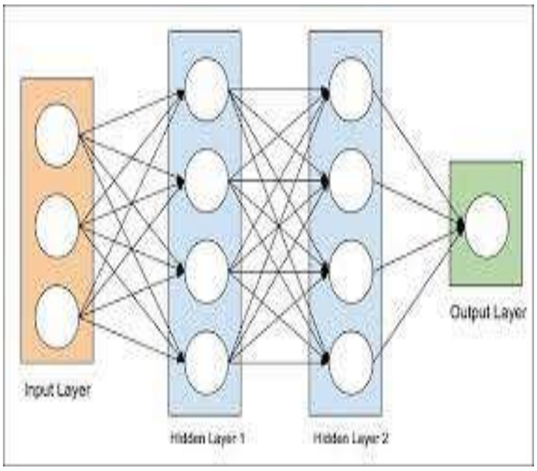


Figure 2 – Neural Network architecture.

IV. EXPERIMENTAL ANALYSIS

Data Gathering

The experimental data for this paper came from the EUVP (Enhancing Underwater Visual Perception) dataset, which is publically accessible at (http://irvlab.cs.umn.edu/resources/euvp-dataset). The EVUP dataset, which contains paired and unpaired image samples of false-positive and false-negative images for training the UE enhancement approach, was introduced by Islam in the year 2020. Islam used seven different cameras to take pictures in various locations and lighting situations. A few of the images were also obtained from YouTube videos that were available to everyone. The accumulation is diverse since it includes images of a range of aquatic environmental conditions with differing turbidities and illumination levels. The EUVP dataset contains different units of poor and good identification rates to allow supervised training of UIE models. The EUVP dataset's total, validation, and training images are displayed in Figure 3.

Dataset Name	Training Pairs	Validation	Total Images
Underwater Dark	5550	570	11670
Underwater ImageNet	3700	1270	8670
Underwater Scenes	2185	130	4500

Figure 3- The figure shows the total images, validation, and training images for the EUVP dataset.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 5 May 2023, pp: 676-684 www.ijaem.net ISSN: 2395-5252

Data Preprocessing

We have to transform these into other forms in order to make the neural network do all the work. The dataset is divided into two categories: Ground Truth and Raw images. Despite the dataset we used having already undergone thorough processing, there is still room for improvement. The processes for pre-processing data are as follows:

- Perusing the input image directory
- Reading each image one at a time.

img=cv2.imread(INP_DIR + str(m))

- Changing the photos from BGR format to RGB format

img = img[:, :, ::-1]

- Norming the visuals

img = np.float32(img) / 255.0

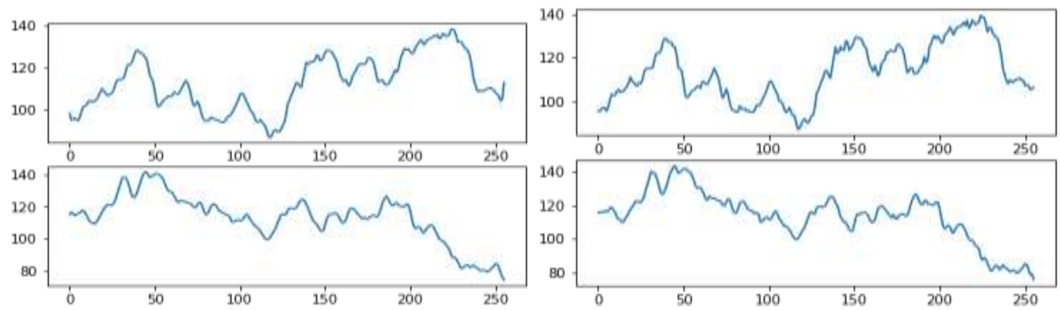
- Using one image at a time, with the image's colour channel 3, height, and width, to create a NumPy vector.

train_x = np.zeros((1, ch, h, w)).astype(np.float32)

- Equalizing each image channel before combining them into one.

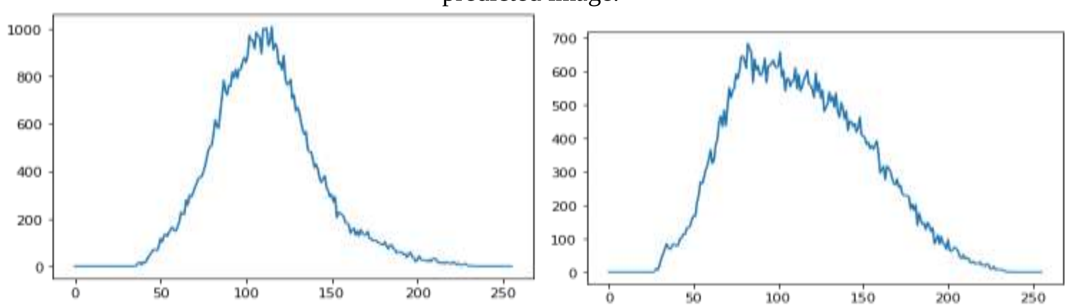
Performing EDA

Exploratory Data Analysis (EDA) is a technique for determining a dataset's key properties. It is used to understand data, contextualise it, understand variables and their interactions, and make suggestions that could help in the creation of estimating procedures. It enables us to synthesize key components like class distribution and size distribution and evaluate the complete dataset. After the investigation, we realized that our dataset could be divided into a variety of groupings, so we categorized and summarised it. To highlight the differences, plot some histogram maps of the original and predicted images.Figure 4 shows the average columns and rows of every pixel of the raw image and predicted image. Figure 5 shows the frequency range of pixels from 0-255 for the raw and predicted images. Figure 6 shows intensity values for every color channel in the raw and predicted image. Figure 7 shows the intensity value bar plot with counts for raw and predicted images. Figure 8 shows the cumulative histogram of raw and predicted images with their intensity values and counts. Figure 9 shows the color histogram of every channel of the raw and predicted image. Figures10, and 11 show the Normal Histogram and Equalized Histogram of the raw image.



(a) Raw Image (b) Predicted Image

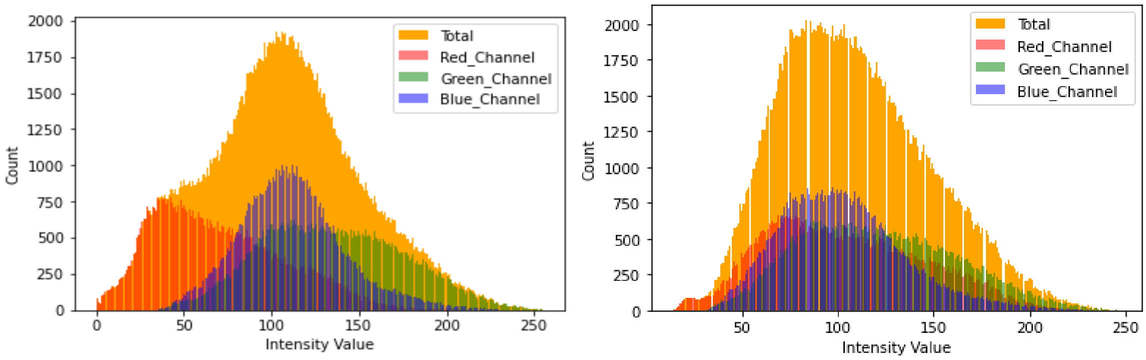
Figure 4- The figure shows the average values of rows and columns of every pixel of the raw image and predicted image.



(a) Raw Image (b) Predicted Image

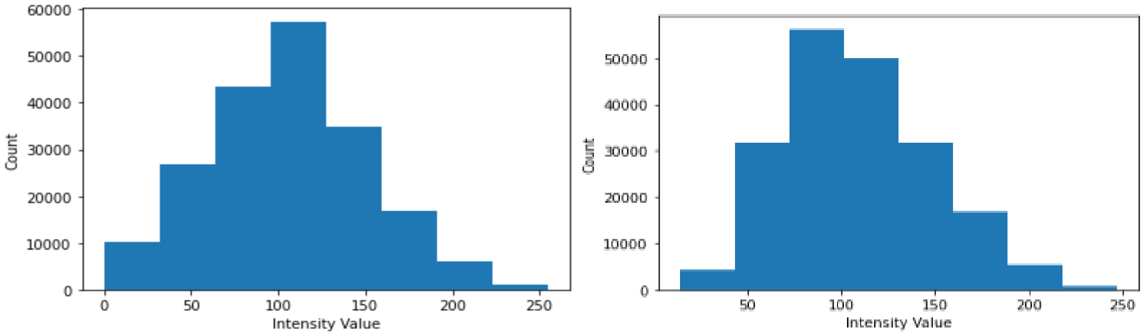
Figure 5- The figure shows the Frequency of pixels in the range 0-255 of Raw image and Predicted Image

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 5 May 2023, pp: 676-684 www.ijaem.net ISSN: 2395-5252



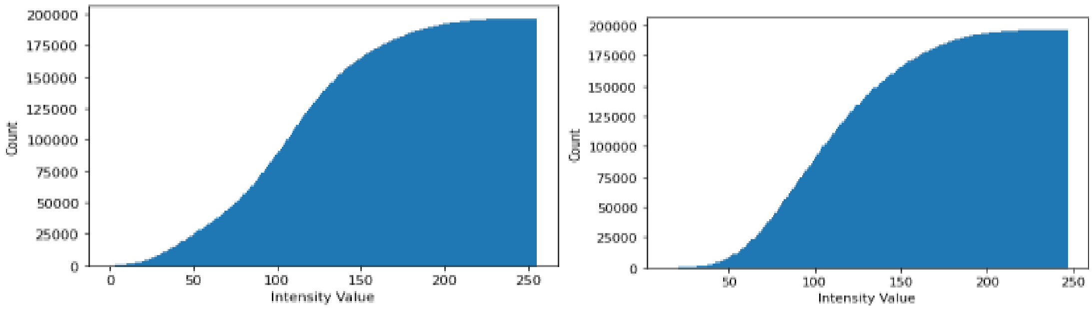
(a) Raw Image (b) Predicted Image

Figure 6- The figure shows the Intensity of every color channel in the Raw image and Predicted Image.



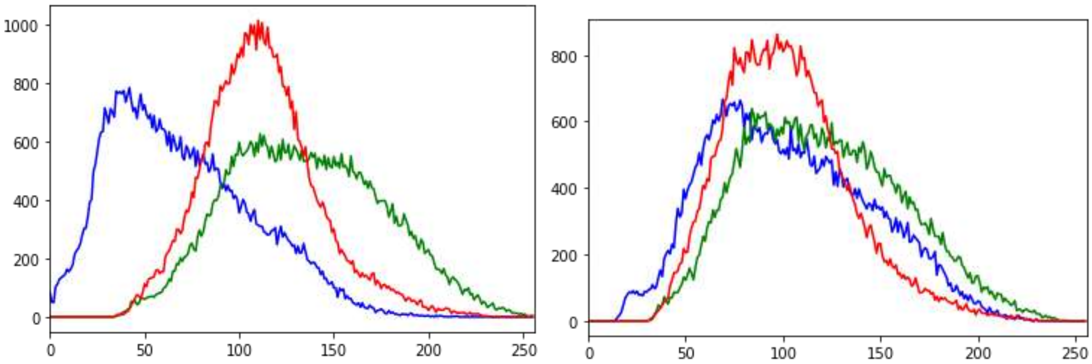
(a) Raw Image (b) Predicted Image

Figure 7- The figure shows the Intensity Bar plot with counts of Raw images and Predicted Image



(a) Raw Image (b) Predicted Image

Figure 8- The figure shows the Cumulative Histogram of the Raw Image and Predicted Image.



(a) Raw Image (b) Predicted Image

Figure 9- The figure shows the Color Histogram of every channel of Raw Image and Predicted Image.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 5 May 2023, pp: 676-684 www.ijaem.net ISSN: 2395-5252

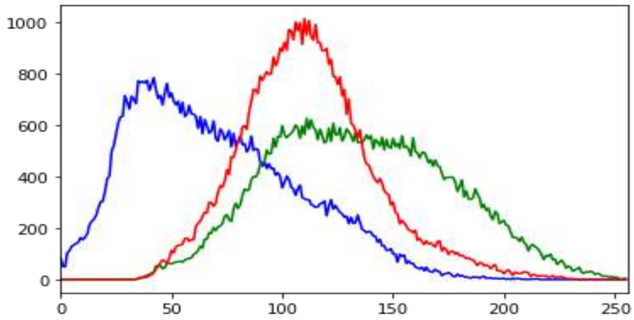


Figure 10- The figure shows the Normal Histogram Raw Image.

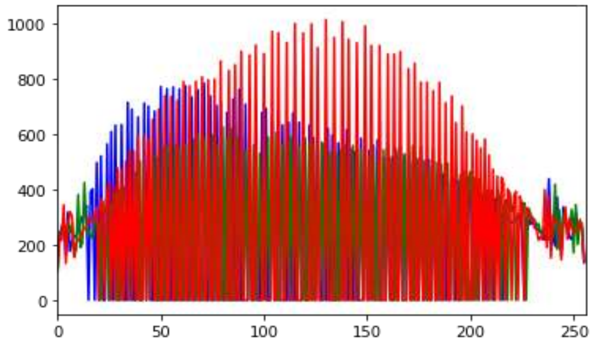


Figure 11- The figure shows the Equalized histogram of the Raw Image.

Proposed Algorithm

1. Gather the EUVP dataset, which is accessible at http://irvlab.cs.umn.edu/resources/euvp-dataset.
2. Reading each image in turn from the source image directory.
3. Normalizing and converting the photos from BGR format to RGB format.
4. Using the color channel, image height, and image width of one image at a time, create a NumPy vector. After adjusting each component of the image, aggregate all of the channels into one.
5. Sending the data to the neural network model so it can train.
6. Saving the improved or forecasted image in a different folder and calculating the values of SSIM, PSNR, RMSE, UIQM, and UCIQE.

Network Analysis

In this section, we'll go over the proposed architecture's descriptions first, then the network processing, and lastly the evaluation metrics. CNN's performance in the machine vision tests was outstanding. Each layer of the neural network's features can be used to extract all of an image's key characteristics. Because of this, we use convolution architectures to remove noise while preserving the key components of the input images. Contrarily, the constant convolutional activity of the CNNs is inadequate to recreate the content in the low-quality image. The layers are then utilized to fine-tune the texture after denoising.The convolutional product's goal is to keep crucial detail features while removing noise. The details of each feature map for each convolution layer are adjusted in the symmetric deconvolution process. It starts with expediting the training procedure. If we want to create a data-driven picture development model, the super-parameters of our system are essential[15].

For UI and ground truth photos, the NN is trained and put to the test. Eighty percent of the dataset is used for training and twenty percent is used to test the model. For hyperparameters training, RELU and Sigmoid activation functions were employed. The improved image is output by the working neural network. The parameters utilized for model training are listed in Table 1:

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 5 May 2023, pp: 676-684 www.ijaem.net ISSN: 2395-5252

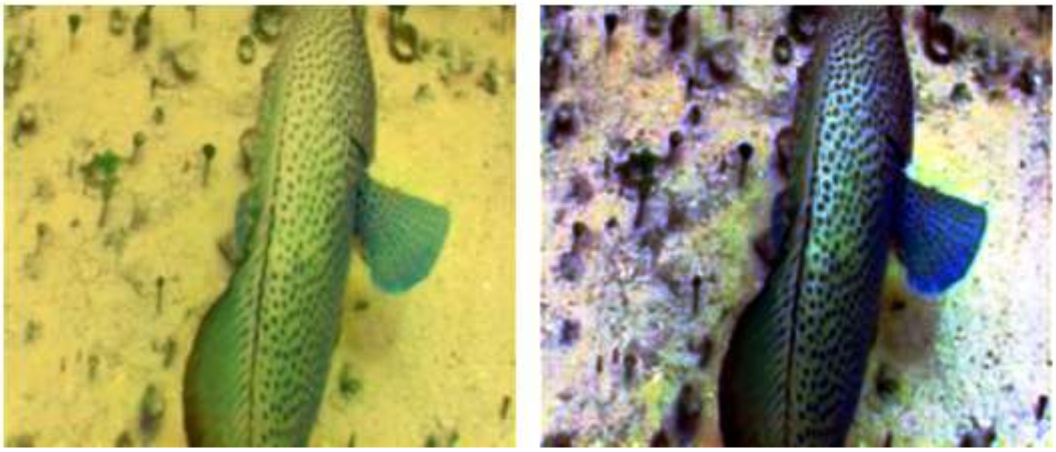
Table1- The table defines the neural network parameters used for training the model.

Optimizer	ADAM
Loss Function	MSE
Epochs	50
Batch Size	1

Table 2- Comparison of evaluated base and proposed neural network results.

Results	RMSE	SSIM	PSNR	UCIQE	UIQM
Base	27.45	0.75	----	0.63	----
Propose	5.8	0.87	33.5	0.33	0.54

After training and testing the model with the parameters shown in table 1, the results of our proposed model were exceptional after the NN training. The proposed model has a higher SSIM of 0.87 and a lower RMSE of 5.8 than the base model. The model's PSNR, UCIQE, and UIQM are 33.5, 0.33, and 0.54, respectively. Table 2 compares the results of the base and proposed models. For visual comparisons, the degraded and enhanced images were shown as the resultant sample enhanced images in figures 13, 14, and 15.



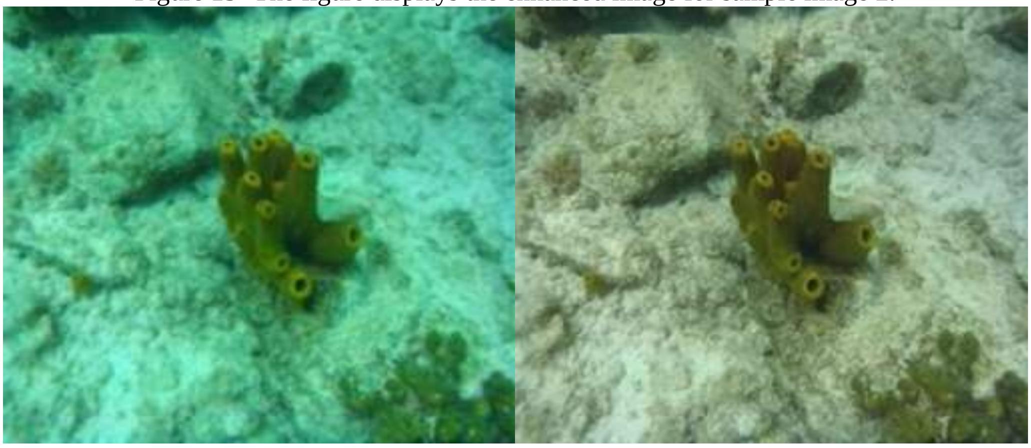
(a) Degraded Image (b) Enhanced Image

Figure-12- The figure displays the enhanced image for sample image 1.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 5 May 2023, pp: 676-684 www.ijaem.net ISSN: 2395-5252

(a) Degraded Image (b) Enhanced Image

Figure 13- The figure displays the enhanced image for sample image 2.



(a) Degraded Image (b) Enhanced Image

Figure 14- The figure displays the enhanced image for sample image 3.

Table 4.1 demonstrates that our suggested DL-based UIE approach outperforms the other approaches. The dataset for training and validation has been segregated. The sample images give visually enhanced results. The proposed neural network framework successfully improves the contrast of the image. As the value of PSNR increases, the overall performance of the proposed approach reveals an improvement in image details. This demonstrates that channelling can be used to repair underwater photos that have been damaged, and the image contrast could be adequately improved.

V. CONCLUSION

In terms of image processing and perception, underwater IE has attracted a lot of interest. Underwater picture enhancement is tough due to the demanding underwater habitat and lighting conditions. Improving pictures is a computer image processing technique that alters visual photographs. Image modification includes things like changing the contrast and color, sharpening or vibrating the image, and so on. We present an UIE approach using DL terminology. The system is based on enhancing procedures that necessitate several inputs that are difficult to foresee at the time of involvement. Following the system's training, a Neural Network-based UIE technique was utilized to correctly enhance photos using only a still raw image as input. The results show that the algorithm can learn to generalize and improve photographs from one region before applying them to another. However, in this situation, the results outperformed other cutting-edge UIE systems.DL-based methods, in most circumstances, lag behind state-of-the-art traditional methods. More crucially, practically all models train networks using synthetic data. The generalization of models is limited by the synthetic training data. As a result, DL-based underwater picture augmentation is still in its early stages, with unreliable and visually undesirable results.

Incorporating UIqualities into evaluation measures is one method.

REFERENCES

[1]. A. Naik, A. Swarnakar, and K. Mittal, “Shallow-UWnet : Compressed Model for Underwater Image Enhancement,” 2021, [Online]. Available: http://arxiv.org/abs/2101.02073.

[2]. M. Moiz Ashrafi, A. Verma, and A. Badholia, “A Review on Underwater Image Enhancement,” Int. J. Sci. Res. Sci. Eng. Technol., pp. 27–34, 2020, doi: 10.32628/ijsrset207313.

[3]. S. Corchs and R. Schettini, “Underwater image processing: State of the art of restoration and image enhancement methods,” EURASIP J. Adv. Signal Process., vol. 2010, no. December, 2010, doi: 10.1155/2010/746052.

[4]. T. Ancuti, C., Ancuti, C. O., Haber, “Enhancing underwater images and video by fusion.,” IEEE Int. Conf. Comput. Vis. Pattern Recognit., 2012.

[5]. S. Anwar and C. Li, “Diving deeper into underwater image enhancement: A survey,” Signal Process. Image Commun., vol. 89, 2020, doi: 10.1016/j.image.2020.115978.

[6]. Y. Han, L. Huang, Z. Hong, S. Cao, Y. Zhang, and J. Wang, “Deep supervised residual dense network for underwater image enhancement,” Sensors, vol. 21, no. 9, 2021, doi: 10.3390/s21093289.

[7]. S. Corchs and R. Schettini, “Underwater image processing: State of the art of restoration and image enhancement methods,” EURASIP J. Adv. Signal Process., vol. 2010, 2010, doi: 10.1155/2010/746052.

[8]. W. Shamsudin, N., Ahmad, “Significance Level of Image Enhancement Techniques for Underwater Images.,” Int. Conf. Comput. Inf. Sci. (ICCIS), 2012.

[9]. P. Uplavikar, Z. Wu, and Z. Wang, “All-In-One Underwater Image Enhancement using Domain-Adversarial Learning,” 2019, [Online]. Available: http://arxiv.org/abs/1905.13342.

[10]. Y. Guo, H. Li, and P. Zhuang, “Underwater Image Enhancement Using a Multiscale,” vol. 45, no. 3, pp. 862–870, 2020.

[11]. F. Li, D. Lu, C. L. Lu, and Q. Jiang, “Underwater Imaging Formation Model-Embedded Multiscale Deep Neural Network for Underwater Image Enhancement,” Math. Probl. Eng., vol. 2022, 2022, doi: 10.1155/2022/8330985.

[12]. A. Sivaanpu, R. Priyadarshani, T. Kokul, and A. Ramanan, “Underwater Image Enhancement Using Dual Convolutional Neural Network with Skip Connections,” ICARC 2022 - 2nd Int. Conf. Adv. Res. Comput. Towar. a Digit. Empower. Soc., no. April, pp. 224–229, 2022, doi: 10.1109/ICARC54489.2022.9753886.

[13]. T. Kang, “Using Neural Networks for Image Classification,” 2015.

[14]. D. Li, L. Deng, and Z. Cai, “Research on image classification method based on convolutional neural network,” Neural Comput. Appl., vol. 7, 2020, doi: 10.1007/s00521-020-04930-7.

[15]. Jerry wei, “AlexNet: The Architecture that Challenged CNNs,” towards data science, 2019. .