A Hybrid Approach for Underwater Image Enhancement using CNN and GAN

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***Abstract*—Underwater image-capturing technology has advanced over the years, and varieties of artificial intelligence-based applications have been developed on digital and synthetic images. The low-quality and low-resolution underwater images are challenging factors for use in existing image processing in computer vision applications. Degraded or low-quality photos are common issues in the underwater imaging process due to natural factors like low illumination and scattering. The recent techniques use deep learning architectures like CNN, GAN, or other models for image enhancement. Although adversarial-based architectures provide good perceptual quality, they performed worse in quantitative tests compared with convolutional-based networks. A hybrid technique is proposed in this paper that blends both designs to gain advantages of the CNN and GAN architectures. The generator component produces or makes images, which contributes to the creation of a sizable training set. The EUVP dataset is used for experimentation for model training and testing. The PSNR score was observed to measure the visual quality of the resultant images produced by models. The proposed system was able to provide an improved image with a higher PSNR score and SSIM score with state-of-the-art methods.**

Keywords—Convolutional neural network (CNN); generative adversarial networks (GAN); enhancing underwater visual perception (EUVP); underwater images; image enhancement; computer vision; artificial intelligence

I. INTRODUCTION

Underwater imaging involves capturing images of objects and creatures that can only be seen underwater using specialized tools and procedures. For research projects, studies of various aquatic animals, and other undersea items, the ocean floor is always a fascinating subject. Fish and marine mammals are popular subjects for photographers, but they also look for coral reefs, underwater cave networks, underwater landscapes, crustaceans, seaweeds, and so on. When researchers need to look at objects on the seabed over time, underwater photography is highly helpful. Numerous aquatic animals can be found below the surface of the water and are harmed by the disposal of plastics and other garbage. Ocean exploration [1] and mapping will help to close knowledge gaps in areas such as tectonics, maritime hazards, etc. Enhancing scientific understanding of the deep sea will aid in managing and utilizing ocean resources sustainably.

When light travels through water, it degrades the image in ways that are not seen in typical airborne photos. Normal images are frequently of high quality; therefore image enhancement is rarely necessary. However, the quality is quite poor for underwater photos because of the way light scatters in the water, which makes image processing challenging. The quality of images recently received more attention due to it being a crucial component of image processing. Image enhancement [2] is the process of enhancing the image quality while preserving all the information thereby producing results that are better suited for display or to prepare images for additional analysis in a variety of computer vision applications, such as object detection, image classification, scene understanding, and many other things. Underexposure, overexposure, low contrast, backlit images, improper colour balance, and out-of-focus subjects are some of the challenges [3] faced by underwater images. Other challenges in underwater imaging can be categorized as the need for adequate resolution and appropriate illumination conditions in order to provide high-quality images. The clarity of underwater images is crucial for many scientific and engineering uses in the ocean, including marine biology research and ocean rescue as well. Light of different wavelengths is absorbed in an underwater environment [4] at different rates, producing distinct colour casts. Light scattering [4] also reduces contrast and softens visual details. A lot of features hidden under the water can be shown by boosting an image's resolution, which can then be used by underwater researchers to enhance marine technology without endangering aquatic life. Therefore, techniques for underwater picture rectification are needed for both computer applications and scientific research. Both optical and acoustic technologies are employed to gather underwater data.

Contrarily, image processing offers a practical means of obtaining high-quality low-cost photos and videos. In the last ten years, the improvement and restoration of images from deep learning continued to attract attention. For a range of technical and scientific tasks, clear underwater photographs and recordings can offer vital information about the undersea habitat. However, the impacts of quality depletion, particularly the effects of bouncing back at vast distances, usually severely harm raw underwater photos and films [5]. The main causes of emerging problems are water's selective absorption and dispersion of light, in addition to the usage of synthetic illumination in deep water. The poor contrast and brightness, colour variations, hazy features, and uneven bright spot of the damaged underwater photos limit their practical applicability.

More focus has been placed on underwater image enhancement techniques as a crucial processing step. Due to the challenges in taking underwater images, their high cost, and the low quality problems brought on by low illumination and light scattering under the water, a robust image improvement model would be extremely helpful in underwater research. These enhanced images can be applied to further tasks like segmentation, object detection, and others. Image Enhancement methods span the spectrum from the conventional, such as histogram equalization [6] and physical model-based methods [7], to the data-driven, such as convolutional neural networks [8] and generative adversarial networks [9].

Over the past few decades, deep learning techniques [10,11] have developed quickly and are now often utilized in a wide range of computer vision and image processing tasks. A way to utilize generative networks is image enhancement or super-resolution. Likewise CNNs outperforms traditional image enhancement because they search for patterns in the data that is provided. Convolutional layers are used to stack them and create intangible concepts. Comparing the state-of-the-art techniques, it is evident that adversarial networks place a greater emphasis on enhancing the visual quality of the photos. Convolutional networks, however, provide accurate quantitative results.

This study examines the shortcomings of current image enhancement techniques and suggests a hybrid solution for improving underwater images. The most recent image enhancement methods are examined in order to raise the photos' perceptual and quantitative quality. In order to obtain the favorable aspects of both models, two state-of-the-art methods are combined. To improve the poor-quality images, the proposed model is developed utilizing deep convolutional neural networks [12] and generative adversarial networks [13]. The underlying problem consists of increasing perceptual quality [14] and better performance in quantitative tests as well.

The concept of underwater imaging, its importance, challenges, and the premise of this paper are briefly discussed in Section I. The significant background information from related works is briefly introduced in Section II. The main portion of this study is introduced in Section III. The algorithm suggested in this paper was tested and describes the results of those tests and conducts an unbiased analysis of the algorithm's performance in Section IV. A summary and analysis of this paper's findings are provided in Section V.

II. Related Works

Multiple techniques exist for improving and saving underwater photographs. Various techniques make use of physical models, while others don't. The Jaffe-McGlamery model [15] provides a precise physical representation for underwater imaging. Between the underwater photographs and the recovered images in a physical model, the model forges a link. By calculating the light's penetration and determining the ambient light of the surrounding underwater environment, one can produce reconstructed underwater images. Herng-Hua Chang [16] suggested a resilient single underwater image restoration system for enhancing graphic quality. Sheezan [17] described a restoration method for underwater pictures that prioritizes aesthetic quality. A red-channel method was suggested by Galdran [18] to correct underneath images. Preprocessing underwater monocular vision with an improved DCP technique was presented by Tang et al. [19].

The traditional model-free technique focuses on changing the pixels of underwater photos, offering a more direct way to improve underwater photography than physical model-based improvement and rebuilding. Examples of techniques include white balance, gamma correction, histogram equalization, wavelet modification, and the Retinex algorithm. In order to produce thorough, high-quality photographs, experts typically utilize multiple techniques because underwater photography can degrade in a variety of ways. Examples include the blending of histogram equalization and wavelet transformation, the blending of wavelet transformation, white balance, and histogram equalization, and the blending of histogram equalization, white balance, and gamma correction.

New techniques for image processing have emerged as a result of the development of artificial intelligence (AI) over the preceding ten years. Neural networks (NN) and support vector machines (SVM) are good examples. Deep learning is used to improve photographs, notably image dehazing [20], as discussed by Jisnu, K & Meena, Gaurav. A network of deep neural networks was implemented by Li et al. [21] to de-scatter the underwater image. The use of a deep convolutional neural network (CNN) has been recommended by Perez et al. [22] to dehaze underwater shots. Deep CNN was implemented by Wang et al. [23] to color-correct and eliminate haze from underwater photographs. Cao et al. [24] exhibited clear latent deep CNN underwater reconstruction images.

Ground truth for underwater images can be challenging, so the typical deep learning framework can only be used to train models using ground truth from unique underwater images. The use of GAN by Fabbri et al. [25] improved the aesthetic appeal of aquatic scenes. Using an unsupervised GAN, Li et al. [26] described real-time underwater photo colour correction. A generative adversarial model with cycle consistency was employed by Li et al. The output of underwater photography will be fed into a neural network to build CNN models. The use of GAN to enhance the visual appeal of underwater photos was introduced by the author [25].

In order to increase underwater image quality from the perspectives of colour balance and dehazing, CNN is employed in the study. Despite the fact that it has been shown that GAN is mostly successful in reducing colour variance in underwater photographs. The clarity of underwater photographs can be increased by using a complete eliminating hazing model, which reduces the cumulative mistakes that arise from measuring background illumination and light transmission individually when a standard recovery model is applied. The employment of CNN in the single device eliminating hazing model, GAN colour adjusting, the improvement of ground truth, and the use of the blending technique for improving contrast are a few of the highlights.

The recommended picture improvement technique is tested on a large number of underwater photos from EUVP dataset [27], and some of the results are presented.

III. Proposed Method

When compared to GAN-based models, CNN models are more concerned with improving numerical parameters while GAN-based models are more interested in the perceived quality of the improved images. Although the deep learning-based method for underwater image enhancement has made good progress, there is still much potential for development, particularly in the method's qualitative and quantitative capabilities. In order to address those issues, the paper suggests a hybrid strategy; thereby, performed an experiment combining GAN and CNN as a hybrid technique to get an enhanced image with better quantitative value and perceptual quality. We attempted the hybrid approach in two different ways. Initially, CNN and GAN were two parallel systems combined with concatenation. But because the two models must be trained independently, there was a large time commitment. The two models were afterward tested in a pipeline. The basic flow diagram of the system is discussed in the below section and briefly explains how the system works from the normal CNN and GAN to a hybrid architecture in which the input images are passed through both to get an enhanced image. This project will make use of the EUVP dataset [27], which will provide a detailed look.

A. Architecture of the Proposed System

Fig. 1 shows the hybrid system requires both CNN and GAN connected in a pipeline. The input image is passed through the pipeline architecture, thereby obtaining an enhanced image. The restored images are created with the help of the animation class of matplotlib. In the GAN architecture, both the generator and the discriminator work together. The generator tries to produce better images after each epoch of the training and the discriminator acts like a binary classifier to detect real or fake images. In the CNN architecture, the input images pass through the layers and obtain the features of the input image. And these outputs of both GAN and CNN combined to get the resultant enhanced image. The loss function is attempted to be minimized by the generator and maximized by the discriminator as in a min-max game.

B. Dataset

1) EUVP dataset: The EUVP (Enhancing Underwater Visual Perception) dataset[27] offers multiple sets of paired and unpaired image examples of low and acceptable visual clarity in order to facilitate the supervised training of underwater picture enhancement algorithms. Table I shows the paired image details from the dataset[27] and Fig. 2 gives few examples of the paired images. In Table II, the details of the unpaired images are depicted and Fig. 3 shows some sample images from the unpaired set of the dataset[27].

TABLE I. Paired Image Details Dataset from EUVP Dataset[27]

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

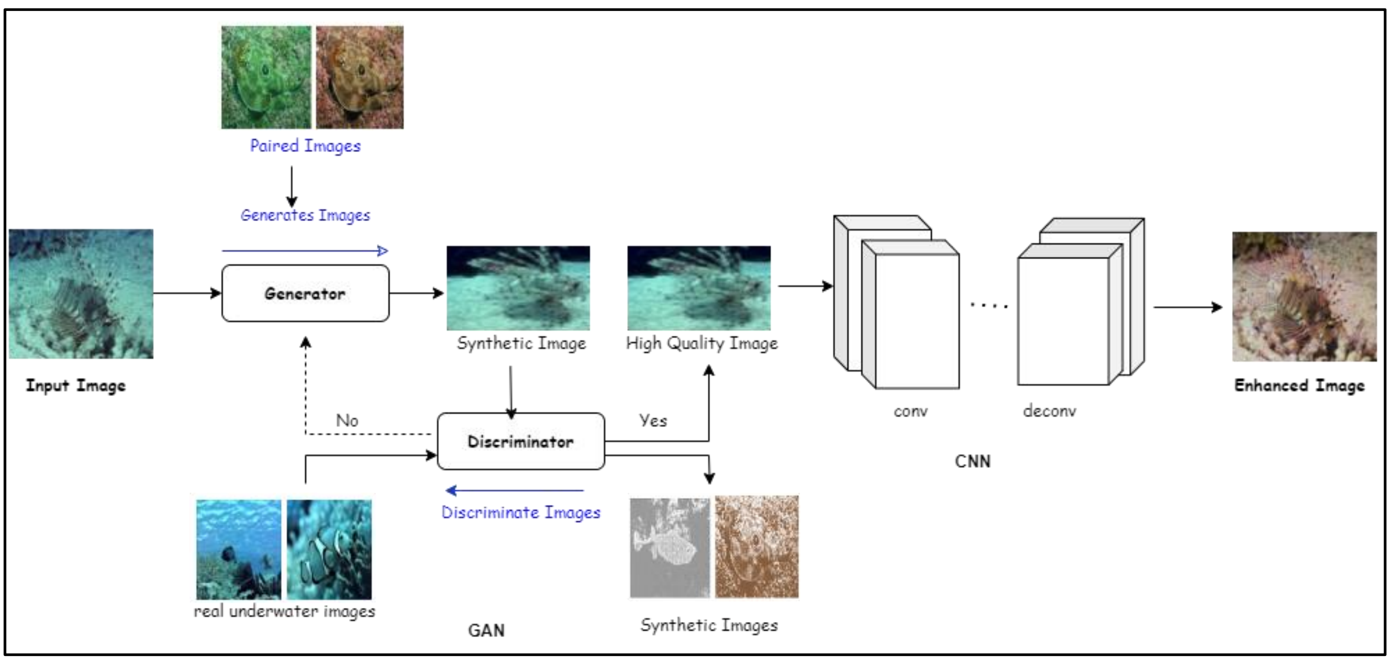

Fig. 1. Implementation flow using the suggested system, from raw input image to improved image

Fig. 2. Samples of the paired images from the EUVP dataset[27].

TABLE II. UNPAIRED IMAGE DETAILS DATASET FROM EUVP DATASET [27]

Poor Quality	**Good Quality**	**Validation**	**Total Images**
3195	3140	330	6665

Fig. 3. Samples of the unpaired images from the EUVP dataset [27].

C. Platform and Specifications

The studies were carried out using a Google Colab Pro cloud-based subscription. 24GB CPU RAM and 16GB VRAM of the Tesla V100 GPU were used. We also ran some local tests on NVIDIA RTX 3060 GPUs with 6GB VRAM and 16GB CPU RAM. The complete application was written in the Python 3.7 programming language using the Pytorch module. To validate the project and see how it is advancing the state-of-the-art models used numerous experiments that were carried out.

IV. RESULTS AND INFERENCE

Section IV explains many experiments carried out while the application was being developed and how measurements are utilized which are compared using results from other models. In this chapter, various screenshots of the findings are shown. Finally, all comparisons are shown in tabular style with the results of the baseline model.

A. Metrics For Evaluation

1) Peak signal-to-noise ratio (PSNR): The peak signal-to-noise ratio (PSNR) is used to interpret the image[28]. The signal-to-noise ratio is a term used in engineering to convey the association between a signal's maximum power and the power of corrupting noise that reduces the accuracy of its representation. Due to the fact that many signals have a broad dynamic range, PSNR is frequently expressed as a logarithmic value employing the decibel scale. PSNR is widely used to gauge the quality of reconstruction for lossy-compressed images and movies.

$$PSNR = 20\log_{10}(MAX/(MSE)^{½}) \quad (1)$$

where MAX is the highest pixel value that the image can contain and MSE is Mean Squared Error.

2) Structural Similarity Index (SSIM): The Structural Similarity Index (SSIM)[28], a perceptual metric, quantifies the extent to which imagery is lost due to problems with data transmission or other processing steps like data encoding. The Structural SIMilarity (SSIM) index is a tool for calculating how similar two images are. On the assumption that the other image is thought to be of ideal quality, the SSIM index can be used to assess the quality of one of the images being compared.

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

where, μ_x is the pixel sample mean of x , μ_y is the pixel sample mean of y, σ_x^2 is the variance of x, σ_y^2 is the variance of y, σ_{xy} is the covariance of x and y, $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$ are two variables to stabilize the division with weak denominator and L is the dynamic range of the pixel values, $k_1 = 0.1$ and $k_2 = 0.3$ by default.

3) Loss function: The first description of the typical GAN loss function [29], often known as the min-max loss, was made in a 2014 article titled "Generative Adversarial Networks" by Ian Goodfellow et al. The resulting value is enhanced by the discriminator, while it is diminished by the generator. This explanation of the defeat seemed to work well when viewed as a min-max game. In reality, it saturates the generator, which means that if it falls behind the discriminator during training, it commonly stops.

$$E_x[\log(D(x))] + E_z[\log(1-D(G(z)))] \quad (3)$$

Discriminator loss and Generator loss are two additional categories that can be tailored to the Standard GAN loss function.

Generator Loss:

$$\nabla\theta_g(1/m)\Sigma_{i=1}^{m} \log(1-D(G(z^{(i)}))) \quad (4)$$

Discriminator Loss:

$$\nabla\theta_d(1/m)\Sigma_{i=1}^{m} [\log D(x^{(i)}) + \log(1-D(G(z^{(i)})))] \quad (5)$$

In this function:

D(x) is the discriminator's estimate of the probability that real data instance x is real, E_x is the expected value over all real data instances, G(z) is the generator's output when given noise z, D(G(z)) is the discriminator's estimate of the probability that a fake instance is real, E_z is the expected value over all random inputs to the generator (in effect, the expected value over all generated fake instances G(z)).

B. Experiments and Results

The Underwater_dark set from the EUVP dataset, which contains 5550 pairs of photos for training as two sets, is used to train the suggested model. One group includes low-resolution (or grey) photographs, while the other has upgraded (or coloured) images. For every pair, both sets share the same filenames. Another 570 images were used for validation. As a total, we have used 11,670 images from the dataset [27] for the experimentation and implementation. The degraded photos that were utilized for training are shown in Fig. 4. And Fig. 5 explains the generator and discriminator loss obtained while training. It is evident from Table III that the suggested hybrid technique performs better than the current models. The results demonstrate that, in comparison to our hybrid approach, the current models do not provide good quantitative results. The suggested approach produced better quantitative results with increased visual quality, as seen in Fig. 6 and Fig. 7. The outcomes of our hybrid technique are displayed in Fig. 6 by comparison with the input test image and the ground truth. The findings of the suggested approach are also compared to those of the current methods in Fig. 7 where our hybrid method makes a distinct quality difference.

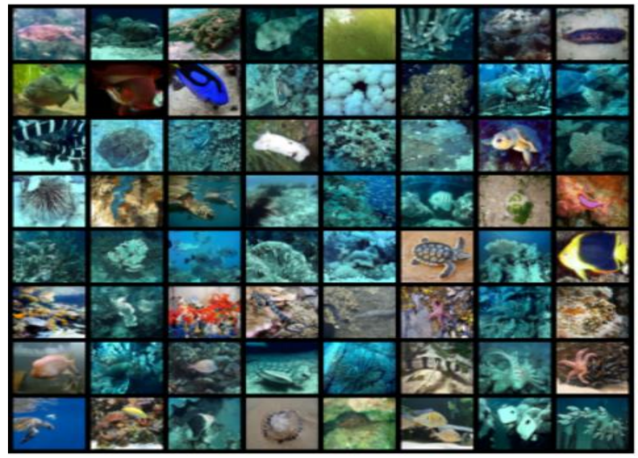

Fig. 4. Different training images from the EUVP dataset.

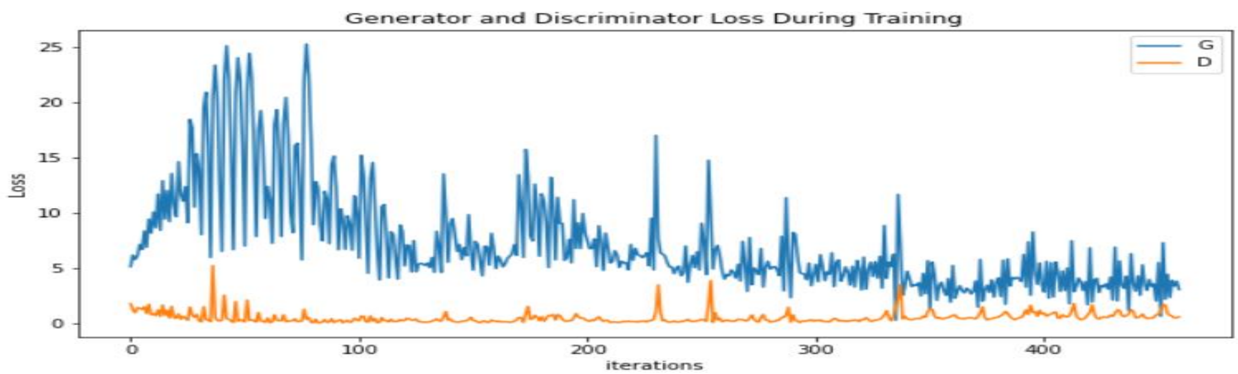

Fig. 5. The graph for generator and discriminator loss during training.

TABLE III. PSNR AND SSIM SCORES OF FIVE DIFFERENT IMAGES

Input Image	CNN		GAN		Hybrid Method	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
(a)	**14.46**	0.4575	16.89	0.3635	18.96	0.4365
(b)	14.27	0.4532	17.36	0.4152	18.59	0.4712
(c)	12.78	**0.5012**	**18.64**	**0.7958**	19.44	0.8862
(d)	11.52	0.3589	15.48	0.5433	20.36	0.8578
(e)	11.33	0.2985	16.52	0.4056	**20.67**	**0.9558**

Fig. 6. The results obtained from the hybrid architecture (from left: test image, ground truth, and prediction on test image).

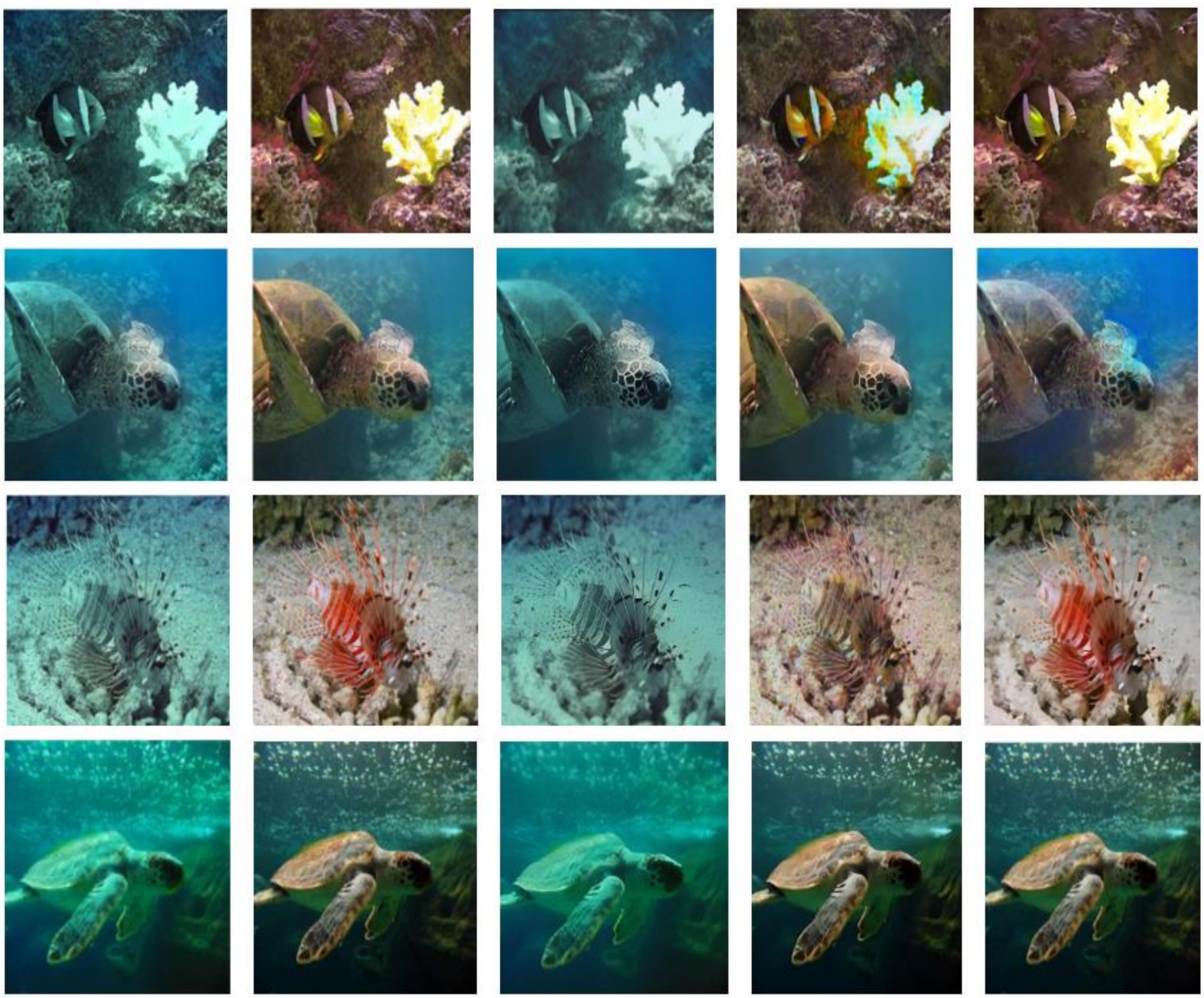

Fig. 7. The results obtained from the different models (from left: test image, ground truth, CNN result, GAN result, and hybrid model result).

V. Conclusion and Future Scope

Due to the visual characteristics of light in water, an image acquired underwater degrades. However, traditional forms are insufficient for accurate reconstruction due to the deterioration of the observed image. We suggested a hybrid method for enhancing underwater descriptions in this research. The hybrid technique is with CNN and GAN, which produces better results. According to experimental data, the suggested technique outperforms the standard procedures when combined in visual and quantitative evaluation. The proposed model can improve the detailed information of the image by enhancing it, according to comparisons made between it and enhancement algorithms recently proposed. Although this method is best suited for enhancing images with fluctuating lighting levels, it has significant limitations when it comes to effectively restoring the details of extended exposure areas. However, augmentation restricts the local dark region when the lighting is too unbalanced, calling for further research. Another issue with the current system is we need to train a lot of data. This could take up a lot of time and space and be very complex in training. We performed various experiments and recorded the results for the proposed architecture.

As a future enhancement, the upgraded images can be taken as the input and can perform image segmentation and object detection as well to create an awareness about the pollution under the water and thereby help the aquatic lives to get a better life.

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