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Optimizing Underwater Vision: A Rigorous Investigation into Cnn's Deep Image Enhancement for Subaquatic Scenes

Abstract: - In this paper, Convolutional Neural Networks were used to enhance the visual fidelity of underwater images. The UWCNN is introduced in this article, which utilizes underwater scene priors and a CNN model to improve underwater photos. The UWCNN model proposes a method where the clear latent underwater image is immediately rebuilt using the underwater scene as training data, rather than relying on parameter guessing in an underwater imaging model. Our UWCNN model may be used for frame-by-frame augmentation in underwater videos because to its lightweight network structure and efficient training data. In this dataset for underwater image deterioration by integrating an underwater photography physical model with optical characteristics of underwater landscapes are provided which includes a wide range of water types and degradation levels. Alternatively, one might choose to go light. A Neural Network (CNN) model is constructed using the related training data in order to enhance the quality of underwater scenes. Ultimately, the UWCNN model is used to improve the quality of underwater videos. The efficacy of our technology is shown via the analysis of both authentic and synthetic underwater photos.

Keywords: CNN, Photo enrichment, color balance, Image Processing

Introduction

The use of autonomous and remotely piloted underwater vehicles is vital for underwater scene perception and interpretation. It is usual to utilize these vehicles to explore and engage with marine habitats. Because of this, it is more difficult to accomplish tasks such as pattern recognition, object detection, and feature extraction from raw underwater photos and videos. The fact that most deep networks are trained using high-quality photographs or presume clear images as inputs is the reason. Dissolved organic compounds (DOCs), micro phytoplankton, and non-algal particles all degrade underwater photography because they absorb and scatter light. When it comes to underwater robot inspection and marine environmental monitoring, problems with absorption and dispersion make it difficult to understand and recognize images. When applied to underwater photos, standard image enhancement techniques [1][2] [15][16][8] have drawbacks as well. Due to insufficient training data, it is difficult to effectively improve underwater images and videos using deep learning. Classification, analysis, segmentation, and other current deep learning-based techniques are far more effective. In order to boost underwater vision quality and performance on high-level vision tasks, image synthesis and enhancement technologies must be developed. These absorption and dispersion issues impede underwater robot inspections and marine environmental surveillance. When photography underwater, traditional picture enhancing technologies have limits.

Contributions: solution from start to finish, using a unique CNN architecture trained on underwater scenes previously, for the generation of underwater pictures. This technology precisely recreates the original colours and look of underwater photographs. Because of the network's lightweight construction, the suggested approach may readily be expanded to video taken underwater. As a result, we are now offering an underwater photosynthesis technology that can mimic a wide spectrum of degraded underwater pictures. An underwater visual synthesis system capable of behaving many different situations has been developed to our knowledge. It is possible to utilize our picture synthesis to train networks and assess the quality of full- reference image synthesis. Reconstructing the clear latent underwater picture is possible thanks to an improved CNN model that minimizes multi-term losses.

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Because of its light-weight network architecture and successful training data, the suggested model may be used to underwater video for frame-by- frame augmentation. Both synthetic and genuine underwater photographs and videos can benefit from our technique's vast variety of color and visibility options. It is possible to get outstanding results using a lightweight network structure that incorporates prior information important to pattern recognition, visual interpretation, and so on.

I. Related Work

This section largely introduces the generally used physical models for underwater image enhancement, which include the air scattering model, simplified underwater image production model, and an updated model. Deep network training data synthesis and design may be constructed on top of these models, providing insight into how underwater photos deteriorate. There are several types of underwater picture enhancement and restoration procedures that may be classified according to their perspectives. This work identified and assessed three types of approaches for underwater picture enhancement, restoration, and supplemental information. Because there has been limited research on underwater video improvement and restoration, we will focus on image processing approaches in this part.

a). *Underwater Image Enhancement Method:* Li et al. [1] focused on image dehazing and colour correction as a stage of underwater image enhancement. To combine a colour-corrected and contrast-improved underwater image, Ancuti et al. [1] utilized an input. Four weights are used in the multi-scale fusion procedure to determine which pixel has the best chance of showing up in the final image. Multi-scale fusion using an image colour before to correct colour casts in the underwater image and a modified image dehazing algorithm to improve visibility, [2] describes a hybrid solution. It was proposed by Li et al. that a cross-domain mapping functions between underwater and air images can be used to correct underwater image colour. Using multiscale, dense concatenation, and residual learning techniques. inspired by generative adversarial networks, Guo et al. proposed a multiscale dense GAN for underwater image enhancement (GANs). Prior to this, Ancuti et al. [5] made significant progress by limiting the effects of over enhancement and overexposure. Li et al. [3] recently proposed a deep baseline model based on paired underwater photos and related reference images. The enhanced results yield a plethora of options for selecting these reference photos. restoration is also an option.

b). *Underwater Image Restoration Method:* An inverse approach to the problem is frequently used by underwater image restoration algorithms, which first build physical models of the degradation before making model parameter estimates. With the help of a wavelength-dependent compensation strategy, the underwater images of Chiang and Chen [1] can be dehazed and artificial light influences removed. Colours associated with short wavelengths, such as red and orange, were retrieved using a Red Channel technique [10]. An improvement on the previous dark channel prior [16] was introduced by Drews et al. [18] with the UDCP underwater dark-channel prior. When white or artificial light is present in underwater scenes, the UDCP may be able to estimate medium transmission in some cases. To improve underwater images, Li et al. [19] combined a contrast-enhancing technique with a dehazing technique. With this technique, Peng and his colleagues corrected underwater photos using a combination of blurry images and light absorption. According to Li et al. [19], an underwater picture colour restoration model based on CNNs could be developed using poorly supervised learning from synthetic underwater photos.

c). *Deep Underwater Image Enhancement Algorithms:* Using the underwater image creation model, the attenuation coefficients of various water types are used to synthesize ten types of underwater image datasets. A wide range of ocean and coastal water conditions are depicted in these underwater photo collections, from clear to murky. Finally, ten UWCNN models were trained for each of the ten types of underwater photos. The '2 and SSIM loss functions are combined to learn the UWCNN model's parameters. The UWCNN makes extensive use of the Tensor Flow framework's kernel sizes and ADAM . [1] 's underwater image formulation paradigm is used here. Models like this one are commonly used in underwater image restoration techniques.

$$U(x) = I(x) \times T(x) + B1 \times T(x) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(a)}$$

Where, U(x) is obtained underwater image , A point in the underwater scene known as 'x' is where we want to find the clear latent image, or scene radiance, I(x) (images are denoted in strong capital letters for clarity). The wavelength of the red, green, and blue channels of light is B, as is the homogeneous global background light, as is the wavelength of the red, green, and blue channels of light. As a rule of thumb, an underwater image's colour cast and contrast reduction are caused by T(x), the scene's relative radiance as seen by the camera after it has bounced off of the water's surface at point x. It's possible to think of T(x) as an expression of light's wavelength divided by the scene point x's distance (d(x)) from the camera.

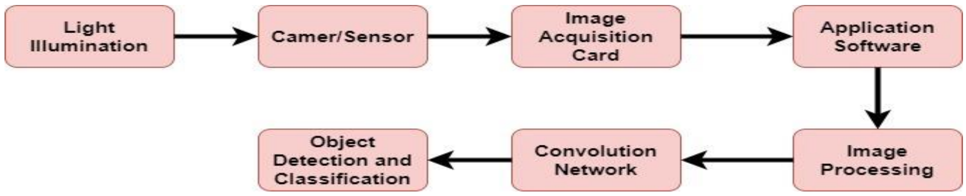


Fig. 1: Basic CNN Architecture [1]

As illustrated in Fig. 1, wavelength-dependent attenuation coefficients of different media. It is possible to assume that before and after it travels through the transmission medium, a light beam's energy is equal to the sum of its pre- and post-transmission values, E(x, 0, d(x) (x). This ratio, N, is the normalized residual energy ratio for each unit of propagated distance. Water's value fluctuates depending on the wavelength of light it emits. Because of the lower refractive index and more absorption of light in open water, photos shot underwater tend to show red light as blue goes into much into on this. For example, dehazing and picture deblurring have been utilized, as well as super resolution for image deterioration. In a way, the underwater image degradation model is similar to the picture dehazing model, but it's more sophisticated since light's wavelength-dependent absorption and scattering qualities complicate the calculations even more. To replicate a blurred image, one may use convolutional operations inside an image deblurring model to get a low-resolution representation. Alternatively, down sampling can be employed to generate a low-resolution image.

II. PROPOSED METHOD

Convolutional neural networks (CNNs), also known as deep learning neural networks, are a subclass of CNN. For the sake of simplicity, consider CNN as a machine learning algorithm that can take an input image and determine the importance of various aspects and objects in the image (using learnable weights and biases), and then distinguish between them. The images are used to extract features by CNN. The following elements make up any CNN: The grayscale image that serves as the input layer. Second, the Output layer, which can be either a binary or multi-class label Neural Networks have three hidden layers: convolution, ReLU (rectified linear unit), and the pooling layers. Understanding that ANN, or Artificial Neural Networks, cannot extract image features due to their multi-neuron construction is critical. This is where a convolution and pooling layer combination comes into play. We also need a fully connected neural network to perform classification because the convolution and pooling layers are unable to do so. There are a number of advantages to the Convolutional independent network, such as multidimensional data input and fewer parameters. Overfitting can occur because of parts of connections within a fully associated layer, even though this is the system's primary goal. The use of the denoising technique is anticipated to effectively decrease the amount of data, information, and the quantity of covered units. This will enable the framework to acquire an unparalleled elemental representation of the event data. As an example, input data degradation and shrouded unit layer yield pollution are both used in the reenactment, and a correlation is shown. CNN has been widely used to examine voice and image recognition. The multilayer neural system known as CNN was initially well-prepared. CNN uses weight sharing to reduce the model's randomness and the weights' overall volume.

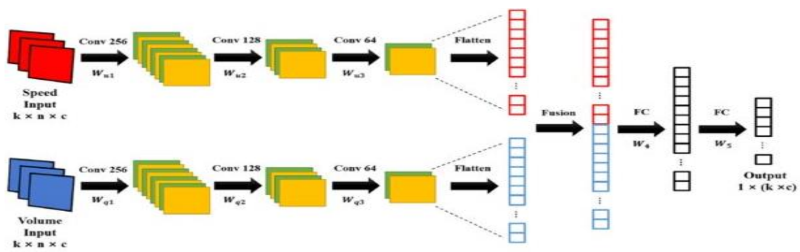


Fig. 2: CNN Network Model

Fig. 2 illustrates the Convolution neutral network model process. CNN has been used to enhance underwater images. The color-corrected picture and transmission map may be estimated using the mappings learned by the suggested networks from the input underwater images. Additional labels are unnecessary on target scenes.

Considerations: Unlike standard end to end strategies, which train the mapping function, here network is given priority to learn the difference between a synthetic underwater image and its class counterpart. In order to predict the latent image I which is given by following equation

$$I = f1(u)\text{................................}(b)$$

Convolution filters are applied to various layers of an underwater image before the final loss layer is reached. A vanishing gradient is possible even though the network is not intended to very deep. Prior to applying loss function on the networks output(U), learning the residuals are mandatory by combining the network inputs with its output(U1)

$$I = U + U1 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.(c)$$

Where ‘I’ is the element wise addition operation.

Next step is to consider enhancing units (E-Unit) which are designed in modular format. The initial operation of the convolution and ReLU pair is considered as I^{th} block size is z1, 0=r, if r and c stands for ReLU and Convolution.

CNN Architecture:

The layers of a convolution neural network are always fully associated. A huge parameter set that is unusable for learning is created if an image has a high goal and has many hidden units running, for example. The local gathering document is used by CNN to claim that an image is convolution. There are a lot of convolution bits. This field estimate with an extraordinary load between yield maps has been agreed upon by all of the components of the convolution. Any number of convolutions can be applied to the entire image. As a result, the parameters are determined by the size of the local collection, and the convolution bit length is thus increased. There are many layers of concealment in a CNN. For the convolutional layer, and thus the sub-examination, shrouded layers are an excellent analogy. All of the image’s convolutional parts are used in the convolution layer. Images are re-created as a component map with an expanded component. Fig. 2 shows that the Convolutional Neural Network has some advantages, and that it can handle 2D images correctly, which is appropriate for advanced image processing, as shown. Discovering a better way to speed up the system’s learning process will be our side project. A Convolutional Neural Network consists of three main parts: The layer that pools resources. Layers that are completely interconnected. Layers of convolution. Image handling assignments include tasks such as enhancing images, they have a wide range of objectives Values of the components Corrupted photographs closely resemble their real-world counterparts, resulting in little changes in normal pixel values. This characteristic is unique. The first portion of this chapter examines the influence of varying degrees of model depth. The SSIM and Euclidean misfortunes are compared to determine their adequacy. In this study, a CNN model has been developed to assess the performance of low-light picture enhancement tasks. The model has shown advancements in super goals and image denoising techniques. The integration of the CNN pattern into our suggested CNN model, along with other conventional complexity upgrading procedures, may be achieved both inside deep learning-based approaches and in traditional contexts.

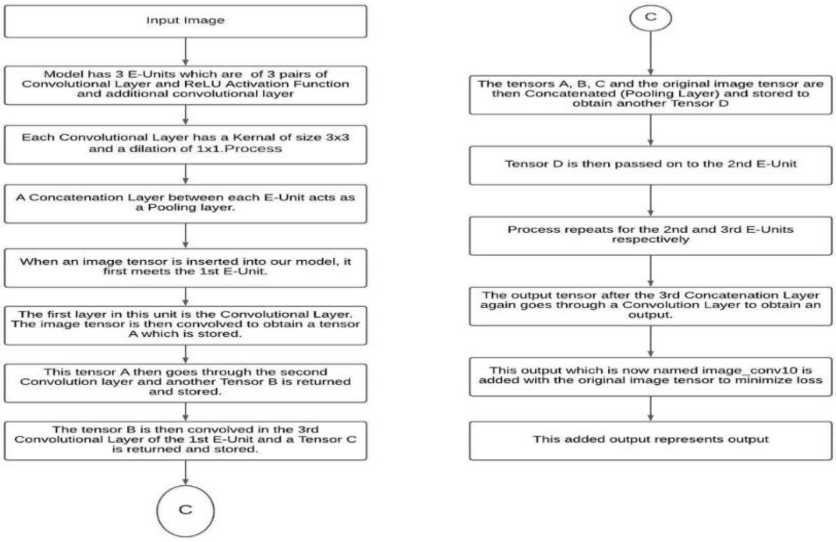


Figure 3: Proposed Methodology

In this section, we will elucidate the intricacies of the suggested Unified Word Count Neural Network (UWCNN) model, followed by a postprocessing phase aimed at enhancing the already remarkable outcomes that as shown in figure 3.

1. The model is composed of three E-Units, each consisting of three pairs of Convolutional Layer and ReLU Activation Function, along with an extra convolutional layer.
2. A Kernel with dimensions of 3x3 and a dilation of 1x1 is present in each Convolutional Layer.
3. The Concatenation Layer serves as a Pooling layer between each E-Unit.
4. In the process of incorporating an image tensor into our model, it first encounters the first E-Unit.
5. The Convolutional Layer is the first layer in this unit. The tensor of the picture is then convolved to provide a tensor A, which is subsequently stored.
6. The tensor A is then passed via the second Convolution layer, resulting in the return and storage of another tensor B.
7. In the 3rd Convolutional Layer of the 1st E-Unit, the tensor B undergoes convolution, resulting in the return and storage of a Tensor C.
8. In the Pooling Layer, the tensors A, B, C, and the original image tensor are concatenated and then stored to generate a new tensor D.
9. The Tensor D is then transferred to the second E-Unit.
10. The procedure is iterated for the second and third E-Units alike.
11. Following the 3rd Concatenation Layer, the output tensor is subjected to a Convolution Layer to provide an output.
12. To minimise loss, the original image tensor is combined with the output, which is now referred to as imageconv10.
13. The additional output corresponds to the output of a CNN.

III. Experimental Evaluation

A comparison of current underwater image enhancing systems is made in this section, using both synthetic and real-world images. There is also a comparative study of several methods on underwater films. A number of strategies have been examined and contrasted, including: UDCP, RED , ODM , and UIBLA . We run the authors' source code using the requested parameter to acquire the best results for an objective evaluation settings. When light-attenuation coefficients are not available in real-world photos, we apply each of the ten UWCNN models we learnt and provide the results that are more aesthetically attractive. We use ADAM to train our model, and the learning rate is set at 0.0002, 1 to 0.9, 2 to 0.999. Throughout the training process, we maintain a constant learning rate. The batch size has been set to sixteen. Over 20 epochs, optimizing a model takes about three hours. On an

Intel(R) i7-6700k CPU, 32GB RAM, and an Nvidia GTX 1080 Ti GPU, we use Tensor Flow as the deep learning framework.

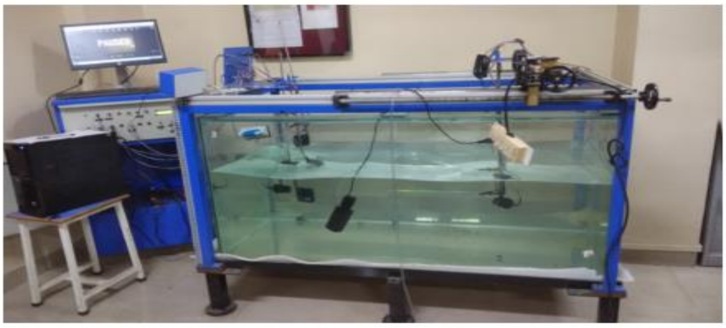


Fig. 4: Underwater Setup-RAIT

Firstly, we will provide the results of enhancing underwater photographs using synthetic underwater images obtained from our test dataset. Our methodology effectively reinstates a visually pleasing texture and vibrant, but authentic, hues. To put it simply, our results look like ground truth when compared to other methodologies. To ensure that the recovered photographs are accurate, a synthetic test set of 2495 images is employed for each kind. Table 2 shows three separate measures for testing accuracy: MSE, PSNR, and SSIM. PSNR (Potential Signal to Noise Ratio) measures how near a picture is to the actual world compared to its MSE (lower PSNR). Higher SSIM scores are indicative of a more realistic picture structure and are thus considered in the analysis. The hue and texture of our completed items closely resemble those seen in natural environments.

The results are summarized in the following table 1 & table 2 for different dataset. The bolded values indicate the best outcomes. It may be deduced that our technique demonstrates efficacy and durability, since it surpasses all other strategies examined in terms of metrics and types of deterioration. Our technique demonstrates superior SSIM responsiveness, surpassing the second-best methodology by a minimum of 10%. Similarly, our Peak Signal-to-Noise Ratio (PSNR) exhibits superior performance (as shown by the Mean Squared Error (MSE) scores) compared to the methodologies that have been compared too. Genuine submerged photos are explored from different picture taker assortment caught utilizing optical camera and arrangement shown in Fig. 4. Here few different submerged photos at various depth have been picked from standard database available online and we have also consider our own picture of scuba images. The framework created ready to acknowledge png and jpeg organizations of pictures. (Hp CORE i3, CPU @1.70 GHz, Windows 7-64 piece) gadget used to run the framework utilizing MATLAB R2015a.

1. Assessment of a real-life underwater image:

In this section, proposed strategy has been tested using real-world underwater images. Fig. 6 shows the contrasts between our strategy and those of our rivals. Tones, brightness, and contrast may be seen in the underwater photographs utilized in this research. According to [2, 4], the histogram equalization approach produces better outcomes than the judgements that are tilted toward overexposure or over enhancing. A user survey was conducted in order to collect real-world feedback and measure subjective visual quality, with the aim of obtaining a more impartial evaluation. Collection of images and papers from the Internet was used for this project. Fig. 5 demonstrates some of the findings from this dataset. All Figures depicts some of the associated consequences. On a computer screen, the findings of user research are presented in random order. There are 20 image processing experts in the room. A one -to-five scale is used by each participant to score the outcomes, with one being the worst and five representing the best. In Table 3 based on the average subjective evaluation. In terms of underwater photography, proposed UWCNN approach receives the best subjective visual scores, indicating that it has the potential to perform better.

2. Evaluation Metrics:

Underwater picture quality may be improved by the use of automatic assessment measures and assessments of the human visual system (HVS). SNR, PSNR, MSE, SSIM, and PCQI are four of the most often used metrics in picture improvement and restoration, and two of them are especially created for underwater image enhancement. Specifically, the UCIQE and UIQM, Lastly, we thoroughly examine all the evaluation metrics and analyze their respective merits and drawbacks. The human visual evaluation and its relevance are also described in a report that we offer. Signal measurements such as Mean Square Error (MSE) and PSNR are the starting points for our discussion. It is the goal of the MSE to offer a quantifiable measure of how closely the two signals are related. The initial signal is usually one of the signals.

3. Human Visual System

Human volunteers are utilized to assess the quality of the anticipated pictures in an attempt to add perceptual measurements because there is a shortage of genuine ground truth data. Depending on the competition, these human inputs may be crowd-sourced or provided by experts. However, no results have been obtained using any of these techniques. Prososed method’s findings to the most recent and most advanced approaches for increasing underwater image quality using synthetic and real-world photographs. In the absence of light-attenuation coefficients, UWCNN models are applied to real-world photos, and the more aesthetically pleasing results are given. Advancements includes, examining the possibility of choosing the optimal model using a classification process. A synthetic validation set consisting of 2495 samples of each kind was used to assess the accuracy of the recovered images.

4. *Parameters to be used to Quantify Accuracy of image*:

1. ***SNR:*** Signal-to-noise ratio (SNR) is used in imaging to characterize image quality. The sensitivity of a (digital or film) imaging system is typically described in the terms of the signal level that yields a threshold level of SNR.

$$SNR = 20\, log_{10}(\frac{Average(XY)}{standard(XY)}) \ldots\ldots\ldots\ldots\ldots (1)$$

2. ***PSNR***: The ratio between the maximum possible power to the power of corrupting noise is know as Peak Signal to Noise Ratio. It affects the fidelity of its representation. It can be also said that it is the logarithmic function of peak value of image and mean square error.

$$PSNR(X,Y) = 10\, log_{10}(\frac{255^2}{MSE(X,Y)}) \ldots\ldots\ldots\ldots\ldots (2)$$

3. ***MSE: Mean Square Error***

$$MSE(X,Y) = 1/N \sum_{i=1}^{N} (e_i^2) = 1/N \sum_{i=1}^{N} (x_i - y_i)^2) \quad \ldots \ldots (3)$$

4. ***SSIM:*** Symmetric Local SSIM statics are estimated using Gaussian weighting methods. To measure overall image quality, the mean SSIM index pools the spatial SSIM values

$$\textbf{SSIM: SSIM} = 1/M \sum_{i=1}^{M} SSIM(x_j - y_j) \ldots (4)$$

5. **UICM**: The underwater image colourfulness measure Overall colourfulness is given by

$$\textbf{UICM} = \sqrt[-0.0268]{u_\alpha, RG + u_\alpha YB} + \sqrt[0.1586]{u_\alpha, RG + u_\alpha YB} \quad \ldots\ldots\ldots\ldots (5)$$

6. **ENTROP**Y: Entropy is the fundamental concept of Shannon information theory [23,24]. It is usually considered in the framework of measure theory. Entropy provides information for the homogeneity of the existing distribution.

$$H(F) = -\sum_{i=0}^{255} P_i\, log_2\, P_i \ldots\ldots\ldots\ldots\ldots \quad (6)$$

7. **BRISQUE:** Blind / Referenceless Image Spatial Quality Evaluator (BRISQUE) no reference image quality score, BRISQUE analyses image naturalness (or lack thereof) by extracting point wise statistics of local normalised luminance signals.

IV. Results

1. Qualitative Analysis

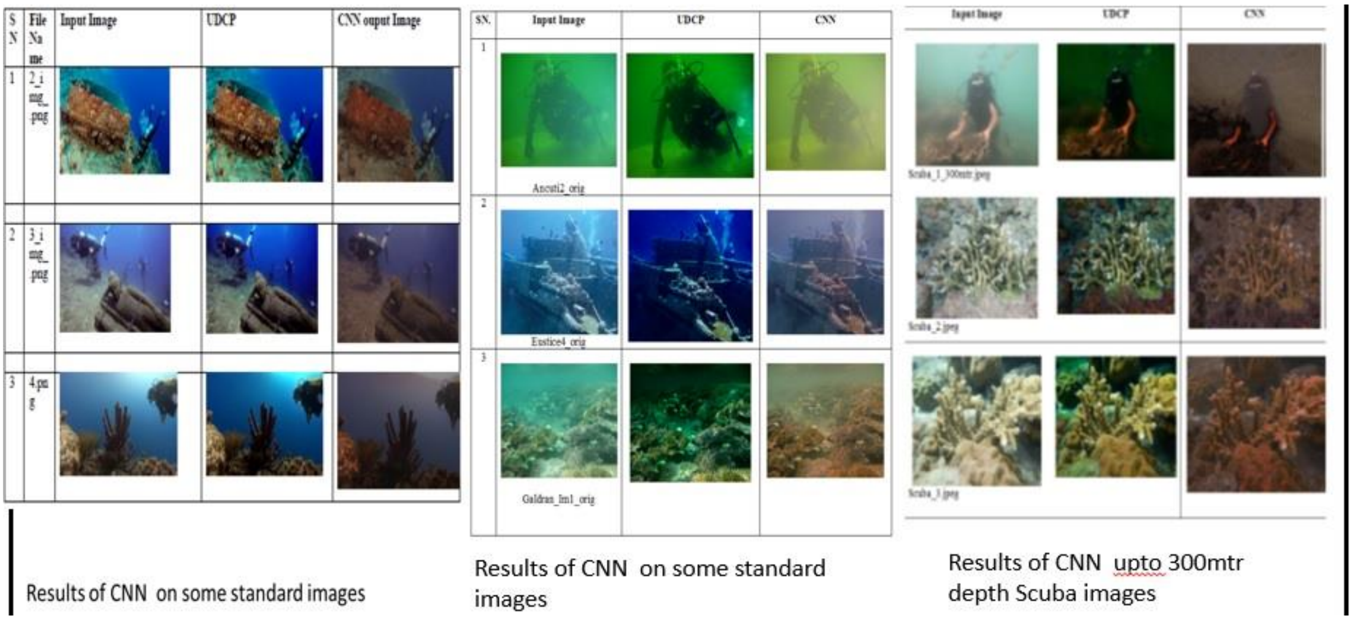


Fig. 5: Results-1 for standard datasets at various depth

For qualitative evaluation, various datasets cosidering in Fig. 5, Fig 6, Fig. 7 and Fig. 8 are shown as, Sample of the data (a)Original underwater photos as input image (b) the UDCP test results and (c) the UWCNN output proposed method results, When the latent pictures are reconstructed, they are accurate and colorful since our methods eliminate all of the tones such as blue-green, blue-green, and greenish tones.

Our technique keeps the original color distribution of the underwater picture, as seen in Fig. 5 and 6 (the reddish color around the coral in Fig. 5 and Fig. 11). Fig. 8 depicts a failed instance where it intensifies the greenish tint and yields unpleasant outcomes. Fig. 6 Color casts are eliminated and contrast and brightness are increased, resulting in a more pleasurable viewing experience. There are no extra colors introduced in this method (e.g., the reddish color around the coral in Fig. 6), but this method improves contrast and performs similarly to the ODM while preserving the original image's true color distribution (see Fig. 5 and 6). Visual perception observed is very good here in this method which improve the quality of resulted image.

2. Quantitative Analysis: Table 1, shows the MSE, PSNR, and SSIM to quantify accuracy. When the MSE (PSNR) is lower, images are in closer proximity to their tagged counterparts. The closer a picture is to the label in terms of structure and texture, the higher the SSIM score. The SSIM measure illustrates this point. What you see here are the averages. Values in bold indicate the most desirable results.

SN	Image	SNR		PSNR		MSE	
		UDCP	CNN	UDCP	CNN	UDCP	CNN
1	2_img	1.19583	1.38558	24.05	20.82	256.074	537.764
3	3_img	1.24694	1.25375	15.35	16.9	1897.37	1326.39
4	4_img	1.08764	1.06241	15.96	16.17	1646.93	1571.35
1	Ancuti2	0.820994	1.56414	13.41	14.63	2968.68	2238.34
2	Eustice4	0.826607	1.66728	11.13	16.58	5012.26	1429.5
3	Fish	0.980024	1.61293	10.26	17.61	6124.83	1126.5
4	Galdran1	1.0499	1.80248	10.34	18.51	6008.44	917.25
5	Ocean2	0.848613	1.76926	9.89	15.061	6670.3	2028.84
6	reef1	0.87942	1.4178	13.97	19.44	2608.77	739.935
7	reef2	0.95917	1.54952	11.86	19.34	4237.61	756.701
8	reef3	1.21025	1.83325	13.78	17.91	2722.21	1052.93

Table 1: Parameter results for standard datasets-1

SN.	Image	STRSIM		ENTROPY		BRISQUE		UICM	
		UDCP	CNN	UDCP	CNN	UDCP	CNN	UDCP	CNN
1	2_img	0.873	0.810	6.62	6.702	18.15	13.35	14.98	19.54
3	3_img	0.768	0.68	7.49	6.38	18.52	12.80	19.97	17.43
4	4.png	0.73	0.598	7.302	5.99	31.52	35.88	16.29	21.15
1	Ancuti2	0.42	0.74	5.95	7.063	15.24	27.22	6.11	5.48
2	Eustice4	0.425	0.83	5.98	7.005	21.71	23.28	4.67	17.24
3	fish	0.47	0.81	6.69	7.06	11.35	18.23	14.35	16.41
4	Galdran1	0.51	0.85	6.47	7.25	3.88	9.03	5.42	18.59
5	ocean2	0.44	0.81	5.799	7.17	27.45	25.39	3.96	4.51
6	reef1	0.74	0.81	6.66	6.72	15.744	2.69	8.22	14.62
7	reef2	0.57	0.84	6.50	6.77	22.52	11.01	17.26	17.52
8	reef3	0.61	0.845	6.49	6.98	36.06	37.22	15.72	19.83

Table 2: Parameter results for standard datasets-2

Table 2 uses the STRSIM, ENTROPY, BRISQUE, UICM to quantify accuracy and the STRSIM measure which is illustrated.

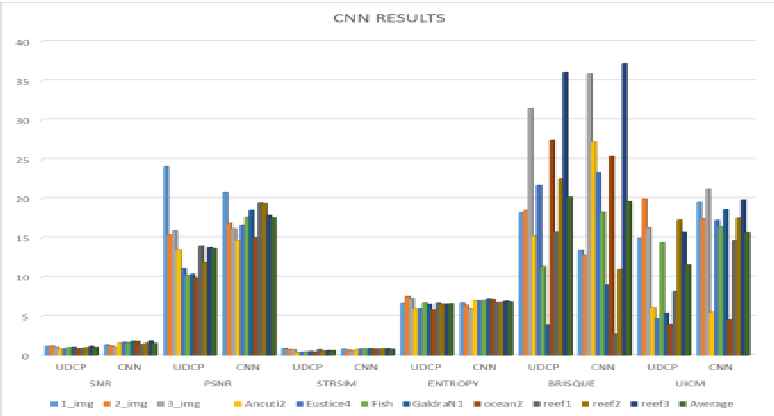


Fig. 6: CNN Result bar Chart

Fig 6 depicts the statistics of graphical representation for the data taken in fig 7 and its parameter values are shown in table 1 & 2. here, we found the most desirable results using this method for crucial images having depth more than 200 meter.

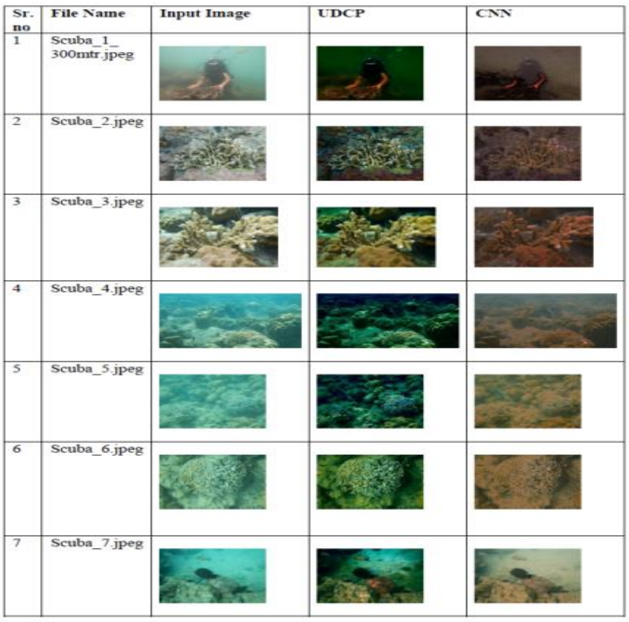


Fig. 7: Result-1 for Scuba images

All Scuba image results are shown here in Fig. 7. From the results shown it is observed that using CNN we can reduced the color cast but the perceptible quality is not as good with this algorithm.

SN	Image	SNR		PSNR		MSE	
		UDCP	CNN	UDCP	CNN	UDCP	CNN
1	Scuba_100mtr	0.823373	1.03284	6.22	15.82	15518.8	1700.59
2	Scuba_2.jpeg	1.58978	1.49598	10.58	19.89	5685.56	668.54
3	Scuba_3.jpeg	1.39801	1.23972	12.16	20.85	3956	534.411
4	Scuba_4.jpeg	0.863673	1.64171	8.72	18.31	8736.27	959.51
5	Scuba_5.jpeg	0.95621	1.6338	8.73	18.05	8706.59	1018.37
6	Scuba_6.jpeg	1.26895	1.60085	12.39	19.78	3752.45	683.705
7	Scuba_7.jpeg	1.21829	1.83275	11.38	13.94	4734.35	2625.46
8	Still_8.bmp	1.4437	1.64772	16.35	23	1508.6	325.553
9	Still_9.bmp	1.01254	2.09681	9.27	11.34	7700.2	4777.84
10	Still_10.bmp	1.06478	2.58453	7.88	10.02	10600.4	6466.23

Table 3: Results Considering own dataset Scuba images-parameter-1

SN	ImageName	STRSIM		ENTROPY		BRISQUE		UICM	
		UDCP	CNN	UDCP	CNN	UDCP	CNN	UDCP	CNN
1	Scuba _1	0.249	0.459	5.29	5.348	59.9	76.6	15.4	12.5
2	Scuba _2	0.682	0.811	7.19	6.46	5.54	8.69	20.70	0.279
3	Scuba _3	0.701	0.80	7.50	6.41	19.6	29.18	21.27	2.83
4	Scuba _4	0.36	0.77	5.89	6.98	19.25	24.35	6.52	20.55
5	Scuba _5	0.328	0.82	6.03	7.14	33.07	41.56	5.92	20.64
6	Scuba _6	0.658	0.866	7.33	7.176	79.61	27.16	2.12	10.65
7	Scuba_7	0.55	0.79	6.88	7.31	30.91	34.5	12.39	19.1
8	Still _8.bmp	0.757	0.88	7.39	6.79	55.82	45.04	5.26	6.25
9	Still _9.bmp	0.34	0.69	6.60	7.60	59.93	43.78	12.05	15.16
10	Still _10.bmp	0.3	0.67	5.9	7.04	58.15	43.79	10.5	11.85

Table 4: Results Considering own dataset Scuba images-parameter-2

The parameter results are shown in Table 3 and table 4 for the Scuba images, it is shown separately since these are ours own contribution to perform image enhancement with UWCNN, Also Bar chart is shown in Fig. 8, It is clearly observed that BRISQUE function does well for UWCNN model.

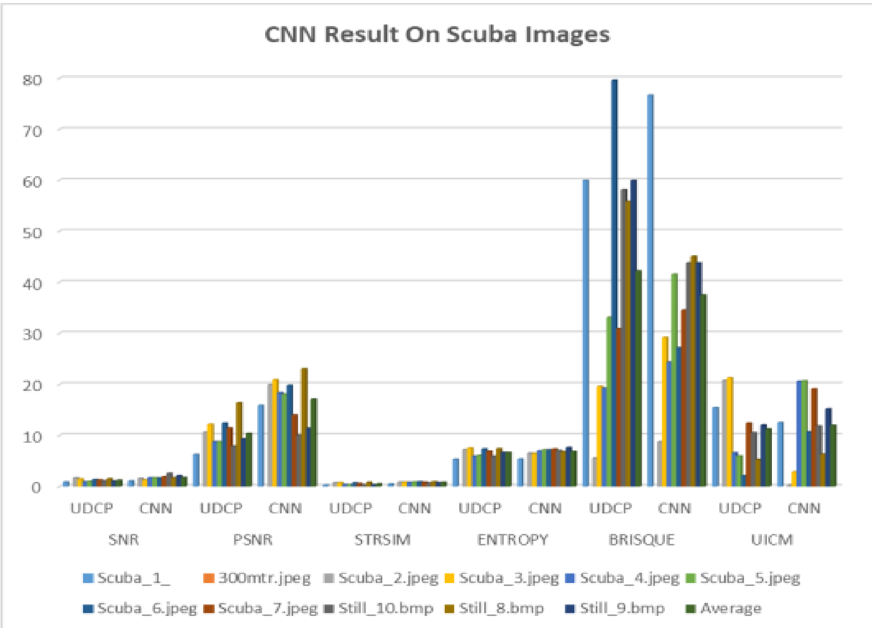


Fig. 8: CNN Results bar chart on Scuba Images

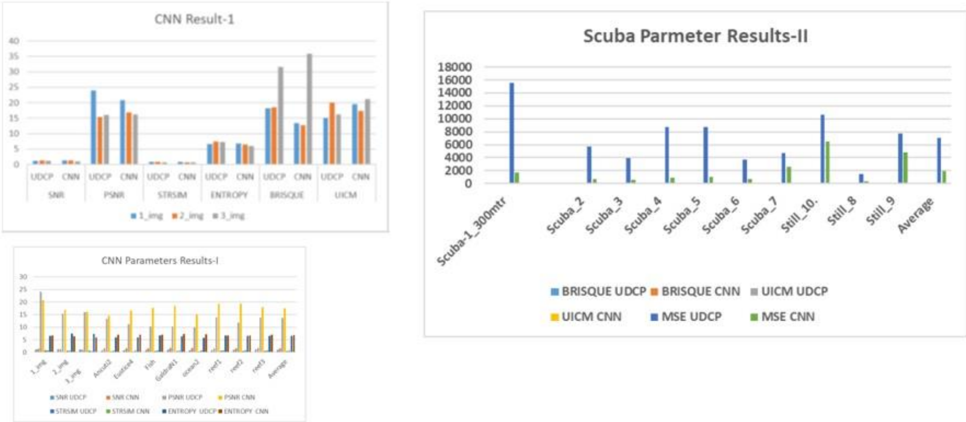
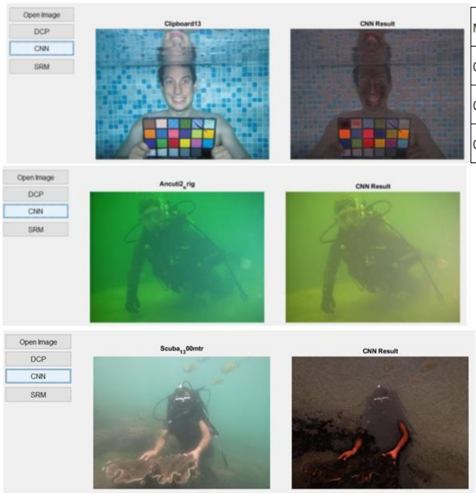


Fig. 9: UWCNN Bar chart of Three different datasets with all parameters

In Fig 9 three different datasets are compared with UWCNN to get the optimized results CNN results-1 indicates Bar chart of three images, CNN parameter reults -1 indicates bar chart obtained for standard images, and Scuba parameter result-II indicates bar chart of Scuba images at different depth. To quantify accuracy STRSIM, ENTROPY, BRISQUE, UICM parameters are considered. From these results it is observed that we can reduce color cast but the perceptible quality is not good for this algorithm.



Method	File Name	CIE2000	Qu	PCQI	UIQM	UCIQE	SNR	PSNR	SSIM	MSE
CNN	Clipboard13	8.7983	0.7122	0.9992	4.651	0.4544	6.0754	10.9018	0.2544	5.28E+03
CNN	Ancuti2_orig	53.9274	0.8112	0.9995	2.8693	0.3627	5.8776	13.78	0.346	2.72E+03
CNN	Scuba_1_300mtr	23.2522	0.3204	0.9987	2.3894	0.433	4.239	9.1479	-0.0493	7.91E+03

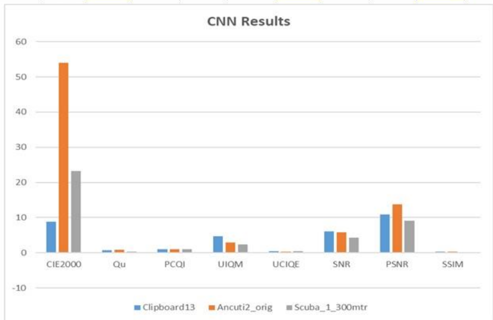


Fig. 10. Details of CNN Result 1- for four images with Parameter and bar chart

It is observed in the Fig 10, CNN method at various depth extract the features but as we go beyond 200 meter depth the actual color perceptibility is not possible.

Sr. No.	Image Name	SNR		PSNR		STRSIM		ENTROPY		BRISQUE		UICM		MSE	
		UDCP	CNN	UDCP	CNN	UDCP	CNN	UDCP	CNN	UDCP	CNN	UDCP	CNN	UDCP	CNN
1	1_img	1.19583	1.38558	24.05	20.82	0.872535	0.810183	6.61922	6.70188	18.1464	13.3536	14.9822	19.5369	256.074	537.764
2	2_img	1.24694	1.25375	15.35	16.9	0.763048	0.680249	7.49623	6.38053	18.5162	12.8036	19.9754	17.4288	1897.37	1326.39
3	3_img	1.08764	1.06241	15.96	16.17	0.726928	0.598142	7.30216	5.98851	31.5207	35.8782	16.2795	21.1509	1646.93	1571.35
4	Ancuti2	0.820994	1.56414	13.41	14.63	0.416109	0.741903	5.94785	7.06287	15.2444	27.2181	6.10913	5.4817	2968.68	2238.34
5	Eustice4	0.826607	1.66728	11.13	16.58	0.425373	0.826072	5.98439	7.00536	21.7116	23.2815	4.67065	17.2377	5012.26	1429.5
6	Fish	0.980024	1.61293	10.26	17.61	0.470889	0.81002	6.69119	7.06015	11.3494	18.2251	14.3542	16.4061	6124.83	1126.5
7	Galdran	1.0499	1.80248	10.34	18.51	0.50728	0.853245	6.46884	7.25127	3.88002	9.02733	5.41678	18.5914	6008.44	917.25
8	ocean2	0.848613	1.76926	9.89	15.061	0.44509	0.807092	5.79898	7.16893	27.4493	25.3859	3.95549	4.51156	6670.3	2028.84
9	reef1	0.87942	1.4178	13.97	19.44	0.742857	0.809099	6.66312	6.71681	15.744	2.69261	8.21994	14.6269	2608.77	739.935
10	reef2	0.95917	1.54952	11.86	19.34	0.5678	0.843438	6.50154	6.77151	22.5207	11.01	17.2577	17.5259	4237.61	756.701
11	reef3	1.21025	1.83325	13.78	17.91	0.609613	0.844896	6.49895	6.97478	36.0609	37.2216	15.7238	19.8387	2722.21	1052.93
	Average	1.009581	1.538036	13.63636	17.54282	0.595229	0.784031	6.542952	6.825691	20.19487	19.64523	11.54044	15.66696	3650.316	1247.773

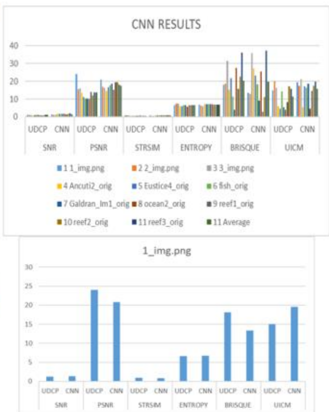


Fig.: 11 **CNN Results-2 Compared with UDCP**

Now we have considered standard dataset of 10 images and compared our results with UDCP, it is found that proposed method works well than UDCP specially for the Entropy, BRISQUE, and UICM, which shows that color casting is good by using this method than the UDCP.

3. Future and Emerging Directions: In recent years, advances in deep learning algorithms have made underwater picture improvement a well-established study topic. When compared to other picture enhancing techniques like super-resolution, deblurring, and dehazing, the performance is still insufficient in many areas. The direction of underwater image enhancement still has plenty of space for development. we'll take a look at some of the possibilities for the future, because of the scarcity of representative real-world underwater photos and the accompanying ground truth images, underwater image enhancement systems frequently use synthetic images for training. Testing rather than training models is the most typical use of the limited datasets that contain both underwater and reference photographs. In an effort to improve underwater photo enhancement models' performance, and provide reliable feedback on the image quality of enhanced outcomes, this may be of use

4. Objective functions and evaluation metrics: Today's algorithms are primarily dependent on image-enhancing methods' goal functions. The ocean's physical model properties are ignored, despite the fact that these functions generate excellent results. So, underwater image improvement has stalled since there are no appropriate metrics and failure scenarios to evaluate the results of the enhancements made. As an example, the visual findings shown in Figures 1-3 do not match the quantitative data shown in Fig.10. In Fig. 16 Detailed Results of three different images with different depth is shown and is observed that CNN does not gives good color casting for deep underwater images. For underwater image improvement research, additional specialized goal functions and assessment metrics are needed.

V. Conclusion

The efficacy and robustness of our system have been shown via evidence. This technique is made more effective by using just ten convolution layers and sixteen feature mappings for each layer. Therefore, the training and testing processes are completed in a shorter amount of time. According to the results of our network, residual learning, dense concatenation, and SSIM loss are all contributors to increased performance in terms of both quantity and quality. These are all elements that lead to enhanced performance. It is essential to take into consideration the low contrast of an indoor training dataset while developing new projects for study in the future. A single blind UWCNN model will be able to more effectively forecast the proper output with the aid of this particular measure. Pattern recognition and computer vision are two fields that make use of deep models. These models feature resilient network topologies and losses, both of which have the potential to be efficiently used to improve our strategic approach.

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