Comparison of Deep Learning Methods for Underwater Image Enhancement

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Abstract. Underwater image enhancement is an important process in image processing due to the images often suffering from severe degradation causes by the nature of light and underwater environment. The purpose of this research is to study the existing methods and algorithms for enhancing underwater images. In this paper, we compared 3 different deep learning-based methods (i.e. Water-Net, Shallow-UWnet, Deep Learning and Image Formation Model) for underwater image enhancement. Furthermore, we proposed an enhancement method based on white balance, adaptive gamma correction, sharpening and multi-scale fusion technique. The result of our proposed method is fed into the deep learning-based models. A real-world dataset which is the Underwater Image Enhancement Benchmark (UIEB) dataset is used for the model training and testing. Experimental results show that our proposed method improves the colour hue, image clarity and achieves higher scores in terms PSNR, SSIM and UIQM metrics.

Keywords: Underwater image enhancement · deep learning · fusion · image formation model · comprehensive evaluation

1 Introduction

Due to the growing demand for high-quality images in various applications, underwater image processing has carved itself a special identity in the field of research. However, underwater images frequently suffer from significant deterioration issues as a result of light absorption and scattering, compromising their accuracy and usability in underwater applications. Therefore, the degraded images taken in an underwater environment must be enhanced.

The quality of the picture and video suffers when images or videos are shot in an underwater environment because of the nature of the light. The relationship of light, transmission medium, camera, and scene are depicted in Fig. 1. Blue colour and green colour wavelengths reach deeper lengths than red colour wavelengths that vanish beyond 5 m depending on light attenuation, resulting in images that are primarily blue and green in tone [1].

Moreover, the particles present in the water absorb most of the light energy and modify the path of light before it reaches the camera, resulting in images with poor

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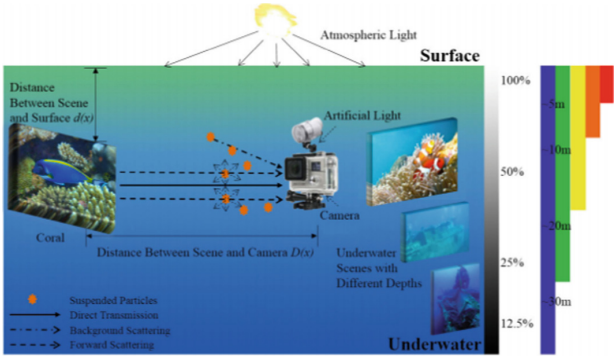

Fig. 1. Change in the images with the depth of water illustration [1]

contrast, blur, and haze. Dissolved organic debris and microscopic floating particles known as 'sea snow' have an impact on underwater image quality as it introduces noise and increase the effects of scattering [2]. These negative effects impair visibility, contrast, and produce colour casts, limiting the practical uses of underwater image and video in the field of study. To overcome the problem mentioned, multiple image enhancement methods can be implemented to the underwater images to get a clear image.

Underwater picture enhancement has received an increasing amount of study work over the previous few decades. The use of underwater image demand increases in numerous areas such as underwater microscopic detection, autonomous underwater vehicle, mine detection, and telecommunication cable terrain scanning. However, this sector confronts challenges surrounding the underwater image as there are still many advancements required to create a clearer image in an underwater setting. Currently, several researchers have presented a variety of underwater image enhancing approaches. However, most of the method are based on traditional machine learning approaches. Deep learning methods are still new in the image processing and the number of researchers employing the deep learning-based method to enhance underwater pictures is still minimal, despite their superior image enhancement performance. In this study, we performed a comparative study between the existing deep learning-based models while incorporating our proposed enhancement method.

2 Literature Review

2.1 Underwater Image Enhancement Method

Enhancing the underwater images is an essential step to getting information on the underwater resources. A few methods have been developed, which may be classified into five categories: frequency domain-based, spatial domain-based, colour constancy-based, fusion-based, and deep learning-based.

Frequency domain-based is progressively progressing as it effectively removes noise in images [3]. It does not, however, improve contrast or do colour correction which causes this method receiving less attention. Moreover, spatial domain-based method such as

Gamma Correction, Generalized Unsharp Masking (GUM), Histogram Equalization (HE), and Contrast Limited Adaptive Histogram Equalization (CLAHE) made great progress in the field of image enhancement since it is mature and simple to adopt, and it has been improved to combat the deterioration of the underwater image [4]. This method typically demands the employment of colour correction and noise reduction techniques in combination. Furthermore, White Balance and Retinex are the main components of colour constancy. White Balance is largely concerned with fixing the issue of colour casts in objects under various lighting situations. Retinex is an automated program that allows people to examine their surroundings under changing lighting conditions. It is predicated on the concept of colour constancy.

Next, fusion techniques are mostly derived from contrast stretching, detail improvement, colour balancing, colour correction, and other factors. Experiment research found that this strategy might enhance the exposure of global contrast, dark areas, and image edge details. However, the weighted coefficients are challenging to calculate in the fusion process for varied underwater environments [2].

Fusion technique is firstly introduced in [5] where the researcher proposed a multi-scale fusion solution for improving underwater pictures and videos by mixing a contrast-enhanced picture with a colour-corrected picture. However, the method showed a limitation when facing with pictures of deep underwater scenes captured with a mediocre strobe and artificial light as the bluish appearance still appears even after enhancement. Therefore, this limitation has been further improved by the researcher in their most recent work in [6]. They suggested a single-image solution that does not need specialist hardware or knowledge of underwater conditions or scene layout. The approach relies on the fusion of multiple inputs, however the two inputs to merge are obtained by altering the contrast and sharpening a white-balanced version of a single original input picture. The white balancing procedure reduces the colour cast created by underwater light dispersion, giving the sub-sea photos a more realistic aspect. The fusion process is implemented on many scales, resulting in artifact-free blending. We can compare the results in Fig. 2 where we see that the method in [6] beats the white balancing scheme reported in [5] in circumstances where the red channel of the underwater picture is greatly reduced.

Finally, deep learning has grown in popularity in recent years as its performance in computer vision and image processing applications such as picture segmentation, image identification, and object recognition has improved. However, the demand for a high number of label pictures, which are challenging to gather in reality limits deep learning-based underwater image enhancement [2].

Researcher in [7] suggested a new method for enhancing underwater image by merging the recently proposed revised image formation model with the existing deep learning-based image enhancement method. On numerous datasets, the proposed method produces good image-enhancing outcomes, with gains in both visual quality and quantitative measures when compared to existing methods. Simultaneously, the computation speed has substantially improved, allowing it to satisfy the real-time computing needs of the future underwater platform (Fig. 3).

Next, [8] presented a CNN-based framework for enhancing underwater images called UIE-Net. The proposed model consists of three parts: Sharing Networks(S-Net), Colour Correction Networks (CC-Net), and Haze Removal Networks (HR-Net). Furthermore,

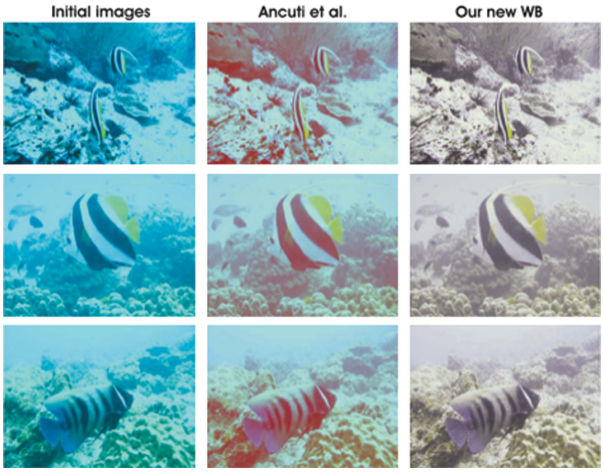

Fig. 2. Visual comparison white balance method in [5] and [6]

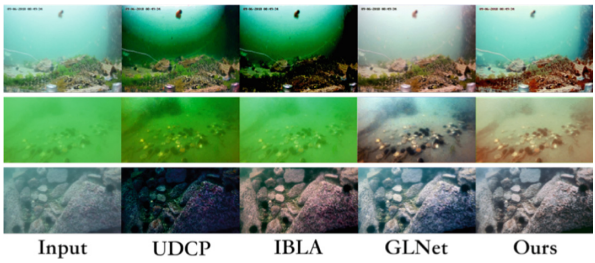

Fig. 3. Visual comparison of different underwater image enhancement methods in [7]

for the first time, they offer a pixel disruptive method that efficiently enhances convergent speed and accuracy. Figure 4 depicts the results of the CC-Net and HR-Net.

Moreover, authors in [9] developed an underwater picture improvement procedure based on deep learning principles, and the accuracy levels are examined by comparing the proposed CNN logic to the traditional SVM scheme. The generated scenario is sent into IBM's Statistical Package for the Social Sciences (SPSS) software testing tool, which is used to assess the stability of the proposed design as well as the instrument's long-term accuracy metrics (Fig. 5).

Other than that, the CNN model is also applied in [10], where they present Water-Net, a gated CNN model for underwater picture improvement. The suggested Water-Net baseline is designed to facilitate the development of deep learning-based underwater image enhancement as well as to highlight the UIEB's applicability for training CNNs. First, the researcher creates three inputs based on underwater picture degradation features by using Histogram Equalization, Gamma Correction, and White Balance algorithms to an underwater image. The White Balance approach attempts to fix colour casts and Histogram Equalization aims to increase contrast while Gamma Correction goals is to brighten dark regions. The findings proved that the Water-Net effectively eliminates haze

Fig. 4. Colour correction results from CC-Net, and contrast enhancement results from HR-Net [8]

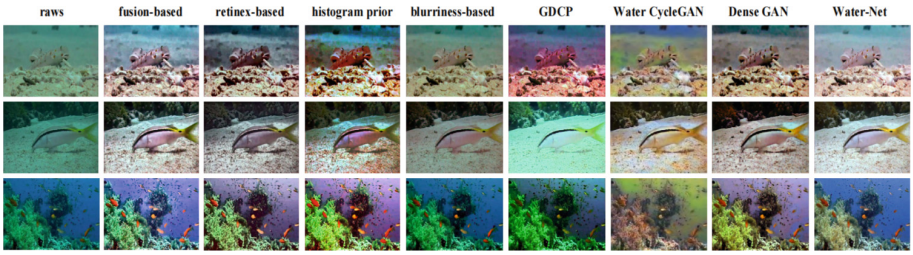

Fig. 5. The final enhanced results being compared with Water-Net in [10]

from underwater photos, lowers colour casts, and achieves higher visual quality than the original input's reference images. This is due to Water-Net's ability to learn the future attributes of excellent visual quality from an underwater image collection via perceptual loss optimization.

Next, CNN and Generative Adversarial Network (GAN)-based models have significant computational and memory needs, making them difficult to deploy for real-time underwater picture improvement tasks. As a result, Shallow-UWnet was proposed [11] to increase the operability of machine learning models by minimizing computation time and memory requirements while keeping performance comparable to other models. When compared to existing models in Fig. 6, including the Water-Net model in [10], the proposed Shallow-UWnet model achieves equivalent performance. Furthermore, the proposed model can analyse test images more quickly, resulting it appropriate for real-time image enhancement tasks.

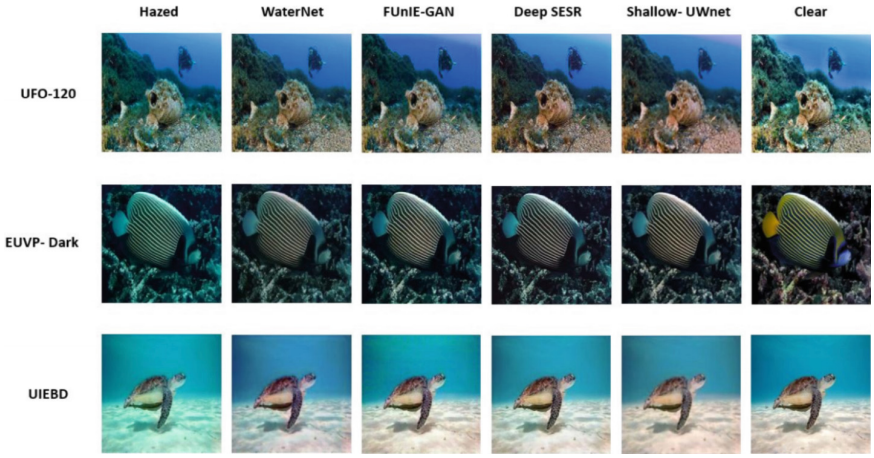

Fig. 6. Underwater Image Enhancement for multiple datasets and Model [11]

2.2 Underwater Image Quality Evaluation

Due to the nature of underwater environment that is more complicated than the rain and other natural environments, assessing the quality of underwater images is more difficult. There are two types of evaluation methods that will be used in this study: quantitative evaluation and qualitative evaluation.

The qualitative evaluation consists primarily of the tester observing an image and performing an analysis of the image's quality. Images are subjected to repeated observation experiments by a group of testers. While qualitative evaluation is important as a baseline, it is time-consuming and difficult to implement into practical applications [4]. As a result, quantitative evaluation is more widely accepted and reliable. Non-reference evaluation and full-reference evaluation are the two types of quantitative evaluation.

Although the real ground truth pictures may differ from the reference images, the findings of full-reference image quality evaluation utilizing reference photos can offer realistic feedback on the performance of different approaches to some extent [10]. The three most widely used metrics for full-reference evaluation are mean square error (MSE), peak signal-to-noise ratio (PSNR) and structural similarity measure (SSIM). Image differences between the reference and distorted pictures are usually computed using MSE and PSNR.

Researcher in [12] introduced an underwater image quality measure (UIQM) approach for assessing quality of underwater photos based on their colour, sharpness, and contrast. Furthermore, [13] proposed an underwater colour image quality technique (UCIQE) that aims to quantify non-uniform noise, blurring, and colour cast in underwater architecture and sensor pictures. It translates underwater photos to CLELAB colour space from the RGB colour system, which is more similar to human vision perception.

3 Methodology

3.1 Dataset

The data that is used in this project is the underwater image enhancement benchmark (UIEB), a large-scale real-world dataset from [10]. UIEB contains 950 actual underwater photos shot in natural, artificial, or a combination of the two light sources. The UIEB dataset is distinguished from prior datasets by the presence of similar reference images for 890 underwater images. The reference photos are developed with 12 distinct image improvement methods, 9 of which are methods specialized for underwater image enhancement. Therefore, in total, The UIEB contains 890 raw underwater photos, 60 challenging underwater images, and high-quality reference images.

3.2 Data Pre-processing

Our proposed enhancement method requires the raw images to go through 4 image enhancement processes before feeding the images into the model. This will help the model to provide a better outcome and a more visually pleasing image. Figure 7 shows the general structure of data pre-processing. Therefore, White Balance, Adaptive Gamma Correction and Sharpening will be first applied to the images. The output from all the image enhancement mentioned will be fused together based on multiscale fusion in [6].

For white balancing and sharpening, the algorithm in [6] will be applied as it delivers acceptable visual performance for reasonably distorted underwater images, able to removes the blue tone the best. The sharpening algorithm able to compensate for the haziness of the white balanced picture.

Gamma Correction helps to lighten up dark regions in the raw images. We studied the traditional gamma correction and the adaptive gamma correction algorithm proposed in [14]. We compared the result and adaptive gamma correction performs the best in quantitative and qualitative evaluation. Therefore, the adaptive gamma correction is chosen to be implemented in our proposed method.

For the fusion process, we will be applying the fusion process proposed in [6]. The first input will be produced from Gamma Correction of the white balanced picture version before the image goes through multiscale fusion. Gamma Correction is effective for improving global contrast, which is necessary because white-balanced underwater photos tend to be overly bright. This adjustment boosts contrast between darker and brighter parts at the price of loss detail in the under/overexposed areas. The second output will be derived from sharpening as it can compensate the haziness from the white balanced picture.

3.3 Deep Learning

Once the data pre-processing process is complete, the output image will be input into the three different deep learning models that we mentioned in the previous chapter. However, for the deep learning model proposed in [6], which is Water-Net, the model used 4 different input images which are derived from the raw image, Histogram Equalization, Gamma Correction and White Balance (Figs. 8, 9 and 10).

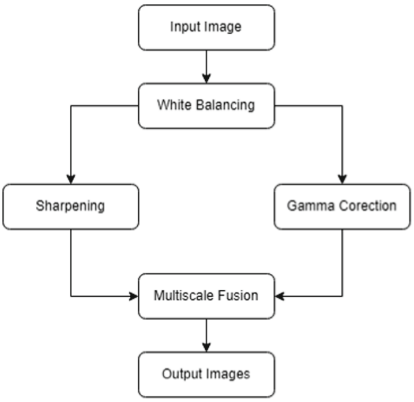

Fig. 7. Data Pre-Processing Overview

3.3.1 Water-Net

From Fig. 11, the White Balance, Histogram Equalization and Gamma Correction input and the original input is feed into the Water-Net to get their confidence maps. The confidence maps consist of a few sets of Conv-ReLU with different kernel sizes. We enhance the three inputs using three Feature Transformation Units (FTUs) before conducting fusion. FTU's objective is to decrease artefacts and colour casts caused by the three algorithms. Finally, to obtain the final improved image, all of the improved inputs are multiplied with the three learnt confidence maps [10].

$$I_{en} = R_{WB} \cdot C_{WB} + R_{HE} \cdot C_{HE} + R_{GC} \cdot C_{GC} \tag{1}$$

where I_{en} represents the improved result; $\cdot$ represent the element wise production of matrices; R_{WB}, R_{HE}, and R_{GC} are the improved results of the input after being processed by Histogram Equalization, Gamma Correction, and White Balance algorithms, respectively; C_{WB}, C_{HE}, and C_{GC} are the learned confidence maps.

3.3.2 Deep Learning and Image Formation Model (DLIFM)

From Fig. 8, the input image will be firstly fed into the backscatter estimation module. Once it completes, the input image and the output from the backscatter estimation module will then be fed into the direct-transmission estimation module. Finally, a reconstruction calculation will be performed, and the final enhanced image will be produced.

From Fig. 9, we can see that two sets of 3×3 convolution kernels, one global mean pooling layer, and two groups of 1×1 convolution kernels comprise the backscatter estimation module. The number of convolution kernels in each group is 3.

From Fig. 10 shows that the backscatter estimation is initially concatenated with the input image using the direct transmission estimation module, and the succeeding process contains three groups of 3×3 dilated convolutional kernels and one group of 3×3 normal convolutional kernels. The number of dilated convolution kernels in each group is 8, while the number of normal convolution kernels in the final group is 3. The dilated convolution may increase the receptive field without adding more

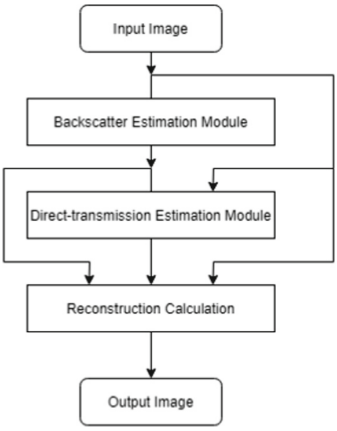

Fig. 8. General Structure of DLIFM [7]

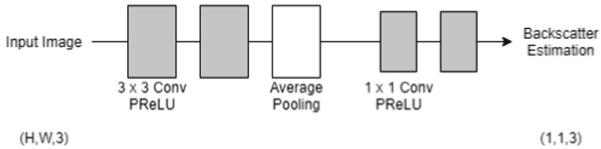

Fig. 9. Backscatter Estimation Module [7]

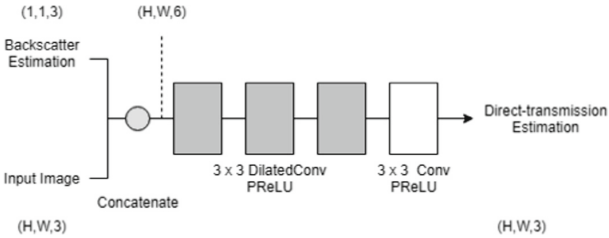

Fig. 10. Direct-transmission Estimation Module [7]

parameters by filling more zeros in the convolution kernel. The model uses the hybrid dilated convolution design technique, which means that various dilation rates are used for sequential dilated convolution processes. The dilation rates of the module's three groups of dilated convolution kernels are [1, 2, 5].

3.3.3 Shallow-UWnet

Figure 12 shows the model architecture of Shallow-UWnet. The model is made up of a fully connected convolution network that is coupled in sequence to three densely connected convolutional blocks. Using a skip connection, the input picture is connected to the output of every block. The Shallow-UWnet model receives a 256 × 256 RGB underwater picture as input. The raw input image is transmitted via the first layer of

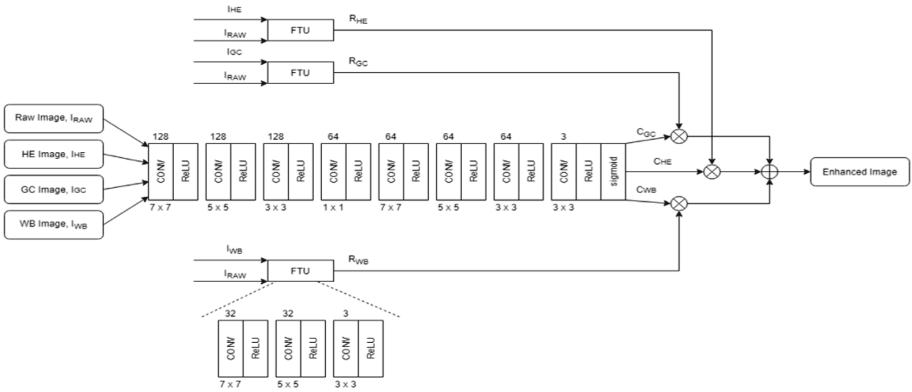

Fig. 11. Model Architecture of Water-Net [9]

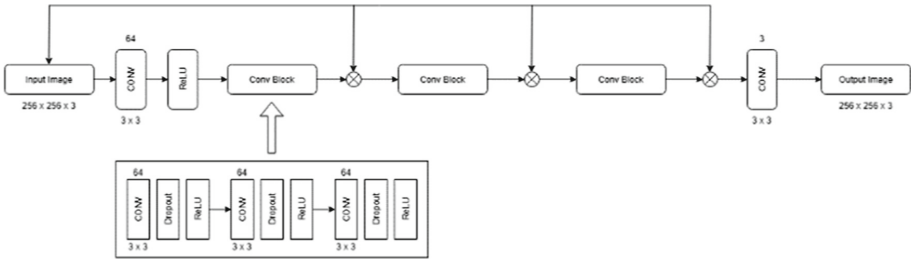

Fig. 12. Model Architecture of Shallow-UWnet [10]

convolution layer with the kernel size 3 × 3 in order to create 64 feature maps, then a ReLU activation layer, followed by three convolution blocks linked together. The improved underwater image is generated by a final convolution layer with three kernels.

The ConvBlocks are made up of two convolution layer sets, each set contains a dropout and ReLU activation function. Then, the result is transmitted into another set of Conv-ReLU pairs, that allows the raw picture derived by the skip connection to be concatenated. The sequence of ConvBlocks, together with the skip connection, functions to be a deterrent to the network overfitting over the train data. As a result, the network's generalization is supported.

The raw input picture is concatenated to the output of each residual block by using the skip connections. The skip connection would place more weight on the channels associated with the raw input image than on the channels generated by the ConvBlock in the event of a vanishing gradient issue. As a result, feature learning from each block is ensured, as is the incorporation of crucial properties from the basic raw image.

3.4 Implementation

The training set for the deep learning model is generated using a collection of 800 sets of pictures retrieved from the UIEB dataset. Since deep learning made frequent use of resizing training data to a fixed size, the training data is downsized to 112 × 112 for Water-Net model while for Shallow-UWnet and Deep Learning and Image Formation, the training data is downsized to 256 × 256. The remaining 90 pairs of images in the UIEB is used as the testing set. For training the deep learning model, the batch size is set to 2, the learning rate is 0.001 while the number of epochs is 20. The training data is used to train the 3 deep learning models after the data pre-processing process.

3.5 Evaluation Metrics

To evaluate the result of the deep learning quantitatively, we evaluate the result by implementing PSNR, SSIM for the full reference metrics while UIQM for non-reference metrics.

PSNR measures the ratio of maximum feasible signal power to distorting noise power, which determines the quality of its representation. In terms of picture content, a high PSNR score indicates the enhanced image is more identical to the reference image. PNSR can be calculated as follows:

$$PSNR = 10 \log_{10} \frac{L^2}{MSE} \tag{2}$$

where the dynamic range, L, of image pixel intensities.

According to [15], we regard x and y to be regions drawn from the two separate pictures but positions to be evaluated against one another. SSIM considers three factors: the similarity of the patch luminance (x, y), contrasts $c(x, y)$, and the local structures $s(x, y)$. Simple statistics are used to represent and compute the similarities, which are then blended to yield local SSIM as follows:

$$\begin{aligned} SSIM &= l(x, y).c(x, y).s(x, y) \\ &= \left(\frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}\right)\left(\frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}\right)\left(\frac{\sigma_{xy} + C_3}{\sigma_x + \sigma_y + C_3}\right) \end{aligned} \tag{3}$$

UIQM value that is high indicates a result that is more in accordance with human visual perception. UIQM can be calculated as follows:

$$UIQM = c_1 \times UICM + c_2 \times UISM + c_3 \times UIConM \tag{4}$$

4 Results

Table 1 displays the values for the performance metrics on the UIEB test set for the Water-Net, DLIFM, and Shallow-UWnet. In terms of full-reference metrics, Water-Net model performed better in all the metrics followed by DLIFM because the multi-scale fusion result image is fed into the model together with the respective result for

Table 1. Quantitative results for deep learning model

Model	Method	PSNR	SSIM	UIQM
Water-Net [10]	Original Method	18.99	0.67	0.302
	Proposed Method	**20.78**	**0.86**	**0.51**
DLIFM [7]	Original Method	19.37	**0.88**	0.45
	Proposed Method	**20.19**	0.85	**0.66**
Shallow-UWnet [6]	Original Method	**18.99**	0.67	0.28
	Proposed Method	18.73	**0.79**	**0.55**

adaptive gamma correction, white balance and histogram equalization. DLIFM obtained the highest score in terms of UIQM. This can be seen in Fig. 13 where we observed that the images produced by the DLIFM model is sharper as they have better balance of chroma, saturation, and contrast. For Shallow-UWnet, the images have a darker tone and overall looks blurry compared to the other two methods.

When we compared the enhancement method of the 3 deep learning models proposed in their paper to our proposed method, there are improvement in our proposed method in terms of quantitative evaluation and qualitative evaluation. Firstly, for Water-Net, the proposed method achieved higher value in PSNR, SSIM and UIQM compared to the method in [10]. From Fig. 13, we observed that the proposed method can correct the colour bias of the underwater images better compared to the initial method. Even though the SSIM value for DLIFM are slightly lower for the proposed method, it is still considered better since it achieves higher value for the PSNR and UIQM. The proposed method improved the contrast and the detail clarity compared to the method in [7]. The image produced by proposed method for Shallow-UWnet are more sharpened and the colour hue are more balanced compared to image produced by [11] method.

5 Conclusion

There are a number of researchers proposed a variety of underwater image enhancement approaches. However, majority of the previous work focuses on implementing traditional image enhancement method and deep learning-based methods are still new in the image processing. The number of researchers employing the deep learning-based method to enhance underwater pictures is still minimal. In this paper, we performed a comparative study between the three existing deep learning-based models. We also proposed a method where that combines multi-scale fusion technique with the deep learning methods. Our proposed method provides a good image enhancement result. There is improvement in terms of quantitative metrics and visual quality for the deep learning models incorporated with the proposed method compared to the original methods.

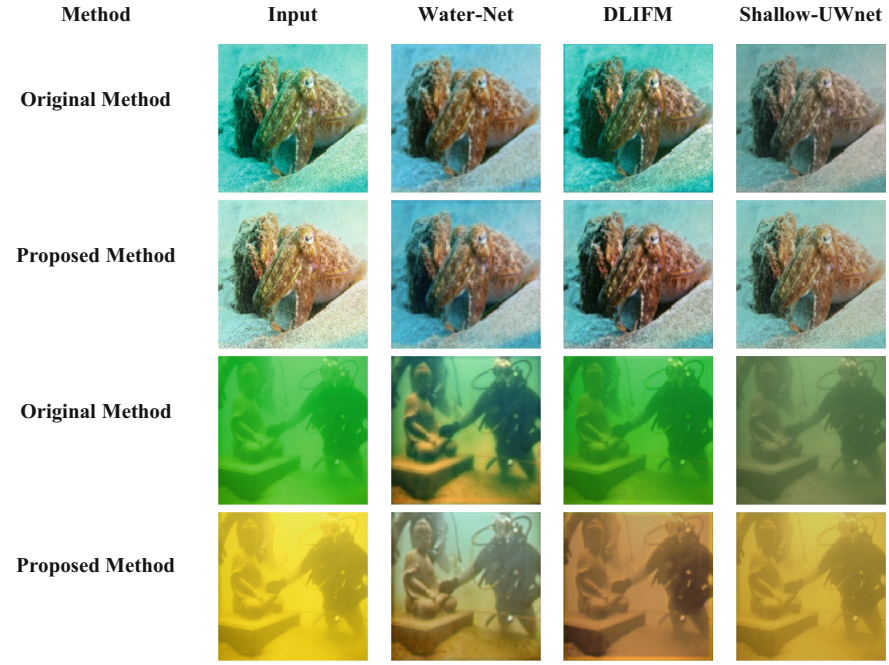

Fig. 13. Visual comparison of different deep learning-based underwater image enhancement model results with the proposed method

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Authors' Contributions. Study conception and design, analysis and interpretation of results: An'nissa Jobli, Noramiza Hashim;

Draft manuscript preparation: An'nissa Jobli;

All authors reviewed the results and approved the final version of the manuscript.

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