Underwater Image Quality Enhancement By Using Convolutional Neural Network Based Algorithm

(Peningkatan Kualiti Imej Bawah Air Dengan Menggunakan Algoritma Berasaskan Rangkaian Neural Konvolusi)

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***Abstract*— Image processing is a challenging field of study that focuses on enhancing visual information for human interpretation and implementing autonomous machine perception. Image enhancement, a common method in image processing, involves improving the visual quality of an image. Image enhancement in underwater surveillance is essential for various applications, including oceanic geological exploration, resource exploitation, ecological research. However, the visual perception of underwater imaging is affected by various environmental factors such as attenuation and absorption of light. The primary challenge is that underwater images often appear with haze-like effect, low contrast and sharpness and colour bias. This paper proposes a new deep learning-based underwater image quality enhancement by combining the image formation model and white balance model to improve the overall quality of underwater images in terms of haze removal, improve contrast and sharpness, and colour balance. Experimental results demonstrate the advantages of the proposed method in improving visual quality by eliminating the influence of underwater environmental factors, removed haze, increased contrast and sharpness, restore and balancing colours. These results are further supported by quantitative metric, indicating improvement of 2.80%, 4.67%, 5.22% and 2.69% in entropy, PCQI, UIQM and UCIQE respectively, as compared to image formation model. In terms of future research, it is recommended that the study integrates both models into a unified framework and explores expanded dataset training.**

Keywords—Underwater Image, Deep Learning, Image Processing, Image Formation Model, White Balance

I. INTRODUCTION

Digital image processing, a field that involves the manipulation of digital images using computers, has evolved to address a broad spectrum of applications spanning the electromagnetic spectrum, from gamma to radio waves. Images, composed of discrete pixels, undergo processes categorized as low, medium, and high level, with applications in medical imaging, remote sensing, surveillance, and more [1]. Specifically, underwater surveillance, a less developed area until recently, faces unique challenges such as low illumination, limited visibility, and underwater haze.

In the realm of underwater surveillance, the degradation of image quality is exacerbated by light attenuation and absorption in aquatic environments. Reflection, refraction, and scattering lead to a reduction in light intensity, causing a haze-like effect. Additionally, wavelength-dependent light absorption results in color distortion and a prevalent bluish and greenish tone in underwater images [2]. Traditional underwater image enhancement methods, relying on single-purpose approaches and heuristic algorithms, struggle to adapt to diverse underwater scenes [3].

The core challenge addressed in this paper is the comprehensive enhancement of underwater images by addressing degradation factors such as light attenuation, absorption, and scattering. The study aims to overcome the limitations of traditional methods by proposing a more versatile solution. The key focus is on developing a dual Convolutional Neural Network (CNN)-based image enhancement method to produce high-quality results in underwater color images. This novel approach aims to enhance adaptability and effectiveness in handling the intricate and varied patterns present in diverse underwater scenes, offering a promising solution for improved underwater surveillance and exploration.

II. OBJECTIVE

A. To implement underwater image formation model by removing haze-like effect in the underwater images.

B. To develop a fusion of white balance model and underwater image formation model to increase sharpness, contrast and colour balance in the degraded underwater colour images.

III. LITERATURE REVIEW

A. Underwater Imaging Model

Underwater imaging models serve as mathematical representations designed to emulate the impact of underwater conditions on image formation. In an ideal scenario, where imaging occurs in a medium without any interference with reflected light, the digital camera captures the precise optical energy reflected from the scene, resulting in a perfect image [2]. However, underwater image formation is considerably more challenging than outdoor imaging due to the intricate nature of the underwater environment. The process is influenced by factors such as the medium, light absorption and attenuation, scattering, and color distortion, posing significant challenges to the accurate representation of underwater scenes.

1) Jaffe-McGlamery Underwater Imaging Model

The Jaffe-McGlamery underwater imaging model stands out as a widely adopted and prominent model in the field. Figure 1 visually represents the process of light propagation from a source to a camera, according to the Jaffe-McGlamery model. This model delineates various pathways for light to travel from the source to the scene and ultimately to the camera's image plane. These pathways are classified into three types: direct light, representing light directly reflected from the scene without scattering by suspended particles; forward scattered light, signifying light reflected from the scene and scattered by particles in the water; and back scattered light, denoting light reflected from the source and scattered by particles in the water [4]. The Jaffe-McGlamery model provides a comprehensive framework for understanding the complex interplay of light in underwater environments, contributing significantly to the analysis and enhancement of underwater images.

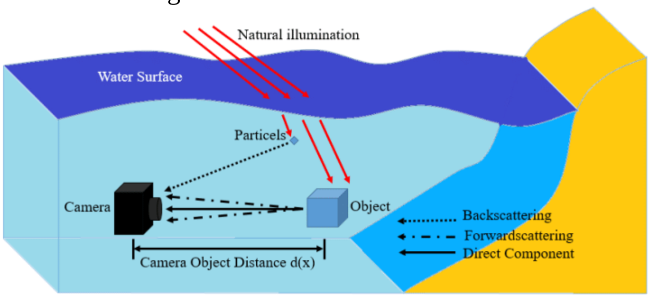

Figure 1. Jaffe-McGlamery Underwater Imaging Model

Based on this model, the received light intensity by a camera is expressed as the sum of three pathways:

$$L_T = L_d + L_f + L_b \tag{1}$$

where L_T denotes the total light intensity received by camera, L_d, L_f, and L_b represent the direct, forward-scatter and backward scatter light respectively.

2) Narasimhan Imaging Model

In practical underwater imaging scenarios, where the medium introduces absorption and scattering, the formation of the underwater image is intricately detailed. The total light intensity captured by the camera underwater is just the combination of direct transmission light and back scattered light [5]. Forward scattered light has been eliminated due to insignificant contribute to the degradation of an underwater image especially when the camera is nearby the captured scene.

For direct light, the attenuation of optical energy is assumed to be an exponentially decaying process. Hence, the direct light L_d is denoted as

$$L_d = J(x)e^{-\beta(x)d} \tag{2}$$

where $J(x)$ is the true intensity value of the scene, $\beta(x)$ is the coefficient of the attenuation of light and d is the distance from the camera to the scene.

For backward scattered light, it is cause by the scattering of environmental illumination by suspended particle. Therefore, the backward scattered light L_b is expressed as

$$L_b = L_\infty(x)(1 - e^{-\beta(x)d}) \tag{3}$$

where $L_\infty(x)$ is the background light.

Thus, the final equation of Narasimhan image model based on equation (1) is denoted as

$$L_T = J(x)t(x) + L_\infty\big(1 - t(x)\big) \tag{4}$$

where $t(x)$ is the direct transmission mapping as a function to replace $e^{-\beta(x)d}$.

3) A Revised Image Formation Model

Common methods for enhancing underwater images often simplify the calculation by treating the t(x) of three channels of an RGB image as one mapping, neglecting the variation in the attenuation coefficient β in t(x) between different colour channels. As a result, the enhanced images may still exhibit colour bias.

To address this limitation, Akkaynak & Treibitz [6] conducted a comprehensive study involving numerous underwater experiments. They introduced a revised model, expressed in equation (5), which takes into account the optical imaging properties of the underwater environment and adjusts the attenuation coefficient to accommodate potential variations in different color channels.

$$L_c(x) = J_c(x)e^{-\beta_C^D(V_D)d} + L_c^\infty\left(1 - e^{-\beta_C^B(V_B)d}\right) \tag{5}$$

where $c \in \{R, G, B\}$ denotes the three colour channels, β_C^D and β_C^B denotes the attenuation coefficients for direct-transmission light and backward scattered light, d is the transmission distance between scene and camera and $V_D = \{d, \rho, E, S_c, a, b\}$ and $V_B = \{E, S_c, a, b\}$ denote the attenuation coefficients dependencies of direct-transmission and backward scattered.

B. Deep Learning-Based Underwater Image Enhancement

Deep learning networks, particularly Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have emerged as pivotal tools for enhancing underwater images. Traditional model-based methods often face challenges in adaptability due to the reliance on estimated values for transmission graphs and image parameters. In contrast, deep learning, integrated with physical models, leverages CNNs' feature extraction capabilities to solve parameter values, such as transmission mapping, leading to improved adaptability.

CNNs, replacing assumptions of traditional methods, demonstrate their learning prowess by directly outputting enhanced underwater images after operations like convolution, pooling, and deconvolution. This eliminates constraints imposed by model assumptions and enables the direct learning of the mapping relationship between original and clear underwater images [3]. On the other hand, Goodfellow et al. [7] introduced GANs, which employ a game-like learning framework with a generator and discriminator to enhance image quality. GANs have proven effective in various applications, including image generation, enhancement, restoration, and style transfer.

While CNNs are primarily used for supervised learning, learning mappings between input and enhanced images, GANs operate in an unsupervised manner, not requiring paired input-output data. The choice between CNN and GAN depends on data availability and desired generative and discriminative capabilities. However, CNNs are more computationally efficient compared to GAN. The training and inference processes for CNNs are typically faster, making then suitable for real-time applications, where quick processing is crucial.

C. Haze Removal

In the realm of underwater image enhancement, addressing haze removal stands out as a paramount challenge crucial for restoring clarity and visibility. Several researchers have made noteworthy contributions, particularly leveraging deep Convolutional Neural Network (CNN) architectures.

Cai et al. [8] presented DehazeNet, a pioneering work focused on underwater dehazing. This CNN-based approach estimates the transmission map to restore haze-free images, incorporating established assumptions and priors in image dehazing. Wang et al. [9] tackled color distortion and visibility issues in underwater images using a UIE-net, a CNN-based model addressing both color correction and haze removal. Perez et al. [10]and Pan et al. [11] similarly employed CNNs in their respective schemes for dehazing underwater images. Yang and Sun [12] introduced a unique approach with the proximal dehaze-net, utilizing CNNs to learn proximal operators. Li et al. [13] addressed computational complexities by developing the U45 dataset and introducing a fused adversarial network for comprehensive underwater image enhancement. Their multi-term loss function effectively corrected colors, resulting in visually pleasing enhancements. Chen et al. [14] proposed an innovative approach by combining a revised image formation model with a CNN, incorporating rectified linear unit activation functions and dilated convolutions. This method enhances the network's fitting ability, producing dehazed images that preserve underwater scene details. However, challenges in color correction accuracy persist in this method.

D. Color Restoration

In the domain of underwater image enhancement, color restoration is a crucial aspect following haze removal, aiming to overcome color distortion induced by light absorption and scattering. Several studies have contributed significantly to addressing this challenge:

Li et al. [15] introduced a technique employing the CycleGAN framework for color correction in underwater images. Katherine et al. [16] devised a two-stage neural network architecture, distinctively handling image depth estimation and color correction. Fu and Cao [17] presented a neural network merging global and local information to enhance underwater images. Liu et al. [18] utilized a deep residual network combined with CycleGAN to generate artificial underwater images, emphasizing improvements in color correction and resolution enhancement. Lu et al. [19] employed a deep CNN with depth estimation in a light field imaging approach for color restoration. Hu et al. [20] proposed a Transmission Estimation Network (T-network) and a Global Ambient Light Estimation Network (A-network) for underwater image enhancement, focusing on color correction and addressing halo artifacts. Yu et al. [21] introduced a conditional generative adversarial network for underwater image restoration, utilizing a gradient penalty term and perceptual loss for improved visual quality through color restoration. Uplavikar et al. [22] developed an enhancement technique with domain-agnostic features, adapting to diverse underwater conditions. Li et al. [23] proposed a CNN-based image enhancement scheme using underwater scene priors, with a primary focus on color restoration by directly reconstructing latent underwater images. In the realm of white balance methods, Afifi and Brown [24] proposed a deep neural network using a CNN architecture for end-to-end training to correct white balance, mapping input images to two extra white balance parameters for accurate color correction. This method holds promise for underwater color restoration by training the model with a dataset encompassing white balance settings corresponding to underwater illumination.

IV. METHODOLOGY

The core idea of the proposed method is to use convolutional neural networks to form two deep learning models which are image formation model and white balance model and train the models to perform enhancement task.

A. Image Formation Model

Image formation model is designed by using CNNs to fit multiple components in the revised image formation model. Based on the equation (5), it can be further rewrite as

$$J_c(x) = (L_c(x) - L_c^{\infty})e^{\beta_c^D d} + L_c^{\infty} e^{(\beta_c^D - \beta_c^B)d} \qquad (6)$$

According to the research from Akkaynak & Treibitz (2018), the difference between β_c^D and β_c^B is very small and approximated as 0 at distances greater than 3m. Thus, equation (6) can again be approximated as

$$J_c(x) = (L_c(x) - L_c^{\infty})e^{\beta_c^D d} + L_c^{\infty} \qquad (7)$$

As shown in Figure 2, the framework of image formation model consists of three parts: backward scatter estimation module which to estimation L_c^{∞} in equation (7), direct-transmission estimation module uses to estimate $e^{\beta_c^D d}$ in equation (7) and reformation calculation to obtain the dehaze image, in which the influence of the underwater environment is eliminated.

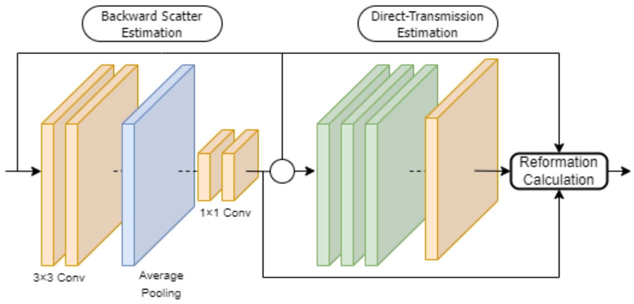

Figure 2. Framework of Image Formation Model

1) Backward Scatter Estimation Module

The backward scatter estimation module includes two groups of convolution layer with 3×3 kernel size, one adaptive average pooling layer and another two group of convolution layer with 1×1 kernel size. All the convolution layer designed with 3 input channels and 3 output channels. For the activation function of the convolution operation, the parametric rectified linear unit (PReLU) is chosen. The detailed structure is shown in Figure 3.

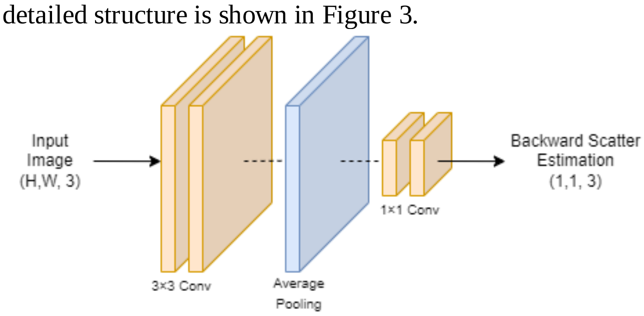

Figure 3. Backward Scatter Estimation Module

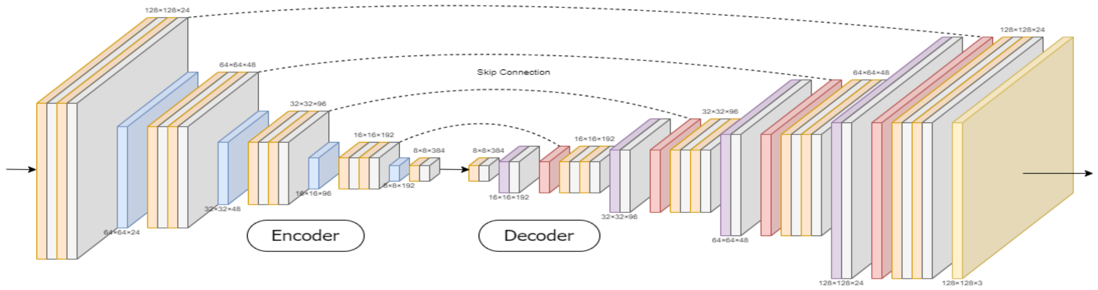

Figure 5. Framework of White Balance Model

2) Direct-Tranmission Estimation Module

The direct-transmission estimation module includes three groups of dilated convolutional layers with 3×3 kernel size and one group of normal convolutional layer with same kernel size. The first dilated convolutional layer designed with 6 input channels and 8 output channels and another two dilated convolutional layers designed with 8 input and output channel. The last layer consists of 8 inputs channels and 3 output channels. The concatenation of backscatter estimation with the input image will then pass into this module to compute the direct transmission mapping. The detail structure is shown in Figure 4.

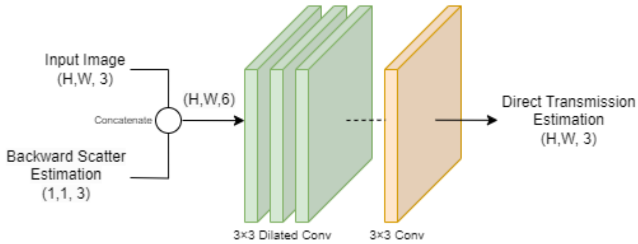

Figure 4. Direct-Transmission Estimation Module

B. White Balance Model

White Balance Model is also designed using CNNs in a U-Net architecture with multi-scale skip connections between encoder and decoders. As shown in Figure 5, the framework consists of two main units: first is a 4-level encoder that is responsible for extracting a multi-scale latent representation of input image; second part includes 4-level decoders. Each part has a different bottleneck and transposed convolutional layers.

1) Encoder

For the encoder part, it can be described as a reconstruction function to reverses the camera-rendered underwater colour image back to its corresponding raw colour image with the current WB setting applied. At the first level, the convolutional layers have 24 channels and the number of channels is doubled for the subsequent level where second, third and fourth level have 48, 86 and 192 channels respectively for each convolutional layer as illustrated in Figure 6. The latent representations will then pass to decoder unit.

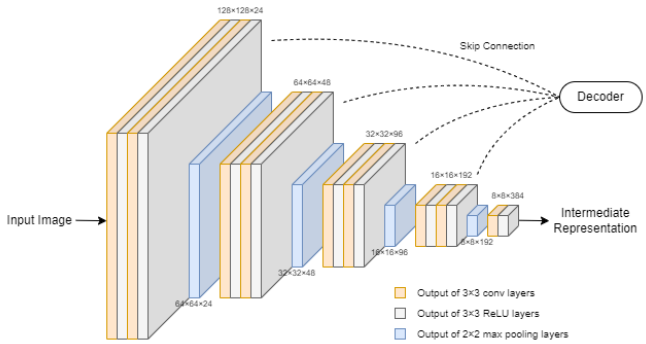

Figure 6. Encoder

2) Decoder

As displayed in Figure 7, Decoder part has the similar architecture with encoder but in reverse order. It will receive latent representation from encoder and act as an unknown camera rendering function that accepts it and renders it with the target auto WB setting to a RGB colour space encoding. The output is the enhanced image with correct WB setting.

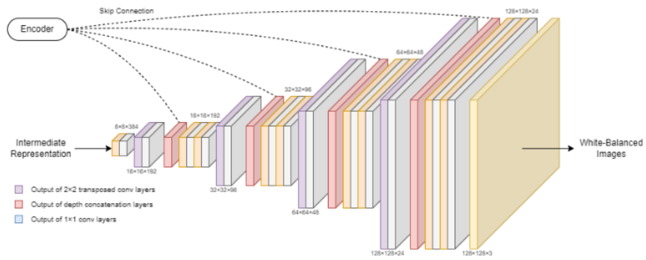

Figure 7. Decoder

C. Training Phase

1) Dataset

The underwater datasets used in the deep learning model training are the UIEB [13] and EUVP [25] dataset, which collects a large number of underwater images taken in real scene together with corresponding enhanced images obtained by variety of existing algorithms. The total number of underwater images used for training process is 3075 which 890 images from UIEB dataset and 2185 images from EUVP dataset.

2) Traning Parameters

For image formation model, the training process is performed for 3000 iterations (epochs) using the adaptive moment estimation (Adam optimizer), with batch size of 1, learning rate is 0.001 and 1 worker involved. The mean square error is used as loss function to calculate the difference between the enhanced image and target image. The mean square function is shown in Equation (8):

$$MSE = \frac{1}{MN}\sum_{i=0}^{M}\sum_{j=0}^{N}\left(I_{en}(i,j) - I_{ref}(i,j)\right)^2 \qquad (8)$$

where M and N are the numbers of rows and columns in the input images, i and j are the coordinates of a pixel in the input images, I_{en} is the enhanced image and I_{ref} is the target image.

On the other hand, the white balance model was trained with specific parameters: a batch size of 16, a learning rate set to 0.0001, 4 workers involved, and the training process spanned 3000 epochs. The loss function is calculated by using mean absolute error and the equation is expressed as

$$MAE = \frac{1}{MN}\sum_{i=0}^{M}\sum_{j=0}^{N}\left|I_{en}(i,j) - I_{ref}(i,j)\right| \qquad (9)$$

D. Testing Phase

The last procedure of the proposed method is color mapping. The white balance model is able to process input images in their original dimensions with the restriction that the dimensions should be multiple of 2^4, as the model is designed with 4 level encoder and decoder with 2×2 max pooling and transposed convolutional layers. Hence, all the inputs images will resize to a dimension of 656 pixel with original scale ratio to ensure a consistent run time for any sized input images [24]. The white balance model is applied on this resized image to produce down-sampled enhanced image. A colour mapping function, M is computed between resized input and enhanced output image and applied to the original input. The final output is obtained using the following equation:

$$I^e = M\psi(I^i) \qquad (10)$$

where I^e is enhanced image with original resolution, M is the mapping function between the resized input and enhanced output image and $\psi(I^i)$ is the polynomial kernel function of original input image.

In order to evaluate the effectiveness of the proposed method in this project, a total of 55 underwater which consists of 20 hazy images, 10 low contrast and sharpness images and 25 greenish and bluish images are chosen from UIEB dataset.

V. Result and Discussion

In the analysis of results, the effectiveness is evaluated in terms of visual quality and quantitative metrics. The results of the proposed method are compared with output from single model and ground truth.

A. Qualitative Results

For hazy images, the visual quality results of the proposed method are compared with the results of the image formation model, as shown in Figure 8. From the result, it is clear that both the image formation model and proposed method effectively reduced the hazy effect in the images. However, a closer look reveals that proposed method provides better visual clarity compared to the image formation model. While the image formation model still leaves some haze, proposed method produces clearer outputs.

For low contrast and sharpness images, the visual quality results of the proposed method are compared with the results of the two single models which are image formation model and white balance model, as shown in Figure 9. From the results, it is evident that both the image formation model and proposed method effectively enhance the contrast and sharpness of the underwater images. However, the white balance model performed slightly worse, as some images remained dark, and the edges were not clear enough. Comparing the outputs of the image formation model and the proposed method, the latter appears clearer, brighter, and with higher contrast, making the edges more discernible.

For greenish and bluish images, the visual quality results of the proposed method are compared with the results of the two single models which are image formation model and white balance model, as shown in Figure 10. The results indicate that both the image formation model and proposed method effectively remove the greenish and bluish effects in underwater images. However, the white balance model performed slightly less effectively, leaving some images with a small amount of greenish and bluish tone. Comparing the outputs of the image formation model and the proposed method, the latter shows superior performance in colour balancing, with most of the images appearing clear and restored in colour.

B. Quantitative Results

The quantitative metrics used in evaluate the result of underwater image enhancement can be divided into two categories: full reference metrics and non-reference metrics. Calculating full-reference metrics requires two images such as original image and enhanced image to enabling the calculation between these two images. The full reference metric used in this project is structural similarity index measure (SSIM). Non-reference metrics directly use the single processed image to calculate the color, contrast, sharpness, etc. and then combine them into one overall metric. Commonly used non-reference metrics include entropy, Patch-Based Contrast Quality Index (PCQI), underwater image quality measure (UIQM) and underwater color image quality evaluation (UCIQE).

For hazy images, Table 2 shows the average values of SSIM and Entropy obtained from each method and input image. It is evident that the proposed method achieves lowest SSIM value of 0.6268 and highest entropy value of 7.5553. This suggests that the proposed method is more effective at enhancing underwater images in terms of haze removal and produced high quality results compared to the image formation model. In summary, the proposed method is able to improve in haze removal effectiveness by approximately 15.38% in SSIM and 2.80% in entropy as compared to image formation model.

For low contrast and sharpness images, Table 1 shows the average values of PCQI and UIQM obtained from each method and input image. It shown that the proposed method achieves highest PCQI value of 1.3703 and highest UIQM value of 1.1896. This indicates that the proposed method is more successful in enhancing underwater images by improving contrast and sharpness, resulting in high-quality outcomes compared to the image formation model and white balance model. In summary, the proposed method demonstrates an enhancement in improving contrast and sharpness of the image by approximately 4.67% in PCQI and 5.22 % in UIQM as compared to image formation model.

For greenish and bluish images, Table 3 shows the average values of UCIQE obtained from each method and input image. It is evident that the proposed method achieves highest value of 79.3077. This suggests that the proposed method is more effective in removing the greenish and bluish effects, as well as in colour balance and colour restoration, resulting in high-quality underwater colour images compared to the image formation model and white balance model. In summary, the proposed method demonstrates an enhancement in restoring and balancing the colour in the image by approximately 2.69% in UCIQE as compared to image formation model.

Table 1. Summary of SSIM and Entropy of Proposed System for Hazy Images

Metrics	SSIM	Entropy
Input	1.0000	6.3342
IF	0.7408	7.3498
Proposed	**0.6268**	**7.5553**

Table 2. Summary of PCQI and UIQM of Proposed System for Low Contrast and Sharpness Images

Metrics	PCQI	UIQM
Input	1.0543	0.6810
IF	1.3092	1.1306
WB	1.1858	0.9283
Proposed	**1.3703**	**1.1896**

Table 3. Summary of UCIQE of Proposed System for Greenish and Bluish Images

Metrics	UCIQE
Input	54.6248
IF	77.2292
WB	73.0024
Proposed	**79.3077**

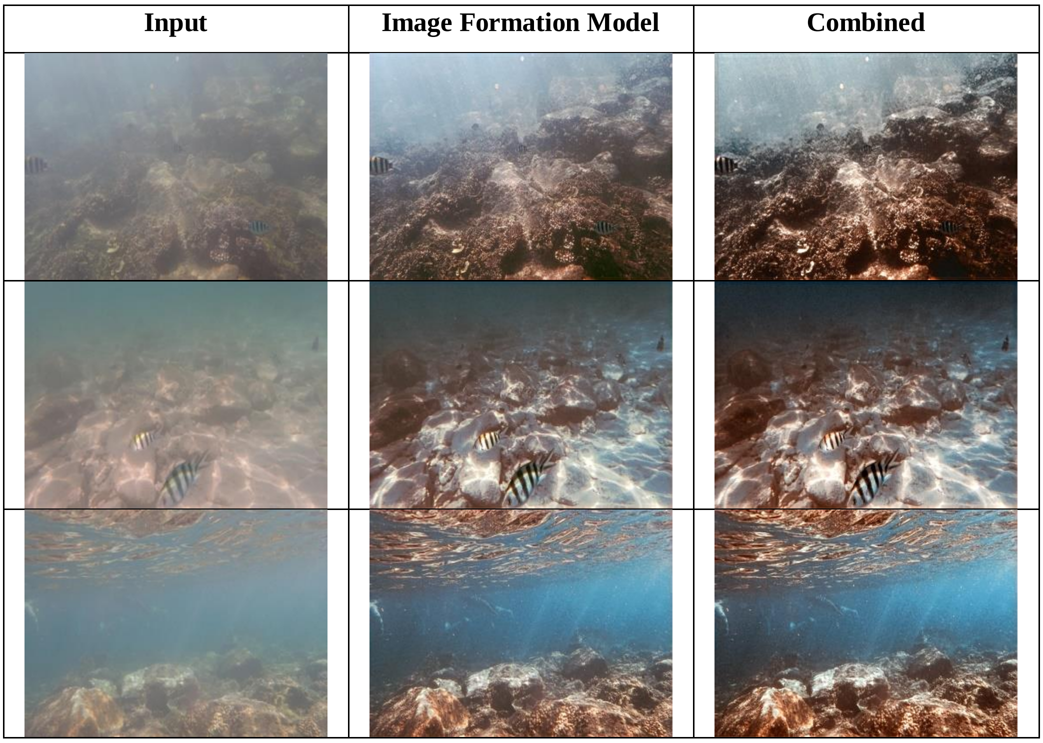

Figure 8. Visual Quality Results of Proposed System for Hazy Images

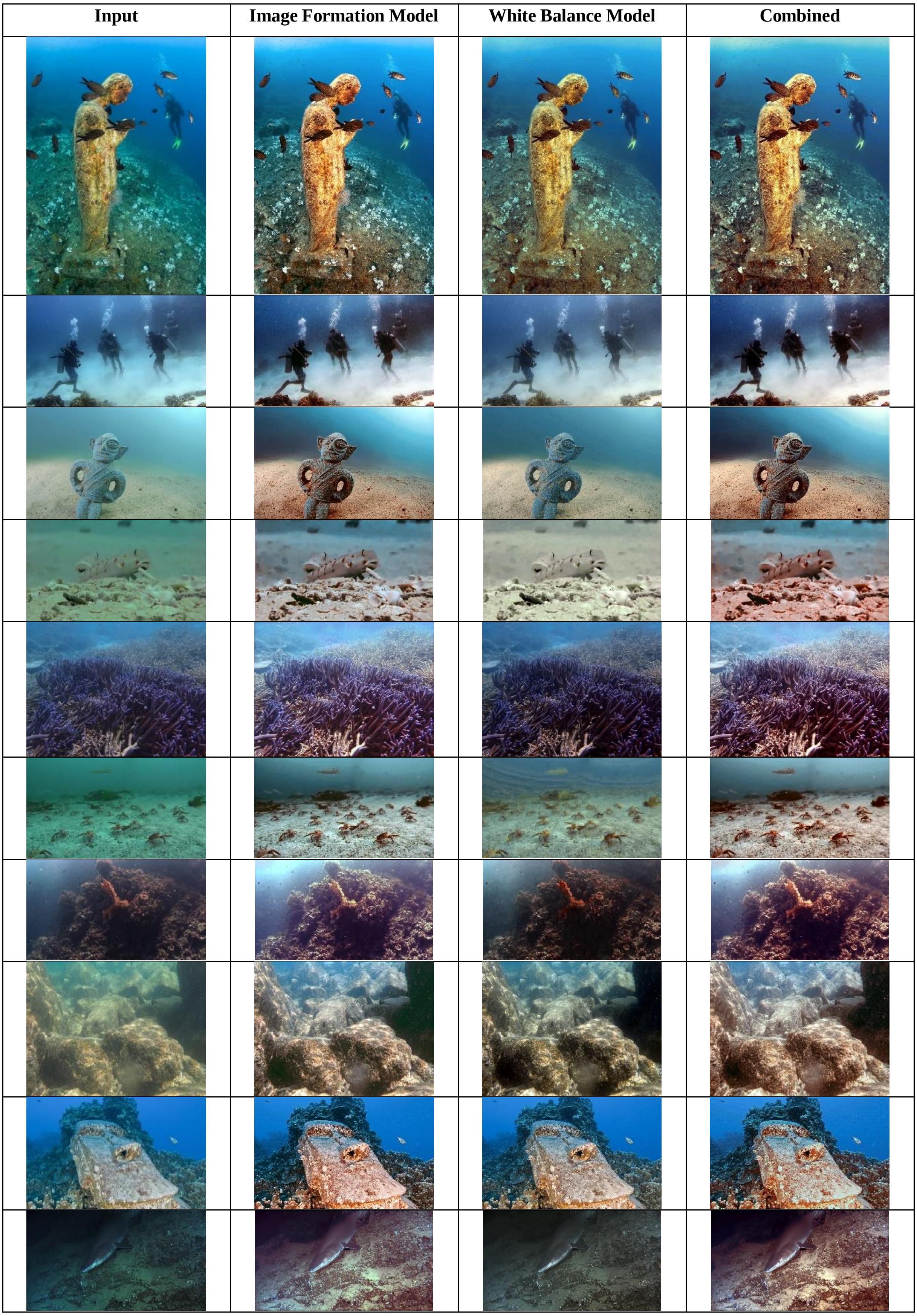

Figure 9. Visual Quality Results of Proposed System for Low Contrast and Sharpness Images

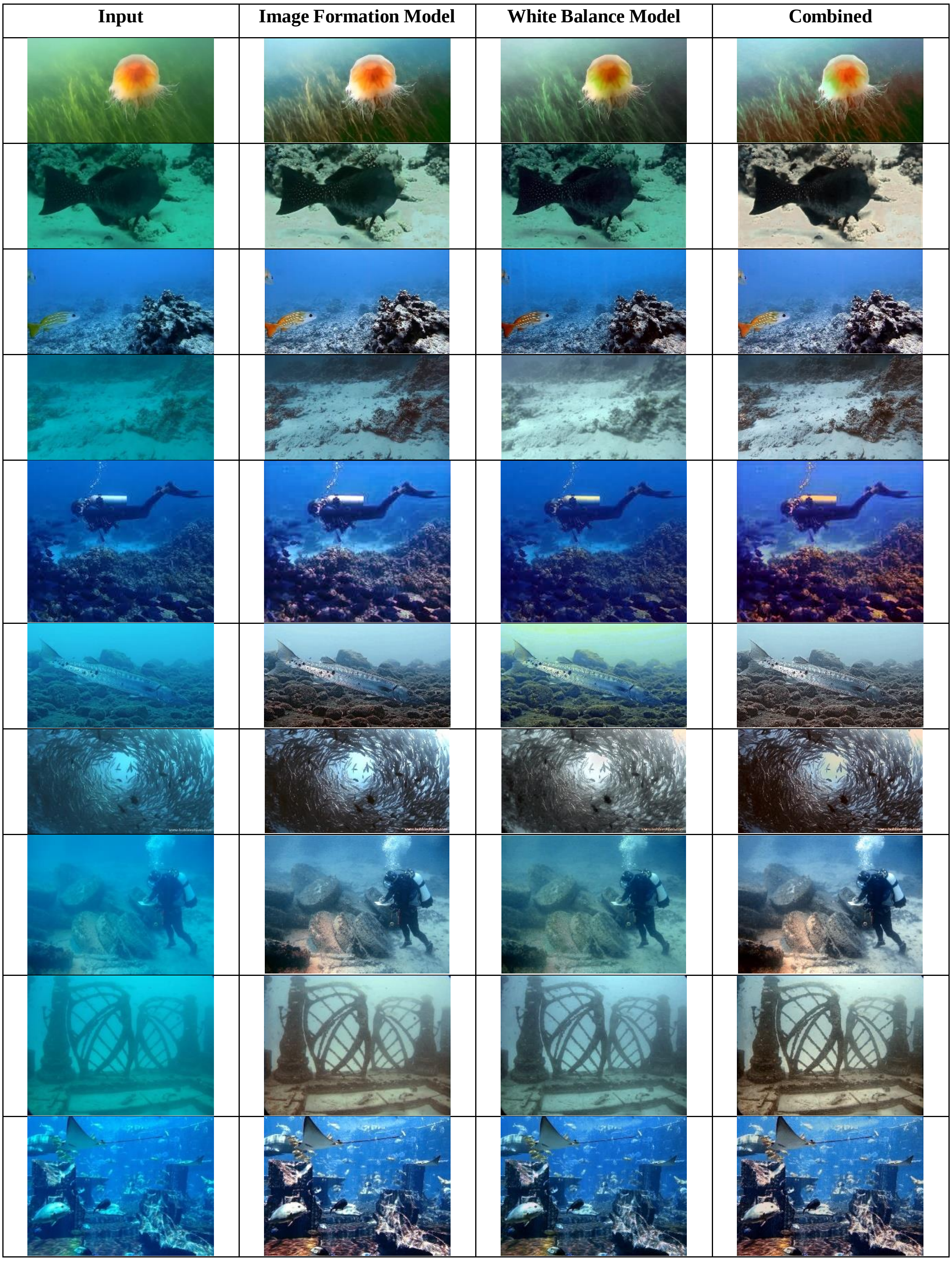

Figure 10. Visual Quality Results of Proposed System for Greenish and Bluish Images

VI. CONCLUSION

In this paper, a deep learning-based underwater image enhancement system was proposed and implemented. The primary objective was to achieve high-quality underwater images, driven by the fact that the existing underwater image enhancement is still in a developmental stage and lacks comprehensiveness. Hence, the proposed system leverages a convolutional neural network in both the image formation and white balance model, combing them sequentially. The proposed method achieves good underwater image enhancement results, with improvements in both visual quality and quantitative metrics compared to existing methods in term of haze removal, increase contrast and sharpness and color balance and restoration.

In the pursuit of advancing the proposed image enhancement system for underwater images, future research endeavors are directed towards addressing identified limitations and enhancing the model's efficacy. A key focus lies in the integration of the image formation and white balance models into a unified framework, aiming to streamline processes, enhance computational efficiency, and improve adaptability. This integration seeks to simplify parameter tuning, mitigate challenges associated with managing separate models, and demonstrate a more effective approach to underwater image enhancement. Additionally, recognizing the scarcity of diverse underwater datasets, future investigations aim to explore the impact of incorporating varied datasets encompassing different underwater scene environments. By exposing the model to a broader range of scenarios, including diverse lighting conditions, water clarity levels, and underwater terrains, the objective is to empower the model with a more comprehensive understanding of the complexities inherent in the underwater environment. This approach is anticipated to enhance the model's ability to navigate diverse underwater conditions, resulting in a more nuanced and effective image enhancement process.

ACKNOWLEDGEMENT

The authors would like to acknowledge to those who are directly or indirectly involved in the process of completing this final year project.

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