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Conference Paper · February 2022

DOI: 10.1109/ICARC54489.2022.9753886

Anparasy Sivaanpu
University of Vavuniya

Kokul Thanikasalam
University of Jaffna

Amirthalingam Ramanan
University of Jaffna

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Anparasy Sivaanpu
Department of Computer Science
University of Jaffna
anpusuji@gmail.com

Rasika Priyadarshani
Department of Computer Science
University of Jaffna
akh.rasika.priyadarshani@gmail.com

Thanikasalam Kokul
Department of Computer Science
University of Jaffna
kokul@univ.jfn.ac.lk

Amirthalingam Ramanan
Department of Computer Science
University of Jaffna
a.ramanan@univ.jfn.ac.lk

Abstract—**Underwater images in high quality are important for many applications but they are often in poor quality since they suffer from fog, low brightness, colour distortion, and reduced contrast. Underwater image quality is degraded with the depth of the water since the red light is absorbed more than blue and green lights and the light is scattered by the suspended particles. Although several traditional and deep learning based approaches are proposed to enhance and restore the image, producing a high quality enhanced image with natural colour is still challenging. In this paper, a novel convolutional neural network architecture is proposed and it has two identical branches to input a raw degraded image and a colour balanced image. Dense blocks are utilized to train the model with fewer parameters. In addition, skip connections are introduced over the dense blocks to preserve the spatial information. The proposed approach is evaluated on publicly available UIEB dataset and shows 28.67 of PSNR value, and 0.89 of SSIM index, which are better than the state-of-the-art approaches.**

Keywords—Underwater Image Enhancement, Convolutional Neural Network, Deep Learning, Skip Connections.

I. Introduction

Underwater images are widely used to explore and analyse the underwater environment. Quality of underwater images are always poor since they have a foggy appearance, low brightness, colour distortion, uneven illumination, and reduced contrast. Due to the poor quality, obtaining useful features and information from underwater images is difficult for many applications such as underwater archaeology [1], underwater species identification [2], inspection of underwater cables [3] and infrastructures [4] and control of submarines and Autonomous Underwater Vehicles (AUVs) [5]. Although several hardware equipment [6] are used for underwater image enhancement, they are expensive and need expert knowledge and training. Therefore, over the past few years, computer vision based automated approaches are widely used for underwater image enhancement.

Several factors diminish the quality of underwater images. In underwater, red light is absorbed more faster since its wavelength is higher than other lights [7]. Therefore, natural colour information is always missing in underwater images since these images are often in a bluish or greenish colour in most situations. Further, depth and water type also causes colour distortion in underwater images. In addition, suspended particles [8] in underwater changes the light propagation direction and hence produces a foggy appearance in underwater images with low contrast. Moreover, due to the camera motion [9], underwater images suffer from noise and blurring effects. Fig.1 shows a set of underwater images with various degradation issues.

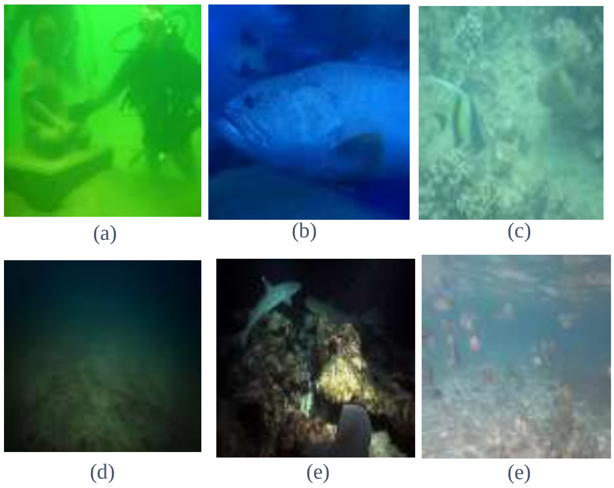

Fig. 1: Illustration of underwater images with various degradation issues. (a) greenish image. (b) bluish image. (c) blurred image. (d) low brightness image. (f) uneven illumination image. (f) low contrast image.

Underwater image enhancement is a well-known problem in computer vision and numerous solutions have been developed in recent years using traditional and deep learning based techniques. Traditional approaches can be grouped as enhancement methods and restoration methods based on the technique they have used. Traditional image enhancement based methods are focused to improve the visual quality of underwater images using simplified image processing techniques such as Gamma correction [10] and colour balancing [10, 11]. Although these approaches are able to recover the natural colours, their overall results are poor because they do not account for light propagation in underwater.

Image restoration based traditional approaches [12-14] analyse the light propagation and transmission in underwater and then propose a scattering model to restore the details. In these approaches, scene depth is important to estimate the transmission and light propagation and hence these methods rely on some prior assumptions [14, 15] since estimating the depth of a scene from a single image is not an easy task. Since these approaches are more complex and hence inflexible to implement for real-world applications.

Recent approaches rely on deep learning based techniques to enhance the underwater images. In these approaches

[16-18], end-to-end Convolutional Neural Network (CNN) architectures are used to calculate the transmission and to restore the details in underwater images. Due to the lack of a huge quantity of training data, CNN based underwater enhancement approaches are struggling to generalize the model through a large number of parameters. In a few approaches [8, 9, 19, 20], synthetic images and Generative Adversarial Network (GAN) are used to manage the training data deficiency. Although these approaches showed significant performance improvement in underwater image enhancement, they assume the transmission is same in all three channels of a degraded underwater image, hence their colour restoration capability is poor than traditional image enhancement techniques.

Traditional image enhancement approaches are inadequate at recovering details but can produce images with more natural colours. On the contrary, deep learning based approaches are able to recover the details but are poor in colour restoration. To obtain an image with more recovered details and natural colours, we propose a novel dual-CNN architecture for underwater image enhancement. We feed a raw degraded image and a colour balanced image of that raw image to the network to produce an enhanced image with natural colours and more details. The proposed network architecture has two CNN branches in the front to capture the features of raw and colour balanced images and then the enhanced image is produced by combining the features of these branches. In addition, skip connections are introduced in between the layers to speedup the model convergence and preserve the spatial information. The proposed approach is compared with state-of-the-art approaches on a publicly available benchmark dataset and outperforms them significantly. Moreover, a comprehensive ablation study is conducted to demonstrate the efficacy of the proposed CNN architecture.

II. Related Work

In recent years a few deep learning based approaches and several traditional approaches are proposed for underwater image restoration and enhancement. In this section, the most relevant and recent literature are reviewed. Experimental reviews on underwater image enhancement and restoration can be found in [7, 21].

Traditional image enhancement approaches are intended to improve the visual quality of underwater images by using various colour correction techniques with different colour models, and contrast adjustment algorithms such as histogram equalization and Gamma correction. Majority of the model-free approaches produce enhanced images with more realistic and natural colours. Ancuti et al., [10] used white balancing and Gamma correction with an image sharpening technique. Fu et al., [11] used colour correction and contrast balancing algorithms for underwater image enhancement. Sanila et al., [22] used white balancing to enhance the contrast of underwater images. Based on the inspiration of the human visual system, Zhang et al., [23] proposed an approach using bilateral filter and trilateral filter to enhance the colours of images. An adaptive contrast enhancement is proposed by Zhang et al., [24]. Sophiya and Gisha [25] used a white balancing technique to improve the colours of an image. Marques and Albu [26] generated two images using contrast adjustment and darkness removal algorithms and then combined them using a multi-scale fusion technique. Since image enhancement based traditional approaches use simple and pixel-wise calculations, they are easy to implement, computationally efficient and hence suitable for real-time applications. Although these approaches enhance the image to some extent, their image enhancement performance is inadequate as they produce under or over enhanced scenes in some situations.

Image restoration based traditional approaches are objective to recover the details in an underwater image. These approaches consider the physical features of light propagation in underwater and then identify the important parameters of light scattering such as attenuation and transmission map to construct an image degradation model. Since the light propagation in underwater and foggy scenes are similar, several defogging techniques [27, 28] are applied for underwater image restoration. Based on the observation that red light is absorbed more in underwater than the green and blue lights, Galdran et al., [12] developed a restoration approach. Peng et al., [13] recovered the images by estimating the distance between camera and objects based on the blurriness in image scenes. Jiang et al., [29] transferred the learned knowledge from image defogging to underwater restoration through a domain adaptation technique. Liu and Liang [30] estimated the underwater light by using wavelength-dependent attenuation and then calculated the transmission in each colour channel. Lee et al., [31] used a super-pixel based dark channel prior technique. Yao and Xiang [32] estimated the ambient light in underwater by using the difference between blue and red lights. Based on the observation of blurriness in images, Peng and Cosman [33] estimated the depth of scenes and light absorption. Image restoration performance of these approaches are dependent on accurate depth estimation of scenes. Since the depth calculation from a single image is difficult, most of these approaches rely on some assumptions and prior knowledge. In addition, since these approaches are dependent on many physical parameters they are difficult to implement and inappropriate for real-time tasks.

Recently many researchers use end-to-end deep learning techniques to train a model for underwater image enhancement and restoration. Differing from traditional approaches, deep learning based approaches are not estimating any light propagation parameters and are able to enhance raw underwater images. Guo et al., [34] obtained the confidence maps using a gated fusion CNN and then fused it with the degraded image to obtain the enhanced image. Li et al., [35] proposed a light-weighted CNN architecture using synthetic and real-world images. A conditional Generative Adversarial Network (cGAN) is utilized by Yang et al., [9] to produce natural enhanced images. Islam et al., [17] proposed a residual network based generative CNN architecture which is able to restore the contrast and other details in higher resolution images. In [19], a cycle consistent adversarial network is trained in a weakly supervised manner. A multiscale dense GAN architecture is proposed by Guo et al., [8] for underwater image enhancement. Cho and Kim [36] proposed an autoencoder CNN architecture with skip connections between front and deeper layers and then evaluated the performance on a synthetic image dataset. Training data deficiency is the major limitation in deep learning based approaches since a massive underwater image dataset is not yet available. Due to this limitation, most of these approaches are still struggling to improve the image quality beyond some extent. Moreover, since the spatial information is lost in deeper CNN layers, most of the deep

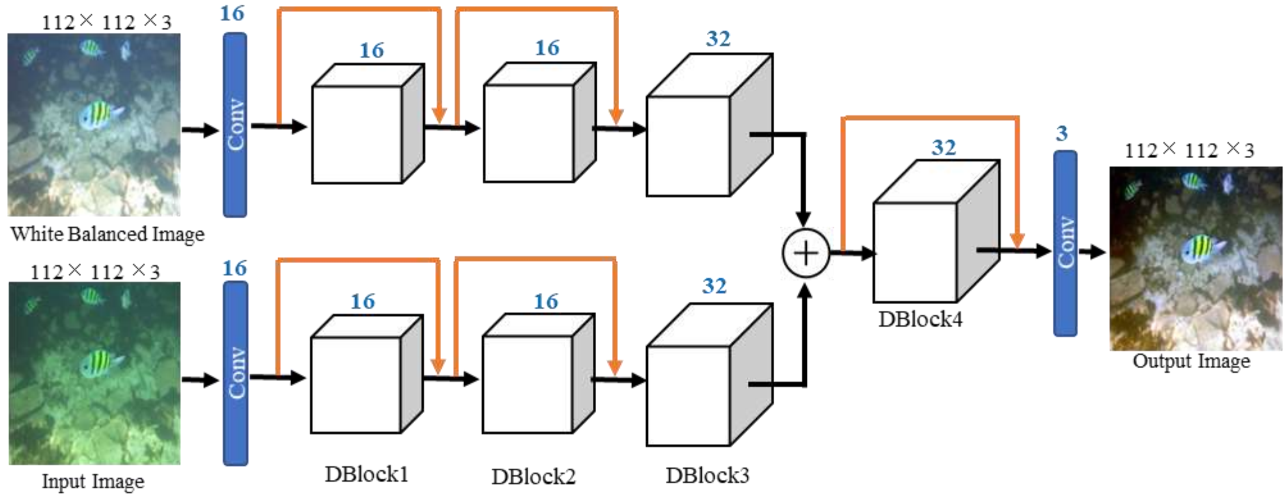

Fig. 2: Proposed network architecture. It inputs raw degraded image and white balanced image and produces an enhanced image as the output. It has two identical branches and each branch has three dense blocks (DBlock) with skip connections (denoted in orange). Output of both branches are added using an element-wise addition operation. Number of feature channels are denoted on the top of each convolutional and dense blocks.

learning based approaches produce an enhanced image with unnatural colours.

To overcome the drawback of deep learning based underwater enhancement approaches, a novel CNN architecture is proposed and that is able to produce high quality enhanced images with realistic colours by using training samples.

III. Methodology

The proposed CNN architecture for underwater image enhancement produces enhanced images with realistic and natural colours. Raw degraded images and its colour balanced image are fed to the proposed network architecture. The proposed network architecture has two identical CNN branches to capture the hierarchical features of raw and colour balanced images as shown in Fig.2. We have utilized the Dense CNN blocks [37] in these branches as they are able to generalize the model using fewer training samples. In addition, the proposed network architecture has several skip connections in between the dense blocks to optimize the CNN architecture with a fewer number of parameters. We justify the design of the proposed network architecture through a detailed ablation study.

A. Data Pre-processing

In the preliminary step of this study, degraded underwater images and corresponding reference (non-degraded) images (non-degraded) are collected from a publicly available benchmark dataset. Then the bilinear interpolation technique is utilized to resize the images to a fixed size (112 × 112).

B. Colour Balanced Image generation

It is noted that CNN based underwater image enhancement approaches are struggling to produce enhanced images with realistic and natural colours [7]. Since raw underwater images are always in bluish or greenish colours, CNN based approaches faced difficulties to produce an enhanced image with natural colours. To solve this issue, we feed raw and colour balanced image to the proposed network architecture to produce a better enhanced image.

We have used a colour balancing technique to generate the colour balance image from the raw image. It is noticed that green channel is preserved better than other two channels in an underwater image [10]. By assuming all channels should have the same mean in enhanced image, we used the following equation to produce a colour balanced image (I^{cb}) from the raw image I^{raw}.

$$
\begin{aligned}
I_r^{cb}(x) &= I_r^{raw}(x) + \beta.\left(\bar{I}_g^{raw} - \bar{I}_r^{raw}\right) \times \\
&\quad (1 - I_r^{raw}(x)).I_g^{raw}(x)\,, \\
I_b^{cb}(x) &= I_b^{raw}(x) + \beta.\left(\bar{I}_g^{raw} - \bar{I}_b^{raw}\right) \times \\
&\quad (1 - I_b^{raw}(x)).I_g^{raw}(x)
\end{aligned}
\tag{1}
$$

where $\bar{I}_r^{raw}$, $\bar{I}_g^{raw}$ and $\bar{I}_b^{raw r}$ are the mean of red, green and blue channels of a raw image, respectively. β is a parameter

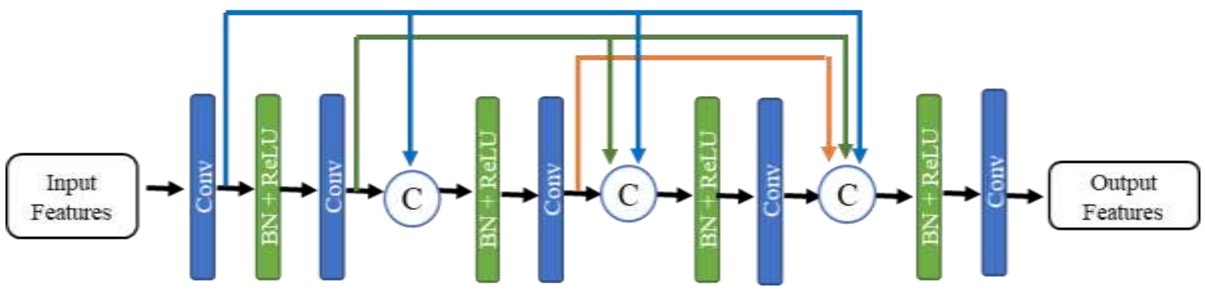

Fig.3: An illustration of the Dense Block (denoted as DBlock in Fig.2). In a block, all convolutional layers are having equal number of feature channels and same size of kernels. The © notation denotes concatenation operation.

and is set empirically to a fixed value throughout the experiment.

C. Proposed Network Architecture

The proposed network architecture has two identical CNN branches. Raw degraded image and corresponding colour balanced image pairs are fed to these branches. As shown in Fig.2, these two separate CNN branches are combined in deeper layers and then the combined features are captured using a few more convolutional layers. Each branch takes the input images with the size of 112×112×3 and then the proposed network architecture produces the enhanced image with the same size of inputs.

The proposed network architecture has a convolutional layer in the front of each branch and which has 16 filters with the kernel size of 5×5. As shown in Fig.2, the proposed network architecture has three dense blocks in each branch and one dense block in combined network. As shown in Fig.3, each dense block of the proposed network architecture has four convolutional layers. Within a particular dense block, all convolutional layers have the same number of filters with equal kernel sizes. Batch normalization is introduced in between convolutional layers and Rectified Linear Unit (ReLU) function is used to activate the features. Similar to the DenseNet [37] model, within a dense block, the n^{th} layer obtains the feature maps of all previous layers $(f_1, f_2, \dots, f_{n-1})$ and then applies a non-linear transformation function $H_n(.)$ to produce the output feature map f_n as follows:

$$f_n = H_n\left([f_1, f_2, \dots, f_{n-1}]\right) \qquad (2)$$

where $[f_1, f_2, \dots, f_{n-1}]$ denotes the feature maps concatenation operation of the layers $1, 2, \dots, n-1$. As denoted in Fig.2, first two dense blocks in each branch have 16 filters while remaining dense blocks have 32 filters. After the three dense blocks, the final output feature maps of raw image branch $(f^{raw}_{m\times m\times c})$ and colour balanced image branch $(f^{cb}_{m\times m\times c})$ are added to produce the combined feature map $(f^{C}_{m\times m\times c})$ as follows:

$$f^{C}_{m\times m\times c} = f^{raw}_{m\times m\times c} \oplus f^{cb}_{m\times m\times c} \qquad (3)$$

where $\oplus$ denotes element-wise addition operation. After this addition process, a dense block is used to capture the information from combined features. Finally, at the end of the proposed network architecture, a single convolutional layer is used to produce the enhanced image. In the proposed network architecture, spatial dimension of the feature maps is kept to be 112×112 in the convolutional layers and dense blocks.

We noticed that the proposed architecture is struggling to optimize the model and takes too much of epochs to achieve an optimal network. Also, spatial information is diluted in deeper layers and which is important for image restoration. To solve these issues, we introduced the skip connections (shown as yellow in Fig.2) in between the dense blocks in branches and combined network of the proposed architecture. Since these skip connections are concatenating front and end dense blocks, spatial information of input images is preserved and also the model is optimized within fewer epochs.

D. Training

The proposed network architecture is trained for a fixed number of epochs and the best performing model is used for testing. In each epoch, a set of raw images (I^{raw}) and colour balanced images (I^{cb}) are fed to the proposed network architecture and then the obtained output (I^{out}) is compared with the undegraded reference (I^{ref}) image. The Mean Square Error (MSE) loss function is used to measure error in each iteration as follows:

$$\text{MSE} = \frac{1}{s \times s}\sum_{i=1}^{s}\sum_{j=1}^{s}\left[I^{out}_{(i,j)} - I^{ref}_{(i,j)}\right]^2 \qquad (4)$$

where s is the size of the image. During training, all hyper parameters are tuned based on the validation results.

IV. Experimental Setup

A. Implementation Details

We have utilized the Keras library in Google Colab platform to implement the methodology. An NVIDIA K80 GPU is used in the experiments. The Adam optimization function is used with the learning rate of 0.001. The proposed architecture is trained for 30 epochs with the batch size of 16. The code of this work is publicly available at https://github.com/RPRO5/Deep-Learning-based-UIE.

B. Dataset

Until recently, evaluating the performances of underwater images was a challenging task since the benchmark datasets have no reference images. Therefore, synthetic images are used in the evaluation even though their outputs are unnatural. Recently, the Underwater Image Enhancement Benchmark (UIEB) Dataset [34] was constructed with 890 real-world images and corresponding undegraded reference images. In this dataset, all the images are in the size of 640 × 480. Similar to other researchers, we used the first 800 images for training and the remaining images for testing as to compare the performances. Also, we have used 20% of training images for validation.

C. Evaluation Criteria

To test the performance of the proposed approach, we employed the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) as metrics. SSIM metric is used to compute the similarity between the reference image (I^{ref}) and output image (I^{out}) based on the contrast, luminance, and structure. It is calculated as:

$$\text{SSIM} = \frac{(2\mu_r\mu_o + C_1)(2\sigma_{ro} + C_2)}{(\mu_r^2 + \mu_o^2 + C_1)(\sigma_r^2 + \sigma_o^2 + C_2)} \qquad (5)$$

where μ_r and μ_o are the mean of reference image and output image, respectively. σ_r^2 and σ_o^2 are the variance of reference and output image, respectively. C_1 and C_2 are the variables. PSNR metric is used to measure the similarity between I^{ref} and I^{out} based on their pixel values. PSNR is computed as:

$$\text{PSNR} = 10\,log_{10}\left(\frac{MAX^2_{I^{ref}}}{MSE}\right). \qquad (6)$$

where $MAX_{I^{ref}}$ is the maximum intensity value in the reference image. We used the Equation 4 to compute the MSE. A higher SSIM and PSNR values denotes that reference image is much close to the output image.

D. Ablation Studies

Efficiency of the proposed enhancing method is mainly dependent on the CNN architecture. Therefore, we conducted an ablation study to verify the proposed CNN architectural design. The test data of the UIEB dataset is used in this study.

The proposed network architecture has two identical CNN branches and it inputs raw and colour balanced images. To justify the design of dual CNN architecture, we evaluated the performance of single networks with single inputs.

TABLE 1: PERFORMANCE COMPARISON OF NETWORK BRANCHES

Network Design	PSNR	SSIM
Single network, input: raw image	28.32	0.79
Single network, input:colour balanced image	28.40	0.82
Dual network, input: raw and colour balanced image	**28.67**	**0.89**

The proposed dual network design gains knowledge by combining raw and colour balanced images using the dual CNN architecture, according to the evaluation results in Table 1.

We utilised the dense blocks in the proposed dual network design. While all previous layers are directly connected with a layer in a dense block, a non-dense block has not any such connections. In both settings, the number of convolutional layers and other parameters are kept the same. Table 2 summarizes the evaluation results of the proposed network architecture *with* and *without* the dense blocks.

TABLE 2: EFFECTIVENESS OF DENSE BLOCKS

Network Design	PSNR	SSIM
Without dense blocks	28.19	0.75
With dense blocks	**28.41**	**0.87**

Based on the results, it can be clearly seen that dense blocks significantly contribute to enhance the performance.

In addition to the dense blocks, we have introduced skip connections over the dense blocks to preserve the spatial information and to optimize the model with fewer number of parameters. Table 3 justifies this design with other network settings.

TABLE 3: EVALUATION WITH AND WITHOUT SKIP CONNECTIONS

Network Design	PSNR	SSIM
Without skip connections over the dense blocks	28.41	0.87
With skip connections over the dense blocks	**28.67**	**0.89**

E. Testing Results

We evaluated the enhancement performance of the proposed approach on the UIEB dataset. Similar to other researchers, the first 800 images are used for training and the remaining are used for testing. We compared the performance with several deep learning based approaches [8, 17, 19, 34, 35, 38, 39] and traditional approaches [10, 25, 26, 31-33]. Table 4 provides the comparison.

TABLE 4: COMPARISON WITH STATE-OF-THE-ART APPROACHES

Approach	PSNR	SSIM
Guo et al., (2019) [8]	17.28	0.44
Guo et al., (2018) [19]	15.75	0.52
Peng and Cosman (2017) [33]	14.01	0.53
Islam et al., (2017) [17]	16.65	0.57
Yao and Xiang (2018) [32]	12.80	0.65
Yang et al., (2020) [39]	17.72	0.66
Anwar and Porikli (2020) [35]	19.51	0.73
Ancuti et al., (2018) [10]	19.60	0.76
Guo et al., (2019) [34]	19.11	0.80
Sharma et al. (2021) [38]	21.57	0.80
Marques and Albu (2020) [26]	20.33	0.80
Lee et al., (2020) [31]	18.60	0.85
Sophiya Philip (2019) [25]	21.45	0.87
Proposed approach (Ours)	**28.67**	**0.89**

The proposed approach clearly outperforms state-of-the-art approaches in underwater image enhancement, as demonstrated by the experimental findings. In addition to the quantitative comparison, we have compared the performance using few real-world images. Fig.4 compares the qualitative comparison with other four best performing approaches. Proposed method produces the enhanced image with realistic and natural colours than the other approaches as shown in this figure.

V. CONCLUSION

In this paper, we proposed a novel CNN architecture for underwater image enhancement. It has two identical CNN branches to input raw degraded image and the corresponding colour balanced image. The dense blocks are utilized in the proposed network to optimize the model with fewer number of parameters. In addition, skip connections are introduced in between the layer blocks to preserve the spatial information throughout the network. A detailed ablation study is conducted to justify the network design. The proposed model

(a) (b) (c) (d) (e) (f)

Fig.4: Qualitative comparison with other best performing approaches. (a). Degraded raw image. (b) Sophiya Philip [25] ‘s output. (c) Lee et al., [31]’s output, (d) Marques and Albu [26] ‘s output. (e) Sharma et al.[36] ‘s output. (f) output of proposed approach.

is evaluated on UIEB dataset and showed 28.67 PSNR and 0.89 SSIM index.

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