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Dark Lighter Pro-Net: A Deep Learning Model for Enhancement of Low Light Underwater Images

Divya Midhunchakkaravarthy[1], Katakam Ranganarayana[1*], Vejendla Lakshman Narayana[2]

[1] Department of Computer Science and Engineering, Lincoln University College, Petaling Jaya 47301, Malaysia
[2] Department of Computer Science and Engineering, Vignan's Nirula Institute of Technology and Science for Women, Guntur I522009, India

Corresponding Author Email: katakamranganarayana@gmail.com

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ABSTRACT

Numerous real-time applications, such as underwater object detection, security and surveillance, autonomous underwater vehicles, and marine life monitoring, have benefited from newly developed methods for enhancing the quality of images. This research focuses on Low Light Underwater Images (LLUWIs) during processing. Light absorption in water causes most underwater images to exhibit low-level illuminations, color distortion, and noise. New deep learning-based methods have been developed to improve image quality. To address this issue, this research presents a model called Dark Lighter Pro-Net (DLPN). For the purpose of improving low-light images, DLPN is a model based on CNN. A unique feature of DLPN is its hybrid design, which integrates attention modules to improve darker areas, physics-driven restoration to fix color distortions, and residual refinement to maintain small details throughout the process. This integration ensures an improvement process that outperforms both traditional and deep learning-based methods for improving underwater images. The proposed model outperforms both raw LLUWI and previous models in terms of the Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR). The specific PSNR gain achieved by DLPN is 31.6 dB (from 5.28 dB to 36.92 dB), and the SSIM improvement is 63.5% (from 0.262 to 0.90). With its perceptual quality and consistently higher quantitative results, DLPN outperforms state-of-the-art approaches like WaterNet, Physical model Guided Generative Adversarial Networks (PUGAN), and Ard-GAN. The proposed model outperforms the current model, confirming the algorithm's robustness. The proposed enhancement model significantly improves the visual quality of the images.

1. INTRODUCTION

The water holds a wealth of useful materials. vice maintenance, object detection, search and salvage, and image processing are all operations that rely on underwater images [1]. Due to the presence of suspended particles and the attenuation of light under water, the underwater optical images exhibit poor quality. These defects include color distortion, low contrast, and blurred details [2]. Improving and restoring the deteriorating underwater pictures is necessary to acquire more underwater information [3].

Nevertheless, capturing clear, detailed underwater images isn't without its challenges. Color shifts, distorted details, and reduced contrast are common complaints from underwater images as a result of light dispersion and the challenging underwater conditions [4]. Clearness, color accuracy, and sharpness are all negatively affected, especially in murky or deep water conditions [5]. Consequently, Underwater Image Enhancement (UIE) techniques are vital for improving underwater image quality, providing clearer pictures for uses like monitoring and inspections.

There was a time, over a decade ago, when most methods for improving underwater images relied on physical models or did not use physical models at all [6]. But when convolutional neural networks first came out, researchers started to pay more attention to deep learning-based UIE techniques. Using historical data to estimate the parameters utilized in image generation, physical-model-based approaches can increase the quality of underwater images by turning the physical process backwards [7]. However, due to the ever-changing nature of the marine environment, these stated traits may not be applicable in all situations [8]. To increase features like brightness, saturation, and contrast, most non-physical model-based techniques use image processing to change the pixel values [9].

Although these methods work, they have numerous drawbacks, such as being very conditional, losing information, experiencing color shifts, and having trouble restoring visual attributes that have been lost [10]. Improved underwater photography is a direct result of the widespread use of deep learning techniques, which have proven effective in fields such as high-resolution images, segmentation, and object recognition [11]. In this domain, Generative Adversarial Network (GAN) and Convolutional Neural Network (CNN) architectures are king when it comes to deep learning models [12]. In order to directly comprehend the connection between real and degraded images from training data, they make use of their powerful fitting skills [13]. Many issues remain unresolved in UIE that relies on deep learning, despite considerable progress in this area [14]. Uneven augmentation may result from the fact that most existing approaches focus on improving images in the spatial domain, which is where most underwater images are degraded [15]. As a result, there may be cases where the image's brightness is increased at the cost of noise, or where the image's clarity is diminished to improve color restoration [16]. The capturing of underwater images is a difficult task, and the process of underwater image capturing and its effects are shown in Figure 1.

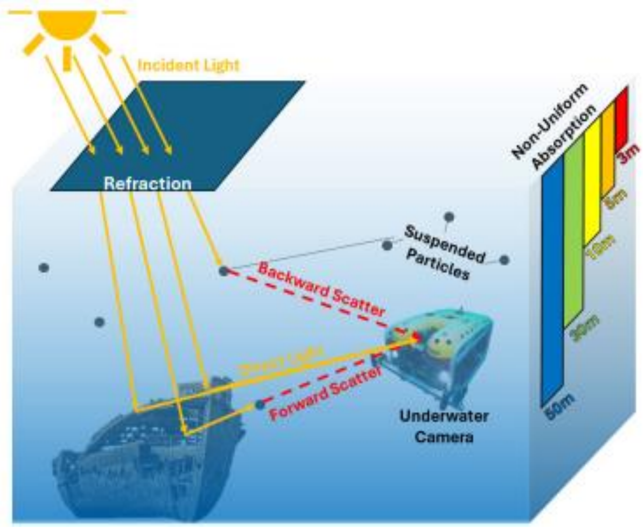

Figure 1. Underwater image capturing

Based on the study, this work uses CNN's deep learning design to present a UWI improvement technique based on enhanced DarkLighter Pro-Net. Low-quality underwater photos are fed into the end-to-end framework of the approach, which produces processed, enhanced underwater photos as output. The following is a summary of the study's main contributions:

- An underwater image enhancement structure is designed, and a Dark Lighter Pro Net (DLPN) framework is proposed.
- The network model is processed on the standard Underwater Image Enhancement Benchmark (UIEB) dataset. The images in this dataset are captured under different environmental conditions underwater.
- Attention Guided Enhancement Network (AGE) is designed to perform enhancement on darker areas utilizing the channel and spatial network.
- After processing the images using the DLPN model, the metric is evaluated to prove the effectiveness of the designed model.

The proposed DLPN is unique since it is a CNN framework that integrates attention-guided enhancement, physics-based color restoration, and multi-stage residual refinement. Instead of using uniform enhancement like traditional models do, DLPN incorporates an AGE module that uses spatial and channel attention to specifically improve darker parts while preventing overexposure in brighter areas. Also, the Physics-Guided Color Restoration (PGCR) part is great for restoring natural colors that get messed up in low-light underwater settings since it precisely models water's light absorption and wavelength-dependent dispersion. Using skip connections, a Multi-Stage Residual Refinement (MRR) technique progressively refines tiny features over various scales, further preserving structural integrity. Unlike previous approaches, DLPN takes a holistic view, allowing it to tackle light loss, color distortion, and texture deterioration all at once.

2. RELATED WORK

Both physics-based and non-physics-based approaches are mostly part of traditional methodologies. The goal of physics-based approaches is to restore images by estimating characteristics like attenuation and scattering, which turn the imaging process backwards. Some methods that have been utilized to restore natural looks include attenuation priors and color correction models. Although these techniques work well in lab settings, they don't apply to the wide variety of underwater situations. Histogram equalization, fusion-based methods, and relative global histogram stretching are examples of pixel-level changes used by non-physics-based approaches. Even though these techniques enhance contrast, they frequently cause color changes, artifacts, and the loss of structural details, particularly in low-light situations.

Research into using deep learning for UIE tasks started when CNNs were popular. Models that learn mappings between degraded and augmented pictures utilize convolutional layers. Examples of such models are Under Water Convolution Neural Networks (UWCNNs) and UIEC^2-Net. By accurately capturing intricate non-linear correlations in picture attributes, these CNN-based approaches surpass conventional methods. While some of these models do a good job in well-lit environments, others aren't great at restoring natural colors or fine details when the lighting is really dim.

Underwater picture augmentation has also seen extensive research into GANs. By learning distributions of real-world underwater imagery, models like WaterGAN, F-GAN, and PUGAN produce aesthetically pleasing outcomes. Although GAN-based methods are great at making realistic images, they can be unstable during training, sometimes show details that don't really exist, and do a poor job of maintaining the input images' structural integrity. Also, GAN models are computationally costly and typically necessitate a lot of training data.

In order to develop and use marine resources, underwater imaging systems have become important hardware equipment. Unfortunately, underwater visual perception has frequently suffered from a significant decline in quality due to the complicated physical environment beneath the sea. In response to these concerns, we developed Principal Component Fusion of Foreground and Background (PCFB), an underwater image enhancement method based on principal component fusion of foreground and background. In order to fix color distortion and make the a and b channel pixel values equal in the CIELab color model, Zhang et al. [1] offered a color balance-guided color correction method. After that, the author took the color-corrected image and applied a contrast enhancement approach based on the percentile maximum and a dehazing strategy calculated by a multilayer transmission map [2].

In order to capture photos and aid in a variety of marine research activities, optical imaging cameras are currently utilized on underwater vehicles. There have been numerous strategies suggested for improving the signal-to-noise ratio and reducing backscattering noise in underwater photographs in recent years. Nevertheless, these algorithms are primarily designed for jobs involving underwater picture augmentation in well-lit environments. Therefore, the performance of these algorithms on low-light underwater scene photos remains unknown. Images captured in low-light underwater environments often have poor visual clarity and higher noise, making them more prone to artifacts when enhanced. Xie et al. [3] proposed a new underwater image enhancement network to address the issue of significant degradation of underwater image quality in low illumination environments after conducting a comprehensive study of existing methods for underwater image enhancement and low illumination image enhancement based on deep learning. This will help bridge the gap in existing solutions.

The transmission of light through water is a significant challenge to autonomous underwater robotic image processing. Although image restoration methods can successfully eliminate haze from a damaged image, they require numerous photographs taken from the same spot, which precludes their usage in a real-time system. Perez et al. [4] recommended a deep learning approach because of the impressive track record of these methods in solving other image processing challenges, like object detection and colorization. By using image restoration techniques to train a convolutional neural network, it is possible to dehaze individual photos more effectively than existing methods of image improvement. In order to demonstrate the neural network's generalizability, it is trained using photos from various places and with diverse attributes.

Underwater, image capture devices aren't very good at capturing high-resolution photographs, and the gear is pricey. It is feasible to restore and enhance picture quality using image processing algorithms instead of expensive and dependable picture-capturing software. The challenging but increasingly popular endeavor of creating and reconstructing an underwater image has been gaining steam in recent years. The objective is to enhance underwater photographs by utilizing deep learning models to eliminate graininess, fine-tune, and sharpen the images. Kumar et al. [5] employed GAN-augmented datasets, namely Enhancing Underwater Visual Perception (EUVP) and Underwater Image Enhancement Benchmark (UIEB), to train four CNN-based models: two with three layers and two with two layers.

Severe illumination degradation makes low-light underwater image enhancement a difficult problem to solve, even using state-of-the-art deep-learning techniques. We introduce a Retinex-guided Mamba network for low-light underwater image enhancement (RM-UIE) with two paths for rectification of reflectance and illumination maps to solve this problem. To be more specific, Yan et al. [6] created a Multi-scale Retinex Estimator (MRE) to split the input picture into two intermediate spaces that roughly match the target illumination and reflectance maps. After that, we come up with an 8-Direction Mamba Block (8D-MB) to improve lighting and reflectance maps. Enhanced spatial connection extraction is possible because of the 8D-MB's central operator, a new eight-direction Mamba scanning technology. Lastly, the suggested strategy proves to be much superior to current methods in terms of illumination and detail restoration, as shown by thorough quantitative and qualitative trials conducted on popular datasets.

Color distortion, reduced contrasts, and fuzzy details are common visual degradation issues with underwater photographs captured with underwater cameras. The present research trend treats each of these problems independently, which makes it hard to consistently increase the sharpness of underwater images. Uneven coloring in the texture of the photos, over-enhancement, and over-saturation of certain areas are all common results of this method. In order to improve the brightness, sharpness, and reduction of over-contrast amplification of underwater images while preserving their structure, Priyadharshini et al. [7] aimed to present an ensemble deep learning approach, a spatial approach, and a deep learning method. Through comparison with other models and testing on several datasets, including the UEIB and EUVP datasets, we demonstrate the generalizability of the suggested CNN model.

Due to factors such as light scattering, color distortion, and reduced visibility, underwater imaging is an intricate process. Kumar et al. [8] introduced a new framework called Hybrid Transformer Network optimized using Particle Swarm Optimization (HTN-PSO), which is built on a hybrid transformer network to improve underwater image quality and solve these challenges. For efficient feature capturing and long-range dependency modeling, the HTN-PSO framework merges the advantages of transformer models with convolutional neural networks. Concurrently, PSO enhances underwater photos to their fullest potential by optimizing the transformer's parameters. The four primary steps of the suggested framework are as follows: data enhancement, pre-processing, feature extraction with HTN-PSO, and improved picture reconstruction. Evaluations of HTN-PSO's performance include both subjective evaluations and objective quality indicators like Underwater Image Quality Measure (UIQM), Naturalness Image Quality Evaluator (NIQE), Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE).

Further, to improve the efficiency and effectiveness of the enhancement of underwater images, a DLPN model is designed in this paper. The DLPN utilizes the CNN structure and is specifically designed for underwater images. The methodology is discussed in Section 3.

Both physical-model-based and non-physical-model-based methods of improving underwater images have their limits. Underwater light propagation can be inverted using physical-model-based approaches that estimate environmental factors [17]; however, these assumptions are not universal and frequently fail in different underwater environments [18]. While methods that don't rely on physical models can enhance visibility, they often result in information loss, false color changes, and problems with retrieving small details due to their reliance on pixel values like brightness, contrast, and saturation.

3. METHODOLOGY

To circumvent these restrictions, the proposed DLPN framework incorporates three supplementary techniques. To avoid overexposing lighter areas, AGE adaptively brightens darker ones. In contrast to earlier deep learning methods, PGCR takes absorption and scattering effects into account while restoring natural hues [19]. Last but not least, MRR solves the problem of texture degradation that often occurs in

CNN and GAN-based approaches by gradually refining tiny details across scales. Through this integration, DLPN can tackle illumination loss, color distortion, and structural detail preservation all at once, outperforming state-of-the-art methods [20].

The images captured underwater suffer from a lower level of illumination [21], distortion in the colour of the image due to water scattering, and the noise present in the water environment [22]. Some of the traditional enhancement algorithms discussed in Section 2 failed to perform in extremely low-light conditions. The improvement in contrast and visibility is achieved successfully using a deep learning enhancement model. The darker lighter pro net model focuses on lower light and illumination-degraded images. The framework and design structure of DLPN are shown in Figure 2.

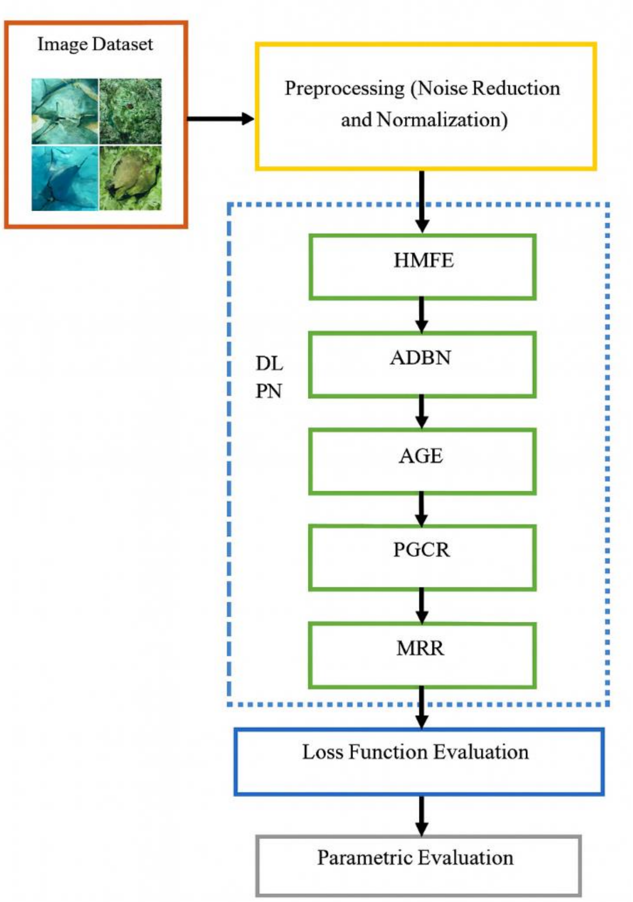

Figure 2. Framework of the proposed model

The mathematical notations are discussed here:

$I \in [0,1]^{H\times W\times 3}$ indicates an observed low-light underwater RGB image (input).

$J \in [0,1]^{H\times W\times 3J}$ indicates a restored/enhanced RGB image (ground truth or target).

J represents network output (enhanced image).

X indicates pixel location, $x \in \Omega$, where Ω indexes the $H \times W$ grid.

$F^{(l)} \in R^{Hl\times Wl\times Cl}$ indicates the feature tensor at layer l.

$A_s(x) \in [0,1]$ represents the spatial attention scalar at pixel x.

$A_c \in [0,1]^C$ represents the channel attention vector (per-channel gating).

A(x) indicates combined attention applied to features (explained below).

d(x) represents the depth/scene distance at pixel x (meters or relative scale).

β_λ and α_λ indicate the wavelength-dependent attenuation coefficient for color channel $\lambda \in \{R,G,B\}$.

B_λ represents the global background.

L indicates the total training loss.

3.1 Preprocessing

In this stage, the noise in the input data is reduced, and the values of the pixels are normalized for robust enhancement. The underwater images have noise because of absorption in water and the scattering problem. A non-local mean denoising filter is used to remove the noise in the image, and the structure of the image is preserved. The denoising of the image is performed using Eq. (1).

$$I_D(x,y) = \sum_{p \in \mathcal{N}(x,y)} w(x,y,p)\, I(p) \tag{1}$$

Here, the term $\mathcal{N}(x,y)$ is the neighbour pixel of the image, and the term $w(x,y,p)$ is the similar range of weights between the pixels.

The normalization helps the value of pixels to fall in a specific area for further processing of the image and ensures to have a consistent progress when working with a neural network. The pixel values are normalized between the range of 0 to 1, which allows the training process in networks to be stable. The normalization of the image given in Eq. (2).

$$I_N = \frac{I_D - I_{min}}{I_{max} - I_{min}} \tag{2}$$

3.2 Design of DLPN

The DLPN model is designed utilizing many aspects, like attention, physics-based restoration, and residual refinement for improving the quality of the enhanced image.

A. Hybrid Multiscale Feature Extraction (HMFE)

In this process, the hierarchical features are extracted using the convolutional layers and transformer layers. This stage extracts fine features and coarse structure of the image by preserving the global structure of the image. The convolution extraction of the feature process utilizes three layers and is defined as Eqs. (3)-(5):

$$F_1 = \sigma(W_1 \times I_N + b_1) \tag{3}$$

$$F_2 = \sigma(W_2 \times F_1 + b_2) \tag{4}$$

$$F_3 = \sigma(W_3 \times F_2 + b_3) \tag{5}$$

The transformer extraction of features helps in capturing of global illumination patterns of the image. The use of self-attention enhances the global structure of the image without losing the spatial details. The delf-attention factor is given in Eq. (6).

$$A(Q,K,V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{6}$$

The final features in this stage are a combination of CNN and the transformer features and are given in Eq. (7).

$$Final_F = Concat\ (F_3, A(Q,K,V)) \quad (7)$$

B. Adaptive Dual Batch Normalization (ADBN)

The contrast of the input image is normalized adaptively using ADBN. This improves the training process of underwater images in the network. This allows us to normalize the contrast of the image by applying a specific batch normalization for the regions that are darker and for brighter regions. By this process, the over-enhancement of the bright region is prevented by enhancing the dark regions. The ADBN is evaluated using Eq. (8).

$$I_{Norm} = \gamma_d \frac{(I-\mu_d)}{\sigma_d} + \beta_d + \gamma_d \frac{(I-\mu_b)}{\sigma_b} + \beta_b \quad (8)$$

C. AGE

In this stage, the regions of the image are darker and enhanced with the help of attention. Two attention models are considered, one is spatial attention (S_A), which improves the darker region of the image, and the other one is channel attention (C_A) which enhances the colour contrast of the image. The combination of spatial and channel attention provides a final attention map.

$$S_A = \sigma(W_s * I_{norm} + b_s) \quad (9)$$

$$C_A = Softmax(W_c * GAP(I_{norm})) \quad (10)$$

The final enhanced attention model is given in Eq. (11).

$$I_{enhanced} = S_A . C_A . I_{norm} \quad (11)$$

D. Physics Guided Colour Restoration (PGCR)

The PGCR allows a model of physics in evaluating factors like light absorption and scattering. This helps in restoring the natural colour in the image by understanding the concept of physics in the underwater conditions. The restoration of true colours of the underwater image is given in Eq. (12).

$$I_{restored} = I_{enhanced} \times e^{d.\lambda} \quad (12)$$

where, the term d is said to be the depth attenuation factor and term λ is the wavelength-dependent coefficient of absorption.

The colours of the image restoration underwater will be performed depending on the physics.

E. MRR

The details of the image are refined using residual learning. The MRR uses a three-level residual learning, which provides a higher scope of detailed enhancement. At every level, a skip connection in the residual network refines the details of the image. The final output of the enhanced image is given by Eq. (13).

$$I_{final} = I_{restored} + R_1 + R_2 + R_3 \quad (13)$$

Here, the terms R_1, R_2, R_3 are the residual enhancement at different scales.

3.3 Loss function

The loss function is evaluated to minimize the errors in the enhancements. The loss function is a measure of the output image obtained from the model with respect to the ground truth image results. The loss function in this model is evaluated using L1 loss, SSIM, and perceptual loss and is given in Eq. (14).

$$Loss = \lambda_1 \times L1 + \lambda_2 \times SSIM + \lambda_3 \times Perceptual\ loss \quad (14)$$

L1 is given as L1 = Mean [abs(true output-predicted output)], and SSIM is given as SSIM = 1 - SSIM (true output, predicted output).

Here the terms λ_1, λ_2, and λ_3 are the constant values. In our design the term $\lambda_1 = 0.6$, $\lambda_2 = 0.3$ and $\lambda_3 = 0.1$ are considered to evaluate the loss function.

At different spatial dimensions, degradations occur underwater in different ways. On one hand, ambient lighting and color casts are large-scale processes, whereas small suspended particles induce local dispersion. Both global illumination patterns and fine texture may go unnoticed by a CNN operating on a single scale. By merging convolutional multi-scale features with a transformer/self-attention branch that records long-range lighting patterns, HMFE can extract both local (fine) and global (coarse) information. This makes the correction of colors and lighting more consistent worldwide while also improving local detail recovery (edges, textures).

Because degradations under the water might manifest on both a local and global scale, the first part, HMFE, is crucial. Local scattering is caused by suspended particles, while global color shifts and illumination loss are caused by light attenuation. By utilizing transformer-based self-attention [23], HMFE can simulate global lighting patterns and extract local texture features using convolutional layers. This synergy strikes a good balance between regional sharpness and general aesthetic cohesion by restoring fine details to the improved image without sacrificing global color uniformity [24].

In order to fix the issue of underwater photographs having inconsistent lighting, the ADBN module is used. When using a traditional batch normalization method, just one normalization is applied to the entire image. This can cause some parts to be too enhanced while others are under-normalized [25]. With the use of a learnt mask, ADBN introduces independent normalization statistics for light and dark areas, allowing for adaptive normalization to take place. This guarantees steady training and better contrast preservation by preventing over-exposure of already bright areas and allowing effective correction of darker portions.

To fix the areas that need it the most, the AGE module applies enhancements selectively. Global amplification can make previously clear parts of an underwater picture noisier, and not all parts of the image require equal improvement. AGE prevents the network from excessively amplifying noise while still prioritizing crucial structures and color adjustments. A composite loss function is used to train DLPN in an end-to-end fashion. Losses at the pixel level (L) are a part of the overall loss. Rather than relying on individual supervision, the attention modules improve their weights with the rest of the network through backpropagation. This guarantees that both the spatial and channel attention adjust dynamically to the data.

The PGCR module is a crucial component of the DLPN framework because it corrects colour distortions by explicitly modeling underwater light absorption and scattering. In this model, the observed pixel intensity is expressed as $I\lambda(x) = J\lambda(x)t\lambda(x) + B\lambda(1 - t\lambda(x))$ is the captured intensity in channel $\lambda \in \{R,G,B\}$ is the true scene radiance, B_λ is the global background light, and $t_\lambda(x) = \exp(-\beta\lambda d(x))$ is the transmission that depends on the scene depth d(x) and the wavelength-dependent attenuation coefficient β_λ. By inverting this model, the true colour values $J_\lambda(x)$ can be recovered. A central challenge in PGCR is estimating the depth d(x) or transmission $t_\lambda(x)$, since ground-truth depth maps are rarely available for real underwater datasets. To address this, several strategies are employed. One approach is to train a small CNN sub-network to estimate relative depth maps directly, enabling the network to learn depth cues in a weakly supervised way. Alternatively, the model can bypass explicit depth estimation by directly predicting transmission maps for each channel through a lightweight prediction head, ensuring differentiability and physical interpretability. Depth can also be approximated using priors such as the red-channel or dark-channel assumptions, which exploit the faster attenuation of red light as a depth cue. In some cases, external monocular depth estimators trained on large-scale natural datasets can provide approximate depth maps that serve as additional guidance. Hybrid methods that combine learned predictions with physics-inspired priors or smoothness regularization often achieve the most robust performance. By integrating these strategies, PGCR ensures physically consistent colour correction, avoids unrealistic over-saturation, and generalizes effectively across diverse underwater environments.

4. RESULTS AND DISCUSSIONS

This section provides the platform utilized for UWIE and forecasts the parameters evaluated for assessing the designed model. The comparison of evaluated parameters is tabularized and compared with existing techniques.

4.1 System environment

The underwater image dataset is processed utilizing an Intel Core i10 processor, with an NVIDIA GeForce 4090 graphics card, 32GB RAM, and 1TB of space. A MATLAB deep learning framework is designed for processing the images in the dataset. The neural network tools and imaging tools available in MATLAB made the work easier to understand and process the Low Light Underwater Images (LLUWIs) effectively with the designed model.

4.2 Parameters evaluated

Evaluation of parameters is very important to identify the effectiveness of the suggested model. The improvement in the value of parameters helps the author to judge the efficiency of the presented work. Some of the parameters evaluated are Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Entropy, Absolute Brightness (AB), Visual Information Fidelity (VIF), Underwater Image Quality Measure (UIQM), and Universal Image Quality Index (UIQI). The detailed version of the parameters is discussed below.

A. PSNR

The metric PSNR measures the quality of an image by comparing it with the ground-truth image. The PSNR evaluates the amount of distortion introduced and is improved in the image. It is calculated using the mean square error and is given in Eq. (15):

$$PSNR = 10\ log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{15}$$

where, the term max is the high pixel value, which is 255 for an image with 8-bit.

$$MSE = \frac{1}{m \times n}\sum_{i=1}^{m}\sum_{j=1}^{n}[I(i,j) - K(i,j)]^2 \tag{16}$$

The first term $I(i,j)$ is the value of pixels in the original image and the second term $K(i,j)$ is the value of pixels in the distorted image. The dimensions of the image are termed as m, n.

B. SSIM

The similarity level of achieved output w.r.t to the ground-truth image need to be evaluated to check the luminance level and contrast level of image. If the SSIM value is high then the quality of the output image is said to be effective. The SSIM is evaluated using Eq. (17):

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{17}$$

The mean value of the image is termed as μ_x and μ_y. The variance value of the image is termed as σ_x and σ_y. The covariance is given as σ_{xy}.

C. Entropy

The measure of uncertainty of an image is said to be entropy. The information present in the image is validated using the entropy metric in analysis of images. The evaluation of entropy is given in Eq. (18):

$$E_n = -\sum_{i=0}^{I_l - 1} I_p(i) log_2 I_p(i) \tag{18}$$

Here, I_l is the number of intensity levels, and its probability is termed as I_p. If the entropy of a processed image is high, then the image is said to be a detailed and quality image.

D. AB

The overall brightness of the enhanced image is measured. It can be evaluated as the average intensity of pixels among the colour channels.

E. VIF

The information between the original image and the processed image is measured using this metric. The quality of the image will be assessed using Eq. (19):

$$VIF = \frac{\sum MI\ b/w\ original\ image\ and\ distorted\ image}{\sum MI\ b/w\ original\ and\ noise} \tag{19}$$

The value of VIF states the information present in the image that is processed. When its value is equal to one, then the image is said to be perfectly reconstructed.

F. UIQM

This parameter is different from measure metrics. UIQM helps in quantifying the visual perception of humans for the image, which is processed and enhanced. The UIQM values are evaluated using the colour measure, sharpness measure, and contrast measure, and are given in Eq. (20):

$$UIQM = w_1 \times UICM + w_2 \times UISM + w_3 \times UIConM \tag{20}$$

where, w_1, w_2, w_3 are the weight factors to be adjusted based on the significance of the requirement. Each metric in equation

6 is computed separately, and the final UIQM is evaluated. The quality of the image is said to be effective when the value of UIQM is high.

G. UIQI

The degree to which a distorted image resembles its original reference is measured by this evaluation metric. It assesses an image's contrast loss, brightness variations, and structural deformation. The value of UIQI is evaluated using Eq. (21):

$$UIQI = \frac{4.\sigma_{xy}.\mu_x.\mu_y}{(\sigma_x^2 + \sigma_y^2).(\mu_x^2 + \mu_y^2)} \tag{21}$$

Here, factor x refers to the original image and factor y refers to the distorted image. All the above metrics are evaluated and discussed in the following.

4.3 Experimental findings

This study takes into consideration a UIEB that contains 950 real-world underwater photographs, 890 of which have the associated reference images. The remaining 60 underwater photos for which adequate reference photographs are not available are treated as problematic data. The dataset offers a realistic basis for creating and evaluating improvement algorithms since it contains photos taken in a variety of underwater settings. The examination of underwater image enhancement techniques using this dataset and assessing the relevant metrics.

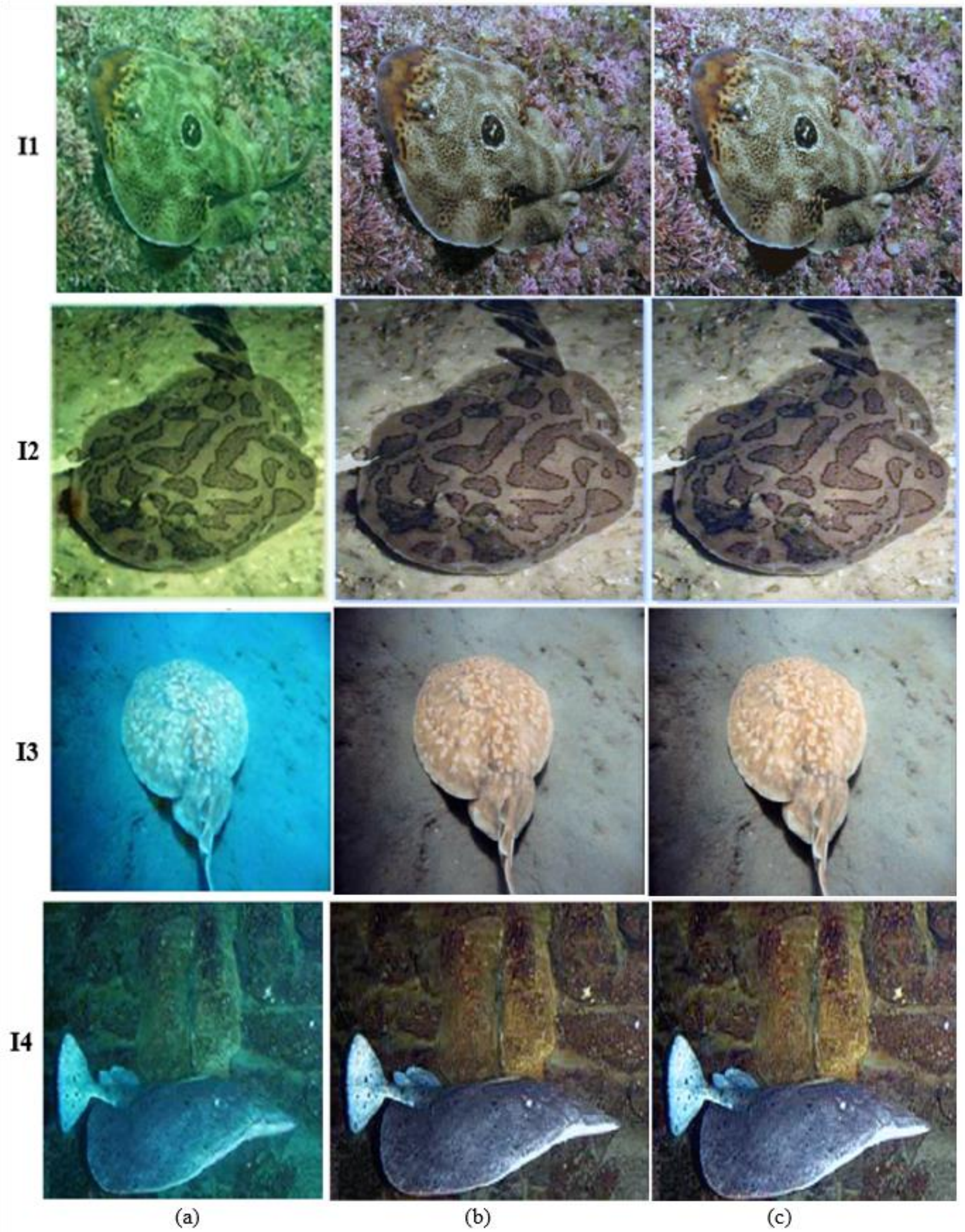

Figure 3. LLUWIs enhancement results (a) Input image (b) Output using Ard-GAN network (c) Proposed output using DLPN

Table 1. Results of parameters evaluated

Input / Parameter	PSNR	MAE	SSIM	VIF	AB	Entropy	UIQM	UIQI
I1	35.15	0.61	0.895	0.761	161.4	6.94	2.336	0.610
I2	36.64	0.62	0.881	0.771	157.3	6.9	2.330	0.612
I3	37.18	0.614	0.884	0.775	158.8	6.97	2.389	0.612
I4	36.92	0.653	0.890	0.791	158.34	6.96	2.37	0.616

Table 2. Comparison of parameters evaluated

Parameter / Technique	Ard-GAN Net	DLPN
PSNR	35.52	36.92
MAE	0.647	0.624
SSIM	0.86	0.90
VIF	0.791	0.745
AB	157.8	158.34
Entropy	6.84	6.94
UIQM	2.31	2.35
UIQI	0.60	0.616

Table 3. Parametric comparison with input

Image / Parameter	Input (LLUWI)			Output (DLPN)		
	SSIM	PSNR	UIQM	SSIM	PSNR	UIQM
I1	0.262	5.28	0.024	0.895	35.15	2.336
I2	0.139	6.21	0.032	0.88	36.64	2.330
I3	0.218	6.56	0.021	0.884	37.18	2.389
I4	0.184	5.66	0.042	0.890	36.92	2.37

Table 4. Comparison of metrics with existing methods

Method and References	PSNR	SSIM (%)
Relative Global Histogram Stretching [12]	19.72	83.9
Underwater Light Attenuation Prior [14]	16.33	75.8
Minimal Loss and Locally Contrast Enhancement [16]	19.82	83.5
Lite Enhance Net [18]	23.82	88
Physical Model GANs [19]	18.22	72.7
Physically Guided Network with Frequency–Spatial Attention [20]	22.50	81.6
Fast GAN [23]	23.89	81.8
Water Net [25]	27.74	89
Proposed: DLPN	**36.92**	**90**

The underwater images have lower light illumination, and there is a need to enhance the images for better understanding and visual quality. In Figure 3, the input LLUWI is considered and processing. The obtained enhanced output result using two different models is shown in Figure 3. The parameters evaluated in the process of enhancing the different images in the dataset are shown in Table 1.

The proposed dark lighter pro net achieves better results when compared to the existing Ard-GAN Net model, and is shown in Table 2. The results shown in Table 2 are the average of the results achieved after performing enhancement on different types of images. The proposed DLPN model achieves a PSNR of 36.2 and an SSIM of 89.9%.

The value of SSIM and PSNR obtained using the proposed Darker pro net model is compared with the input LLUWI. The images in the dataset are of low intensity, and the PSNR and SSIM are evaluated to compare with the enhancement model. By this comparison, the level of enhancement performed using the proposed model can be identified. The values are shown in Table 3.

The input image in the dataset has a PSNR of 5.28 and is improved to 35.15 using DLPN, and the SSIM of 26% improved to 89.5% using DLPN. The higher the value of PSNR and SSIM, the better the visual quality of the image. There is an improvement of 63.5% in SSIM, which showcases the efficiency of the proposed model. Table 4 showcases the comparative analysis of existing models with proposed models.

From Table 4, the designed DLPN has a higher PSNR of 36.92 and SSIM of 90% when compared to other existing models.

DLPN still has trouble processing images taken in highly murky seas or at extremely low depths, when the red channel data is practically nonexistent. The need for powerful computers also makes it difficult to deploy in real time on embedded underwater devices. A fairer image will emerge from the results section after these issues are addressed.

5. CONCLUSION

A CNN-based low-light improvement model called DLPN was created especially for processing images underwater. To increase visibility and colour accuracy, it makes use of residual learning, contrast enhancement, and lighting adjustment. In low light, images maintain their structural integrity while increasing details attributable to the model's hybrid function of loss and learning through perception. When it came to improving underwater images taken in low light, the proposed DLPN was far better. With a PSNR of 36.92 dB, DLPN outperformed the next-best approach, PCAFANet, which had a PSNR of 27.74 dB, by more than 9 dB. Similarly, DLPN achieved a 90% SSIM, surpassing previous models like WaterNet (88% accuracy) and FGAN (83.5%), and improved from input photos with SSIM as low as 0.18–0.26. From almost nil in raw inputs to 2.33–2.39 after refinement, UIQM showed significant improvement in visual quality metrics. These findings demonstrate that DLPN can effectively improve visibility in underwater settings with degradation, while also retaining fine picture structures and increasing color fidelity. Limitations persist notwithstanding these advancements. The hybrid feature extraction and multi-stage residual refinement design of DLPN makes real-time processing on low-power devices hard because of the significant computational resources it requires. In addition, processing speed and scalability to high-resolution, continuous video streams are limited, even though structural fidelity is kept. Furthermore, AUVs and ROVs might be enhanced in real-time using DLPN by compressing models or redesigning networks to make them lightweight. This would allow for DLPN to be scaled for deployment on embedded devices. This shows the efficiency of the proposed model in improving the visual quality of the image. The limitation of the proposed model is that it requires high computational power due to the lower speed of processing. The model improves the speed on high-end devices. There is a further need to improve the value of PSNR and SSIM, for which meta-heuristics algorithms need to be incorporated with a deep learning model. The involvement of optimization techniques can help deep tuning of pixels in the image to enhance the quality. The model can be extended to other image processing applications where low-light, weak contrast images are achieved. Future research should automate hyperparameter tuning using metaheuristic optimization to increase PSNR and SSIM values, use temporal coherence across frames to extend DLPN to real-time video enhancement, create lightweight variants by pruning, quantization, or knowledge distillation to make the model suitable for embedded hardware, and investigate multi-modal fusion to overcome visibility limitations in particularly turbid waters. Following these steps would make DLPN a more flexible tool for future underwater vision systems, as its uses would be broadened beyond only improving static images.

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