http://doi.org/10.35784/iapgos.7197

received: 02.02.2025 | revised: 02.06.2025 | accepted: 30.11.2025 | available online: 20.12.2025

IMPROVING UNDERWATER VISUALS BY FUSION OF DEEP-RETINEX AND GAN FOR ENHANCED IMAGE QUALITY IN SUBAQUATIC ENVIRONMENTS

Anuradha Chinta[1], Bharath Kumar Surla[2], Chaitanya Kodali[2]

[1]Siddhartha Academy of Higher Education Deemed to be University, Department of Computer Science and Engineering, Vijayawada, India, [2]Siddhartha Academy of Higher Education Deemed to be University, Department of Artificial Intelligence and Data Science, Vijayawada, India

Abstract. *The enhancement of subaquatic images is crucial for various applications such as marine resource development, underwater photography, surveillance, and scientific imaging. However, the underwater environment presents challenges like color distortion, low contrast, and poor visibility, which traditional image processing techniques struggle to address effectively. In response, this study proposes an innovative approach named Deep-Retinex-GAN, which integrates Deep Retinex preprocessing and Generative Adversarial Networks (GANs) to refine underwater images. Initially, the subaquatic images are processed using Deep Retinex to separate them into reflectance and illumination components, reducing color distortion and enhancing contrast. Subsequently, the reflectance-enhanced images are used as conditional inputs for a GAN model, allowing it to learn the mapping to a target domain with improved illumination, texture, and sharpness. Experimental evaluations conducted on both synthetic and real-world underwater image datasets demonstrate the superior performance of the proposed method compared to existing techniques, achieving a PSNR of 34.741 dB, an SSIM of 0.978, and a CF(ΔE) of 8.2, as well as noticeable artifact reduction. Qualitative assessments further highlight the method's ability to produce visually pleasing and realistic results. The proposed approach shows strong potential for a broad range of underwater applications, including photography, surveillance, exploration, and scientific research, by significantly enhancing the quality and interpretability of underwater imagery across diverse domains.*

Keywords: subaquatic images, visual Improvement, Deep Retinex, GAN, color fidelity, PSNR

POPRAWA JAKOŚCI OBRAZÓW PODWODNYCH POPRZEZ POŁĄCZENIE METODY DEEP-RETINEX I SIECI GAN

Streszczenie. *Ulepszanie obrazów podwodnych ma kluczowe znaczenie dla różnych zastosowań, takich jak rozwój zasobów morskich, fotografia podwodna, nadzór i obrazowanie naukowe. Jednak środowisko podwodne stwarza wyzwania, takie jak zniekształcenie kolorów, niski kontrast i słaba widoczność, z którymi tradycyjne techniki przetwarzania obrazów z trudnością sobie radzą skutecznie. W odpowiedzi na to wyzwanie w niniejszym artykule zaproponowano innowacyjne podejście o nazwie Deep Retinex GAN, które łączy wstępne przetwarzanie Deep Retinex i generatywne sieci przeciwstawne (GAN) w celu udoskonalenia obrazów podwodnych. Początkowo obrazy podwodne są przetwarzane przy użyciu Deep Retinex w celu rozdzielenia ich na składniki refleksyjne i iluminacyjne, co zmniejsza zniekształcenia kolorów i poprawia kontrast. Następnie obrazy o zwiększonej refleksyjności są wykorzystywane jako dane wejściowe warunkowe dla modelu GAN, umożliwiając mu naukę mapowania do domeny docelowej o lepszym oświetleniu, teksturze i ostrości. Oceny eksperymentalne przeprowadzone zarówno na syntetycznych, jak i rzeczywistych zbiorach danych obrazów podwodnych wykazują przewagę proponowanej metody w porównaniu z istniejącymi technikami, osiągając PSNR na poziomie 34,741 dB, SSIM na poziomie 0,978 i CF(ΔE) na poziomie 8,2, a także zauważalną redukcję artefaktów. Oceny jakościowe dodatkowo podkreślają zdolność tej metody do uzyskiwania przyjemnych dla oka i realistycznych wyników. Proponowane podejście wykazuje duży potencjał w szerokim zakresie zastosowań podwodnych, w tym fotografii, nadzoru, eksploracji i badań naukowych, poprzez znaczne poprawienie jakości i interpretowalności obrazów podwodnych w różnych dziedzinach.*

Słowa kluczowe: obrazy podwodne, poprawa wzroku, Deep Retinex, GAN, PSNR, wierność kolorów

Introduction

Improving the quality of subaquatic images is vital for various applications such as marine resource development, underwater photography, surveillance, and scientific imaging. However, the subaquatic environment presents challenges like color inaccuracy, poor contrast, and reduced quality, which traditional image processing techniques struggle to address effectively. In response, this study proposes an innovative approach named Deep-RetiNex-GAN, which integrates Deep Retinex preprocessing and Generative Adversarial Networks (GANs) to improve the quality of subaquatic visuals. Initially, the Deep Retinex technique processes the underwater images by decomposing them into reflectance and illumination components. This step removes lighting effects, improves color accuracy, and boosts contrast. Subsequently, the reflectance-enhanced images are input into a conditional GAN model for further refinement. In this setup, the reflectance component acts as the conditional input, enabling the GAN to learn the mapping to a target domain with improved illumination, texture, and sharpness.

Experimental evaluations demonstrate the superior performance of the proposed Deep Retinex-GAN approach compared to existing methods in terms of image enhancement quality. The method is assessed on various underwater image datasets, including synthetic and real-world scenarios, showing significant improvements in visual quality metrics such as color fidelity, contrast enhancement, and artifact reduction. Fig. 1 represents the images from dataset [30], consists of underwater and its ground truth images.

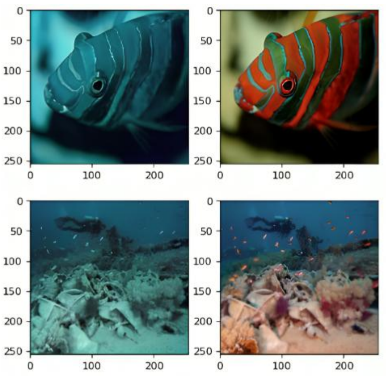

Fig. 1. Images vary from underwater and ground truth images

Furthermore, qualitative assessments underscore the ability of the approach to produce visually pleasing results with a natural and realistic appearance.

1. Literature review

Wang et al.[18] in the year 2023 introduced the Self-Adversarial GAN (SA-GAN) technique aimed at improving underwater image quality by leveraging paired raw and high-quality natural images. SA-GAN employs a self-adversarial approach utilizing two discriminators to enhance image quality.

Through experiments conducted on actual underwater images and the UIEBD dataset,it was evident that SA-GAN outperforms existing methods in restoring underwater image coloration. In 2022, Estra et al. [2] introduced a machine learning approach for enhancing submerged LiDAR images within a Generative Adversarial Network (GAN) framework. This technique incorporates a correntropy-based perceptual loss specifically tailored for LiDAR image enhancement and includes simulated degraded data for training purposes. Validation of the proposed method was conducted using LiDAR data collected from the Unobtrusive Multi-static Serial LiDAR Imager (UMSLI) system at two test facilities. Results indicated improved image quality and reduced noise artifacts compared to the previous employment of a bilateral filter within the UMSLI framework. In 2020, Xueyang Fu and Xiangyong Cao [3] introduced a two-branch network that merges deep learning with traditional image enhancement techniques to enhance underwater image quality. This approach tackles challenges such as color distortion and reduced contrast resulting fromlight absorption and scattering in underwater settings. Through a comprehensive evaluation encompassing both qualitative and quantitative analyses, their proposed approach showcased superior performance when compared to various existing techniques. Liu et al. [7] in the year 2021 introduced a unified method for enhancing underwater images, blending the revised submerged visual formation model (Akkaynak-Treibitz model) with a generative adversarial network (GAN). The physical model serves as a guide for network learning, while GAN aids in estimating coefficients. Through thorough experimentation and comparisons with leading methods using diverse underwater datasets, the efficacy of their approach was demonstrated. Wu et al. [19] in the year 2022 introduced Fusion Water-GAN (FW-GAN), a multi-scale fusion generative adversarial network designed to elevate submerged image quality. Consisting of four convolution branches, the model iteratively refines input features and encodes the initial input. Multi-scale fusion connections amalgamate prior features, while a channel attention decoder generates improved outcomes. Kumar et al. [6] in the year 2023 concentrated on improving underwater images through deep learning techniques. Crafted four CNN models, consisting of two with three layers and two with five layers, all trained on GAN-augmented datasets (EUVP and UIEB) to enhance image quality. Among these models, the 5-layered variant, optimized with SGD, exhibited the most superior performance. introduced a technique rooted in Retinex-inspired color correction and fusion technology [24]. The objective of this approach is to correct color casts induced by underwater light scattering while simultaneously improving edge sharpness, detail clarity, color fidelity, and overall contrast in subaquatic images. It entails the fusion of three images derived from a locally enhanced contrast version, a detailed rendition, and a globally enhanced contrast version of the corrected underwater image. Furthermore, the method integrates a detailed differential pyramid into the multi-scale fusion procedure. Shen et al. [15] in the year 2023 explored a fully unsupervised convolutional neural network-based strategy for improving underwater images, labeled the Underwater Image Enhancement (UUIE) technique, employing pseudo-Retinex decomposition. Established a connection between the underwater imaging model and the Retinex model, utilizing terrestrial images for model training. By employing self-supervision, the approach estimated pseudo-illumination and pseudo-reflection maps, subsequently reconstructing the enhanced image. Additionally, the UUIE method showed promise for extending its applicability to tasks like image dehazing and low-light enhancement. Empirical results on synthetic and real-world datasets highlighted the efficacy of the proposed approach. In 2021, Jiang et al. [26] presented an approach targeting the alignment of synthetic and real-world underwater images through transfer learning, particularly utilizing in-air image dehazing for underwater image enhancement. Their framework comprises two key modules: domain adaptation for style transfer and domain adaptation for image enhancement. The style transfer module works to translate original underwater images into an intermediate domain to alleviate color inconsistencies, while the image enhancement module concentrates on mitigating haze-like effects and enhancing overall image quality. Through experimentation across various real-world underwater scenarios, the method demonstrated its capacity to produce visually satisfying results compared to conventional approaches and those based on deep learning. In 2023, Zhou et al. [28] introduced a method that centers on assessing feature drift levels across different image regions through the analysis of their statistical characteristics. This approach aims to address challenges such as uneven feature representation drift, as well as issues related to low contrast and poor visibility frequently encountered in underwater imagery. Incorporating a color correction approach that utilizes subinterval linear transformation and a variational model, alongside a multi-interval subhistogram equalization method, is part of the methodology aimed at enhancing image contrast. Through this approach, significant improvements in the visual quality of degraded images are achieved, surpassing many existing state-of-the-art methods. In 2021, Moghimi and Mohanna [12] provided a comprehensive review of algorithms and techniques used for improving underwater images in both real-time and non-real-time scenarios. Also, discussed the challenges of underwater which degrade image quality and hinder real-time processing. The authors examined various strategies for enhancing underwater image quality, covering, color correction, de-hazing, de-flickering, de-scattering, image restoration, and denoising.

2. Methodology

The proposed system is to develop an advanced image enhancement technique. With the aim of notably enhancing the perceptual clarity of underwater visuals. This involves integrating the preprocessing capabilities of Deep Retinex for effective color and contrast enhancement with the generative capabilities of Generative Adversarial Networks (GANs) to produce visually appealing and realistic results. Also, as ensembling these two different models that works on image enhancement which helps the overall output to be well enhanced and produce a visually pleased enhanced image.

2.1. Process flow

Fig. 2 depicts the process flow of implementing the model using Deep Retinex and the GAN model for enhancing the underwater images. In the initial stage, collected the EUVP (Enhanced Underwater Visual Perception) data. Initially, collected the dataset from the Minnesota Interactive Robotics and Vision Laboratory website [31]. The dataset consists of images of paired and unpaired dataset. Next step includes preprocessing of images in the dataset using Retinex which erases the color distortion and noise from the corners of the visual data. Now these processed images are being used as input for the GAN model which acts as the core of the project. Here, the task is being split since the GAN is a large working model that takes a significant amount of time. Therefore, the tasks for each model are being divided to enhance the effectiveness of the model.

The visual data is tested using various models that are existed in GAN and Retinex models. Each image is extracted from the dataset and model checks for the noise that the model can remove and now the noise is being removed by Retinex model i.e., Black borders, color distortion. The Enhancement model goes through training, testing, and hyperparameters, perform well on various images that are available other than dataset images related to Underwater Images that are to be Enhanced. Eventually, the web application utilizes the Enhancement model to provide enhanced version of underwater images enhancement model to provide enhanced version of underwater images. Dataset images related to underwater images that are to be enhanced. Finally, the trained enhancement model is integrated into a web application, allowing users to upload underwater images and obtain enhanced results with improved quality and clarity. The process includes ensembling of the two different models one is Retinex which helps in decomposing input images into reflectance and illumination components, effectively mitigating problem such as color distortion and low contrast commonly observed. This preprocessing step enhances the input images by separating intrinsic scene colors from lighting effects from under water images. Now these images which are preprocessed were sent to GAN to learn and generate realistic and visually appealing images. Subsequently, based on the performance of the model, as it is well trained and tested now deployed it as a web page that enables users to access the enhanced image from the raw or unenhanced underwater images after uploading it.

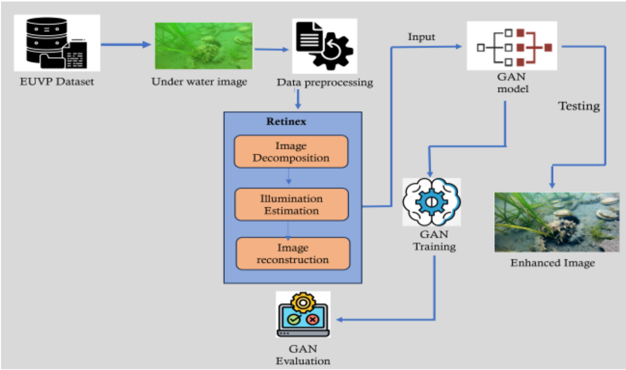

Fig. 2. Process flow of the proposed model

2.2. Architecture selection

Approaches such as GAN, Cyclic GAN, CNN, and Wavelet Compensation and Image Dehazing (WCID) Technique [16] aim to enhance perceptual visibility, retain texture details, and mitigate noise effects. Additionally, the Contrast Limited Adaptive Histogram Equalization (CLAHE) Technique [4] seeks to achieve similar outcomes.in contrast to AHE, aims to limit contrast by adjusting the histogram. It also mitigates noise by constraining the histogram to a specific value. This technique is applicable to the RGB color model. Dark Channel Prior Method (DCP) Technique [5], is adapted to enhance underwater images by mitigating turbidity caused by water particles and light dispersion. Leveraging low-intensity pixels in local patches, it estimates haze thickness and facilitates high-quality image recovery from underwater haze. Discrete Cosine Transform (DCT) Method [13], along with Discrete Cosine Transformation (DCT) with Dynamic Histogram Equalization (DHE) [14] to address issues like blurring, uneven lighting, and low contrast caused by water turbulence; Contrast Enhancement/ Maximization Method [5], it concentrates on improving contrast and color of Subaquatic visuals which greatly contributing to Increasing image visibility underwater. Homomorphic Filtering Technique [13], The technique enhances digital images by preprocessing them, particularly useful for addressing issues like poor lighting in underwater photography, where images often suffer from low illumination and haze. Homomorphic technique is applied for preprocessing underwater images, addressing issues of poor illumination commonly observed in hazy underwater conditions. This frequency-based filter corrects non-uniform lighting, enhancing image contrast and sharpening edges simultaneously. Color Correction Method [23], To address color distribution, the method adopts the gray world assumption and employs White Balance Technique to eliminate unrealistic color casts, ensuring natural-looking objects. This technique measures the light source's color temperature, indicating the relative warmth or coolness of white light. Additionally, Guided Filtering Technique [27] is utilized to counter absorption, dispersion, and artificial lighting distortions in underwater optical images. It compensates for discrepancies along the propagation path, enhancing scenes by reducing noise, improving exposure, and boosting overall contrast. This method significantly enhances fine details and edge clarity, crucial for precise subaquatic image analysis. Furthermore, Histogram Equalization Technique is applied to correct images suffering from bright or faded backgrounds and frontal areas, mapping gray levels based on input gray level probability distributions.

These techniques collectively contribute to subaquatic image enhancement, with authors selecting based on the specific noise being addressed. In this study, an Ensembled model of Retinex and GAN has demonstrated superior efficiency compared to other models on EUVP dataset.

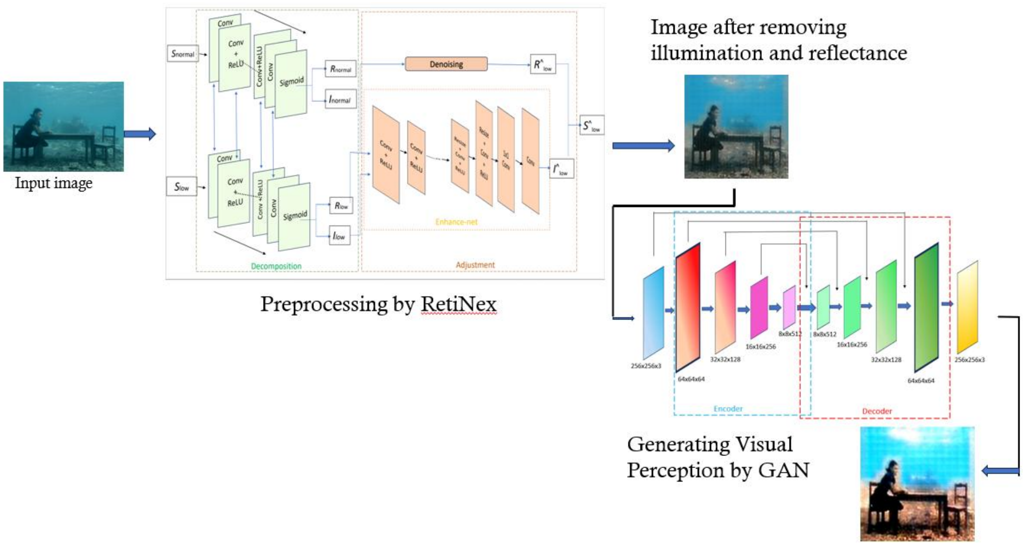

Fig. 3. Architecture of the proposed model

2.2.1. Deep Retinex architecture

The Deep Retinex framework, an evolution of the general Retinex method, upholds the essential image processing procedures aimed at enhancing visual quality. However, in Deep Retinex, these procedures are enhanced by integrating deep learning methodologies. Initially, the process entails image decomposition, separating the input into reflectance and illumination elements to isolate intrinsic scene attributes from lighting conditions. Following this, dynamic range compression is employed to maintain detail integrity across varying brightness levels, thereby augmenting overall contrast. Color constancy techniques persist, ensuring uniform color representation irrespective of lighting fluctuations by addressing color casts and adjusting balance. In Deep Retinex, local contrast enhancement techniques are further refined, utilizing deep neural networks to selectively boost contrast based on local attributes, enabling more adaptable and precise adjustments. Additionally, the incorporation of deep learning facilitates more sophisticated adaptive filtering techniques, enhancing noise reduction while safeguarding crucial image characteristics. Overall, the Deep Retinex framework builds upon the principles of the general Retinex approach, elevating its capabilities through the integration of deep learning methodologies. The adoption of the Retinex architecture for preprocessing underwater images marks a notable stride in underwater imaging technology. Originating from image processing, the Retinex model operates by disentangling images into their reflectance and illumination components, thereby aiding in enhancing visual quality. In the realm of underwater imaging, this methodology is pivotal in overcoming challenges such as hue alteration and insufficient contrast, prevalent due to factors like water turbidity and light attenuation. At the outset, an initial stage in Fig. 4 employs a dedicated network known as Decom-Net to partition the observed image into two distinct components: a reflectance aspect that remains unaffected by changes in lighting and an illumination aspect designed to maintain smoothness in structure.

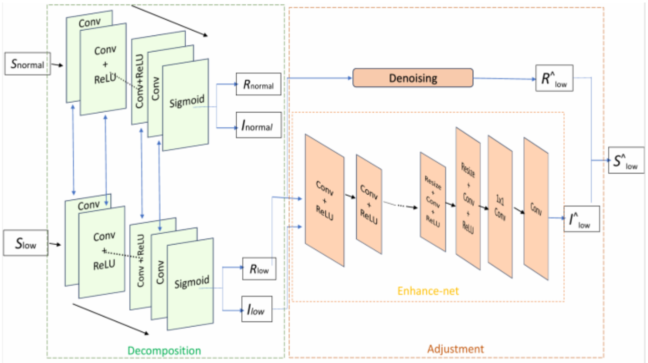

Fig. 4. Deep Retinex architecture used in proposed model

The training regimen of Decom-Net adheres to two primary constraints. Firstly, it ensures that both low-light and normal-light images share identical reflectance properties. Secondly, it aims to produce an illumination map characterized by smoothness while maintaining crucial structural features, achieved by employing a structure-aware total variation loss. Decom-Net handles both the low-light image (S_{low}) and the normal-light image (S_{normal}) as inputs, leading to the determination of their corresponding reflectance (R_{low} and R_{normal}) and illumination (I_low and I_normal) components. Initially, features are extracted from the input images using a 3×3 convolutional layer. Subsequent transformations involve multiple 3×3 convolutional layers, each incorporating Rectified Linear Unit (ReLU) activation functions, thereby facilitating the conversion of RGB images into reflectance and illumination representations. The reflectance and illumination components are then projected from the feature space using a final 3×3 convolutional layer, with the sigmoid function applied to ensure that both R and I are confined within the [0, 1] range. In essence, Decom-Net represents a paradigm shift in underwater image processing, offering a sophisticated solution for segmenting images into their constituent components and facilitating subsequent enhancement. By adhering to stringent constraints and leveraging advanced neural network architectures, Decom-Net stands poised to revolutionize the field, unlocking new avenues for enhancing underwater visual perception and advancing the state-of-the-art in computer vision. The Retinex model that used in our solution to remove the low contrast and low light noise. Which helps the underwater images to be get removed of noise. The algorithm preprocesses an image dataset using a Deep-Retinex model by iterating through each image category, performing denoising, cropping, and reshaping. It then batches the preprocessed images by type and compiles them into a final dataset until all categories are processed.

2.2.2. GAN architecture

A Generative Adversarial Network (GAN) consists of two neural networks: a generator and a discriminator. The generator network receives random noise as input and produces synthetic data samples, like images, aiming to replicate real data from the training set. Conversely, the discriminator network's role is to differentiate between real data samples from the training set and those fabricated by the generator. Throughout the training process, the generator's objective is to create samples that closely resemble real data, while the discriminator strives to accurately distinguish between real and synthetic samples. This adversarial mechanism drives both networks to improve iteratively, with the generator honing its ability to generate realistic samples and the discriminator refining its skill in identifying real from fake data. Over time, as training advances, the generator steadily enhances its output until the generated samples closely approximate real-world data.

In the realm of underwater image enhancement, GANs have emerged as a solution to address issues stemming from reduced clarity, color shifts and insufficient contrast. Through harnessing the generative prowess of GANs, scientists have devised models capable of generating refined renditions of underwater images. Here, the generator network is trained to create images boasting enhancements in contrast, sharpness, and color balance, while the discriminator network scrutinizes the authenticity of these improvements. Integrating GANs with Deep Retinex preprocessing further augments performance. Deep Retinex preprocessing decomposes input images into reflectance and illumination components, effectively addressing color distortion and low contrast. The reflectance-enhanced images serve as conditional inputs to the GAN model, enabling it to learn and generate more realistic enhancements that rectify deficiencies in illumination, texture, and sharpness. After undergoing preprocessing using Retinex techniques to address issues like color shifts and low visibility, the enhanced underwater images enter the encoder network of the Generative Adversarial Network (GAN) represented in Fig. 5.

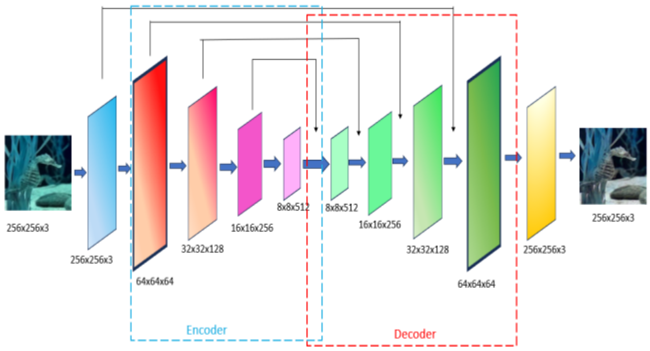

Fig. 5. GAN architecture used in proposed model

Here, multiple convolutional layers extract high-level features, utilizing filters to capture spatial patterns and details. Following each convolutional layer, normalization techniques such as batch normalization may be applied to stabilize training. The encoded features then traverse to the generator network, consisting of decoding layers, typically transpose convolutional or upsampling layers. These layers progressively increase spatial dimensions while decreasing the number of channels. Post each decoding layer, normalization techniques may again stabilize training. Meanwhile, the discriminator network evaluates synthetic images produced by the generator, distinguishing between real and synthetic ones, providing feedback for refinement. The proposed GAN architecture comprises a generator and a discriminator with distinct configurations. Both networks operate on input images of 256×256×3. The generator uses kernel sizes of 3, 4, and 5, starts with 32 filters, and consists of 14 layers, employing ReLU activation and batch normalization throughout.

It produces enhanced images with three output channels and uses UpSampling2D for up-sampling. The discriminator, in contrast, uses a fixed kernel size of 3, begins with 32 filters, and consists of 4 layers, yielding a single-channel output for the validity score. It applies SeparableConv2D combined with MaxPooling2D for down-sampling, along with ReLU activation and batch normalization. Both networks are optimized with the Adam optimizer (learning rate of 0.0003, $\beta 1 = 0.5$) and trained with a batch size of 8. The loss formulation includes Mean Squared Error (MSE) and total generative loss for the generator, while the discriminator is trained using MSE, ensuring balanced dynamics and stable training throughout the process.

2.3. Dataset

The Enhanced Underwater Visual Perception (EUVP) dataset is meticulously curated to include both paired and unpaired image samples, representing various levels of perceptual quality. In the paired dataset, corresponding images with perceptual differences are provided, enabling direct comparison and supervised training of subaquatic image enhancement models. Meanwhile, the unpaired dataset contains images without direct counterparts but still exhibiting perceptual variations, allowing for generalization of enhancement techniques across diverse underwater scenes. This comprehensive dataset spans different underwater environments, such as oceans, lakes, and rivers, capturing varying lighting conditions, water turbidity levels, and aquatic life. Annotated with detailed ground truth labels and metadata, the EUVP dataset facilitates algorithm development and evaluation in underwater image processing and computer vision. Regular updates and expansions ensure its relevance to the latest advancements in underwater perception technologies. As a result, the EUVP dataset serves as a vital resource for benchmarking algorithms, fostering collaboration among researchers, and driving progress in underwater image processing and computer vision research.

EUVP contains:

I. Paired Data: consists of data from three other paired datasets that are Underwater Dark, Underwater ImageNet and Underwater scenes data. Underwater Dark data consists of 11,670 images of which 5,550 are used as Training pairs and 570 as Validation images. Underwater ImageNet dataset consists of 8,670 images of which 3,700 are used as training pairs and 1,270 images are used for validation. Underwater Scenes dataset consists of 4,500 images of which 2,185 are used as training pairs and 130 images for validation. Table 1 represents the number of images that are present from each of the dataset that contributed to form a paired data.

Table 1. Statistics of three datasets that present in paired data

Name of dataset	Training Pairs	Validation	Total Images
Underwater Dark	5,550	570	11,670
Underwater ImageNet	3,700	1,270	8,670
Underwater Scenes	2,185	130	4,500

This paired data consists of two classes mapped with each other. One class is Distorted and another one is its corresponding Ground truth data or image. Fig. 6 represents the sample images of the datasets that include mapping of Ground truth and distorted images extracted from three underwater datasets.

II. Unpaired Data: this consists of data that have no mappings from underwater and ground truth images. Table 2 representing the details regarding the unpaired dataset.

Table 2. Number of images present in unpaired data

No. of Poor Quality	No. of Good Quality	Validation	Total Images
3,195	3,140	330	6,665

It has total of 6,665 images of which 3,195 images are of Poor Quality, 3,140 of Good Quality, and 330 images for validation. Fig. 7 represents the images related to Good and poor quality images that are mapped each other as shown.

Fig. 6. Sample images of paired dataset

Fig. 7. Sample images of unpaired dataset

Finally, the overall dataset is sent as input for the ensembled model to generate the enhanced images of underwater.

2.4. Results and analysis

The effectiveness of the proposed Deep-RetiNex-GAN approach underwent extensive evaluation across a range of underwater image datasets, covering synthetic and real- world scenarios. The evaluation involved the use of diverse quantitative metrics, including,

a) Peak Signal-to-Noise Ratio (PSNR): It quantifies image quality by comparing the maximum signal value to the noise level. It's widely used in image processing to assess fidelity, with higher values indicating better quality. It can be calculated using below formulae

$$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{1}$$

Here, MAX represents the highest attainable pixel values, while MSE denotes the Mean Squared Error computed among corresponding patches in the images.

b) Structural Similarity Index Measure (SSIM) serves as a metric for assessing the similarity among two images, relying on their structural information**.** t evaluates the luminance, contrast, and structure similarities between corresponding patches in the images.

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{2}$$

where $\mu_{x,}$ μ_y represents the mean values of original and enhanced images. σ_x^2, σ_y^2 are variances of images. c_1 and c_2 serve the purpose of stabilizing the division process, particularly when encountering weak denominators.

c) Color Fidelity (ΔE):

$$\Delta E = \sqrt{(L_1^* - L_2^*)^2 + (a_1^* - a_2^*)^2 + (b_1^* - b_2^*)^2} \tag{3}$$

where L^*, $a^*$and b^* represent the coordinates in the CIELAB color space for the reference and enhanced images, respectively. Smaller ΔE values indicate better color fidelity and preservation of the original color appearance.

Were utilized to gauge the enhancement quality. The findings unveiled substantial improvements in image enhancement quality compared to existing methods, notably in color fidelity, contrast, and artifact reduction. Moreover, qualitative assessments were carried out to evaluate the perceptual quality of the enhanced images. Visual inspection and comparison of images pre and post-enhancement demonstrated the capability of the Deep-RetiNex-GAN approach to yield visually appealing results with a natural and authentic appearance. The enhanced images exhibited noticeable enhancements in illumination, texture, and sharpness, collectively contributing to their enhanced perceptual quality. For the finest enhanced images, PSNR values surpassing 30 dB denote commendable image quality, while values nearing 50 dB suggest outstanding Quality. SSIM values nearing 1 signify substantial likeness between images, with those exceeding

0.9 often regarded as exceptional whereas Lower MSE values are preferred, with values approaching zero indicating minimal distortion and superior image quality. The choice of Retinex preprocessing is done because it performs well on low-light images and removes the effect of illumination and reflectance. The Retinex with Deep Learning Network was chosen for its ability to extract and enhance image features. As shown in Fig. 8, its training and validation accuracy reaches ~60%, which serves as an indicator of its feature-learning ability rather than a classification metric. Training for more epochs is expected to further improve this result. Importantly, the quality of the final enhanced images is evaluated using established metrics such as PSNR, SSIM, and ΔE, ensuring robust and visually superior outcomes regardless of the accuracy measure.

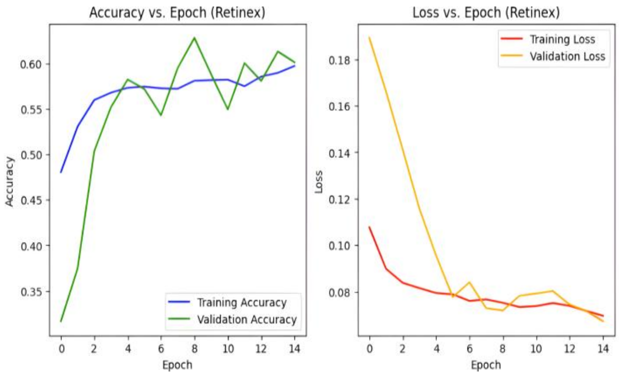

Fig. 8. Graphs that represents accuracy and loss generated by Retinex model

Now as the training and testing using Retinex model is performed and created a pipeline for the Retinex generated preprocessed images will act as input to the Generative Adversarial Network (GAN) and the model performs further enhancement to preprocessed data which will further produce good PSNR, SSIM, and ΔE values. Now, GAN will be trained and validated. The performance of the GAN model is plotted in the graph shown in Fig. 9.

The trend of loss values which were generated by Generator and Discriminator that involved in training the GAN model's architecture plays a major role in evaluating The performance of the model, as illustrated in above Fig. 9, is depicted by plotting training steps on the X-axis against Loss values on the Y-axis.

After training Retinex and GAN till they achieve good accuracy and loss values, tested with an underwater image which is not present in the dataset as shown in Fig. 10a. The proposed model will clear the noise that occurs due to reflectance, luminescence, and enhance the image as shown in Fig. 10b which is the final output of the Deep-Retinex-GAN model.

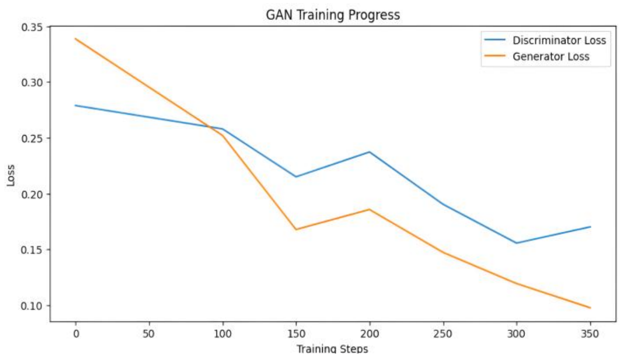

Fig. 9. Graph plotted based on loss values of generator and discriminator

Table. 3 represents a comparison of various research studies on image quality enhancement, focusing on PSNR, SSIM, and Color Fidelity metrics.

(a) (b)

Fig. 10. Final output of the proposed model

Table. 3. Comparison table

Literature	PSNR	SSIM	Color Fidelity
Li et al. (2016) [9]	24.5	0.5121	10.2
Yang et al. (2020) [21]	17.715	0.6552	8.5
Zhou et al. (2022) [29]	24.312	0.852	7.8
Yin et al. (2022) [22]	24.422	0.930	7.5
Lyu et al. (2022) [10]	24.046	0.8087	8.0
Xue et al. (2023) [20]	19.768	0.847	7.2
Dharwadkar et al. (2022) [1]	23.807	0.789	8.7
Mei et al. (2022) [11]	34.464	0.984	6.1
Li et al. (2022) [8]	20.701	0.704	7.6
Zhang et al. (2023) [25]	35.41	0.93	7.9
Singh & Bhat (2024) [17]	18.92	0.486	8.1
Our research	34.741	0.978	8.2

3. Conclusion

Through this paper, discussed about the fusion of Deep-Retinex preprocessing and GANs presents a promising avenue for improving underwater image quality. Our project has effectively showcased the efficacy of this approach in addressing common challenges such as color distortion, low contrast, and limited visibility in underwater imaging. Leveraging the EUVP dataset has enabled us to train and assess our models comprehensively, ensuring their effectiveness across diverse underwater environments. Proposed model shows a PSNR of 34.7 and an SSIM of 0.97, placing it among the higher-performing models in terms of these metrics. Compared to studies like Li et al.(2016) which have a PSNR of 24.5 and SSIM of 0.5121,Singh & Bhat (2024)[33], which have a PSNR of 18.92 and an SSIM of 0.486 on the image from the dataset and proposed model demonstrates superior signal and structural quality. However, our model's The Color Fidelity (ΔE) of 8.2 is significantly higher than that of most other methods, indicating excellent color accuracy and faithful reproduction. Combined with substantial gains in PSNR, SSIM, and overall visual clarity, this result reflects a well-balanced and robust enhancement, yielding underwater images with superior color reproduction, contrast, and perceptual quality. The integration of Deep-Retinex preprocessing helps in mitigating the adverse effects of underwater conditions by restoring the natural appearance of underwater scenes. When combined with GANs, which are known for their powerful image generation and enhancement capabilities, the resultant images exhibit a level of clarity and detail previously unattainable with traditional methods. Furthermore, the enhanced image quality facilitates more accurate data collection and analysis, thereby contributing to more informed decision-making in marine conservation efforts. Overall, our research demonstrates a significant step forward in overcoming the technical barriers of underwater imaging, promising a new era of high-quality visual data acquisition beneath the waves.

References

[1] Dharwadkar N. V., Yadav M. A., Kadampur M. A.: Improving the quality of underwater imaging using deep convolution neural networks. Iran Journal of Computer Science 5(2), 2022, 127–41.
[2] Estrada D. C. et al.: Underwater LiDAR image enhancement using a GAN based machine learning technique. IEEE Sensors Journal 22(5), 2022, 4438–4451.
[3] Fu X., Cao X.: Underwater image enhancement with global–local networks and compressed-histogram equalization. Signal Processing: Image Communication 86, 2020, 115892.
[4] Garg D., Garg N. K., Kumar M.: Underwater image enhancement using blending of CLAHE and percentile methodologies. Multimedia Tools and Applications 77, 2018, 26545–26561.
[5] Guo Q. et al.: Underwater image enhancement based on the dark channel prior and attenuation compensation. Journal of Ocean University of China 16, 2017, 757–765.
[6] Kumar N. et al.: Underwater Image Enhancement using deep learning. Multimedia Tools and Applications 82(30), 2023, 46789–46809.
[7] Liu X., Gao Z., Chen B. M.: IPMGAN: Integrating physical model and generative adversarial network for underwater image enhancement. Neurocomputing 453, 2021, 538–551.
[8] Li X. et al.: Enhancing underwater image via adaptive color and contrast enhancement, and denoising. Engineering Applications of Artificial Intelligence 111, 2022, 104759.
[9] Li Y. et al.: Underwater image de-scattering and classification by deep neural network. Computers & Electrical Engineering 54, 2016, 68–77.
[10] Lyu Z. et al.: An efficient learning-based method for underwater image enhancement. Displays 74, 2020, 102174.
[11] Mei X. et al.: UIR-Net: A Simple and Effective Baseline for Underwater Image Restoration and Enhancement. Remote Sensing 15(1), 2022, 39.
[12] Moghimi M. K., Mohanna F.: Real-time underwater image enhancement: a systematic review. Journal of Real-Time Image Processing 18(5), 2021, 1509–1525.
[13] Pawar M., Talbar S.: Local entropy maximization based image fusion for contrast enhancement of mammogram. Journal of King Saud University-Computer and Information Sciences 33(2), 2021, 150–160.
[14] Sharma S., Varma T.: Graph signal processing based underwater image enhancement techniques. Engineering Science and Technology, an International Journal 32, 2022, 101059.
[15] Shen Z. et al.: Pseudo-Retinex decomposition-based unsupervised underwater image enhancement and beyond. Digital Signal Processing 137, 2023, 103993.
[16] Shirkande S., Lengare M.: A System Design for Combined Approach of WCID and Wavelet Transformation to Optimize the Underwater Image Enhancement. In Applications of Artificial Intelligence in Engineering: First Global Conference on Artificial Intelligence and Applications (GCAIA 2020). Springer Singapore, 813–818.
[17] Singh N., Bhat A.: A robust model for improving the quality of underwater images using enhancement techniques. Multimedia Tools and Applications 83(1), 2024, 2267–2288.
[18] Wang H. et al.: Self-adversarial generative adversarial network for underwater image enhancement. IEEE Journal of Oceanic Engineering 49(1), 2024, 237–248.
[19] Wu J. et al.: FW-GAN: Underwater image enhancement using generative adversarial network with multi-scale fusion. Signal Processing: Image Communication 109, 2022, 116855.
[20] Xue X. et al.: Investigating intrinsic degradation factors by multi-branch aggregation for real-world underwater image enhancement. Pattern recognition 133, 2023, 109041.
[21] Yang M. et al.: Underwater image enhancement based on conditional generative adversarial network. Signal Processing: Image Communication 81, 2020, 115723.
[22] Yin S. et al.: Degradation-aware and color-corrected network for underwater image enhancement. Knowledge-Based Systems 258, 2022, 109997.
[23] Yu H. et al.: Underwater image enhancement based on color-line model and homomorphic filtering. Signal, Image and Video Processing 16(1), 2022, 83–91.
[24] Zhang W., Dong L., Xu W.: Retinex-inspired color correction and detail preserved fusion for underwater image enhancement. Computers and Electronics in Agriculture 192, 2022, 106585.
[25] Zhang W. et al.: A framework for the efficient enhancement of non-uniform illumination underwater image using convolution neural network. Computers & Graphics 112, 2023, 60–71.
[26] Zhang W. et al.: Underwater image enhancement via minimal color loss and locally adaptive contrast enhancement. IEEE Transactions on Image Processing 31, 2022, 3997–4010.
[27] Zhang W., Wang Y., Li C.: Underwater image enhancement by attenuated color channel correction and detail preserved contrast enhancement. IEEE Journal of Oceanic Engineering 47(3), 2022, 718–735.
[28] Zhou, J. et al.: Underwater image enhancement method via multi-interval subhistogram perspective equalization. IEEE Journal of Oceanic Engineering 48(2), 2023, 474–488.
[29] Zhou J. et al.: Underwater image enhancement method with light scattering characteristics. Computers and Electrical Engineering 100, 2022, 107898.
[30] EUVP dataset. Kaggle, 15.06.2023. [https://www.kaggle.com/datasets/pamuduranasinghe/euvp-dataset] (accessed: 16.02.2024).
[31] EUVP dataset. Minnesota Interactive Robotics and vision Laboratory, 9.02.2020 [https://irvlab.cs.umn.edu/resources/euvp-dataset].

Ph.D. Anuradha Chinta
e-mail: anuradha.chinta@vrsiddhartha.ac.in

She is B.Tech, M.Tech, Ph.D., an assistant professor in the Department of Computer Science and Engineering (CSE) at Siddhartha Academy of Higher Education Deemed to be University, Vijayawada, Andhra Pradesh. She received her Ph.D. in data mining from Acharya Nagarjuna University, Guntur in 2021, following her M.Tech in CSE from Jawaharlal Nehru Technological University Kakinada (JNTUK) in 2014. With a research focus on data mining, artificial intelligence, and machine learning.

https://orcid.org/0000-0002-2241-2220

Eng. Bharath Kumar Surla
e-mail: itsbharatkumar.s2003@gmail.com

Bharath Kumar Surla is currently a Student researcher in the Artificial Intelligence and Data Science program at Siddhartha Academy of Higher Education Deemed to be University, Vijayawada, Andhra Pradesh. Expected to graduate in 2025. His research interests focus on artificial intelligence, image processing, and natural language processing. He is also a Treasurer of VRS ACM SIGKDD Student chapter.

https://orcid.org/0009-0005-7144-9141

Eng. Chaitanya Kodali
e-mail: kodalichaitanya1409@gmail.com

Chaitanya Kodali is currently a student researcher in the artificial intelligence and data science program at Siddhartha Academy of Higher Education Deemed to be University, Vijayawada, Andhra Pradesh. Expected to graduate in 2025. His research interests focus on Internet of Things, image processing, and deep learning.

https://orcid.org/0009-0000-0786-474X