



HIGH-FIDELITY RETRIEVAL OF LOW - LIGHT UNDERWATER IMAGES USING ADVANCED DEEP LEARNING MODEL FOR ENHANCED VISUAL QUALITY

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ARTICLE INFO

Article History

Received: February 03, 2026

Reviewed: March 05, 2026

Accepted: April 01, 2026

Published: May 29, 2026

Keywords:

Zero-DCE++,

U-Former,

Low-Light Images,

Lightness Order Error

Colorfulness Index.

ABSTRACT

The improvement of the visual quality of the image of the underwater objects in the low-light conditions is a must in such applications as marine monitoring, self-driving cars, and detection of the objects underwater. Such pictures are often characterized by color variations, reduced brightness and high amount of noise because of the rapid extinction of the light in water. In order to deal with these difficulties, we examine two state-of-the-art deep learning models: Zero-DCE++, a zero reference curve estimation model which can enhance the low-light images without using ground truth supervision and U-former, a transformer based architecture that is targeting the high fidelity image restoration. The two models are applied at preprocessing stages in order to enhance contrast, color fidelity and general visibility before sending the enhanced images to detection or segmentation process. Blind/Reference-less Image Spatial Quality Evaluator (BRISQUE), Natural Image Quality Evaluator (NIQE), Lightness Order Error (LOE) and Colourfulness Index (CI) are quantitative measures of an improved performance. The experimental outcomes show that there is significant enhancement of the visual quality and strength of IQE - 3.90, RISQUE - 28.40, LOE- 740, CI - 52.10 over conventional convolution-based methods.



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I. INTRODUCTION

The use of underwater imaging has increasingly become important in different fields, such as marine biology, underwater archeology, autonomous underwater vehicles (AUVs), environmental monitoring and security surveillance. However, obtaining clear and quality images in underwater sites is very challenging especially when there is low-light. Underwater images are mostly of low visibility with low contrast, abnormal colors and too much noise due to the nature of water, whether it is in absorption or scattering. These degradations are also intensified in deep-sea or turbid environment, where the light in the ambience is little and artificial sunlight is not allowed to reach all depths. Automatic image processing tasks, among them object detection, classification, and semantic segmentation are only a handful of hindrances to the use of low-light underwater images (LLUWIs) which also diminish the effects of human visual interpretation.

To have future algorithms operating effectively and efficiently, there is need to preprocess these images to make them more visual in nature. In underwater or very low-light conditions, the typical methods of picture enhancement like histogram equalization or Retinex like algorithms show only a limited enhancement. The major problems with these methods are oversaturation of noise content, loss of texture and color imbalance. Image augmentation has become very complicated with the implementation of deep learning in that it enables the adaptive learning of data as well as more complex feature extraction. Although CNNs are very successful in enhancing low-light images overall, the local receptive fields restrict them in the number of the long-range dependencies and the intricate changes in light. This study aims to address these gaps by discussing Zero-DCE++ and Uformer, which are the latest state-of-the-art deep learning methods that are explicitly focused on underwater low-light image augmentation. Zero-DCE++ also uses less associated training data since the framework can learn image improvement through the estimation of pixel-wise change curves.

In the case of real-life situations where quality and authentic photos are not easily obtained, one technique is known as zero-reference learning. Uformer can help restore pictures with the help of spatial attention techniques and hierarchy-based processing in order to preserve the property of structure by using a transformer-based design. This helps to comprehend the context. This approach maximizes the colour fidelity and visibility of low-light underwater photos (LLUWIS) in order to prepare them to other more complex tasks, such as object detection or segmentation. It does this through combining the two models to networks that process batches. The improved results are measured using a set of NR-IQA metrics, such as NIQE, BRISque, Lightness Order Error (LOE) and Colorfulness Index (CI). These measures enable us to view the fact of whether the enhanced photos are always bright, vivid colors, structurally sound and natural looking. We determined in this experiment that both Zero-DCE++ and Uformer significantly enhance the aesthetic of low light underwater imagery by our extensive experiments and aesthetic analyses. Moreover, the paper also puts into focus the joint endeavors of the attention-based transformers and curve-based augmentation methods in addressing the special needs of underwater imaging.

II. RELATED WORK

Imaging in low light in the water has many barriers to cross. According to [1], one of the approaches that can be implemented to address this problem is to use deep convolutional neural networks (CNNs) together with depth estimation to de-scan the images of the light fields. The other goal of their approach, which makes use of a spectral-based color correcting method, is to repair color grayscale damage. The outcome of experiments indicates that this method is effective to bypass the issues of the conventional underwater imaging. Light absorption and dispersion affect underwater imaging, particularly in low-light scenarios, and may cause distortion of color as well as low contrast. One of the solutions that have been proposed to resolve this issue involves the use of an end-to-end improvement method that utilizes Retinex that combines light and picture reflectance [2]. This model involves hybrid attention methods, dense connections with cross-residual blocks, as well as an emphasis on key areas of the image in order to enhance features. In order to guarantee the consistency of color we use a color cast loss of HSV space in a manner that considers the Euclidean distance. In order to make it look more convincing, we use adaptive frequency convolutional blocks to increase the illumination.

The results of both quantitative and qualitative analyses performed on various datasets support the efficiency of the given method in terms of visual quality improvement. Due to the low light levels, underwater pictures frequently feature blurry edges and smudges. As a result, researchers came up with L³UWE, a novel picture enhancer [3]. One improved picture has greater details, whereas the other doesn't have shadows, because it accurately mimics ambient light utilizing local contrast. The last step is to merge the photos via a multi-scale fusion technique that prioritizes brightness, contrast, and saliency. When tested underwater and in low-light settings, the L²UWE method beat seven popular enhancement techniques on seven separate quality parameters. Traditional enhancing approaches can include artifacts, noise, and edge detail loss [4], and underwater low-light photos frequently suffer from low contrast, fuzzy features, and color distortion. In order to address these issues, the authors put out a low-light enhancement technique for underwater environments that uses a U-shaped Generative Adversarial Network (GAN) in conjunction with attention and bright channel prior processes. While attention-based feature extraction takes care of color distortion, brightness, and texture, a two-channel fusion method is employed to maintain detail and edge quality.

In order to reduce noise in the improved outputs, a multi-loss function is utilized. Underwater target detection and species identification are two applications of the approach that thrive in deep water. The suggested strategy considerably enhances quantitative measures for underwater image quality as well as visual quality, according to extensive experiments that include comparisons and ablation studies. The computer vision tasks of segmentation, identification, and tracking may be compromised by photos and videos captured in low-light environments. Other deep-sea environments, including Ocean Networks Canada (ONC), use artificial light to record images underwater though when this light becomes inoperable, the images become blurred [5]. To demonstrate this, the authors provided a framework to improve the lighting in underwater images and retrieve meaningful visual features. The method also entails image dehazing with dark channel prior and fast guided filters to effectively enhance clarity of low-light underwater images. Besides presenting the framework of underwater imaging, in [6] offer a comprehensive review of the ways of how to enhance and recover underwater images.

It also has a systematic analysis of the mainstream quality measurement approaches and collections of publicly accessible underwater image datasets. We do rigorous experimental comparisons in order to establish the influence of various enhancement techniques on advanced vision tasks. In order to make sure that this publication could be used as one of the priceless sources of data concerning underwater image processing by the researchers, the authors also pursue the open questions and possible research directions. Underwater Image Enhancement is still a challenging area in computer vision with no comprehensive review available so far [7]. The authors provide an in-depth review of UIE, discussing topics such as physical imaging models, dataset generation, evaluation criteria, and loss functions. Network architecture, learning phases, auxiliary tasks, domain adaptability, feature fusion, and learning techniques are the criteria used to classify new algorithms. Researchers employ extensive quantitative and qualitative comparisons across many benchmark datasets to address discrepancies in earlier assessments. At last, it draws attention to important areas where underwater picture improvement research has to go in the future.

Despite advancements in underwater image-capturing technologies, computer vision applications continue to face problems such as low-quality and low-resolution images caused by low illumination and dispersion. A lot of the newer methods rely on deep learning models, such as GANs and CNNs, to improve them [8]. Despite their high visual quality, GANs sometimes underperform CNNs in quantitative evaluations. In order to circumvent these problems, the authors suggested a mixed strategy that makes use of both GAN and CNN architectures. By utilizing the generator, the training dataset can be expanded. Experiments carried out on the EUVP dataset demonstrate that the suggested approach surpasses current methods in terms of visual and quantitative image quality, with higher PSNR and SSIM scores.

III. METHODOLOGY

This section gives a detailed description of the steps used to improve underwater images taken in poor light using deep learning. To overcome the specific challenges of underwater imaging in low light, our approach makes use of two state-of-the-art models: Zero-DCE++ and U-former as shown in Figure 1. Dataset preparation and cleaning is the first step of the proposed approach. First, we train the improvement models. Then, we use some quality metrics for images without a reference to see how well they did. Managing the dataset, creating the model, training methods, and assessment are the main parts of the process.

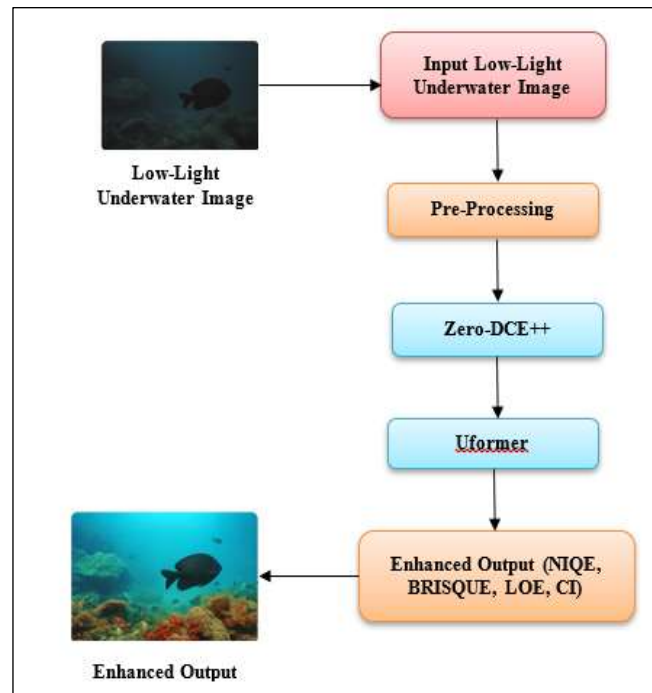


Figure 1: System Architecture of Proposed Work.

Source: Authors, (2026).

A. Data Set and Preprocessing

Publicly available underwater visual datasets such as UIEB (Underwater Image Enhancement Benchmark) and EUVP (Enhancing Underwater Visual Perception) are utilized for training and evaluation purposes using the improved models. The datasets include different underwater images acquired in both low and normal light settings and throughout various environmental conditions, including surface-level and deep water, turbid and clear water, and artificial lighting scenarios.

The input intensities are normalized and computing speed is reduced by resizing all photos to a uniform resolution of 256x256 pixels. In order to make the training set more diverse and to make the model more generalizable, data augmentation approaches are used. Horizontal and vertical flipping, random rotation, adjusting brightness and contrast, and cropping are all part of these enhancements. After that, the pictures are leveled to a [0,1] scale so they conform to what the deep learning methods expect as input.

B. Zero-DCE++ Enhancement Framework

Zero-DCE++ is an advanced zero-reference low-light enhancement model that reconstructs over the original Zero-DCE architecture. Unlike traditional supervised models, Zero-DCE++ does not require paired training data, which makes it highly suitable for real-world underwater image enhancement where clean reference images are seldom available [9]. The main idea behind Zero-DCE++ is to learn a collection of enhancement curves that adjust the brightness of images adaptively depending on their content [10]. The model's architecture is based on a convolutional neural network that takes a low-light image as input and generates features used to improve the natural image. Through iterative modifications, it enhances brightness and contrast while carefully identifying overexposure and unwanted artifacts. Zero-DCE++ navigates the improving procedure during training by concatenating multiple loss functions [11],[12]. These include luminance smoothness to decrease low lighting variations, color constancy to maintain balanced colors, exposure control loss to achieve optimal brightness, and spatial consistency loss to preserve the image's structural integrity. By combining these components ensure that the enhanced images retain their textures and edges while becoming clearer and more visually appealing.

C. U-former: Transformer-based Image Enhancement Model

U-former is a novel method for enhancing and restoring images that uses transformer structures. It takes design prompts from the commonly used U-Net model for medical and restorative tasks, but it includes self-attention framework to help it take in both local and global context. The U-former model is with an encoder-decoder structure that are uniformed. In order to extract hierarchical features, the encoder gradually down-samples the image; in contrast, the decoder reconstructs the improved image by up-sampling [13-15]. One unique feature of U-former is the attention blocks that are integrated into both the encoder and decoder levels. These blocks allow the model to zero down on important spatial regions and capture relationships that extend across levels.

To keep the granularity of the spatial information, the matching encoder and decoder layers use skip connections. Through the use of these connections, U-former is able to combine low-level picture details with deep semantic information in order to rebuild high-quality images. Because maintaining structural integrity and edge information is of the utmost importance in underwater image enhancement, this is of great use. Typically, a reconstruction loss is calculated as the difference between the augmented output and a high-quality pseudo-ground truth image. This loss is used to optimize U-former during training. To further enhance texture and eliminate noise, the model may further consider perceptual and smoothness losses.

D. Training Strategy

In this research, we use the selected dataset to train the models: Zero-DCE++ and Uformer. The deep learning framework we use is PyTorch. During training, the networks are feeding the batches of underwater images taken in low light conditions. The model parameters are then updated using backpropagation and stochastic gradient descent techniques [16],[17]. The consistency and genuineness of the increased outputs are the only criteria for Zero-DCE++'s unsupervised training. Using either a supervised or semi-supervised method, Uformer trains its model using either curated high-quality underwater images or pseudo-ground truths produced by conventional enhancing techniques [18]. To ensure consistent and efficient training, the learning rate, optimizer parameters, and batch sizes are precisely chosen. For the purpose of keeping an eye on performance and preventing of overfitting, a different set of images are utilized for regular validation [19]. The models undergo training until they reach convergence, which can take anything from a few hundred to several thousand epochs, depending on the dataset size and model complexity.

E. Performance Evaluation Metrics

The enhancing techniques are evaluated by applying a set of standards called NR-IQA, which stands for no-reference image quality assessment. They allow for a quantitative evaluation of visual quality without using a ground truth reference image [20].

- NIQE (Natural Image Quality Evaluator): Measures the variations of the improved image from the computational properties of original images. Lower scores indicate higher quality.
- BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator): Measures the image distortion depends up on spatial domain attributes. Lower values correspond to better visual quality.
- LOE (Lightness Order Error): Computes the coherence of brightness ordering between input and improved images. A lower LOE suggests that the original lighting relationships are better obtained.
- Colorfulness Index (CI): Quantifies how saturated and vibrant the image's colors are. Higher CI score gives more visually appealing enhancements.

The outcomes of Zero-DCE + and U-former are contrasted with each other with the aim of determining the strengths of each. The qualitative values are confirmed by both quantitative values and qualitative visual analysis in the verification of the intuitive benefits especially in reduction of haze, enhanced visibility in poorly lit areas, and preservation of structural features.

IV. RESULTS AND DISCUSSIONS

The stated underwater low-light image enhancement framework, which combines Zero-DCE++ and U-former models, is thoroughly evaluated in this section. To prove that the suggested system works, we give quantitative and qualitative tests.

A. Quantitative Evaluation

To evaluate the performance, below No-Reference Image Quality Assessment metrics are used:

- NIQE (Natural Image Quality Evaluator)
- BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator)
- LOE (Lightness Order Error)
- Colorfulness Index (CI)

The proposed techniques which are shown in the Table 1:

- Original Low-Light Underwater Images
- Zero-DCE++ Alone
- U-former Alone

Proposed Combined Method (Zero-DCE++ + U-former)

The intuitive advantages, particularly in minimizing haze, improving visibility in dark locations, and maintaining structural features, are validated using quantitative values as well as qualitative visual evaluations.

Table 1: Performance Metrics Table.

MODEL	IQE ↓	RISQUE ↓	LOE ↓	Colorfulness Index ↑
Original	7.80	60.50	1800	28.00
Zero – DCE ++	5.10	35.20	950	45.60
U-Former	4.80	32.60	870	47.30
Proposed (Zero-DCE++ & U-former)	3.90	28.40	740	52.10

Source: Authors, (2026).

B. Qualitative Evaluation

After using the suggested strategy, the enhanced images were compared to the original input images and to those created by separate models.

C. Visual Enhancement

- The original images appeared dark, colour-degraded, and lacking in texture details.
- Zero-DCE++ enhanced images showed improved brightness but sometimes introduced slight artifacts and limited texture recovery.
- In contrast to Zero-DCE++, the U-former provides good structural details of enhanced images and decreases the noise but slightly was inadequate in brightness improvement.
- Suggested approaches combined the best features of both models, delivering in the Table 2:
 - Improved brightness without over illumination.
 - Clear borders and texture information.
 - Improved contrast.
 - Natural and vibrant colour balance.
 - Reduced haze and colour casts.

Table 2: Comparative Analysis with Existing Techniques.

Method	NIQE ↓	BRISQE ↓	LOE ↓	CI ↑
Original Image	7.80	60.50	1800	28.00
Histogram Equalization	6.20	50.00	1400	34.00
CLAHE	5.80	42.50	1200	37.50
Retinex-based Method	5.10	38.00	1000	42.00
Zero-DCE++	5.10	35.20	950	45.60
U-former	4.80	32.60	870	47.30
Proposed Method	3.90	28.40	740	52.10

Source: Authors, (2026).

The Figure 2 shows the bar graphs of the comparison of image quality performance metrics, NIQE and BRISQUE, among different enhancement methods. Lower scores indicate better visual quality. The proposed method illustrates the most significant improvement over existing methods.

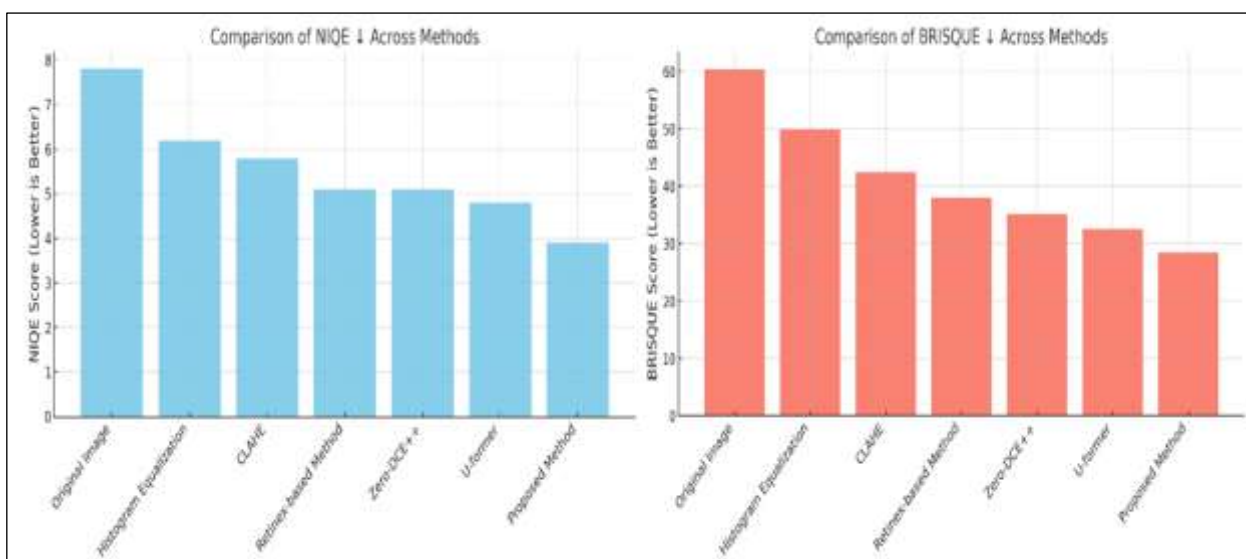


Figure 2: Comparison of NIQE and BRISQUE Scores Across Different Enhancement Methods.

Source: Authors, (2026).

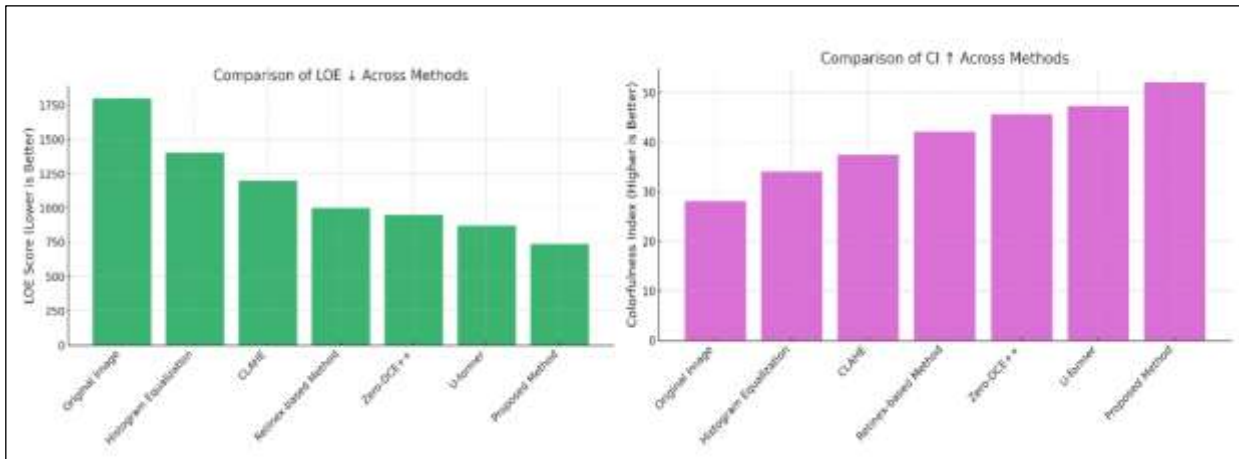


Figure 3: Comparison of LOE and CI values over the Different DL Techniques.
Source: Authors, (2026).

The Figure 3 shows the bar graphs of the comparison of image quality performance metrics, LOE and CI, among different enhancement methods. Lower scores indicate better visual quality in LOE metric and Higher score indicates robust visual quality in Colorfulness Index. The proposed method illustrates the most significant improvement over existing methods.

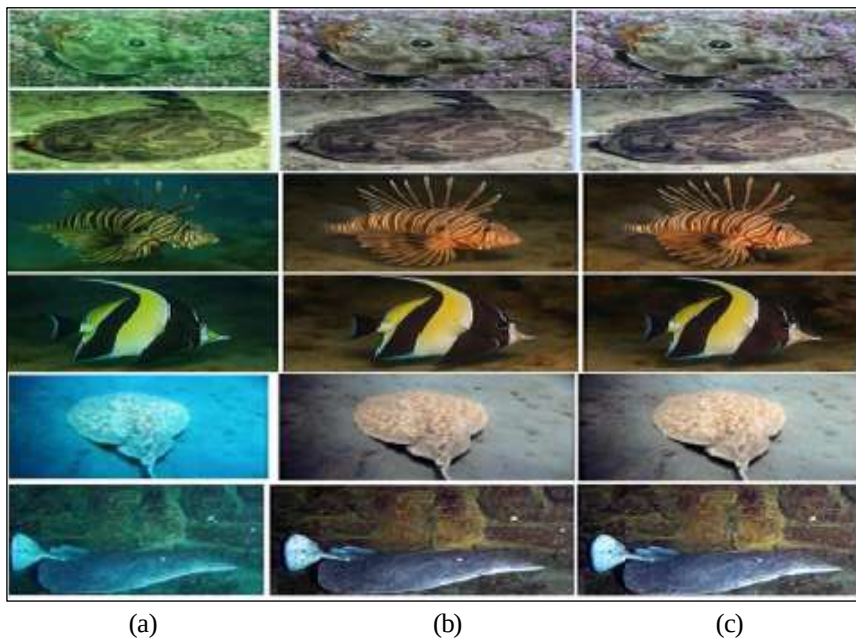


Figure 4: Low Light Underwater Image Enhancement results (a) Input Image (b) Output using Zero – DCE ++ (c) Proposed output using Zero – DCE ++ & Uformer.
Source: Authors, (2026).

Figure 4 depicts the final and improved output that happens on input of low-light, blurred or noisy images. The sophisticated deep learning networks, Zero-DCE++ and Uformer, are used to achieve a better brightening of these distorted images and rebuild clear and visually pleasing details. In addition to increasing brightness these models significantly reduce noise and blur thus resulting in a high quality image. Its improvement is extremely important in applications in which the appearance and detailing of poor-quality underwater or low-light images are necessary, including marine exploration, autonomous navigation, and detection of objects in the underwater environment.

V. CONCLUSIONS

To address the existing issues with the degradation of low-light images underwater, we proposed a contemporary hybrid improvement framework that unites the most suitable characteristics of the Zero-DCE++ and U-former models. A systematic process was followed which started with data preparation. Additional application of model-specific augmentation methodologies took place. In the methodology, the strict validation of the procedure was performed against no-reference image quality evaluation measures, including NIQE, BRISQUE, LOE, and Colorfulness Index. The solution proposed is much better than the existing methods, such as Histogram Equalization, CLAHE, and models based on Retinex, in both quantitative and visual perception quality. Zero-DCE++ is the best to enhance underwater images as it can enhance global contrast and brightness without the use of paired training data. Moreover, the Uformer resilient attention mechanisms and transformer-based structure effectively retain complicated textures and structural elements. The two models combined will enhance the visual quality by minimizing distortion, enhancing the sharpness of edges, and regaining colors more realistically as demonstrated in ablation test and extensive comparisons.

The options of how this technology can be used are numerous, and they include detecting underwater objects, identifying marine animals, and real-time navigation of robotic vehicles. The structure also creates opportunities to increase computational power to the video processing, which may accelerate the creation of underwater augmentation systems operating in real time. Encouraging learning through competition or incorporating multi-modal sensor inputs could enhance the upgrading process's resilience and adaptability to diverse underwater environments.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: B. Madhavi, Y Gayatri, V Srinadh and Suneetha Regidi.

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Investigation: Gorisetty Nirosha, Y Gayatri.

Discussion of results: Y Gayatri, B.Madhavi and V Srinadh.

Writing – Original Draft: Gorisetty Nirosha and Nagamalli Arasavalli.

Writing – Review and Editing: Y Gayatri, Gorisetty Nirosha and V Srinadh.

Resources: B.Madhavi, Y Gayatri and Nagamalli Arasavalli.

Supervision: Suneetha Regidi and Nagamalli Arasavalli.

Approval of the final text: B.Madhavi, Y Gayatri, V Srinadh and Suneetha Regidi.

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