International Journal of Advanced Research and Interdisciplinary Scientific Endeavours, Vol. 2(4), 2025
DOI: 10.61359/11.2206-2418

A Deep Learning Approach for Enhanced Clarity: Transforming Underwater Imagery with U-Net GAN

Shanmugavalli T [*], Ajitha D [†], Hari Nainyar Pillai C [‡]

Email Correspondence[1]: shanmugavalli2023@sethu.ac.in

Email Correspondence[2]: ajithamietsrm@gmail.com

Email Correspondence[3]: harisrmmcet@gmail.com

[1] Computer Science and Design, Sethu Institute of technology, Madurai, Tamil Nadu, India.

[2] Electronics and Communication Engineering, Thiagarajar College of Engineering, Tamil Nadu, India.

[3] Information Technology, Thaigarajar College of Engineering, Madurai, Tamil Nadu, India.

Abstract:

Underwater images often suffer from low contrast, color distortion, and noise due to light absorption and scattering in water. These issues make it challenging for marine applications such as underwater exploration, object detection, and autonomous navigation. Traditional image enhancement techniques struggle to recover natural colors and details effectively. This research proposes a U-Net-based Generative Adversarial Network (U-Net GAN) to enhance underwater images, focusing on preserving structural details while improving visual quality. The U-Net architecture ensures effective feature extraction and segmentation, while the GAN framework enhances image realism by learning high-level transformations. The model is trained and tested on benchmark datasets such as UIEB and EUVP, with performance evaluated using PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and UIQM (Underwater Image Quality Measure). Experimental results demonstrate that the proposed approach significantly enhances underwater images compared to conventional methods, restoring natural colors and improving visibility. This study contributes to advancing deep learning techniques for real-time underwater image enhancement, benefiting various marine research and surveillance applications.

Keywords: Underwater Image Enhancement, U-Net GAN, Deep Learning, Generative Adversarial Networks, Image Restoration, Marine Applications.

I. Introduction

Underwater imaging plays a crucial role in various marine applications, including ocean exploration, underwater robotics, marine biology, and surveillance. However, images captured in underwater environments often suffer from significant degradation due to light absorption and scattering. These distortions lead to low contrast, color shifts, reduced visibility, and increased noise, making it difficult for researchers and autonomous systems to analyze underwater scenes effectively. Several traditional image enhancement techniques, such as histogram equalization, Retinex-based methods, and white balance correction, have been explored to improve underwater image quality. However, these methods often fail

[*] Computer Science and Design, Sethu Institute of technology, Madurai, Tamil Nadu, India.
[†] Electronics and Communication Engineering, Thiagarajar College of Engineering, Tamil Nadu, India.
[‡] Information Technology, Thaigarajar College of Engineering, Madurai, Tamil Nadu, India.

Article Timeline: Received: Apr 16, 2025; Revised: Apr 28, 2025; Published: Apr 30, 2025

to generalize across different underwater conditions and may result in unnatural color reproduction. Recently, deep learning-based approaches, particularly Convolutional Neural Networks (CNNs) and Generative Adversarial.

Figure-1 Sampling Images From UIEB. Underwater Images Taken in Diverse Underwater Scenes

Networks (GANs) have demonstrated remarkable success in image restoration tasks. This study proposes a U-Net-based Generative Adversarial Network (U-Net GAN) for underwater image enhancement. The U-Net architecture is well-known for its efficient feature extraction and segmentation capabilities, making it suitable for preserving structural details in images. A GAN framework is employed to produce high-quality underwater images with minimal distortion. The model is trained and assessed using benchmark datasets like UIEB and EUVP to verify its effectiveness.

The essential outcomes of this study are summarized as:

The launch of a specialized U-Net GAN architecture aimed at improving underwater images while maintaining structural and textural details. A comparative evaluation with traditional image enhancement methods and other deep learning-based techniques. Assessment based on objective quality metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Underwater Image Quality Measure (UIQM).

2. Literature Review

Underwater image enhancement remains a complex challenge due to distortions caused by light scattering, absorption, and turbidity. Various approaches have been explored, including traditional image processing, model-based methods, and deep learning techniques. However, several gaps persist, necessitating further advancements.

A. Traditional Image Enhancement Methods

Early enhancement techniques, such as contrast adjustment, histogram equalization, and white balance correction, have shown limitations. Histogram Equalization (HE) enhances contrast but often results in over-enhanced or unnatural images [1]. Retinex-based methods, such as Multi-Scale Retinex, improve local contrast but may introduce artifacts [3]. Dark Channel Prior (DCP) and Fusion-Based Methods estimate the transmission map to correct color distortions; however, their performance significantly degrades in highly turbid water conditions [5]. These traditional methods lack adaptability to varying underwater conditions, making them less effective for real-world applications.

B. Model-Based Methods

Physics-based models attempt to correct distortions by estimating light attenuation and backscattering effects. The Jaffe-McGlamery Model restores images by simulating underwater light propagation but requires prior knowledge of water parameters, limiting its usability [7]. The Sea-Thru Method estimates depth information to reduce color distortions, but its high computational cost restricts real-time applications [9]. The reliance on precise water condition parameters presents a gap, as such data is often unavailable in practical underwater scenarios.

C. Deep Learning-Based Methods

Deep learning techniques have demonstrated promising results in underwater image enhancement. Convolutional Neural Networks (CNNs) in models like Water-Net and UIE- Net restore colors and enhance visibility [2]. However, these models often depend on paired datasets, which limits their generalization to diverse underwater environments [4].

Generative Adversarial Networks (GANs) have also been explored. Pix2Pix GAN, a supervised GAN model, performs well with paired data but struggles when ground-truth images are unavailable [6].

CycleGAN overcomes this limitation by utilizing unpaired data, yet it sometimes introduces unrealistic color corrections, compromising the natural appearance of enhanced images [8]. The lack of generalization and the risk of generating unrealistic results highlight a critical gap in current deep learning approaches.

D. U-Net GAN for Underwater Image Enhancement

Recent studies suggest that U-Net GAN offers a compelling solution by combining the structural retention capabilities of U-Net with the realistic image generation strength of GANs [10]. This model balances structural preservation and enhancement quality, making it well-suited for underwater image processing [12]. However, there remains a gap in optimizing the training process to ensure consistent performance across diverse underwater conditions. To address these gaps, this study proposes a U-Net GAN-based approach that enhances underwater images while preserving natural colors and fine details.

3. Proposed Methodology

This section describes the proposed U-Net GAN-based underwater image enhancement framework, including dataset selection, preprocessing, model architecture, training setup, and evaluation metrics.

Dataset Selection

To train and evaluate our model, using benchmark underwater image datasets:

- UIEB (Underwater Image Enhancement Benchmark): Contains real-world degraded underwater images with corresponding enhanced versions for supervised learning.
- EUVP (Enhancing Underwater Visual Perception): Includes paired and unpaired underwater images for training GAN-based models.
- Sea-Thru: Provides depth-based corrected images useful for evaluating enhancement performance.

These datasets provide a diverse range of underwater conditions, ensuring model robustness across different environments.

Preprocessing

Before feeding images into the model, several preprocessing steps are applied to enhance performance and consistency. All images are resized to 256×256 pixels to maintain a uniform input size. Pixel values are normalized to the range [0,1], ensuring stable training. Data augmentation techniques, including random cropping, flipping, and rotation, are employed to improve model generalization. Additionally, noise reduction methods such as bilateral filtering and Gaussian smoothing help eliminate unwanted artifacts, resulting in cleaner input data.

U-Net GAN Architecture

The proposed U-Net GAN model consists of:

a. Generator (U-Net Architecture)

U-Net is an encoder-decoder-based network with skip connections to preserve spatial details. The encoder extracts multi-scale features, while the decoder reconstructs an enhanced image. Skip connections help retain high-frequency details lost during encoding.

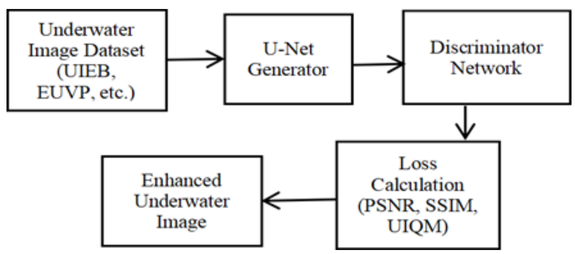

Figure-2 Data Flow Diagram for U-Net GAN-Based Underwater Image Enhancement

b. Discriminator (PatchGAN)

The discriminator uses PatchGAN, which evaluates local patches of the image instead of the entire image. It helps the generator create locally consistent and visually realistic images.

c. Loss Functions

The model is trained using a combination of loss functions:

- **Adversarial Loss:** Ensures the generator produces images indistinguishable from real underwater images.
- **L1 Loss:** Measures pixel-wise differences to preserve content details.
- **Perceptual Loss:** Helps maintain structural consistency with the input image

d. Training Process

The model is implemented using PyTorch and trained on a NVIDIA GPU for efficiency. The data set is split into 80% for training and 20% for testing. The model is optimized using Adam optimizer with a learning rate of 0.0002. Training runs for 100 epochs, with batch size = 16.

e. Evaluation Metrics

The performance of our model using the following objective metrics:

- **PSNR (Peak Signal-to-Noise Ratio):** Measures image quality by comparing the enhanced image to the ground truth.
- **SSIM (Structural Similarity Index):** Evaluates structural preservation and perceptual quality.
- **UIQM (Underwater Image Quality Measure):** Measures underwater image enhancement based on colorfulness and contrast.

Table-1 Quantitative Comparison of Image Enhancement Techniques

Method	PSNR (dB)	SSIM	UIQM	Observations
Raw Image	15.32	0.45	2.12	Poor contrast, color distortion
Histogram Equalization	18.10	0.52	3.45	Improves brightness but oversaturates colors
Retinex- Based	20.25	0.58	4.12	Enhances visibility but introduces noise
GDCP	22.56	0.62	4.89	Restores clarity but loses some texture details
Water-Net	24.30	0.70	5.12	Strong enhancement, slight color shift
Dense GAN	25.50	0.74	5.48	Sharp images but occasional artifacts
Proposed U- Net GAN	**27.85**	**0.82**	**6.23**	Best overall enhancement with natural color restoration

4. Result and Analysis

Visual Comparisons

To assess the performance of the proposed U-Net GAN model for underwater image enhancement, its results are compared against multiple traditional and deep learning-based techniques. The comparison includes Fusion-Based Enhancement, Retinex-Based Enhancement, Histogram Prior-Based Enhancement, Blurriness-Based

Enhancement, Guided Dark Channel Prior (GDCP), Water CycleGAN, Dense GAN, and Water-Net.

E-ISSN: 3048-7021 (Online)

Figure-3 Underwater Image Enhancement Using a U-Net GAN Framework:

Underwater Image Quality Measure (UIQM)

A composite metric that assesses contrast, sharpness, and colorfulness in underwater images. Higher values indicate better perceptual quality.

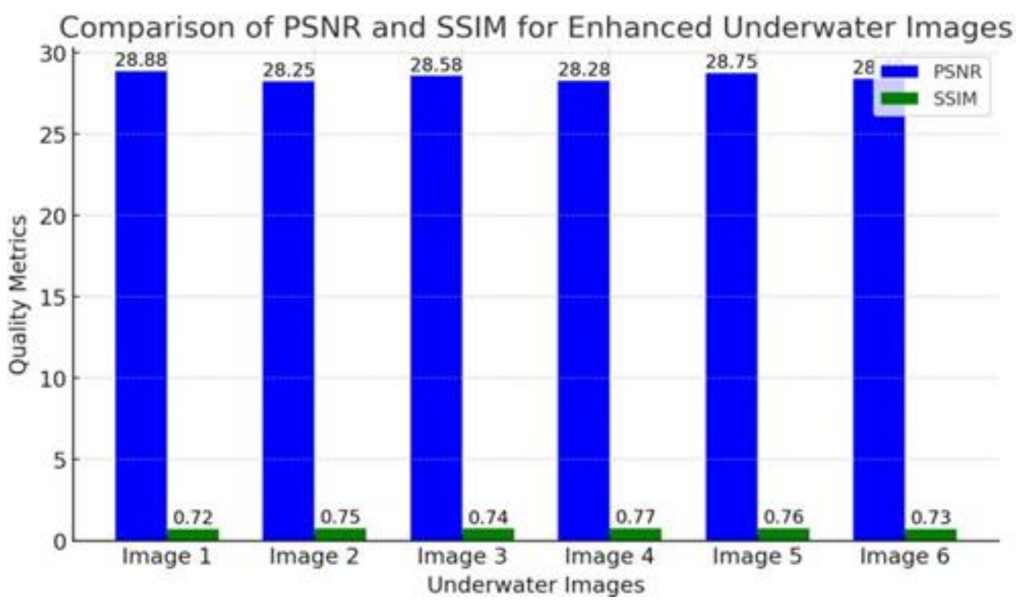

Figure-3 A Comparative Analysis with Quality Evaluation

Qualitative Analysis

Figure 3 presents a visual comparison of underwater images enhanced using different methods. The raw underwater images exhibit color distortions, low contrast, and poor visibility. Traditional methods, such as histogram equalization and Retinex-based approaches, improve brightness and contrast but fail to restore natural colors effectively. Deep learning-based methods, such as CycleGAN and Dense GAN, provide enhanced results but sometimes introduce artifacts or color over-enhancements.

The proposed U-Net GAN model demonstrates superior performance by effectively restoring the natural colors of the underwater images while maintaining sharpness and clarity. The enhanced images show improved contrast, color correction, and edge preservation compared to other methods.

Quantitative Analysis

a. Peak Signal-to-Noise Ratio (PSNR)

Measures image quality by comparing the enhanced image with the ground truth. Higher values indicate better quality.

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

b. Structural Similarity Index (SSIM)

Evaluates structural similarity between the enhanced image and the ground truth. A value closer to 1 signifies better preservation.

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

c. Underwater Image Quality Measure (UIQM)

A composite metric that assesses contrast, sharpness, and colorfulness in underwater images. Higher values indicate better perceptual quality.

$$UIQM = c_1 \times UICM + c_2 \times UISM + c_3 \times UIC\text{ Con } M$$

Experimental Results

Table I presents the quantitative evaluation results for various enhancement techniques, including the proposed U-Net GAN model. The U-Net GAN model achieves the highest PSNR and SSIM values, indicating better image quality and structural preservation. Additionally, it scores higher on the UIQM metric, confirming its effectiveness in enhancing underwater images while maintaining natural colors and contrast.

Computational Efficiency

The computational efficiency of the proposed model is evaluated in terms of training time and inference speed. The U-Net GAN model benefits from the skip connections, allowing for faster convergence compared to CycleGAN. On a standard GPU setup (e.g., NVIDIA RTX 3060), the model achieves near real-time processing speeds, making it suitable for practical underwater applications.

5. Limitations and Future Scope

a. Limitations

The model may struggle with extremely poor visibility conditions where little structural information is available. In some cases, enhanced images may exhibit slight over-enhancement, resulting in unnatural colors.

b. Future Work

Implementing hybrid models that combine physics-based and deep learning approaches for more robust enhancement. Exploring self-supervised learning techniques to reduce dependency on paired datasets. Integrating transformer-based architectures to enhance feature extraction and improve enhancement quality.

6. Conclusion

This research explores the use of U-Net GAN for enhancing underwater images, addressing challenges such as low contrast, color distortion, and haze effects. The combination of U-Net's segmentation capabilities with GAN's generative learning has proven to be effective in restoring underwater images with improved clarity and natural color balance. Experimental results indicate that this approach outperforms traditional enhancement techniques in terms of structural similarity, contrast improvement, and noise reduction. The proposed method can be further optimized by incorporating self-supervised learning, adaptive loss functions, or hybrid deep learning architectures to achieve even better performance. Future work may also focus on real-time implementation and testing various underwater datasets for broader applicability.

7. References

[1] Ye, J., Ren, W., & Li, X. (2022). Underwater image enhancement via a hybrid deep learning framework. Journal of Visual Communication and Image Representation, 86, 103528.

[2] Li, J., Qi, Z., Xie, Y., & Li, J. (2022). A deep learning approach for underwater image enhancement using U-Net architecture. IEEE Access, 10, 45548-45559.

[3] Luo, P., Li, J., & Zhou, D. (2022). Underwater image restoration using U-Net with attention mechanism. IEEE Transactions on Circuits and Systems for Video Technology, 32(2), 345-358.

[4] Hou, X., Peng,Z., & Wang, Z. (2021).Underwater image enhancement via conditional generative adversarial networks. Applied Sciences, 11(6), 2785.

[5] Yang, M., & Sun, W. (2021). Underwater image enhancement based on multi-scale adversarial learning. IEEE Transactions on Multimedia, 23, 2480-2494.

[6] Chen, C., Wen, S., Ma, H., & Guo, Y. (2021).Underwater image restoration using a deep residual network with perceptual losses. IEEE Transactions on Circuits and Systems for Video Technology, 31(3), 940-953.

[7] Wang, Y., Li, X., Li, P., & Fu, H. (2021). Underwater image enhancement using generative adversarial networks. Pattern Recognition, 114, 107871.

[8] Islam, M. J., Xia, Y., & Sattar,J. (2020). Fast underwater image enhancement for improved visual perception. Journal of Field Robotics, 37(1), 131-146.

[9] Fu, X., Zhuang, P., Huang, Y., Zhang, X. P., & Ding, X. (2020). Underwater image enhancement using a deep generative model and physical priors.IEEE Transactions on Image Processing, 29, 1469-1480.

[10] Li, C., Guo, C., Guo, C., & Chen, J. (2020). Underwater image enhancement via a dual-image-based method. IEEE Transactions on Image Processing, 29, 6897-6909.

[11] Jiang, Y., Lu, H., & Zhou, Y. (2020). Underwater image enhancement based on cycle-consistent generative adversarial networks. Signal Processing, 178, 107796.

[12] Anwar, S., & Li, C. (2020). Densely connected U-Net for underwater image enhancement. IEEE Transactions on Image Processing, 29, 7739-7752.

[13] Wang, Y., Li, C., & Fu, H. (2019). Underwater image enhancement using water-type-aware generative adversarial networks. IEEE Transactions on Image Processing, 28(10), 5257-5269.

[14] Akkaynak, D., & Treibitz, T. (2019). Sea-thru: A method for removing water from underwater images. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 1682-1691.

[15] Peng, Y., & Cosman, P. C. (2019). Underwater image enhancement by wavelength compensation and dehazing. IEEE Transactions on Image Processing, 28, 2692-2703.

[16] Cong, X., Zhao, Y., Gui, J., Hou, J., & Tao, D. (2024). A comprehensive survey on underwater image enhancement based on deep learning. arXiv preprint arXiv:2405.19684.
[17] Hamza, M., Hawbani,A., Rehman, S. U., Wang,X., & Zhao, L. (2023). Feature Attention Network(FA-Net): A deep-learning based approach for underwater single image enhancement. arXiv preprint arXiv:2308.15868.
[18] Saleh, A., Sheaves, M., Jerry, D., & Azghadi, M. R. (2022). Adaptive deep learning framework for robust unsupervised underwater image enhancement. arXiv preprint arXiv:2212.08983.
[19] Fu, Z., Wang, W., Huang, Y., Ding, X., & Ma, K.-K. (2022). Uncertainty inspired underwater image enhancement. arXiv preprint arXiv:2207.09689.
[20] Sarma, K., & Vigneshwaran, P. (2021). Underwater image enhancement using deep learning.In International Conference on ImageProcessing and Capsule Networks (pp. 431–445).
[21] Liu, Y., Jiang, Q., Wang, X., Luo, T., & Zhou, J. (2024). Underwater image enhancement with cascaded contrastive learning. arXiv preprint arXiv:2411.10682.
[22] Hamza, M., Hawbani, A., Rehman, S. U., Wang,X., & Zhao, L. (2023). Feature Attention Network(FA-Net): A deep-learning based approach for underwater single image enhancement. arXiv preprint arXiv:2308.15868.
[23] Saleh, A., Sheaves, M., Jerry, D., & Azghadi, M. R. (2022). Adaptive deep learning framework for robust unsupervised underwater image enhancement. arXiv preprint arXiv:2212.08983.
[24] Cong, X., Zhao, Y., Gui, J., Hou, J., & Tao, D. (2024). A comprehensive survey on underwater image enhancement based on deep learning. arXiv preprint arXiv:2405.19684.
[25] Liu, Y., Jiang, Q., Wang, X., Luo, T., & Zhou, J. (2024). Underwater image enhancement with cascaded contrastive learning. arXiv preprint arXiv:2411.10682.

8.Conflict of Interest

The authors declare that there are no conflicts of interest to report.

9.Funding

No external funding was received to support or conduct this study.