VIDWAN Journal of Science, Technology and Innovation
OPEN ACCESS
PEER-REVIEWED - OPEN ACCESS Vol. 01 · Issue 01 · 2026 · pp. 1- 6 | ISSN: APPLIED (Online) | INAGURAL EDITION

A Novel Dataset For Non-Reference Evaluation Of Underwater Image Enhancement

B.SAIRAM
SV EMBEDDED SOLUTIONS, HYDERABAD

ABSTRACT

Photographs taken underwater are very important for studying marine resources, marine ecology, and environmental monitoring because they give a unique view of the world below the surface. The absorption and scattering of light results in color distortion in underwater photographs. The decline significantly impairs their performance in subsequent applications, such as object detection, monitoring, and identification. Consequently, techniques for enhancing underwater photographs seek to augment visual information and rehabilitate image quality. This work will utilize deep learning, physical models, images, and more methodologies as the foundation for the augmentation tactics presented. Simultaneously, we evaluate relevant metrics for the analysis of datasets and underwater photographs. Our primary objective is to conduct a comprehensive review of the advancements in research aimed at enhancing underwater imagery and its implications for the evolution of superior underwater vision systems.

Keywords: *Underwater Image Enhancement; Underwater Image Dataset; Quality Evaluation Metrics.*

Article history: Received 8 July 2026 · Revised 18 July 2026 · Accepted 28 July 2026 · Published 8 August 2026

1. INTRODUCTION

Recent interest in underwater imaging technologies has surged across various areas, including ocean exploration, underwater archeology, marine biology, and underwater robots. The unique optical properties of water, including its capacity to absorb, scatter, and attenuate light, hamper underwater photography. Color distortion, inadequate contrast, and blurred features are potential impediments to subsequent image processing and interpretation tasks.

A multitude of underwater image restoration techniques has been devised to mitigate these challenges and improve the visual quality of underwater images. In underwater applications reliant on image-based analysis and decision-making, these technologies seek to enhance image quality by mitigating light attenuation, augmenting contrast, and rectifying color aberration, among other factors. The objective of this endeavor is to conduct a comprehensive examination of the current methods for enhancing underwater photographs.

A mechanism exists that categorizes these technologies into three groups: image-based, physical models, and deep learning. Refer to Figure 1 for a depiction of the classification procedure. Image-based techniques inadequately convey the essence of underwater photography; yet, they enhance contrast, sharpen edges, and modify colors through pixel value adjustments. To rectify these effects and restore image quality, methodologies grounded in physical models employ mathematical frameworks to elucidate the propagation of light through water and its degree of attenuation. Enhancing underwater photography with deep learning techniques has produced remarkable outcomes in recent years. These technologies provide complex mappings that encompass a range of underwater images from poor to high quality.

Databases of underwater photographs are essential for developing and evaluating techniques to enhance underwater photography. The scholarly community has extensively utilized the publicly accessible datasets of underwater photos provided in this paper. These datasets are excellent for creating and training algorithms that enhance underwater photographs due to their diverse array of underwater settings and imaging conditions. When evaluating the efficacy of various enhancement techniques, it is crucial to examine the final underwater photographs for indications of deterioration. This paper quantitatively evaluates the accuracy and visual quality of underwater photo enhancements by examining various aspects, including both referenced and non-referenced metrics.

By employing these methodologies, we may develop superior algorithms and assess various enhancement strategies with greater impartiality. This research thoroughly explores underwater photo enhancement methods, databases, and standards for assessing underwater image quality. This article seeks to provide scholars and practitioners with a comprehensive overview of the current state of underwater imaging by integrating data from these three domains and proposing directions for future research. We aspire that this assessment will advance underwater photography and its various applications.

2. LITERATURE SURVEY

Sahu, N., & Jena, S. (2024). This paper examines recent advancements in underwater image enhancement techniques, emphasizing the primary challenges posed by dispersion, light absorption, and color degradation. The authors define development strategies into three categories—physics-based, learning-based, and hybrid approaches—enabling a comprehensive assessment of their advantages and disadvantages. The application of machine learning is essential for enhancing visual clarity and recovering lost image attributes. Oceanography, marine biology, and underwater robotics are among the disciplines that have utilized these methodologies, as evidenced by case studies. Researchers are investigating the integration of AI and real-time processing to address scale issues and bridge deficiencies.

Mishra, A., & Reddy, P. (2024). This paper examines convolutional neural networks (CNNs) and generative adversarial networks (GANs) as viable deep learning methodologies for underwater photo restoration. The paper primarily focuses on underwater performance enhancement techniques, loss functions, and datasets. Underwater photographs are enhanced via a distinctive GAN model that mitigates both local and global aberrations. The authors demonstrate substantial improvements in clarity and color harmony relative to other learning-based and conventional methods. The essay addresses potential solutions, including semi-supervised learning, while also highlighting drawbacks such as the requirement for substantial processing capacity and extensive labeled datasets.

Kumar, P., & Singh, A. (2023). The primary objective of this project is to employ generative adversarial networks (GANs) to enhance underwater photographs. The authors employ GANs to develop a technique that enhances texture details while minimizing color distortion. We compare GANs to traditional methods to demonstrate their superior efficacy in eliminating anomalies and maintaining natural hues. The research employs a diverse array of undersea data to guarantee that the model can accommodate various types of water. We want to improve generalization by addressing overfitting and computational efficiency, as well as proposing methods to incorporate physics-based priors into GAN frameworks.

Chen, J., & Lee, C. (2023). Both traditional and advanced computer-based methods for enhancing underwater images are examined. Models developed utilizing deep learning, histogram equalization, and wavelet transform are categorized within this group. The authors evaluate the effectiveness of these approaches in various underwater environments, including deep-sea and turbid conditions. Edge detection and denoising are two of the several preprocessing techniques outlined. The final section of the paper addresses the significance of standardized evaluation criteria in emerging domains such as benchmarking and explainable AI in underwater imaging.

Patel, R., & Shah, M. (2023). This paper compares and contrasts methods utilizing physics and data analysis to enhance underwater images. The performance of the algorithm is assessed using two metrics: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). We discuss practical applications, such as underwater archaeology and coral reef surveillance. The research identifies computational complexity and excessive dependence on singular datasets as significant deficiencies in current methodologies. It is recommended to employ hybrid solutions that integrate deep learning with conventional image processing approaches for enhanced outcomes.

Smith, L., & Alami, M. (2022). This paper introduces a machine learning methodology for enhancing underwater photographs in real-time. The authors propose a workflow utilizing lightweight neural networks to integrate feature extraction, augmentation, and image preparation. There are considerable advantages regarding computing efficiency and clarity relative to conventional methods. Autonomous underwater vehicles

(AUVs) are one of the real-time deployment scenarios examined to underscore the system's potential. The subjects addressed encompass hardware integration, energy efficiency, and prospective initiatives to enhance embedded system models.

Zhang, X., & Huang, L. (2022). The authors address color correcting techniques that enhance underwater photography and the attenuation of light based on wavelength. We introduce a novel method for color restoration by integrating perceptual optimization with statistical techniques. Case studies demonstrate that the algorithm can eradicate visual artifacts while preserving the authenticity of colors. The article proposes a framework for adaptive color correction based on an examination of current enhancement pipelines, which is contingent upon water conditions and evaluates the method's efficacy.

Li, H., & Wang, P. (2022). This survey meticulously analyzes underwater picture enhancement techniques, emphasizing real-time applications that employ Internet of Things (IoT) sensors. The authors evaluate the advantages and disadvantages of optical, computational, and hybrid approaches to ascertain their relative significance. Analyzing the advancements of edge and fog computing in underwater environments for latency mitigation underscores their significance. In addition to emerging technologies such as 5G-enabled underwater networks, we propose methods to enhance the interoperability and scalability of underwater photography systems.

Ghosh, A., & Roy, K. (2021). This paper examines the enhancement of underwater photographs by convolutional neural networks (CNNs) through feature extraction and layer topology improvement. The authors aim to address inadequate lighting and turbulence with their innovative architectural design for underwater cinematography. The trials indicated a significant enhancement in image quality and texture preservation. The essay discusses how transfer learning can enhance training efficiency and reduce data requirements. The potential uses in underwater surveillance and marine research are emphasized.

Rahman, M., & Khan, S. (2021). The authors comprehensively address underwater image enhancement systems, emphasizing algorithmic advancements from 2015 to 2021. Dark channel priors, trained models, and Retinex-based augmentation are among the solutions subjected to rigorous scrutiny. This section addresses many challenges related to underwater imaging, including hardware constraints and computational expenses. The paper determined that a hybrid architecture integrating deep learning with conventional image processing will produce optimal outcomes. Further research could concentrate on creating real-time solutions and flexible algorithms to address unforeseen occurrences.

Choudhary, D., & Verma, T. (2021). This comprehensive review categorizes approaches for enhancing underwater photographs into three primary groups: noise reduction, color correction, and contrast enhancement. The authors evaluate the advantages and disadvantages of each strategy and incorporate case studies to demonstrate their practical application. The emphasis is placed on utilizing conventional metrics to evaluate performance. The current research identifies a deficiency in dataset diversity; the report proposes synthetic data and cross-domain learning as potential solutions to this issue.

Zhou, Y., & Xu, B. (2020). This paper examines recent advancements in learning-based and computational methods for enhancing underwater photography. The authors present a taxonomy for improved methodologies following their investigation on the impact of environmental factors on image quality. Hardware acceleration and edge computing are two potential solutions to the challenges of real-time speed and scalability that we examine. The application of AI in underwater photography is feasible.

Ahmed, M., & Hassan, R. (2020). The authors examine the challenges and potential remedies for enhancing underwater photography by emphasizing environmental uncertainty, sensor constraints, and processing expenses. To enhance image reconstruction techniques, researchers propose a hybrid system that integrates optical modeling with data-driven strategies. We emphasize applications in military, marine biology, and underwater exploration, concentrating on the constraints of real-time implementation.

Kumar, S., & Gupta, N. (2020). This work seeks to enhance underwater images by wavelet tweaks, machine learning, and histogram equalization. A novel method integrating CNNs with wavelet analysis is employed to enhance color and texture balance. Recommendations for hybrid and adaptive methodologies are presented, along with an examination of the challenges associated with altering conventional water usage habits.

Singh, R., & Sharma, A. (2020). The primary objective of this investigation into generative adversarial networks (GANs) and convolutional neural networks (CNNs) is to enhance underwater photos. The authors propose a CNN architecture employing multiple scales to address issues like as dithering and color aberration. Practical applications encompass underwater surveillance and marine research. The report emphasizes the accessibility of information and computational expenses while providing recommendations for additional research.

3. DERWATER IMAGE ENHANCEMENT DATASETS

A substantial quantity of underwater image data is necessary to train and enhance underwater picture enhancement algorithms. During training and evaluation, verify the model's underwater image collection for adequate data, varied aquatic settings, and comprehensive details. The aquatic picture datasets UIEB, UFO, and EUVP consist of paired real-world datasets, with matched and synthetic datasets also accessible. RUIE is a real-world dataset that is unpaired.

These datasets encompass comprehensive image specifications and a wide variety of degradation types. Numerous authentic and fabricated underwater photographs exist from various domains and imaging devices. Utilizing reference photographs or altered images processed with certain algorithms is a standard practice in underwater image enhancement systems. This facilitates the comparison and contrast of outcomes. The underwater images supplied by UIEB consist of 60 problematic photographs alongside 890 original images and their respective high-quality reference photos.

This dataset comprises sixty visually appealing underwater pictures that are challenging owing to the diverse array of underwater scenery, colors, and subjects represented. Furthermore, it comprises high-quality reference photographs. The diverse aquatic environments, graphic components, and color schemes present in this collection are very exceptional. Furthermore, it includes high-quality reference photographs that may be utilized for comprehensive learning and assessment of image quality. The UFO dataset, comprising 1,500 training examples and 120 test samples, is ideally suited for tasks including anomaly detection, superresolution reconstruction, and enhancement of underwater imagery.

The most significant foreground pixels were meticulously selected from this collection, comprising underwater photographs captured in various water types and conditions. Of the 20,000 underwater pictures in the EUVP collection, 12,000 are matched, while 8,000 are unpaired. The EUVP dataset was compiled using many cameras from diverse sea areas and varying visibility conditions. To address the extensive variability in the data, some photographs were sourced from publicly accessible YouTube videos.

The RUIE dataset comprises three subsets: UIQS, UCCS, and UHTS. Among the 3,630 underwater pictures in UIQS, 726 exemplify each of the five quality tiers. Of the 300 underwater photographs in the UCCS sample, 100 display a variant of blue-green or green-blue distortion. The UHTS subset contains 300 underwater images of various marine species, utilized for evaluating detection and classification systems. Eleven distinct image datasets were generated from the RGB-D NYU-v2 indoor dataset, with their attenuation coefficients representing various types of water.

4. QUALITY EVALUATION METRICS

A crucial aspect of assessing image quality is the analysis of visual fidelity. Quantitative evaluations can be classified as either reference image quality assessments or non-reference image quality assessments, based on the manner of reference picture utilization.

Reference Evaluation Metrics

Two widely used metrics for assessing the quality of complete reference pictures are Structural Similarity (SSIM) and Peak Signal to Noise Ratio (PSNR). A prevalent method to assess the quality of the processed image is by examining the PSNR value. Utilizing a neural network or alternative technical methods alters photos substantially from their original forms. Utilize the following procedures to calculate the PSNR for an image of dimensions $m \times n$:

$$PSNR(x,y) = 10 \times \log_{10} \frac{255^2}{E_{MS}} \#(1)$$

$$E_{MS}(x,y) = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{n=0}^{n-1} \|x(i,j) - y(i,j)\|^2 \#(2)$$

where y denotes the processed image, y signifies the clear reference image, and $\boldsymbol{E}$ indicates the mean square error. High PSNR values suggest reduced visual distortion. SSIM employs three criteria to assess image similarity: structural similarity, contrast similarity, and luminance similarity. To calculate the SSIM, employ the given formula:

$$SSIM(x,y) = \left[l(x,y)^{\alpha} \times c(x,y)^{\beta} \times s(x,y)^{\gamma}\right] \#(3)$$

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \#(4)$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2\sigma_y^2 + c_2} \#(5)$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3} \#(6)$$

In this context, $\mathcal{G}$ denotes the reference image that remains unaltered, while $\boldsymbol{x}$ signifies the modified image. A $\mathbf{t}\boldsymbol{x}$ and a $\mathbf{t}\boldsymbol{x}$ denote the mean values of $\boldsymbol{x}$ and $\mathcal{G}$, respectively. The constants $\boldsymbol{ci}$ (for $\boldsymbol{i}$ = 1, 2, and 3) ensure that the denominator does not approach zero. The variances of $\boldsymbol{x}$ and $\mathcal{G}$ are denoted by $A\boldsymbol{x}^2$ and $A\boldsymbol{y}^2$, respectively. The greater the similarity between the two photographs, the higher the SSIM rating, which ranges from 0 to 1. To simplify the calculation, you may assign the values σ = $\boldsymbol{\beta}$ = $\boldsymbol{\gamma}$ = 1 and $\boldsymbol{c}2$ = $2\boldsymbol{c}3$. The subsequent is the streamlined SSIM equation:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \#(7)$$

Non-reference Evaluation Metrics

Photograph quality can be assessed without reference images by two non-reference methods: Underwater Picture Quality Measurement (UIQM) or Underwater Color Image Quality Evaluation (UCIQE) [60]. UCIQE assesses an image's chroma, saturation, and contrast by analyzing color bias, calculating target local contrast, and demonstrating color fidelity through mean saturation. The formula for calculating the UCIQE is as follows:

$$UCIQE = c_1 \times \sigma_c + c_2 \times c_l + c_3 \times \mu_s \#(8)$$

Color, luminance contrast, and mean saturation standard deviations are represented by $\mathtt{W}\boldsymbol{c}$, $\boldsymbol{cl}$, and $\mathbf{ts}$, with corresponding weight coefficients of $\boldsymbol{c}1$, $\boldsymbol{c}2$, and $\boldsymbol{c}3$, respectively. Enhanced picture quality correlates with a higher UCIQE score. UIQM comprises the Underwater Image Colorfulness Measure (UICM), Underwater Image Sharpness Measure (UISM), and Underwater Image Contrast Measure (UIConM). A method to determine UIQM is by use this formula:

$$U\ \ QM = c_1 \times U_{ICM} + c_2 \times U_{ISM} + c_3 \times U_{IConM} \#(9)$$

In UICM, UISM, and UIConM, the weight coefficients are c1, c2, and c3, respectively. The enhancement in image quality correlates with an elevated UIQM grade.

5. CONCLUSION

Currently, the most advanced underwater image enhancing technologies are tailored to specific scenes. Although technologies exist to mitigate many types of underwater image degradation, assessing their effectiveness, universality, and durability remains a challenge. Given the various forms of underwater image deterioration, it is essential to recognize each type and develop a consistent, universal approach to enhance underwater photographs. Examine the multi-frequency attributes of underwater imagery, develop techniques for enhancing underwater images to achieve superior quality, and advocate for the application of this technology in marine biology, underwater rescue, and underwater surveying.

REFERENCES

[1] Sahu, N., & Jena, S. (2024). "Advancements in Underwater Image Enhancement: A Comprehensive Review." Journal of Marine Imaging, 12(1), 34–46.

[2] Mishra, A., & Reddy, P. (2024). "Deep Learning Approaches for Underwater Image Restoration." International Journal of Computer Vision, 48(2), 67–79.

[3] Kumar, P., & Singh, A. (2023). "Enhancing Underwater Imagery Using Generative Adversarial Networks." IEEE Transactions on Image Processing, 11, 14412–14425.

[4] M. Shahimoon, H. Rasheed, D. R. Rao, K. R. Krishnaiah, K. K. Gajula, et al., "Evolving Predictive Models for Customer Churn in Telecommunications," in Proc. 2nd International Conference on New Frontiers in Communication Technologies, 2025.

[5] Chen, J., & Lee, C. (2023). "A Survey on Underwater Image Enhancement Techniques." Sensors, 23(4), 1987.

[6] Patel, R., & Shah, M. (2023). "Comparative Analysis of Underwater Image Enhancement Algorithms." International Journal of Computer Applications, 5(3), 128–135.

[7] Smith, L., & Alami, M. (2022). "Real-Time Underwater Image Enhancement Using Machine Learning." Computers in Biology and Medicine, 146, 105850.

[8] Zhang, X., & Huang, L. (2022). "Color Correction Methods for Underwater Image Processing." Journal of Visual Communication and Image Representation, 28(3), 568–582.

[9] Li, H., & Wang, P. (2022). "Survey on Underwater Image Enhancement Techniques." Journal of Network and Computer Applications, 201, 103456.

[10] Ghosh, A., & Roy, K. (2021). "Underwater Image Enhancement Using Convolutional Neural Networks." IEEE Transactions on Geoscience and Remote Sensing, 68(10), 2903–2915.

[11] Rahman, M., & Khan, S. (2021). "Review of Underwater Image Enhancement Techniques." International Journal of Advanced Computer Science and Applications, 7(4), 214–223.

[12] Choudhary, D., & Verma, T. (2021). "A Comprehensive Review of Underwater Image Enhancement Methods." Journal of Ocean Technology, 5(2), 112–121.

[13] Zhou, Y., & Xu, B. (2020). "Underwater Image Enhancement: A Review of Techniques and Trends." IEEE Communications Magazine, 58(9), 102–109.

[14] Ahmed, M., & Hassan, R. (2020). "Underwater Image Enhancement: Challenges and Future Directions." Journal of Marine Science and Engineering, 22(7), e19600.

[15] Kumar, S., & Gupta, N. (2020). "Review on Underwater Image Enhancement Techniques." International Journal of Emerging Trends in Engineering Research, 8(5), 1326–1334.

[16] Singh, R., & Sharma, A. (2020). "Underwater Image Enhancement Using Deep Learning Techniques." Computers & Electrical Engineering, 84, 106598.

[17] K. K. Gajula, "Leveraging Machine Learning Techniques for Earthquake Impact Analysis and Prediction," ZKG International, vol. 9, no. 2, pp. 909–913, 2024.

[18] K. K. Gajula, "Deep Neural Forecasting Models for Climate Change Analysis Using Multivariate Time-Series Data," Journal of Computational Analysis and Applications, vol. 33, no. 8, pp. 6356–6368, 2024.