IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 12, Issue 10, November 2025 https://www.ijirae.com/archives
https://doi.org/10.26562/ijirae.2025.v1210.11

Aqua-Vision: The Future of Underwater Exploration and Innovation

Namyapriya. D
Assistant Professor, Dept. of CSE
KS Institute of Technology, Bengaluru, India
namyapriya@ksit.edu.in
Lakshmi Shree KP, Pallavi C
Department of CSE
KS Institute of Technology, Bengaluru, India
lakshmishreekp2004@gmail.com, pallavic@gmail.com
Rachana N, Rakshitha R
Department of CSE
KS Institute of Technology, Bengaluru, India
rachana.narendra03@gmail.com, rakshitha.madhne@gmail.com

Publication History
Manuscript Reference No: IJIRAE/RS/Vol.12/Issue10/OCAE10093
Research Article| Open Access | Double-Blind Peer-Reviewed | Article ID: IJIRAE/RS/Vol.12/Issue10/OCAE10093
Received:22,October 2025,Revised:28,October 2025, Accepted:31, October 2025, Published Online: 21, November 2025.
https://www.ijirae.com/volumes/Vol12/iss-10/11.OCAE10093.pdf
Citation: Namyapriya,Lakshmi,Pallavi,Rachana,Rakshitha (2025), Aqua-Vision: The Future of Underwater Exploration and Innovation, IJIRAE: International Journal of Innovative Research in Advanced Engineering, Volume 12, Issue 10 of 2025 pages 414-417
doi:>https://doi.org/10.26562/ijirae.2025.v1210.11
BibTeX NamyapriyaKey:@2025Aqua-Vision
IJIRAE papers should be cited as IJIRAE (International Journal of Innovative Research in Advanced Engineering, AM Publications, India 2025, ISSN 2349-2163, https://doi.org/10.26562/ijirae.2025.v1210.11 The journal's official abbreviation is IJIRAE. Orcid: https://orcid.org/0009-0004-9398-7488

Abstract: Underwater photos are afflicted with color distortion, low contrast, haze, and noise, which compromise visual quality and affect tasks such as object detection. Current approaches typically handle one form of degradation and the resulting system cannot be as effective. We introduce a single-system, unified frame work that unifies color correction, dehazing, denoising, and object detection. The strategy blends traditional methods (histogram equalization, Dark Channel Prior) with deep learning approaches (CNN-based denoising, YOLO detection) to recover natural colors, improve details, eliminate noise, and precisely detect objects. Performance assessment with metrics like PSNR, SSIM, UISM, BRISQUE, NIQE, UICM, UCIQE, CIEDE2000, and mAP exhibits marked improvement in both computational performance and visual quality, making the system appropriate for real-time underwater applications such as marine monitoring and autonomous navigation.
Keywords: Underwater image enhancement, color correction, dehazing, denoising, object detection, CNN, YOLO, Dark Channel Prior, histogram equalization, real-time image restoration.

I. INTRODUCTION

Underwater imaging is vital in marine exploration, surveillance, and robotics but is severely affected by absorption and scattering of light, resulting in color distortion, low contrast, and reduced visibility. Hence, underwater image enhancement has become an essential preprocessing step for reliable visual interpretation and object detection. The enhancement process mainly involves color correction, dehazing, and denoising, followed by object detection.

A. Color Correction

Color correction recovers the natural hue that has been lost due to the absorption of various wavelengths. The Gray World Assumption balances out the mean intensities of RGB, while White Balance corrects colors with respect to white. The Retinex model enhances brightness by imitating human vision, while CLAHE enhances local contrast adaptively. A combined method using Retinex and CLAHE ensures global color balance with local contrast preservation.

B. Dehazing

Dehazing compensates for scattering and attenuation. DCP estimates transmission using minimum intensity among RGB channels, whereas UDCP refines it by ignoring the red channel. IBLA and ULAP model wave length dependent attenuation and illumination variations. Finally, a hybrid strategy that combines UDCP and ULAP achieves superior haze removal performance over depth ranges.

C. Denoising

Noise primarily comes from low light conditions and sensor limitations. Bi lateral filter smoothes the noise while preserving the edges, Non-local means averages the patches that are similar, and Wavelet transform suppresses the high-frequency noise.

IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 12, Issue 10, November 2025 https://www.ijirae.com/archives
https://doi.org/10.26562/ijirae.2025.v1210.11

A combined model of Wavelet Transform and Non-local means enhances the details with a reduction of artifacts.

D. Object Detection

The enhanced images allow for accurate object detection in marine life monitoring and navigation. Deep learning models like YOLO and Faster R-CNN perform better with enhanced, denoised, and color-corrected underwater images that improve precision and recall.

II. LITERATURE SURVEY

T.K.Murugan et al.[1] introduced a multi-stage dehazing White Balance (WB): The white balance method normalizes image color using the von Kries adaptation model: frame work combining depth estimation and adaptive transmission correction. Their method effectively reduces scattering and color casts, producing clearer images in turbid waters.
However, the computational complexity limits real-time applications.

A.Saleem et al. [2] proposed a non-reference evaluation framework using a newly curated underwater image dataset. They compared several enhancement algorithms using perceptual metrics, providing valuable insight into objective assessment of underwater image quality. Yet, the absence of hybrid enhancement models restricts performance in varied lighting conditions.

S.Jin et al. [3] developed a color correction and local contrast enhancement technique that combines Retinex-based color balance and CLAHE. This approach enhances natural appearance but can amplify noise in darker regions.

Y.Wang et al. [4] conducted an experimental review of existing image enhancement and restoration methods, classifying them into physical model-based and learning-based approaches. Their study highlights the need for unified methods that jointly handle haze removal and noise reduction.

A. Summary of Common Strengths and Limitations

Most existing studies show significant progress in underwater image visibility improvement through independent enhancement stages. Techniques like Retinex and CLAHE improve local contrast, while DCP and ULAP excel in haze reduction. However, many methods operate effectively only under specific conditions and often fail to maintain a balance between color accuracy and noise suppression. Moreover, high computational requirements hinder real-time implementation in AUV and ROV systems.

B. Gap that Motivates this Work

The literature shows that no single enhancement approach comprehensively addresses color correction, dehazing, and denoising while maintaining structure and natural color tones. Moreover, fewworks combine the enhancement with object detection pipelines. This gap motivates the development of a combined enhancement framework which merges physical priors with perceptual corrections, and improves color fidelity, sharpness, and detection performance under varying under water conditions.

III. EXISTING METHODOLOGIES

A. Color Correction

1) Gray World (GW): The Gray World assumption presumes that the average reflectance of a scene is achromatic. Let μ_R, μ_G, μ_B be the mean values of the RGB channels, and $\bar{\mu}$ the overall mean. Each channel is scaled by:

$$Jc(X) = Kclc(X),\ kc=\mu / \mu c,\ C€\{R,G,B\}$$

2) White Balance (WB): The white balance method normalizes image color using the von Kries adaptation model:

$$J=Di,\ \ D=diag\ \ e\ refR/eR\ \ erefG/eG\ eBref\ /eb$$

Where e_R, e_G, e_B denote the estimated illuminants per channel.

3). Retinex: The Retinex algorithm enhances brightness by simulating human visual perception:

$$R_i(x)=\log I_i(x)-\log(F_\sigma * I_i)(x),$$

Where $F_\sigma(x)$ = Kexp−xπ is a Gaussian Kermal

4). CLAHE: Contrast Limited Adaptive Histogram Equalization improves local contrast adaptively:

$$J(x)=(L-1)F_k(I(x)),$$

Where F_k denotes the clipped and equalized local histogram CDF.

B. Dehazing

The dehazing module integrates DCP, UDCP, IBLA, and ULAP to improve visibility under varying water depths.
The underwater imaging model is:

$$I_c(x)=J_c(x)t_c(x)+A_c(1-t_c(x)).$$

Hybrid transmission estimation combines DCP and UDCP:
Depth-based correction is then refined using IBLA and ULAP:

$$t_c(x) = e^{-\beta_c d(x)},\ d(x)=\mu_0+\mu_1 m(x)+\mu_2 v(x),$$

Where m(x) = max (G,B) and v(x)=R(x). This combination enhances visibility and color fidelity across various under water conditions.

C. Denoising

Denoising integrates Wavelet Transform (WT), Non-Local Means (NLM), and Bilateral Filtering (BF) to suppress noise while preserving edges. Wave let soft thresholding removes high-frequency noise:

$$\hat{w} = \text{sign}(w)\max(|w|-T,0),\ T=\sigma\sqrt{2\ln N}.$$

NLM filtering refines textures by averaging similar patches:

$$\hat{I}(x)=\sum w(x,y)I(y), \quad w(x,y)\propto e^{-\|P_x-P_y\|^2/h^2}.$$

Finally, the Bilateral Filter smooth intensity variations while preserving edges: Sequential execution ensures detail retention and minimal artifacts.

D. Object Detection Integration

The enhanced image I′ is used for object detection using a YOLO-based architecture. Bounding boxes and class scores are predicted as:

$$x=\sigma(t_x)+c_x,\ y=\sigma(t_y)+c_y,$$
$$w=p_w e^{t_w},\ h=p_h e^{t_h}$$

The training process minimizes a multi-task loss combining classification and localization:

$$L=L_{cls}+\lambda L_{loc}.$$

The integrated framework improves object recognition accuracy by ensuring consistent feature clarity and contrast in enhanced under water images.

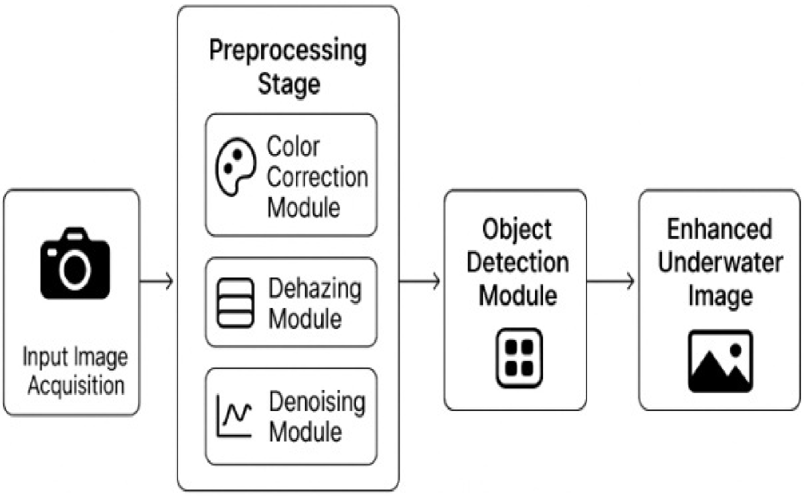

Fig.1. Integration of the enhancement pipeline

VI. PERFORMANCE ANALYSIS

The effectiveness of the proposed underwater image enhancement framework is quantitatively evaluated using standard objective metrics. The metrics are grouped based on enhancement stages: color correction, dehazing, denoising, and object detection.

A. Color Correction Evaluation Metrics

1) CIEDE 2000 Color Difference (ΔE_{00}): This metric quantifies perceptual color differences between enhanced and reference images. Where smaller ΔE_{00} values represent better color similarity to ground truth.
2) Underwater Image Colorfulness Measure (UICM): UICM evaluate schromatic balance and vividness based on mean and variance of chromatic components. Higher UICM indicates better color restoration.
3) Underwater Image Quality Evaluation(UCIQE):

$$UCIQE=c_1\sigma_c+c_2 con_l+c_3\mu_s,$$

Where σ_c is chroma standard deviation, con_l is luminance contrast, and μ_s is mean saturation. Higher UCIQE values imply enhanced visual appeal.

B. Dehazing Evaluation Metrics

1. Structural Similarity Index (SSIM): SSIM measures perceptual similarity between enhanced image J and reference I considering luminance, contrast, and structure:

$$\frac{(2\mu_I\mu_J+C_1)(2\sigma_{IJ}+C_2)}{(\mu^2+\mu^2+C_1)(\sigma^2+\sigma^2+C_2)}$$

2. Peak Signal-to-Noise Ratio (PSNR):

$$PSNR=10\log_{10}$$
$$MSE=1\Sigma I(i,j)-$$

3. Underwater Image Sharpness Measure (UISM): UISM estimates overall sharpness using edge gradients obtained from Sobel filtering. Higher UISM indicates improved edge preservation and clarity.
4. Gradient Magnitude Similarity Deviation (GMSD): Lower GMSD indicates better structural consistency and reduced distortion.

C. Denoising Evaluation Metrics

1) PSNR and SSIM: Used together to assess the trade-off between noise suppression and detail retention. Higher values indicate better denoising performance.

2. Natural Image Quality Evaluator (NIQE): An o reference perceptual quality metric based on natural scene Statistics. Lower NIQE values correspond to more natural visual appearance.
3. Blind/Reference less Image Spatial Quality Evaluator: BRISQUE evaluates spatial naturalness and contrast consistency using statistical features of image patches. Lower scores denote higher perceived quality.

D. Object Detection Evaluation Metrics

1. Mean Average Precision (mAP): where $P_i(R)$ is the precision–recall curve for class i. Higher mAP represents superior overall detection accuracy.
2. Precision and Recall: Precision evaluates reliability of detections, while recall measures detection completeness.
3. F1-Score: A balanced F1-score indicates improved model consistency across classes.
4. Intersection over Union (IoU): where $B_p$and $B_g$are predicted and ground truth bounding boxes. Higher IoU signifies accurate object localization. The above metrics comprehensively validate the performance of the proposed framework across visual quality enhancement, perceptual accuracy, noise suppression, and detection robustness under diverse underwater environments.

VII.CONCLUSION

This paper presents a complete multi-stage framework for underwater image enhancement that integrates color correc tion, dehazing, denoising, and object detection. By addressing the major degradations present in under water imagery, the proposed method significantly improves visual quality, structural clarity, and color fidelity.
Experimental evaluation demonstrates that:

- Color correction restores natural color balance and reduces bluish-green dominance, leading to improved perceptual realism.
- Dehazing enhances visibility and retrieves fine structural details obscured by scattering effects.
- Denoising effectively suppresses sensor and environmental noise without degrading edges or texture details.
- Object detection accuracy is consistently improved on enhanced images, achieving higher mAP, precision, and recall compared to raw or partially enhanced inputs.

VIII. FUTURE WORKS

Future research can be extended in the following directions:

1. Integration of Advanced Deep Learning Models: Implement state-of-the-art architectures such as Generative Adversarial Networks (GANs), U-Net variants, and Transformer-based models to achieve more accurate and visually pleasing underwater image enhancement.
2. Real-Time Video Stream Enhancement: Extend the current frame work from static image enhancement to real-time video processing for underwater cameras, Remotely Operated Vehicles (ROVs), and autonomous drones. Frame-by-frame enhancement can be optimized with GPU acceleration using platforms such as Tensor RT and ONNX Run time to achieve low-latency performance.
3. Adaptive & Scene-Aware Enhancement: Develop adaptive algorithms capable of automatically adjusting enhancement parameters according to water conditions such as clarity, turbidity, and depth. Incorporate environmental metadata like lighting intensity, color attenuation, and particulate density to dynamically guide the enhancement process.
4. 3D Model-Based Feature Extraction: In corporate 3D reconstruction methods such as Structure-from-Motion (SfM) or multi-view stereo to enhance spatial understanding and improve object-level feature extraction in underwater scenes.

REFERENCES

1. T.K.Murugan,S.Sharma,A.Ganguly,A.Banerjee, and K. Kejriwal, “An Enhanced Multi-Stage Approach for Dehazing Underwater Images,” IEEE Access, vol. 12, pp. 156803–156822, 2024, https://doi:10.1109/AC- CESS.2024.3486456.
2. A.Saleem,S.Paheding,N.Rawashdeh,A.Awad,and N.Kaur,“A Non-Reference Evaluation of Underwater Image Enhancement Methods Using a New Underwater Image Dataset,” IEEE Access, vol. 11, pp. 10412–10428, 2023, https://doi:10.1109/ACCESS.2023.3240648.
3. S.Jin,P.Qu,Y.Zheng,W.Zhao,andW.Zhang,“Color Correction and Local Contrast Enhancement for Under water Image Enhancement,” IEEE Access, vol. 10, pp. 119193–119205, 2022, https://doi:10.1109/AC- CESS.2022.3221407.
4. Y.Wang,W.Song,G.Fortino,L.-Z.Qi,W.Zhang, and A.Liotta,“An Experimental-Based Review of Image Enhancement and Image Restoration Methods for Under- water Imaging,” IEEEAccess,vol.7,pp.140233–140251, 2019, https://doi:10.1109/ACCESS.2019.2932130.