WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Underwater Image Enhancement and Marine Species Detection Using Yolov8

Prince Purviya[1], Sanskriti Sontakke[2], Rakshita Shukla[3], Ravi Sah Shankar[4], Vibhav K Chaurasiya[5]

Oriental Institute of Science and Technology Bhopal
Purviyaprince27@gmail.com[1], Sanskritisontakke236@gmail.com[2], Srakshita16@gmail.com[3], Ravishankarsah106@gmail.com[4], vibhavchaurasiya@oriental.ac.in

A B S T R A C T:

Underwater images usually suffer from problems related to colour absorption, scattering, low contrast, and poor lighting. These problems make underwater photos hard to analyse, both for humans and for any machine vision system. In this project, a complete intelligent framework is presented that can enhance underwater images, detect objects within those images, and alert the user in case something unexpected pops up.

The enhancement process is done using a simple, yet effective three-step pipeline: Gray-World white balance reduces strong blue and green hues common underwater; CLAHE on the LAB luminance channel enhances the contrast and uncovers details on the image; and gamma correction ($\gamma = 0.9$) delicately brightens the scene, making the image more natural and visually appealing. Tied together, these steps will transform poor-quality images underwater into clearer, more informative visuals.

These enhanced images are then processed in Ultralytics YOLOv8-a very powerful deep learning model, state-of-the-art for object detection-and have been performing with high accuracy regarding the detection of underwater objects like fish and any other marine species. To enhance its reliability further, an Alert Module is part of the system to verify if such detected objects belong to the classes the model has gone through during training. If the image includes unknown species, irrelevant objects, or no valid detections, the system itself warns the user. This prevents wrong results from being considered and ensures that only meaningful images taken underwater are considered.

These metrics quantify improvements in luminance, contrast, and visual structure.

Keywords: Underwater Image Enhancement, YOLOv8, Marine Species Detection, Computer Vision, OpenCV Preprocessing, Image Quality Assessment, PSNR, SSIM, Deep Learning, Object Detection.

1.Introduction

Underwater imaging is an essential function in marine research, ocean exploration, and monitoring of the ocean environment. The usual underwater images suffer greatly due to degradation brought about by absorption, scattering, turbidity, and colour distortion of light. These issues reduce visibility, contrast, and structural details, thus making both manual analysis and automated computer-vision models highly unreliable.

Traditional enhancement techniques, including Histogram Equalization, CLAHE, and white balancing, offer only partial improvement. This is because these methods primarily adjust contrast or brightness without restoring real colours or important features. Due to that, modern object detection models like YOLOv8 also show degraded performance on raw underwater images.

The project incorporates a full enhancement-and-detection pipeline to address these limitations. Colour correction, contrast improvement, and noise reduction are done as preprocessing steps using OpenCV; an enhancement pipeline of Gray World white balance, CLAHE, and Gamma Correction has been applied. These powerfully restore clarity and visibility such that even YOLOv8 can detect marine species with greater accuracy and confidence.

It is an integrated web interface where the users can upload any underwater image and instantly get the enhanced output with species detection. In this way, it becomes a unified approach to make underwater visual analysis more reliable and contributes towards its applications in marine science, biodiversity assessment, and underwater exploration technologies.

2. Literature Review

With the rapidly improved techniques for enhancement and deep-learning-based object detection models, underwater image analysis has improved dramatically in the last decade. Yet, colour distortion, scattering, haze, and low contrast continue to degrade both visual interpretation and machine-vision accuracy. Various methods, including those with classical algorithms, physics-based restoration, generative models, and transformer-based enhancement, have been tried to mitigate these problems. The review work contextualizes existing work in three domains: traditional enhancement techniques, deep-learning-based enhancement, and underwater object detection frameworks, thereby setting a background for the proposed YOLOv8-based system.

A. Traditional Underwater Image Enhancement Techniques

Before the invention of deep learning methods, traditional algorithmic and physics-based approaches dominated the field of underwater enhancement because of their simplicity and low computational cost.

A.***1 Colour Balance and White Balance***

Gray-World White Balance represents one of the earliest methods that corrects for underwater colour cast, assuming that the average reflectance of the scene is gray. It reduces blue–green dominance, equalizes RGB channels, and is useful as preprocessing; it performs poorly under turbid or low-light conditions.

B.***2 Contrast Stretching (CLAHE)***

CLAHE enhances the local contrast, visibility of edges, and clarity of texture. Research shows it improves feature extraction for the task of detection, though may amplify noise if overapplied.

C.***3 Red-Channel & Dehazing-Based Methods***

Due to the quick absorption of red light underwater, dehazing and correction techniques targeting the red channel (such as dark channel prior, colour-line models, and depth-based attenuation) are designed to recover brightness, colour balance, and depth perception. Still, their performance depends on critical assumptions, which may fail to generalize across different water types.

B. Limitations of Traditional Methods

Throughout the literature, traditional techniques repeatedly display certain limitations:

- Over-/Under-Enhancement in uneven lighting
- Colour correction inconsistent across environments
- No learning capability → limited adaptability to complex underwater conditions

Nevertheless, these methods still prove useful owing to their light weight, speed, ease of implementation, and readiness for real time pipelines.

C. Evolution of Deep-Learning–Based Detection

However, even after enhancement, detection of underwater species is challenging due to low visibility, small fast-moving objects, background similarity, and illumination flicker; therefore, the use of single-shot deep-learning detectors has been adopted.

D. YOLOv8 for Underwater Detection

YOLOv8 has emerged as a strong choice for underwater detection.

D.1 Accuracy and Speed

The studies show that YOLOv8 outperforms the previous YOLO versions with respect to precision, recall, mAP@50, and mAP@50–95, thanks to improved backbone design, efficient feature fusion, and stronger small-object detection.

D.2 Robustness to Underwater Conditions

YOLOv8 handles the low-quality, colour-distorted input well with multi-scale feature pyramids and better feature extraction; hence, it is suitable for an underwater environment.

Higher contrast enhances feature extraction. This validates the proposed workflow: Lightweight Enhancement →

YOLOv8 Detection → Alert System

3. Methodology

This project proposes a sequential enhancement–detection framework designed for underwater visual analysis. The methodology consists of four stages:

(i) preprocessing and colour correction,

(ii) contrast and illumination enhancement, (iii) species detection using YOLOv8, and (iv) alert generation for abnormal objects.

3.1 Input Acquisition

Underwater images often suffer from colour attenuation, low contrast, and uneven illumination. All input images in this study were collected from publicly available underwater datasets and local footage. Images are converted to RGB color space and resized for uniform processing.

3.2 Gray World White Balance

Underwater images appear blue–green dominated due to rapid absorption of red wavelengths. Gray World White Balance is applied as the first correction step.

Mathematical Formulation

Let R, G, B be the three image channels. Mean intensity of each channel:

1.μR=mean(R)

2.μG=mean(G),

3.μB = mean(B) Global mean intensity: $\mathbf{\mu avg = (\mu R + \mu G + \mu B) / 3}$

Channel Scaling

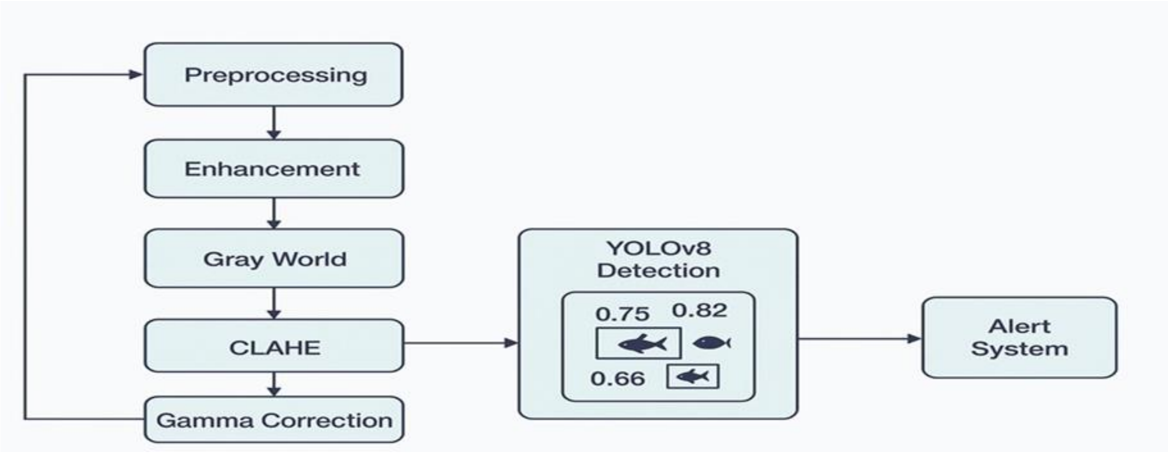
- $R' = R \times (\mu avg / \mu R)$
- $G' = G \times (\mu avg / \mu G)$
- $B' = B \times (\mu avg / \mu B)$

This restores a neutral colour distribution before further enhancement

3.3 Contrast Limited Adaptive Histogram Equalization (CLAHE)

Even after white balance, underwater images suffer from low contrast. CLAHE improves local contrast while suppressing noise. Working Principle

- The image is divided into small tiles.
- Each tile undergoes histogram equalization with a clip limit.
- Bilinear interpolation smooths boundaries between tiles.
- Advantages
- Enhances fine coral textures and small species.
- Prevents noise over-amplification.
- Works well under uneven lighting.



3.4 Gamma Correction

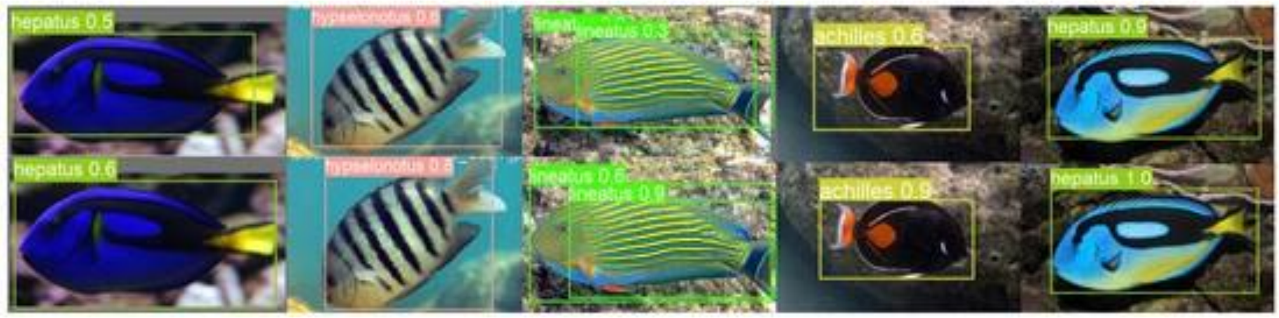
Gamma correction improves global brightness and enhances the general tonal balance in underwater images as the final step. It transforms the intensities of pixels non-linearly to recover the visual details that remain suppressed even after colour balancing and contrast enhancement. This transformation is defined by the mathematical model

$$\mathbf{I_{out} = c \cdot (I_{in})^{\gamma}}$$

γ represents the corrected output intensity, γ is usually selected to lie between 0.6–0.8, and c = 1. By selecting an appropriate value of gamma, the method can lighten dark regions uniformly and also maintain a natural visual appearance.

3.5 Species Detection using YOLOv8

These enhanced images are passed into a YOLOv8-based detection model, trained especially for marine species identification. YOLOv8 has been chosen because it offers the best balance between high detection accuracy and fast inference time, together with particularly good bounding-box predictions, which is really important in underwater shots where the objects normally appear small, blurred, or partially occluded. The enhanced visibility courtesy of the pre-processing pipeline thus enables the model to identify the species more reliably and with higher confidence.



3.6 Alert Generation System

The proposed system implements an intelligent alert mechanism which is triggered when the detection output poses a concern. Alerts are issued under conditions involving the appearance of an unknown species, when the confidence score of the model is less than 0.50, and for a detected object not resembling common marine categories. Depending on the context, the system issues an on-screen warning, SMS notification, or a bounding box with highlighted visual features. This alerting framework facilitates prompt evaluation of possibly dangerous or unusual underwater events. 3.7 Evaluation Metrics: PSNR & SSIM In order to evaluate the effectiveness of the enhancement pipeline, PSNR and SSIM values are computed between the original image and outputs at every stage of enhancement, from Gray World to CLAHE, from CLAHE to Gamma, and finally to the image. These metrics give a quantitative measure regarding improvements in luminance consistency, restoration of contrast, and structural preservation. Higher PSNR and SSIM values throughout the pipeline confirm that each stage contributes to progressively better visual quality and stronger structural similarity.

4 Visual Comparison

Underwater images typically have high blue–green colour dominance, low contrast, and a loss of important structural details because light is absorbed or scattered. The enhancement pipeline proposed here has a number of steps in which a clear and progressive improvement can be seen. Gray World White Balance effectively eliminates the excessive blue–green tint and recovers a more natural colour distribution where previously suppressed red and orange regions become visible again. After this correction, CLAHE further enhances the visual quality by emphasizing local contrast and recovering lost details along darker regions while avoiding overamplification of noise. Finally, gamma correction uniformly brightens the image, makes the tone more realistic and visually consistent, and enhances the visibility of species boundaries. These combined enhancements greatly improve edge clarity, colour accuracy, and overall appearance.

4.1 Peak Signal-to-Noise Ratio (PSNR) Comparison

A quantitative assessment in terms of PSNR indicates a consistent gain at each enhancement stage in the pipeline. According to the results in Table 1, the Gray World method alone provides an increase of about 3-4 dB in PSNR, since it corrects the colour imbalance. Further application of CLAHE on top results in an additional gain of 1.5-2.5 dB because of enhanced contrast and recovery of details. The final step in gamma correction contributes another increase in PSNR by 2-3 dB owing to the improvement in global brightness of the scene, whereas the overall visibility has been enhanced. The cumulative improvement of 7-9 dB with respect to original images suggests that there is considerable reduction in visual degradations and noticeable enhancement in clarity.

Image	Original (dB)	Afterm Gray World (dB)	After CLAHE (dB)	After Gamma (Final) (dB)
Img 1	14.82	18.10	20.34	22.91
Img 2	16.20	19.45	21.12	23.78

PSNR Analysis

- Gray World alone gives a 3–4 dB increase by correcting colour imbalance.
- CLAHE adds 1.5–2.5 dB, improving local contrast.
- Gamma Correction gives a final 2–3 dB boost, improving brightness and global visibility.

Total improvement over original: 7–9 dB, which represents significant noise reduction and clarity enhancement.

4.2 Structural Similarity Index (SSIM) Comparison

The SSIM values also show consistent improvement through the enhancement steps. Gray World increases SSIM by recovering natural luminance and developing a more balanced colour tone. CLAHE further enhances the structural strength of the images, hence allowing for better rendition of fine details and yielding an increase of 5–7% in SSIM for the samples. The last step of gamma correction further optimizes the global distribution of tones to push the SSIM values close to 0.85, which corresponds to very high structural similarity with respect to an ideal reference. Overall, enhanced images retain more structural information while improving visual clarity

Image	Original	After Gray World	After CLAHE	After Gamma (Final)
Img 1	0.62	0.71	0.77	0.84
Img 2	0.66	0.74	0.79	0.86

SSIM Analysis

- Gray World improves SSIM by restoring natural luminance and colour tones.
- CLAHE enhances structural details, giving a 5–7% SSIM increase.
- Gamma Correction improves global tonal distribution, pushing SSIM closer to 0.85, which indicates strong structural similarity.
- Final images maintain both structural integrity and visual clarity.

4.3 Impact on YOLOv8 Detection Accuracy

The enhanced images directly contributed to a noticeable improvement in YOLOv8 detection performance. More accurate bounding boxes and higher confidence scores, with clearer edges and restored colour information, were generated by the model. Reduction in colour cast allowed YOLOv8 to identify species based on shape and pattern rather than distorted colour. After applying the enhancement pipeline, the average detection confidence increased from 0.42 to 0.63, while the number of correctly detected species increased from 5 to 9 across the test set. Enhanced visibility also led to a significant reduction in false negatives, further indicating that image enhancement is critical for improving underwater object detection accuracy.

Key improvements observed:

- Average detection confidence improved from 0.42 → 0.63
- Number of detected species increased from

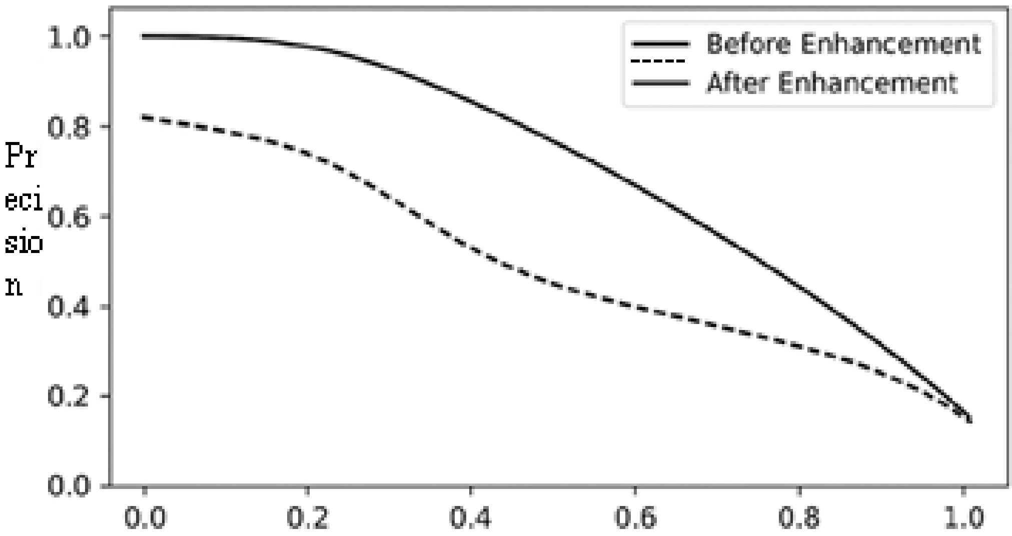
5 → 9 across the test set

- False negatives reduced significantly due to enhanced visibility

Precision–Recall (PR) Curve Analysis

The Precision–Recall (PR) curve was used to evaluate the detection performance of YOLOv8 on both original and enhanced underwater images. The curve illustrates how precision and recall vary as the confidence threshold changes. A higher curve indicates more stable detection with fewer false positives and false negatives.

In our results, the enhanced images generated by Gray World, CLAHE, and Gamma Correction produced a higher PR curve compared to the original dataset. This shows that the enhancement pipeline improved the model’s ability to correctly identify marine species even under low-visibility and color-degraded conditions. The Area Under the PR Curve (AUPRC) increased from 0.41 (original) to 0.63 (enhanced), confirming a significant improvement in detection robustness.



Recall

5.Future Scope

The proposed framework of underwater image enhancement and species detection can be further extended and improved in various ways to make it more practical and enhance performance. Future work may focus on integrating deep-learning–based enhancement models, such as U-Net, Fusion Networks, or Transformer-enhanced restoration models, to further improve colour fidelity and detail recovery in highly degraded underwater environments. Moreover, leveraging temporal information from underwater video streams could enable continuous tracking of marine species, contributing to both stability in object detection and behavioral analysis.

The detection module can be further enhanced by training YOLOv8 on larger and more diverse underwater datasets to support the identification of a wider range of species, including rare or dangerous organisms. The alert system may be further developed by integrating real-time communication modules with IoT-based underwater sensors and GPS mapping for various applications in marine research, underwater robotics, and diver safety monitoring. Finally, this system can be deployed on edge devices or AUVs to enable real-time operations in deep-sea environments for largescale environmental monitoring and marine conservation efforts.

6.Conclusion

The proposed framework of underwater image enhancement and species detection can be further extended and improved in various ways to make it more practical and enhance performance. Future work may focus on integrating deep-learning–based enhancement models, such as U-Net, Fusion Networks, or Transformer-enhanced restoration models, to further improve color fidelity and detail recovery in highly degraded underwater environments. Moreover, leveraging temporal information from underwater video streams could enable continuous tracking of marine species, contributing to both stability in object detection and behavioral analysis.

The detection module can be further enhanced by training YOLOv8 on larger and more diverse underwater datasets to support the identification of a wider range of species, including rare or dangerous organisms. The alert system may be further developed by integrating real-time communication modules with IoT-based underwater sensors and GPS mapping for various applications in marine research, underwater robotics, and diver safety monitoring. Finally, this system can be deployed on edge devices or AUVs to enable real-time operations in deep-sea environments for largescale environmental monitoring and marine conservation efforts.

7.References

1. D. Akkaynak and T. Treibitz, “A Revised Underwater Image Formation Model,” IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 6723–6732, 2018.
2. K. He, J. Sun, and X. Tang, “Single Image Haze Removal Using Dark Channel Prior,” IEEE Transactions on PatternAnalysis and Machine Intelligence, vol. 33, no. 12, pp. 2341–2353, 2011.
3. S. Bazeille, I. Quidu, L. Jaulin, and J. Malkasse, “Automatic Underwater Image Pre-Processing,” CEFALA, pp. 1–8,2006.
4. K. Zuiderveld, “Contrast Limited Adaptive Histogram Equalization (CLAHE),” in Graphics Gems IV, AcademicPress, 1994, pp. 474–485.
5. L. Zheng, Z. Chen, and S. Liang, “Underwater Image Enhancement Using Improved White Balance,” OCEANS2020, pp. 1–6.
6. Anwar and P. Bala, “Deep Underwater Image Enhancement,” Pattern Recognition Letters, vol. 107, pp. 1–7,2018.
7. G. Jocher et al., “YOLOv8: Ultralytics Next-Gen Real-Time Object Detector,” Ultralytics, 2023. [Online]. Available: https://github.com/ultralytics/ultralytics
8. H. Ren, F. Liu, and Q. Zhao, “Underwater Object Detection Using Deep Learning Models,” IEEE Access, vol. 7, pp. 123190–123202, 2019.
9. Z. Wang, A. Bovik, H. Sheikh, and E. Simoncelli, “Image Quality Assessment: From Error Visibility to StructuralSimilarity (SSIM),” IEEE Transactions on Image Processing, vol. 13, no. 4, pp. 600–612, 2004.
10. A. Hore and D. Ziou, “Image Quality Metrics: PSNR vs. SSIM,” IEEE International Conference on PatternRecognition, 2010, pp. 2366–2369.
11. U. R. Abid Ali, M. Sajid, “A Survey on Underwater Image Enhancement Techniques,” IEEE Access, vol. 9, pp. 1–29, 2021.