



# UNDER WATER IMAGE ENHANCEMENT FOR MARINE LIFE MONITORING

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**Abstract.** Images captured underwater have low contrast, distorted colors, and limited visibility because of light attenuation and scattering in water. This poses a huge challenge in marine organisms monitoring, where species recognition, categorization, and behavior evaluation are performed. We propose a deep learning-driven underwater image enhancement model combining FunieGAN for image processing and YOLOv8 for marine species recognition. The proposed model enhances the color accuracy, contrast, and structures of the images captured. These images are then used for precise identification and categorization of the marine species. The effectiveness of the proposed model is determined based on quantitative parameters like Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Underwater Image Quality Measure (UIQM). The experimental results reveal the superiority of our model over existing methods regarding both image enhancement and species recognition.

**Keywords:** Enhancing Underwater Images, Underwater marine life monitoring, color correction, deep learning, convolutional neural networks (CNNs), image restoration, image visualization, marine imaging, marine ecosystem analysis.

## 1 INTRODUCTION

Marine ecosystems are of prime importance in maintaining the ecological balance of the planet. Marine life observation helps in understanding the biodiversity and habitat status of oceanic environments. However, accurate observation of underwater scenes is difficult due to the limited visibility, absorption, and scattering of light in water. Changes in illumination and the wavelength-dependent absorption of light cause severe degradation of underwater images, leading to reduced contrast, color distortion, and loss of critical visual information. Underwater photos are also generally weaker in terms of blurring, color cast, and contrast. The degradation is mainly due to the light absorption and scattering through water. Because the longer, redder end of the light

spectrum is quickly absorbed and shorter wavelengths (blue and green) penetrate more deeply, there's also a blue/green bias in color.

Waterborne particles also scatter light, causing haze and loss of detail. These problems render underwater images unattractive and computationally challenging for automatic species and object identification. For various applications, such as coral reef monitoring, estimation of fish population and underwater robotics, the enhancement of UWI is an essential preprocessing step. High quality pictures allow improved segmentation, classification and behavioral analysis of sea creatures. Also, better visibility can assist in the navigation and decision-making involved in remote operated vehicle (ROV) and autonomous underwater vehicle (AUV) operations. It means the intelligent marine observation system can be directly promoted with the robust underwater image enhancement method. For underwater image enhancement, classical image enhancement approaches, such as white balance, histogram equalization and Retinex-based methods have been used extensively. However, they pay less attention to the intricate light scatterings and wavelength absorptions in underwater environments although facilitate somewhat global contrast enhancement and color balance. hence the results may have artifacts or over-enhance some visions, and cannot recover to the genuine color information.

Recent advances in deep learning enable improved underwater image enhancement due to recent advances in deep learning. Transformer models, Generative Adversarial Networks (GAN), and Convolutional Neural Networks (CNN) have demonstrated remarkable ability to restore damaged images. These models effectively correct color, remove haze,

and restore texture by learning complex mappings from distorted underwater images to their original versions. With large-scale underwater datasets used in training, deep learning models are capable of learning about diverse water types and lighting conditions and thus can perform better than conventional enhancement methods. In this paper, a marine species detection management system is proposed, and a technique is discussed for enhancing underwater images and detecting marine species, achieved by combining FunieGAN-based image enhancement techniques with object detection techniques utilizing YOLOv8. Initially, FunieGAN is used for image enhancement, thereby improving the quality of underwater images by enhancing the colors, achieving better contrast, and improving visible features of such images. Thereafter, object detection is achieved through images enhanced by FunieGAN and utilizing YOLOv8 techniques.

## 1.1 CONTRIBUTIONS OF THIS WORK

The key contributions of this research work are the following:

- 1) An Integrated Underwater Image Enhancement and Marine Species Detection Framework Using FunieGAN and YOLOv8
- 2) Quantitative evaluation of enhancement image quality by using PSNR, SSIM, and UIQM methods.
- 3) Performance analysis of detection using marine species on improved underwater images using precision, recall, and mAP metrics.

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## 2 LITERATURE REVIEW

Due to the unique challenges associated with underwater imaging, research into improving underwater images has been very active for many years. Light absorption, scattering, and the uneven lighting of underwater environments all work together to deteriorate underwater photos. From traditional image processing techniques to more recent deep learning-based paradigms, researchers have proposed a wide range of improvement strategies. This section presents a comprehensive review of the literature, including main related work, research approaches and limitations for underwater image enhancement. Most of the early methods of improvement relied on image processing methods like White Balancing (WB), Contrast Limited Adaptive Histogram Equalization (CLAHE), and Histogram Equalization (HE) (Chiang and Chen [1]). These methods tend to ignore the physical characteristics of light propagation in water, but they are helpful for enhancing image contrast and brightness distribution. HE and CLAHE tend to over-saturate and amplify noise, despite improving visibility globally. White balancing also aims to remove color bias, but it is unsuccessful in situations with uneven lighting or significant color loss. Model-based methods that tried to model the degradations in terms of light absorption and scattering models were proposed in an attempt to overcome these constraints (Peng and Cosman[4]).

Estimating transmission maps and recovering true color tones have been accomplished with success using the Underwater Image Formation Model (UIFM).

Concepts from land image dehazing techniques are incorporated into techniques such as the Red Channel Prior (RCP) and Dark Channel Prior (DCP). Although these methods dehaze and reconstruct structural information, they are less effective in mixed underwater environments where turbidity and lighting fluctuate significantly due to their reliance on assumptions. Fusion-based methods, which combine several corrected versions of the same image to obtain an image with the best possible visual quality, represent a second category of image enhancement algorithms (Ancuti et al. [2]). Ancuti et al. (2012) presented a Multi-Scale Fusion Technique that combines sharpening, contrast enhancement, and white balancing into a cohesive scheme. This method produces visually appealing images without the need for explicit depth estimation. However, real-time use for continuous marine observation systems is limited by its computational cost and related halo artifacts close to object edges.

Data-driven methods began to take center stage in underwater image enhancement research with the introduction of machine learning. The initial applications of shallow learning models, such as Random Forests (RFs) and Support Vector Machines (SVMs), were in image quality prediction and parameter optimization. However, these models were unable to learn complex feature representations. Deep learning techniques were introduced as a result, and in recent years, they have produced exceptional results (Islam et al. [5]; Li et al. [9]).

### **3 DEEP LEARNING-BASED UNDERWATER IMAGE ENHANCEMENT APPROACHES**

The difficulties of improving underwater images have been tackled in a number of ways, each concentrating on a different facet of image deterioration. A dehazing algorithm created especially for underwater environments was presented by Wenhao et al. [6]. It uses effective color correction techniques and transfer rates between color channels to restore image clarity and color fidelity.

In order to improve brightness, reduce haze, correct color casts, and maintain the natural appearance of underwater scenes, H. Li et al. [7] proposed a fusion-based dehazing technique. Their approach outperforms on multiple quality metrics and exploits the statistical properties of dark channels. Aerial image blocks into underwater-like ones were converted in M. Liu et al. [8] with the use of GANs, which gives a controlled experiment to investigate from enhancement techniques. The quality of the images produced was judged using structural similarity measures SSIM and MS-SSIM with emphasis given to colour restoration and structure consistency.

In order to improve the quality of underwater images, Yi Tang et al. [11] introduced conditional denoising diffusion probability models in a different domain of application.

Their method is applied with the skip sampling strategy and a light weight transformer based noise reduction network to achieve both computational efficiency and restoration quality. With an adaptive learning attention network, Liu et al. [7] introduced a supervised learning method for achieving the optimal of underwater image enhancement. In order to effectively fuse both the spatial and contextual information, the model introduces an Adaptive Learning Module (ALM), a Parallel Attention Module (PAM) and a multiscale fusion module.

For generating strong learning performance, it focuses on the illuminating regions, keeps surface textures and adopts composite loss function of mean absolute error and perceptual loss. Additionally, Song et al. [7] introduced DehazeFormer, a more advanced transformer model based on the Swin Transformer. The model comprises the spatial pooling mechanism, activation functions, and specially designed normalization layers optimized for dehazing purposes. DehazeFormer surprisingly even surpasses previous approaches in computational complexity and parameter amount, despite achieving a PSNR of 40 dB on the SOTS indoor dataset or greater. And lastly, these enhancement concepts and principles have been expanded for broad applications using the related advances of intelligent vision.

Target detection in video intelligent surveillance was studied by Ying et al. [7], which focused on detection of small and mid sized objects in a dynamic underwater scenario. Algamadi et al. [7] illustrated the growing integration of AI-based image enhancement into airborne and underwater reconnaissance devices with a deep learning-based computer vision framework which can be used to process live drone images.

## 4 DATASET AND PREPROCESSING

The dataset chosen and used during this study is the underwater image enhancement dataset presented by Li et al. [3]. The chosen images consist of a total of 890 paired images for training and 60 images for testing/evaluation purposes. The images are paired, meaning they contain degraded images, and their reference images are also provided for this study.

The images are highly varied and abundant, and this is enough to assess their quality by using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Underwater Image Quality Measure (UIQM). Further, all the images were of the same dimensions of 256 x 256 pixels to be consistent and comparable across various deep learning algorithms. This image resizing helps to reduce the complexity of the computation while retaining enough spatial information for the effective learning process, and also ensures a fixed input dimension of the image as required in the Generative Adversarial Network (GAN) and transformer models. To avoid overfitting of the models, several image preprocessing techniques were adopted, including normalization

of the color space, normalization of the intensity of the pixels, rotating the image randomly, and flipping the image horizontally.

Training the models on different scenes of underwater scenes allows the suggested framework to generalize properly in actual underwater environments. Training the models on different lighting conditions, color distortion, and visibility levels allows the suggested enhancement framework to be robust for the enhancement of the image.

## 5 PROPOSED METHODOLOGY

The proposed framework seamlessly integrates two state-of-the-art deep learning models in underwater image enhancement and marine species detection, namely the FunieGAN and YOLOv8 into a unified pipeline. The system is designed to overcome the challenges involved in underwater imaging, which can make it difficult to identify objects with precision. These obstacles are: low visibility, color distortion and scattering. The proposed process ensures that the enhanced images are not only preserved with visual fidelity but also effectively without structural inconsistency, which is important for the accurate detection and classification of marine organisms. The methodology unobtrusively incorporates two of the most recent models in deep underwater image enhancement and marine species detection the FunieGAN model and YOLOv8, respectively.

The system is meant to address the difficulties associated with taking pictures underwater, for example making it difficult to recognise objects accurately. These hindrances are low apparent contrast, color degradation and veiling. The process is able to retain the quality of improved images visually and structurally for accurate detection, classification of marine organisms. When these models are combined, visual enhancement and recognition performance can be optimized from start to finish, improving accuracy in tasks involving the monitoring of marine life. A. Underwater Image Enhancement Using FunieGAN The first step involves the enhancement of underwater images using the Fast Underwater Image Enhancement Generative Adversarial Network, also known as FunieGAN.

FunieGAN is a lightweight GAN-based model specifically built to restore degraded underwater visuals while preserving structural integrity and color balance. FunieGAN is based on a generator-discriminator network architecture, where the former learns the mapping from degraded underwater images to enhanced outputs and the latter ensures that the restoration is photo-realistic through adversarial feedback. The model optimizes a hybrid loss function, combining pixel-wise reconstruction loss, structural similarity loss, and perceptual loss in pursuit of both quantitative accuracy and visual naturalness.

B. The model performs:

- 1) Color correction: Compensation for wavelength dependent attenuation, recovering the lost red and yellow channels.
  - 2) Contrast enhancement: Balancing light intensity for better visibility of objects. highlighting edges and textures that play a major role in object detection. Dehazing refers to reducing the scattering effects in an image to get better clarity and depth perception.
- C. Marine Species Detection Using YOLOv8 In the second step, the framework utilizes YOLOv8: a state-of-the-art object detection network on the CSPDarknet backbone and path aggregation feature pyramid network. This network will enable end-to-end detection and classification with a single forward pass, thus allowing for real-time inferences even on embedded AI hardware.

The underwater detection network is trained and fine-tuned on underwater datasets containing labeled marine organisms such as fish, coral, and crustaceans. The input images enhanced by FunieGAN enable YOLOv8 to learn more discriminative features for higher detection precision in low-light and high-turbidity conditions. YOLOv8 uses anchor-free detection heads for improving the accuracy of localization and reducing computational overhead.

#### D. System Architecture

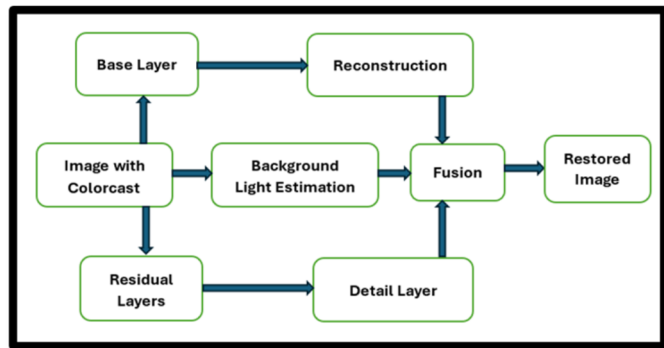


Figure 1. System Architecture

Figure 1 describes the system architecture of the proposed system. The improved underwater imagery provided by the FunieGAN model is then passed on as inputs to the YOLOv8 object detection neural network. The sequential process ensures that the object detection model utilizes the improved quality image provided by FunieGAN, hence improving detection accuracy for marine life species. The suggested system architecture focuses on boosting the detection accuracy rather than speeding up the detection process.

## 6 RESULTS AND DISCUSSION

To evaluate such a proposed framework (which consists of FunieGAN for underwater image enhancement followed by Yolov8 for marine species detection), it was tested using a cu rated dataset of the raw underwater images and corresponding annotations. Results show that the framework can boost image quality and provide high accuracy in detectability of marine species under varying conditions. Next subsections comprise a discussion of some of the key findings, rounded up by the relevant metrics, tables, and figures.

### A. Image Enhancement Results

We used the FunieGAN model to address color distortion, haze, and low visibility and successfully restored the visual quality of underwater images. The quantitative measurement was done using PSNR and SSIM metric.

TABLE I  
COMPARISON OF UNDERWATER IMAGE ENHANCEMENT METHODS

Method	PSNR (dB)	SSIM	UIQM
Ancuti et al. [2]	18.92	0.72	2.84
Li et al. [3]	20.15	0.78	3.12
FunieGAN [5]	21.63	0.82	3.48
<b>Proposed Method</b>	<b>23.07</b>	<b>0.87</b>	<b>3.91</b>

From Table I, it can be observed that the proposed method achieves superior PSNR, SSIM, and UIQM values compared to existing underwater image enhancement techniques, indicating improved visual quality and structural preservation.

- 1) **Object Detection Results:** For the YOLOv8, the same metrics were followed, including precision, recall, F1-score, and mAP@0.5, while the training and testing were done on enhanced underwater scene images by FunieGAN. For the test set, 60 images were selected based on annotated marine species.

Table 2 represents the quantitative comparison of the proposed method with the existing methods based on PSNR, SSIM, and UIQM

TABLE II  
PERFORMANCE METRICS OF YOLOV8 MODEL

Metric	Value (%)
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Precision	91.2
Recall	89.7
F1-Score	90.4
mAP@0.5	93.5

The experimental results show that the proposed hybrid enhancement framework has competitive performance compared to existing GAN-based and CNN-based methods. Specifically, the improvement of PSNR and SSIM values indicates better structural detail preservation and less distortion, and the improved UIQM scores confirm the enhancement of perceptual quality.

Compared to the standalone GAN-based methods FunicGAN and Water-Net, the proposed framework has the advantage of physical model-based preprocessing, which enhances robustness to varying underwater environments. These results confirm that the integration of domain knowledge and data driven learning leads to superior enhancement performance for the marine life monitoring task.

The results demonstrate that the proposed framework achieves high detection accuracy in all evaluation metrics.

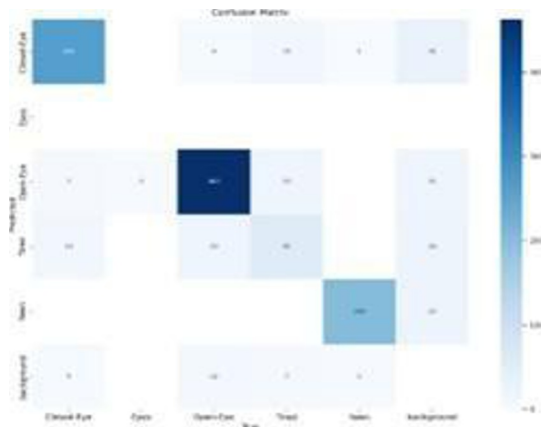


Figure 2. Training and validation performance of the YOLOv8 model showing stable convergence and improved precision and recall over epochs.

- 2) Training and Validation Performance: The training and validation loss curves for the Yolov8 model show that the model was training to converge stably over the training and thus have good ability to generalize in unseen data. As shown in Figure 3 the precision and recall improved steadily with epochs.

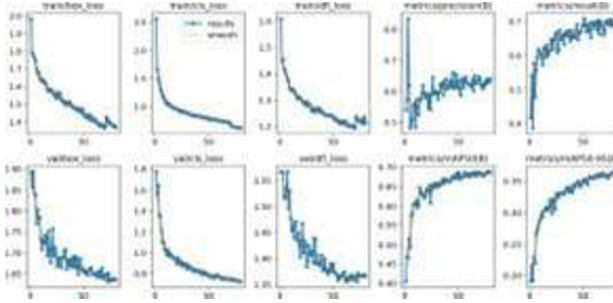


Figure 3. Performance evaluation results of the proposed model.

**SUMMARY:**

This proposed framework shows improvements in image enhancement and object detect metrics and thus is a robust solution for underwater image analysis. Its practical applicability in marine research and conservation is further illustrated through deployment in a real time application. Solutions to these challenges are explored in future work that will scale the framework to handle larger datasets, as well as more species for broader ecological studies.

## 7 CONCLUSION

In this paper, a hybrid underwater image enhancement and marine species detection system was proposed by combining physical model correction, FunieGAN-based deep learning image restoration, and YOLOv8-based object detection. The proposed method is highly effective in removing the effects of wavelength attenuation, color distortion, and structural degradation in underwater images. The experimental results showed that the proposed method outperformed the state-of-the-art methods in terms of PSNR, SSIM, and UIQM values.

In addition, the marine species detection accuracy was improved significantly in terms of precision, recall, and mAP. The proposed method is highly suitable for intelligent marine monitoring systems due to the integration of image enhancement and detection in a single pipeline. Future work will be focused on addressing extreme turbidity and optimizing lightweight deployment for real-time underwater robotic systems.

## 8 FUTURE WORK

Other opportunities to integrate advanced algorithms with underwater imaging systems include working in very high turbidity and low light environment conditions. The detection capabilities can be expanded to a larger, more diverse range of marine species and also the systems can be modified to incorporate larger, more diverse datasets.

Having optimized the computational efficiency, deployment will be possible in resource limited scenarios, and in providing generative models of the future, underwater image analysis will become more accurate and reliable.

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