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Task-Specific Image Enhancement for Underwater Turtle Detection and Segmentation: An Investigation on a Benchmark Dataset

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Abstract: Underwater images often present challenges related to color distortion, low contrast, and loss of texture, severely degrading the performance of computer vision models involved in ecological monitoring or autonomous systems. This work investigates the performance of various enhancement techniques based on two main downstream tasks: turtle detection using the YOLO model and turtle segmentation using SAM. A multi-species dataset of turtles was collected from public resources, and five representative enhancement schemes, including classic contrast enhancement, generative learning-based enhancement, physics-guided correction, fusion-based processing, and the proposed TOUE method, were tested. Experimental results illustrate that the effectiveness of enhancement is very task dependent. That is, TOUE had the best detection accuracy and generalization capability on both the custom dataset and the SUIM benchmark, whereas CLAHE generated the best segmentation accuracy owing to consistent local contrast refinement. No single enhancement method effectively produced the optimal outcome in these two tasks. Guided by this observation, a dual-stage pipeline has been proposed, utilizing TOUE for detection and CLAHE for segmentation, a more reliable end-to-end pipeline for underwater vision. These findings underline the necessity of choosing enhancement methods based on the downstream application and provide, for the first time, a practical framework for optimizing detection-segmentation systems in real underwater scenarios.

Keywords: *Image segmentation, Intelligent vision systems, Marine turtle dataset, Object detection, Segment anything model, Underwater image enhancement,* YOLO

1. Introduction

Underwater imaging has applications in various marine research areas, such as Autonomous Underwater Vehicle (AUV) operations, habitat monitoring, and species identification. However, underwater images often suffer from severe degradation due to wavelength-dependent absorption, color distortion, scattering, and loss of fine texture. These distortions reduce the reliability of intelligent vision systems, especially in tasks that rely on stable feature representations, such as object detection and segmentation. Classic enhancement approaches include histogram equalization and Contrast Limited Adaptive Histogram Equalization (CLAHE), which, though simple, still represent widely used methods for improving local contrast in challenging underwater scenes [1, 2].

On the one hand, fusion-based enhancement techniques combine multiple visual cues into a single image to strengthen structure and highlight salient regions [3]. These have further led to advanced enhancement models that can achieve nonlinear color correction and detail reconstruction. Generative approaches like FUnIE-GAN provide real-time enhancement suitable for underwater robotics [4], while domain-adaptive enhancement strategies aim at normalizing appearance variations with respect to different water conditions [5]. Physics-guided methods, including DeepSeeColor, encode the principles of underwater imaging into learned models to offer effective onboard correction on AUVs [6]. While often visually impressive, these enhancement methods do not reliably improve performance in downstream detection and segmentation, and how they interact with vision models remains poorly understood.

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The YOLO family of detectors has gained pre-eminence in underwater animal monitoring due to their real-time performance and robustness under cluttered aquatic scenarios [7–9]. In turn, underwater segmentation has traversed its course with important datasets, including the SUIM benchmark, that allow encoder–decoder architectures to be adapted for underwater conditions [10,11]. More recently, the introduction of foundation models such as SAM has further shifted the paradigm of this task with prompt-based generalization across a wide variety of image domains [12–14]. Despite these developments, few works have actually analyzed the behavior of a combined YOLO–SAM pipeline for species-specific underwater imaging scenarios under different enhancement methods.

To fill this knowledge gap, this work systematically benchmarks different underwater image enhancement methods, ranging from classical to generative, physics-guided, and fusion-based techniques for underwater turtle detection and segmentation tasks. Beyond that, we propose a Texture-Oriented Underwater Enhancement (TOUE) approach that aims to retain structural texture and luminance stability for better detection. Our experimental results reveal one key observation: underwater image enhancement is a task-specific operation. The proposed TOUE yields the best detection performance, thanks to its own design targeted for preserving texture information, while CLAHE generates the best segmentation outcome as it provides much smoother and contrast-balanced images, which are preferred by SAM. The rest of this paper is organized as follows: Section 2 reviews the related work on underwater enhancement, detection, and segmentation. Section 3 describes the proposed methodology and the detection-segmentation framework. Results and comparative analysis are presented in Section 4. The conclusion of the study is drawn in Section 5 and some future research directions are highlighted.

2. Related Work

Underwater image enhancement has been researched with various methods, including classical, learning-based, and hybrid methods. Among the classical ones, methods such as CLAHE are widely used since they enhance local contrast without excessive amplification of noise [2]. Illumination correction based on the Retinex method and its multi-scale variants improve color stability and visibility by decomposing the image into its illumination and reflectance parts [15]. Saliency cues and multi-band priors are combined in a fusion approach to highlight structural features from challenging underwater scenes [3], while in recent works, a dual-branch fusion looks for color compensation and restoration of contrast in order to increase fidelity within the turbid medium [16].

Deep learning has significantly advanced the performance of enhancement. Generative adversarial approaches, such as FUnIE-GAN, have shown fast restoration suitable for underwater robotics [4], while domain-adaptive enhancement seeks to align synthetic and real underwater distributions for improved generalization [5]. Transformer-based global attention models, such as U-TransEnhance, introduce long-range contextual understanding and have been shown to improve both color consistency and fine-detail preservation [17]. Physics-guided frameworks, including DeepSeeColor, incorporate underwater attenuation models into neural networks to achieve stable, real-time enhancement for AUVs [6]. Surveys and comparative studies have highlighted that underwater enhancement that is visually pleasing does not necessarily provide improved downstream performance, underlining the inconsistencies between enhancement quality and outcomes in either detection or segmentation [18,19,20].

With their speed and robustness in low visibility, enhanced versions of YOLO have been widely used for underwater object detection. In more recent works, improved YOLO models have tackled turbidity and color shifts with multi-scale fusion, attention modules, and degradation-aware blocks. [7, 8, 19] Broader analyses of challenges in underwater vision identify that the basis for accurate object detection consists of well-preserved edge detail, texture structure, and luminance balance-all of which are usually altered by enhancement methods. [21] Other works have looked into the detection reliability across environmental conditions and come to a similar conclusion: Detection performance is very different depending on the nature of the enhancement applied. [22] Ecological monitoring tasks, including the detection and behavioral analysis of sea turtles, were also conducted using YOLO-based networks, thus demonstrating the practicality of one-stage detectors for marine biology. [9, 23]

For pixel-level understanding, the SUIM dataset furnished the ground for underwater segmentation and presented the SUIM-Net, an encoder-decoder architecture specifically crafted for underwater scenes [10]. Multi-scale attention, contextual encoding, and edge-aware refinement have since been integrated into more recent models to improve segmentation accuracy of different underwater distortions [11, 24]. Recent studies showed that the selected enhancement method would affect the segmentation accuracy of EUVP and SUIM datasets, especially when the enhancement changes the texture smoothness, boundary sharpness, or color balance [11, 25].

Recent foundation models, like the Segment Anything Model (SAM), have modified segmentation workflows by allowing for prompt-driven mask generation with generalization capability across broad datasets [12]. Domain-specific variants, such as MedSAM and SAM-Adapter, have shown that, when applied to specialized domains such as medical imaging and environmental analysis, foundation models benefit from domain-specific pre-processing or fine-tuning [13,14,26]. Research into how SAM operates under degraded underwater conditions established enhancement can either improve structural coherence or introduce artifacts which degrade mask quality, depending on the enhancement strategy implemented [27,28].

Despite a growing body of work in this area, few studies have rigorously investigated how enhancement impacts a combined YOLO–SAM pipeline for the analysis of underwater species. Motivated by these gaps, this work investigates various enhancement strategies, including classical, GAN-based, physics-guided, transformer-based, and fusion-based approaches, and proposes a Texture-Oriented Underwater Enhancement approach, namely TOUE. The purpose is to investigate how different enhancement options affect the performance of both detection and segmentation tasks within a unified pipeline of underwater vision.

3. Methodology

This section describes the dataset preparation, image enhancement techniques, the proposed Texture-Oriented Underwater Enhancement (TOUE) method, the YOLO-based detection framework, the SAM-based segmentation pipeline, and the evaluation metrics used in this study. The complete workflow of the proposed system is illustrated in Fig. 1.

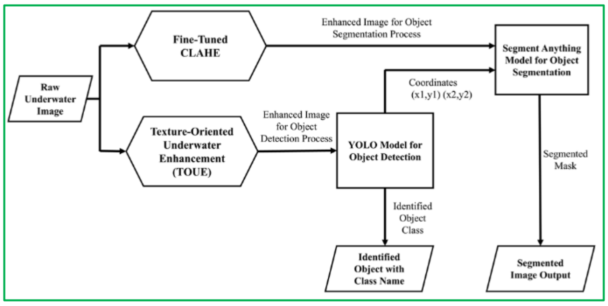

Fig. 1. Overall pipeline of the proposed detection–segmentation framework.

3.1. Dataset Collection and Preparation

A new underwater turtle dataset was created for this research by collecting publicly available and ethically approvable online sources such as Google Images, YouTube video frames, Pinterest, and reputable marine and wildlife organizations like NIO, NOAA, WWF, and the Olive Ridley Project. The dataset consisted of six endangered or critically endangered sea turtle species, namely Green Turtle, Hawksbill Turtle, Olive Ridley Turtle, Kemp's Ridley Turtle, Loggerhead Turtle, and Leatherback Turtle.

A total of 1620 underwater turtle images were kept after thorough manual refinement to eliminate redundant, fuzzy, or poor-quality samples. Using an 80:10:10 ratio, the dataset was split into 1296 training, 162 validation, and 162 testing images. The Roboflow platform was used to annotate every image in order to create bounding boxes for each of the five turtle classes. All ensuing training and performance assessments were based on this annotated dataset.

3.2. Image Enhancement Techniques

Color attenuation, low contrast, backscatter, and loss of fine structural features are common problems with underwater images. This study used a set of enhancement techniques chosen not at random but rather based on their computational characteristics, representativeness of major enhancement paradigms, and relevance in recent underwater imaging research in order to examine how various enhancement strategies impact downstream computer vision tasks.

3.2.1 Rationale for Selecting Enhancement Methods

Five exemplary underwater image improvement methods—classical, deep learning-based, physics-guided, and fusion-based—were chosen to guarantee a thorough and impartial assessment. Each technique reflects a popular strategy in the underwater imaging field and has unique benefits.

- CLAHE (Classical Enhancement): Due to its ease of use, computational effectiveness, and enduring reliability in underwater imagery, CLAHE was selected. It functions as a common baseline in many contemporary enhancement processes and adaptively improves local contrast without excessive noise amplification.
- FUnIE-GAN (Deep Learning–Based Enhancement): Lightweight generative models for quick, real-time underwater augmentation are represented by FUnIE-GAN. It is appropriate for embedded and robotic applications because of its architecture, which offers aesthetically pleasing color correction with low computing overhead.
- DeepSeeColor (Physics-Guided Deep Learning Enhancement): DeepSeeColor restores color integrity in underwater images by modelling the effects of light attenuation and backscatter. It integrates physics-based principles with deep neural networks, providing interpretable corrections while leveraging learning-based priors for robust, real-time enhancement.
- Hybrid Fusion Model (HFM) (Fusion-Based Enhancement): HFM uses a traditional multi-stage fusion technique to combine edge sharpening, contrast refinement, and white balancing. It maintains a minimal computing cost while providing significant visual augmentation. In contrast to slower techniques like BM3D, HFM offers a useful benchmark for assessing TOUE, which likewise employs a fusion-based design.
- TOUE (Proposed Texture-Oriented Enhancement): To maintain the structural and textural signals necessary for object detection, the Texture-Oriented Underwater Enhancement (TOUE) technique was created. It incorporates texture-preserving denoising, regulated red-channel compensation, adaptive gamma correction, modest CLAHE adjustment, brightness balancing, and final sharpening. To enable high-quality YOLO detection, TOUE places a strong emphasis on feature preservation.

For every enhanced variation, a unique YOLO detector was trained, and every enhancement method was used independently throughout the whole dataset of submerged turtles. This regulated arrangement enables a fair and consistent evaluation of the impact of each improvement strategy on downstream item detection and segmentation performance.

3.3. Proposed Texture-Oriented Underwater Enhancement (TOUE)

The TOUE technique was created to maintain fine texture and border information, improve contrast, and improve brightness balance—all of which are critical for accurate identification. There are six consecutive steps in the method:

- White Balance Correction: To reduce underwater color shifts, images are transformed to the LAB color space and the a–b channels are balanced.
- Mild CLAHE Adjustment: To improve local contrast without adding artifacts, the L channel is improved using constrained CLAHE settings.
- Adaptive Gamma Correction: To adjust global brightness, gamma is dynamically changed based on mean luminance.
- Red-Channel Compensation: In underwater images, blue-green dominance is corrected by a low-intensity red-channel boost.
- Texture-Preserving Denoising: Noise is eliminated while structural features are retained using light non-local methods filtering.
- Selective Sharpening: In order to detect turtles, a high-frequency sharpening kernel boosts edge and texture information.

The benefit of texture-focused enhancement was demonstrated by the TOUE-enhanced dataset, which consistently produced the highest YOLO detection accuracy.

3.4. YOLO-Based Detection Framework

The Ultralytics package was used to implement the YOLOv8n model for object detection. An NVIDIA Tesla T4 GPU was used for training on Google Colab. With an input resolution of 640 x 640, a batch size of 16, and the optimizer settings supplied by the default Ultralytics configuration, the model was trained for 100 epochs using the pretrained yolov8n.pt weights. In order to facilitate checkpointing and comparative performance analysis, the training process was set up to save model weights at 50-epoch intervals.

3.5. SAM-Based Segmentation Using YOLO Prompts

The Segment Anything Model (SAM), which generates excellent object masks from rapid inputs, was used for segmentation. In this study, an automated detection–segmentation workflow was made possible by using the bounding boxes that the YOLO detector predicted as prompts to SAM. The segmentation performance was assessed using a subset of 50 turtle images from the SUIM dataset, each with a matching ground-truth mask. Each enhancement technique was applied to the SUIM images prior to segmentation in order to examine the task-specific behaviour of underwater enhancement. The bounding box for each image was supplied by YOLO, which was trained independently on each enhancement-specific dataset. SAM then processed the enhanced SUIM image to produce the segmentation mask. Standard segmentation measures were used to objectively compare the final masks with the ground truth. A consistent and equitable assessment of the ways in which various enhancement tactics affect segmentation accuracy in underwater vision pipelines is made possible by this architecture, which guarantees that SAM functions under the same prompting conditions for all enhancement versions.

Despite providing a segmentation option, YOLO necessitates pixel-level mask annotations, which our turtle dataset does not include. The Segment Anything Model (SAM) was utilized to maintain a constant, training-free segmentation stage without the need for mask labelling. Without domain-specific training, SAM generalizes well to underwater imagery and produces high-quality, boundary-accurate masks from straightforward bounding-box cues. Because of this, SAM is the perfect segmentation module for assessing the impact of image enhancement without requiring the training of a segmentation model.

4. Results and Discussion

YOLO-based turtle detection and SAM-based segmentation are the two main downstream tasks for which this section provides a thorough assessment of the image enhancing techniques. Both the externally obtained SUIM dataset and the proprietary turtle dataset are used to report performance. To demonstrate detection accuracy, segmentation quality, and generalization behaviour, tables and figures are provided.

4.1. YOLO Detection Performance on the Custom Turtle Dataset

The entire turtle dataset was subjected to each enhancement technique, and 1620 images (80:10:10 split) were used to train separate YOLO models. The detection performance on the 162-image test subset is summarized in Table 1.

Table 1. YOLO detection performance on the in-distribution test set across enhancement methods.

Enhancement Method	*Correct*	*Wrong*	*Unrecognized*	*Accuracy (%)*
Original	151	11	0	93.21
CLAHE	151	11	0	93.21
FUnIE-GAN	149	13	0	91.98
DeepSeeColor	152	10	0	93.83
Hybrid Fusion	153	9	0	94.44
TOUE (Proposed)	**153**	**9**	**0**	**94.44**

With 153 accurate detections, the results demonstrate that Hybrid Fusion and TOUE both outperform the others on the custom dataset. This shows that YOLO feature extraction in the training domain is well supported by both contrast-based and texture-oriented fusion techniques.

4.2. YOLO Detection Generalization on SUIM Dataset (50 Images)

To assess robustness to domain shifts, all YOLO models were tested on 50 unseen SUIM turtle images. Table 2 presents the generalization performance.

Table 2. YOLO detection generalization performance on 50 unseen SUIM images.

Enhancement Method	*Correct*	*Wrong*	*Unrecognized*	*Accuracy (%)*
Original	38	11	1	76.00
CLAHE	38	11	1	76.00
FUnIE-GAN	38	10	2	76.00
DeepSeeColor	37	10	3	74.00
Hybrid Fusion	37	11	2	74.00
TOUE (Proposed)	**41**	**7**	**2**	**82.00**

Fig. 2 visualizes the YOLO detections for each enhancement method on SUIM images.

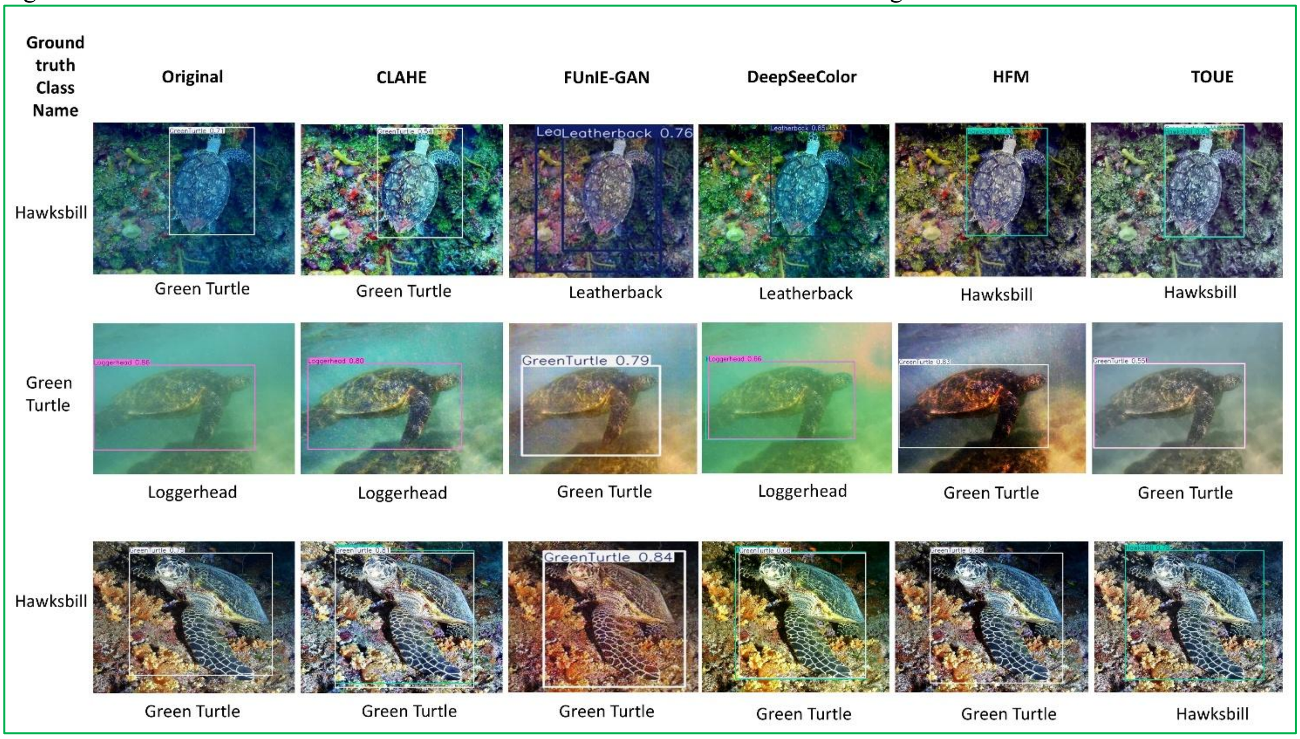

Fig. 2. YOLO generalization ability on SUIM underwater dataset across enhancement methods.

Hybrid Fusion and TOUE performed differently on external data, despite being tied on the in-distribution test set. Hybrid Fusion fell to 37/50, but TOUE outperformed all other approaches with the highest generalization performance (41/50). This suggests that even in domain fluctuation, TOUE preserves texture stability and brightness consistency over a range of underwater conditions, enabling YOLO to extract trustworthy characteristics.

4.3. SAM Segmentation Performance

Segmentation was evaluated on the same 50 SUIM images using YOLO bounding boxes as prompts for SAM. The mIoU and DSC values for each enhancement method are shown in Table 3.

Table 3. SAM segmentation accuracy for different enhanced images.

Enhancement Method	*mIoU*	*DSC (F1)*
Original	0.9334	0.9651
CLAHE	**0.9372**	**0.9673**
FUnIE-GAN	0.8942	0.9412
DeepSeeColor	0.9308	0.9636
HFM	0.9241	0.9595
TOUE	0.9333	0.9651

The SUIM dataset does not include all six turtle species; it contains only a subset (e.g., green turtle, Hawksbill turtle, and

Loggerhead turtle), and our evaluation was therefore limited to these available classes. A visual comparison of segmentation accuracy is shown in Fig. 3.

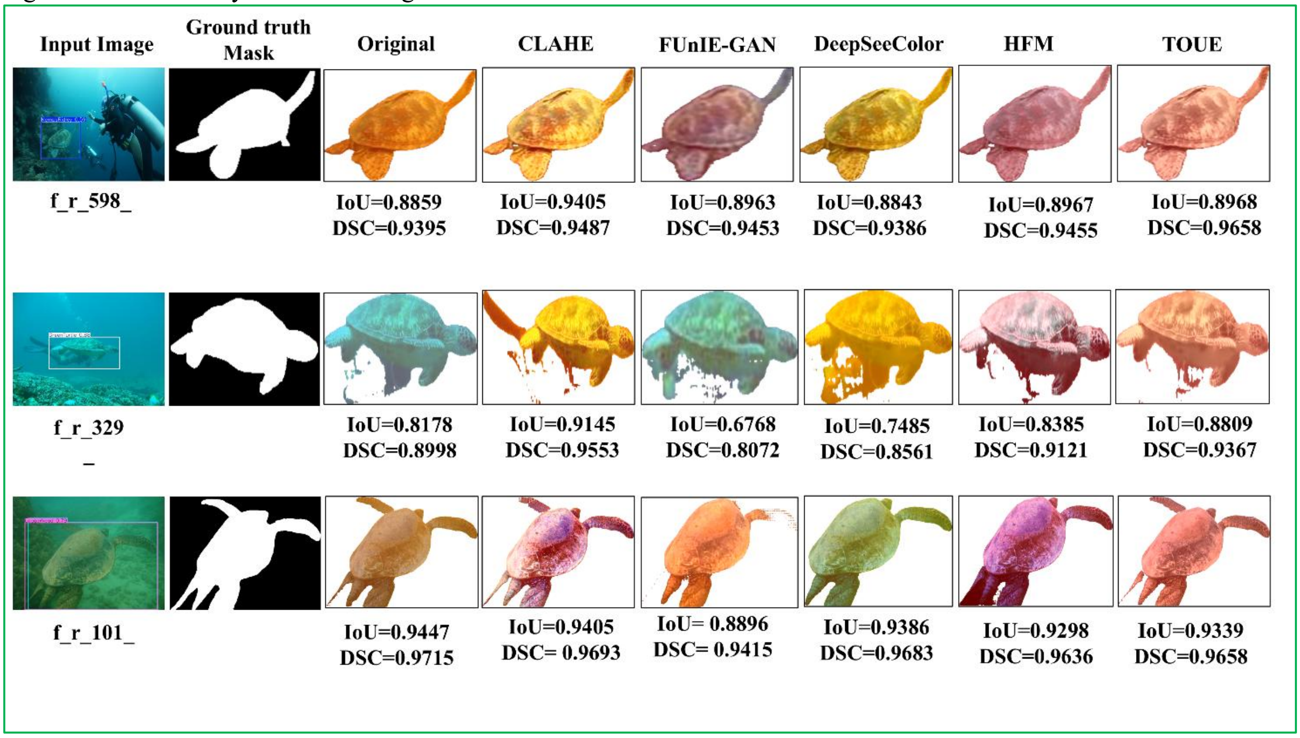

Fig. 3. SAM segmentation performance (mIoU and DSC) for different enhancement methods applied to SUIM turtle images.

4.4. Task-Specific Behaviour of Enhancement Methods

Sections 4.1 to 4.3 collectively indicate that the performance of underwater enhancement is essentially task-dependent, rather than offering uniform advantages across vision modules. TOUE yields the best results in terms of object detection, especially when tested on SUIM images not seen during training, which speaks to its robustness under domain shifts. By contrast, the CLAHE method tends to yield the best segmentation accuracy, particularly in those real-world scenes where boundary clarity is critical-which speaks to its relevance for mask-generation tasks such as those performed by SAM. The Hybrid Fusion Model performs competitively on in-distribution detection but fails to generalize well to independent datasets. On the other hand, DeepSeeColor and FUnIE-GAN tend to generate structural smoothness or color distortions that degrade both object detection and segmentation. Overall, these results confirm that no single enhancement method can yield optimal performance in both object detection and segmentation, thus justifying the incorporation of tasks into the selection of enhancement methods for underwater vision pipelines.

4.5. Generalization Capability of TOUE

While TOUE's performance on the 162-image in-distribution test set was comparable to that of the Hybrid Fusion Model, TOUE showed significantly better generalization on the SUIM benchmark, identifying 41 turtles as opposed to HFM's 37. This discrepancy demonstrates how the two approaches behave differently. When the test images and the training data have comparable visual properties, HFM performs well because it can take use of well-known illumination patterns and color distributions. On the other hand, TOUE is resilient in uncharted territory, managing changes in turbidity, illumination, color fading, and texture deterioration. When faced with real-world underwater pictures, its focus on controlled contrast and the preservation of fine-grained textures makes it more appropriate for YOLO's feature extraction method. For applications where environmental unpredictability is anticipated, TOUE can therefore be viewed as a more broadly applicable enhancement method.

4.6. Combined Detection–Segmentation Pipeline

An optimal two-stage enhancement pipeline was designed to improve both detection and segmentation based on task-specific performance observed. In the first stage, TOUE-enhanced images are fed to the YOLO detector because TOUE maintains fine textures and structural cues, which help in increasing the recognition accuracy, especially across different underwater conditions. In the second stage, images enhanced by CLAHE are fed to the SAM segmentation model because CLAHE produces clearer local contrast and sharper boundaries that assist in accurate mask generation. This combined framework of TOUE-CLAHE performed better than any single enhancement method applied uniformly across both tasks, reinforcing the idea that underwater image enhancement has to be selected judiciously according to the demands of the specific downstream vision module in question.

4.7. Summary of Key Findings

The following important insights can be determined from the experimental results over multiple datasets and enhancement regimes:

- TOUE and Hybrid Fusion showed the best results on a custom detection test set.
- TOUE had the highest generalization on the SUIM

dataset.

- CLAHE produced the best segmentation performance via SAM.
- GAN-based and physics-based methods were less stable across tasks.
- Enhancement methods should be chosen based on the downstream task and not as some general preprocessing method.
- The combined TOUE + CLAHE pipeline offers more reliable performance for underwater detection and segmentation tasks.

5. Conclusion

This paper investigated different underwater image enhancement techniques on YOLO-based turtle detection and SAM-based segmentation using a curated turtle dataset and the SUIM benchmark. The results show that enhancement is inherently task-specific: the proposed TOUE and the Hybrid Fusion Model achieved the highest detection accuracy on the custom dataset, while TOUE further demonstrated stronger generalization on unseen SUIM images due to its texture-preserving design. On the other hand, CLAHE yielded the best segmentation accuracy, indicating that segmentation models benefit more from uniform local contrast than from texture enhancement. These findings highlight that no single enhancement method is optimal for both detection and segmentation and that preprocessing should be selected based on the downstream application. An appropriate dual-stage pipeline is then suggested, where TOUE is used for detection, while CLAHE is applied to segmentation, in order to improve reliability in practical underwater vision systems, including marine species monitoring and autonomous underwater robotics. Future work will explore adaptive, task-aware enhancement strategies and extend the evaluation to broader underwater datasets and real-time deployments.

6. References

[1] Schettini, R., & Corchs, S. (2010). Underwater image processing: state of the art of restoration and image enhancement methods. EURASIP Journal on Advances in Signal Processing, 2010(1). https://doi.org/10.1155/2010/746052

[2] Zuiderveld, K. (1994). Contrast limited adaptive histogram equalization. In Elsevier eBooks (pp. 474–485). https://doi.org/10.1016/b978-0-12-336156-1.50061-6

[3] Ancuti, C. O., Ancuti, C., De Vleeschouwer, C., & Bekaert, P. (2017). Color balance and fusion for underwater image enhancement. IEEE Transactions on Image Processing, 27(1), 379–393. https://doi.org/10.1109/tip.2017.2759252

[4] Islam, J., Xia, Y., & Sattar, J. (2020). Fast underwater image enhancement for improved visual perception. IEEE Robotics and Automation Letters, 5(2), 3227–3234. https://doi.org/10.1109/lra.2020.2974710

[5] Wang, Z., Shen, L., Xu, M., Yu, M., Wang, K., & Lin, Y. (2023). Domain adaptation for underwater image enhancement. IEEE Transactions on Image Processing, 32, 1442–1457. https://doi.org/10.1109/tip.2023.3244647

[6] Jamieson, S., How, J. P., & Girdhar, Y. (2023). DeepSeeColor: Realtime adaptive color correction for autonomous underwater vehicles via deep learning methods. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2303.04025

[7] Li, M., Pang, H., Jiang, C., Li, M., Pang, H., & Jiang, C. (2025). SGL-YOLO: Lightweight underwater object detection algorithm based on feature fusion. Signal Image and Video Processing, 19(16). https://doi.org/10.1007/s11760-025-04962-3

[8] Huang, J., Fang, C., Zheng, X., & Liu, J. (2024). YOLOV8-UC: an improved YOLOV8-Based Underwater Object Detection Algorithm. IEEE Access, 12, 172186–172195. https://doi.org/10.1109/access.2024.3496925

[9] Baek, J., Kim, J., & Kim, C. (2024). Deep learning-based image classification of sea turtles using object detection and instance segmentation models. PLoS ONE, 19(11), e0313323. https://doi.org/10.1371/journal.pone.0313323

[10] Islam, J., Edge, C., Xiao, Y., Luo, P., Mehtaz, M., Morse, C., Enan, S. S., & Sattar, J. (2020). Semantic Segmentation of Underwater Imagery: Dataset and Benchmark. Computer Vision and Pattern Recognition, 1769–1776. https://doi.org/10.1109/iros45743.2020.9340821

[11] Zuo, X., Jiang, J., Shen, J., & Yang, W. (2025). Improving underwater semantic segmentation with underwater image quality attention and muti-scale aggregation attention. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2503.23422

[12] Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A. C., Lo, W., Dollár, P., & Girshick, R. (2023). Segment anything. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2304.02643

[13] Huang, Y., Lai, W., Ji, J., Cao, L., Zhang, S., & Ji, R. (2024). HRSAM: Efficient Interactive Segmentation in High-Resolution Images. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2407.02109

[14] Ma, J., He, Y., Li, F., Han, L., You, C., & Wang, B. (2024). Segment anything in medical images. Nature Communications, 15(1), 654. https://doi.org/10.1038/s41467-024-44824-z

[15] Land, E. H., & McCann, J. J. (1971). Lightness and retinex theory. Journal of the Optical Society of America, 61(1), 1. https://doi.org/10.1364/josa.61.000001

[16] Zhang, D., He, Z., Zhang, X., Wang, Z., Ge, W., Shi, T., & Lin, Y. (2023). Underwater image enhancement via multi-scale fusion and adaptive color-gamma correction in low-light conditions. Engineering Applications of Artificial Intelligence, 126, 106972. https://doi.org/10.1016/j.engappai.2023.106972

[17] Mishra, P., Vipparthi, S. K., & Murala, S. (2025). U-ENHANCE: Underwater image enhancement using WaVELet Triple Self-attention. In Lecture

notes in computer science (pp. 87–104). https://doi.org/10.1007/978-981-96-2641-0_6
[18] Wang, Y., Guo, J., He, W., Gao, H., Yue, H., Zhang, Z., & Li, C. (2023). Is underwater image enhancement all object detectors need? arXiv (Cornell University). https://doi.org/10.48550/arxiv.2311.18814
[19] Lucas, E., Awad, A., Geglio, A., Saleem, A., Moradi, S., Havens, T. C., Galloway, A., & Paheding, S. (2025, February 28). Underwater Image Enhancement and Object Detection: Are Poor Object Detection Results On Enhanced Images Due to Missing Human Labels? In 2025 IEEE/CVF Winter Conference on Applications of Computer Vision Workshops (WACVW). https://doi.org/10.1109/wacvw65960.2025.00167
[20] Yang, M., Hu, J., Li, C., Rohde, G., Du, Y., & Hu, K. (2019). An In-Depth Survey of Underwater image Enhancement and Restoration. IEEE Access, 7, 123638–123657. https://doi.org/10.1109/access.2019.2932611
[21] Nabahirwa, E., Song, W., Zhang, M., Fang, Y., & Ni, Z. (2025). A structured review of underwater object detection challenges and solutions: from traditional to large vision language models. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2509.08490
[22] Awad, A., Saleem, A., Paheding, S., Lucas, E., Al-Ratrout, S., & Havens, T. C. (2024). Beneath the surface: The role of underwater image enhancement in object detection. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2411.14626
[23] Putro, M. D., Mose, Y., Andaria, A. C., Litouw, J., Poekoel, V. C., & Najoan, X. (2024). Streamlining deep learning network for real-time sea turtle detection. Jurnal Rekayasa Elektrika, 20(3). https://doi.org/10.17529/jre.v20i3.35236
[24] Xiao, Z., Li, Z., Li, H., Li, M., Liu, X., & Kong, Y. (2024). Multi-Scale Feature Fusion Enhancement for Underwater Object Detection. Sensors, 24(22), 7201. https://doi.org/10.3390/s24227201
[25] Wang, J., He, X., Shao, F., Lu, G., Hu, R., & Jiang, Q. (2022). Semantic segmentation method of underwater images based on encoder-decoder architecture. PLoS ONE, 17(8), e0272666. https://doi.org/10.1371/journal.pone.0272666
[26] Chen, T., Zhu, L., Ding, C., Cao, R., Wang, Y., Zhang, S., Li, Z., Sun, L., Zang, Y., & Mao, P. (2023). SAM-Adapter: Adapting Segment Anything in under-performed scenes. In Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops (ICCVW 2023) (pp. \–\–). IEEE. https://openaccess.thecvf.com/content/ICCV2023W/VCL/papers/Chen_SAM-Adapter_Adapting_Segment_Anything_in_Underperformed_Scenes_ICCVW_2023_paper.pdf
[27] Hong, Y., Zhou, X., Hua, R., Lv, Q., & Dong, J. (2024). WaterSAM: Adapting SAM for Underwater Object Segmentation. Journal of Marine Science and Engineering, 12(9), 1616. https://doi.org/10.3390/jmse12091616
[28] Abhisheka, T. E., Jagadale, B. N., Madhuri, G. R., & Chandrakantha, T. S. (2024). Enhancing Underwater Image Segmentation Through Deep Learning-Based Image Enhancement Techniques: A Study on EUVP and SUIM Datasets. *Journal of Information Systems Engineering and Management,* 9(4), 31027. https://doi.org/10.52783/jisem.v9i4.78

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Author contributions
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Conflicts of interest
The authors declare no conflicts of interest.

Data Availability
- SUIM Dataset: https://irvlab.cs.umn.edu/resources/suim-dataset
- The base code for the SAM model is available publicly at GitHub repository by the SAM author https://github.com/facebookresearch/segment-anything
- The base code fir the YOLO8 model is available publicly at official website of Ultrlytics Inc. in the URL https://docs.ultralytics.com/models/yolov8/
- The Turtle dataset will be provided upon request to the corresponding author.