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Underwater Object Detection Using Yolov12 Model

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Abstract: *Underwater object detection plays a crucial role in marine biodiversity monitoring, infrastructure inspection, autonomous underwater vehicles, and search-and-rescue missions, but it is severely hindered by visibility degradation caused by light absorption, scattering, color distortion, low contrast, and turbidity. These factors significantly impair the performance of advanced object detectors like YOLOv12, which is primarily trained on clear terrestrial images. This study proposes an enhanced underwater object detection system by integrating a lightweight adaptive visibility enhancement module into the YOLOv12 pipeline. The module dynamically assesses image degradation and adapts enhancement parameters, incorporating a Visibility Estimation Module , Visibility-Conditioned Area Attention , and adaptive gating in the feature pyramid neck to improve feature extraction and robustness while preserving real-time performance. The main objective is to design, implement, and evaluate this visibility-aware framework using PyTorch and publicly available underwater datasets, aiming for superior mean Average Precision, precision, and recall compared to standard YOLOv12 and static enhancement approaches. The proposed system is expected to deliver consistent improvements in detecting small, occluded, or distorted objects, advancing underwater computer vision and supporting practical applications in marine conservation and environmental monitoring.*

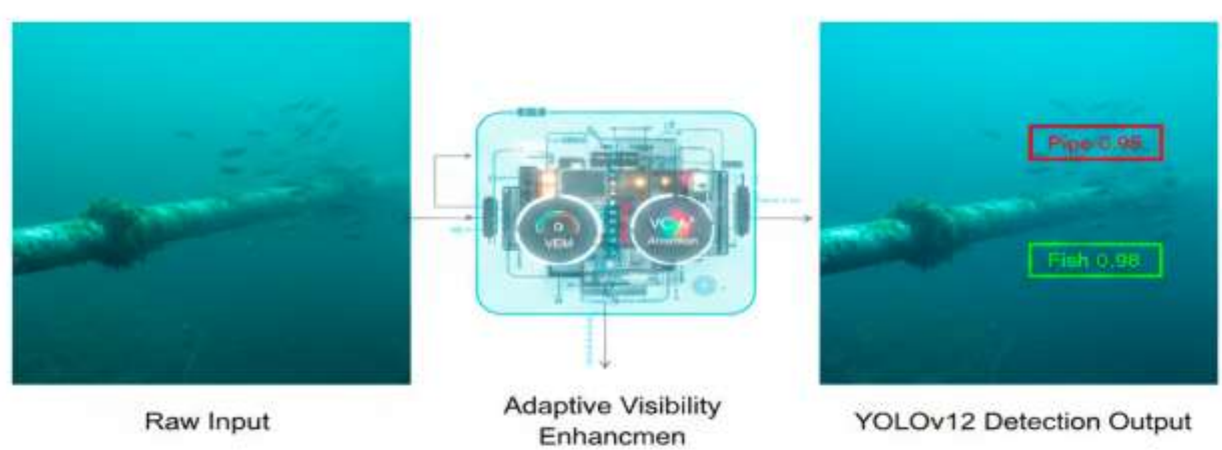

Fig: image showing enhanced adaptive visibility model in yolov12

Keyword: Underwater Object Detection; Yolov12; Adaptive Visibility Enhancement; Underwater Image Degradation; Real Time Object Detection;Deep Learning Computer Vision; Feature Extraction; Attention Mechanism.

1.0 INTRODUCTION

Underwater object detection has become an essential research area within computer vision and marine technology due to its wide application in environmental monitoring, infrastructure inspection, underwater robotics, and search-and-rescue operations. Modern deep learning approaches, particularly single-stage detectors such as the YOLO family, have demonstrated strong real-time performance in terrestrial environments. However, underwater scenes present unique challenges caused by optical distortions, light absorption, scattering effects, turbidity, and color attenuation. These factors degrade visual information and significantly reduce detection accuracy. As a result, many recent studies focus on combining image enhancement techniques with deep learning detection models to improve robustness under degraded underwater conditions. The emergence of advanced architectures such as YOLOv12 provides an opportunity to develop improved frameworks that integrate adaptive preprocessing mechanisms directly within the detection pipeline. This review paper examines existing research on underwater image enhancement, object detection models, and integrated enhancement-detection systems in order to identify limitations and guide the development of an adaptive visibility-aware YOLOv12 detection framework.

1.1 BACKGROUND OF THE STUDY

Underwater environments constitute one of the most complex and strategically important domains on Earth, contributing significantly to ecological balance, economic sustainability and technological advancement. Marine and freshwater ecosystems such as oceans, seas, rivers, and lakes support a vast range of biodiversity, including fish populations, coral reefs, aquatic plants, and microorganisms that are essential to global food chains and climate regulation. Beyond ecological importance, underwater regions serve as major sources of economic activity through fisheries, aquaculture, shipping routes, tourism, and offshore resource extraction. Modern society also relies heavily on submerged infrastructure, including underwater fiber-optic communication cables responsible for global internet connectivity, offshore oil and gas drilling platforms, underwater pipelines and emerging renewable energy systems such as tidal and offshore wind installations[1]. The increasing dependence on these underwater assets has intensified the need for advanced monitoring and inspection technologies capable of operating reliably in harsh aquatic conditions.

As human activities continue to expand into underwater environments, effective monitoring and surveillance have become essential to ensure environmental protection, operational safety and infrastructure integrity. Applications such as marine biodiversity assessment require continuous observation of aquatic species to understand population dynamics and ecosystem health. Offshore oil and gas industries depend on regular underwater inspections to detect structural faults, corrosion, or leaks that could lead to environmental disasters. Similarly, submarine cable operators must monitor underwater communication lines to prevent service disruptions caused by physical damage or environmental hazards. Autonomous Underwater Vehicles (AUVs) and Remotely Operated Vehicles (ROVs) are increasingly deployed for deep-sea exploration, environmental monitoring and search-and-rescue missions in challenging underwater terrains[2][3]. At the core of these applications lies visual perception technology, which allows machines to interpret underwater scenes through image and video data? A fundamental task within these systems is underwater object detection, which involves recognizing and localizing specific targets such as marine organisms, submerged debris, pipelines, underwater vehicles or geological structures within captured visual data.

Despite rapid progress in computer vision and deep learning technologies, underwater object detection remains significantly more challenging than detection tasks conducted in terrestrial or atmospheric environments[4]. The underwater medium introduces complex optical phenomena that degrade image quality and reduce the reliability of visual information. Light propagation in water differs substantially from propagation in air, resulting in significant loss of visual clarity[5]. Water absorbs and scatters light in ways that distort both color and structural details. Suspended particles such as plankton, sediment and micro-organisms create scattering effects that blur object edges and reduce visibility. Water turbidity further intensifies this degradation by obstructing light transmission. Non-uniform illumination occurs due to uneven sunlight penetration, artificial lighting limitations, and dynamic water movement. Motion blur caused by currents or moving cameras introduces additional distortion that affects object boundary definition[6]. Besides, wavelength-dependent color attenuation causes rapid loss of red and orange tones as depth increases, followed by progressive weakening of green wavelengths, leaving underwater images dominated by blue or green types[7]. These combined factors reduce contrast, obscure fine textures, and make objects visually ambiguous, thereby complicating feature extraction and classification processes in computer vision systems.

In recent years, deep learning-based object detection frameworks have achieved exceptional performance across many real-world applications, ranging from autonomous driving to medical imaging and surveillance systems[8]. Convolutional neural networks and transformer-based models have enabled machines to learn complex visual patterns from large datasets, leading to significant improvements in detection accuracy and speed. Among these frameworks, the You Only Look Once (YOLO) family has emerged as a widely adopted solution due to its ability to perform real-time object detection efficiently[9][10]. Unlike two-stage detectors that first generate candidate regions and then classify them, YOLO models perform detection in a single forward pass through the network, enabling faster processing speeds with competitive accuracy levels. YOLOv12, as an advanced evolution of the YOLO architecture, introduces improved backbone structures for feature extraction, enhanced attention mechanisms that focus on relevant spatial regions, better multi-scale detection capabilities for identifying objects of varying sizes and optimized computational efficiency suitable for deployment on resource-constrained systems[11]. These enhancements make YOLOv12 particularly good looking for time-sensitive underwater applications where rapid decision-making is required.

However, despite its strong performance on conventional datasets composed of clear terrestrial images, YOLOv12 faces considerable challenges when applied directly to underwater imagery[12]. Standard training datasets typically contain well-lit scenes with balanced color distributions and minimal visual distortions, conditions that are rarely present underwater. Consequently, the learned feature representations may not generalize effectively to underwater conditions characterized by poor visibility and significant color imbalance[13]. Underwater scenes often lack sharp edges and distinct textures, which are critical signals for deep learning models to recognize objects. This divergence between training data characteristics and real underwater conditions leads to decreased detection accuracy, increased false positives, missed detections and unstable performance across different underwater environments. These limitations reveal a critical gap between state-of-the-art detection models and the specialized requirements of underwater visual analysis[14].

To mitigate underwater visibility challenges, many existing detection pipelines incorporate image enhancement techniques as a preprocessing stage before performing object detection. Traditional enhancement methods such as histogram equalization aim to improve contrast, while contrast stretching expands intensity ranges to make features more distinguishable. Color correction and white balancing attempt to compensate for wavelength attenuation and restore natural color tones, while dehazing techniques reduce the visual effects of scattering particles[15]. Although these approaches can improve visual appearance, they are generally static in nature, relying on fixed parameters or predetermined transformation rules. Because underwater environments are inherently dynamic with changes in lighting conditions, water depth, turbidity levels, and camera motion static enhancement techniques often fail to adapt appropriately[16]. Over-enhancement can introduce artificial artifacts and noise, while insufficient enhancement may leave images too degraded for reliable detection[17]. Consequently, detection performance becomes inconsistent and highly dependent on specific environmental conditions.

To address these limitations, this project proposes the integration of an adaptive visibility enhancement mechanism within the YOLOv12 detection pipeline. Instead of applying uniform preprocessing, the adaptive system dynamically analyzes each underwater image to assess its visibility characteristics, including color distribution, contrast level, brightness and noise patterns[18]. Based on this analysis, the system automatically adjusts enhancement parameters in a context-aware manner to optimize image quality for detection tasks. This adaptive approach allows the preprocessing stage to respond to variations in environmental conditions in real time, ensuring consistent feature clarity across diverse underwater scenarios. By integrating adaptive enhancement directly with the detection framework, the system aims to improve robustness against visibility degradation while preserving computational efficiency required for real-time operation[19]. Ultimately, the proposed solution seeks to enhance detection accuracy, reduce false positives and enable reliable performance in practical applications such as marine ecosystem monitoring, autonomous underwater navigation, underwater infrastructure inspection and disaster response operations.

1.2 PROBLEM STATEMENT.

Underwater object detection systems continue to face significant performance limitations due to the complex and highly variable nature of underwater environments. Unlike terrestrial settings, underwater scenes are affected by wavelength-dependent light absorption that causes rapid color loss, particularly in red and orange spectra, as well as backscatter from suspended particles that introduces haze and visual noise[20]. These factors reduce contrast, blur object boundaries, and obscure fine-grained features that deep learning models rely on for accurate recognition. In addition, variations in depth, water turbidity, and lighting conditions create inconsistent image characteristics across datasets, making it difficult for models trained on standard terrestrial images to generalize effectively[21]. Although modern detection architectures such as YOLOv12 offer strong real-time capabilities, their performance deteriorates when the input data quality is severely degraded. Many current approaches attempt to address this challenge through preprocessing techniques such as contrast enhancement or color correction; however, these methods are typically static and fail to adjust dynamically to changing underwater conditions. Furthermore, the separation between enhancement and detection stages often leads to information loss and suboptimal feature learning[22]. As a result, detection accuracy becomes inconsistent across different underwater scenarios. These limitations highlight the need for an integrated, adaptive detection framework capable of jointly optimizing visibility enhancement and object detection while maintaining computational efficiency suitable for real-time underwater applications.

1.3 OBJECTIVES OF THE STUDY

1.3.1 Main Objective

The main objective of this study is to design, implement, and evaluate an improved underwater object detection system using the YOLOv12 deep learning model by integrating an adaptive visibility enhancement mechanism that addresses underwater image degradation and enhances detection accuracy, robustness, and real-time performance under varying underwater visibility conditions.

1.3.2 Specific Objectives

1. To investigate the impact of underwater visibility degradation (e.g., turbidity, color distortion, and low contrast) on YOLOv12's feature extraction quality and overall object detection accuracy.
2. To develop an adaptive visibility enhancement model that dynamically adjusts enhancement parameters according to the specific characteristics of input underwater images (such as degradation level, lighting, and scattering).
3. To integrate the adaptive visibility enhancement model into the YOLOv12 detection pipeline in an efficient manner, ensuring minimal additional computational overhead and real-time compatibility.
4. To train, evaluate, and compare the performance of the proposed enhanced YOLOv12 system against the standard YOLOv12 model across various underwater visibility conditions, using relevant underwater image datasets and key metrics.

2.0 RELATED WORKS

Related research in underwater object detection has evolved through several major directions, each contributing valuable insights into improving detection performance under challenging environmental conditions.

The first category focuses on applying traditional image enhancement techniques prior to object detection. Researchers implemented methods such as histogram equalization, white balance correction, gamma transformation, contrast enhancement, and underwater dehazing to improve visual clarity before feeding images into detection models[23]. These techniques were attractive because they were computationally simple and easy to integrate into existing pipelines. Experimental evaluations indicated that basic enhancement could improve contrast and highlight certain features, leading to slight improvements in detection accuracy. However, most studies concluded that the effectiveness of traditional enhancement methods was inconsistent because they relied on manually defined parameters that could not adapt to rapidly changing underwater conditions[19]. Variations in water depth, lighting direction, and turbidity frequently reduced the reliability of these techniques in real-world applications.

The second category of related works explored deep learning–based enhancement models that automatically learn restoration functions from large underwater datasets. These models utilized convolutional neural networks and generative architectures to correct color distortions, remove haze-like effects, and enhance texture information. Compared to traditional approaches, learning-based methods produced more natural-looking images and demonstrated greater robustness across different datasets. Several studies reported significant improvements in object detection accuracy when enhanced images were used as model inputs[24]. Detection networks benefited from clearer object boundaries and stronger feature representations, resulting in improved classification confidence and localization precision. Despite these successes, related works identified several challenges, including increased computational complexity, high memory usage, and dependence on large annotated datasets. In addition, many enhancement models prioritized visual realism rather than detection-oriented feature optimization, which sometimes limited their effectiveness in improving detection outcomes[25].

Another stream of related research concentrated on modifying object detection architectures to better accommodate underwater conditions. Researchers enhanced YOLO-based models by integrating spatial and channel attention mechanisms, refining feature pyramid networks, and introducing multi-scale detection layers capable of capturing objects of varying sizes and distances. These improvements allowed detection models to focus more effectively on informative image regions and improved performance in cluttered underwater scenes. Experimental comparisons demonstrated moderate accuracy gains compared to baseline detectors. However, most studies acknowledged that architectural improvements alone could not fully overcome the impact of severely degraded input images. Without sufficient visual detail, even advanced detection models struggled to maintain stable performance in environments with extreme turbidity or low illumination[26].

More recent related works attempted to combine enhancement and detection into unified end-to-end systems. These integrated frameworks connected enhancement modules directly with detection networks and optimized both components jointly to improve task-specific performance. Studies reported that such systems achieved better detection results across a wider range of underwater conditions because enhancement processes were designed to generate features specifically useful for detection rather than general visual restoration. Nevertheless, these approaches introduced increased architectural complexity and computational demands, which limited their scalability and real-time applicability[27]. Heavy network structures required longer training times and more powerful hardware, making them difficult to deploy on underwater robotic platforms with constrained processing capabilities.

Collectively, related works demonstrate steady progress in addressing underwater object detection challenges, yet each category presents inherent limitations. Traditional enhancement techniques offer simplicity but lack adaptability to dynamic environments. Deep learning–based enhancement methods improve visual quality but increase computational overhead and may not always align with detection objectives. Detection model modifications enhance feature extraction but cannot fully compensate for poor image quality. Integrated systems provide improved performance but often sacrifice efficiency and real-time operation. These persistent limitations highlight the need for a balanced solution that combines adaptability, computational efficiency, and task-specific optimization. Consequently, there remains a strong research opportunity to develop an adaptive and lightweight visibility enhancement mechanism that can be seamlessly integrated into modern detection architectures such as YOLOv12 to achieve robust and efficient underwater object detection performance across diverse environmental conditions.

3.0 OBSERVATIONS FROM RELATED WORKS

Analysis of existing research on underwater object detection reveals several recurring patterns and limitations that continue to influence the direction of current studies. One of the most widely reported observations is that underwater image degradation remains the dominant factor affecting detection performance. Environmental conditions such as scattering, light absorption, floating particles, and inconsistent illumination lead to low contrast, color distortion, and blurred object boundaries. These visual distortions weaken feature representation within deep neural networks, causing a significant drop in detection accuracy even when advanced models are used. Many studies demonstrate that detection performance is directly linked to the quality of input data, emphasizing that improvements in model architecture alone are insufficient when the visual signal is severely degraded[28].

Another common finding is that traditional image enhancement techniques provide only limited improvements. Methods such as histogram equalization, white balancing, and contrast stretching are frequently used as preprocessing steps; however, they rely on fixed parameter settings that do not adapt to the continuously changing nature of underwater environments. Because water conditions vary depending on depth, location, and turbidity, static enhancement often produces inconsistent results. In some cases, over-enhancement introduces artifacts that further degrade the usefulness of visual features for detection models. As a result, several researchers argue that enhancement techniques must be adaptive and context-aware rather than static[29].

Deep learning-based restoration approaches represent a significant advancement compared to traditional methods. These approaches use neural networks trained on underwater datasets to learn complex distortion patterns and generate visually clearer images. Studies show that such models improve color restoration, contrast enhancement, and object visibility, which can positively influence detection outcomes. However, a major limitation consistently reported in the literature is increased computational complexity. Many restoration models require additional processing stages that increase inference time and hardware requirements, making them less suitable for real-time applications such as autonomous underwater vehicles and robotic inspection systems. The trade-off between visual improvement and computational efficiency remains a critical challenge[30].

Another observation is that improvements made directly to detection architectures, including the use of attention mechanisms, multi-scale feature extraction, and advanced backbone networks, provide performance gains but cannot fully compensate for severely degraded inputs. Even highly optimized detection models struggle when trained or tested on images with extreme visibility loss. This suggests that improving detection performance requires a combined strategy that addresses both input quality and feature extraction simultaneously. Researchers increasingly recognize that focusing solely on detection algorithms without addressing environmental distortions produces limited long-term progress[31].

Integrated enhancement-detection frameworks have emerged as a promising direction in recent studies. These systems attempt to jointly optimize image restoration and object detection within a unified architecture. Results from several experiments indicate that integrated models can outperform separate pipelines by preserving feature consistency between enhancement and detection stages. Nevertheless, many of these frameworks introduce significant computational overhead and increased model complexity, which restrict their practical deployment in real-time underwater operations. Additionally, some integrated models lack adaptability to different underwater conditions, reducing their effectiveness when applied outside controlled experimental datasets.

Further observations indicate that dataset limitations continue to affect model performance and generalization. Many underwater datasets are relatively small or focus on specific environmental conditions, leading to models that perform well in certain scenarios but poorly in others. Variations in camera quality, lighting conditions, and object types also create challenges for consistent evaluation across studies. Researchers emphasize the importance of developing more diverse and representative datasets that capture real-world variability in underwater environments.

Overall, the literature highlights a clear gap between theoretical model improvements and practical deployment requirements. While advances in deep learning architectures and enhancement techniques have improved detection accuracy under certain conditions, many existing solutions remain computationally expensive or lack adaptability. These findings collectively emphasize the importance of developing lightweight, adaptive enhancement mechanisms that can be seamlessly integrated into real-time detection pipelines. Such approaches have the potential to address the core challenges identified across related works by balancing visual enhancement, detection accuracy, and computational efficiency within a single unified framework.\

4.0 CONCLUSION.

Underwater object detection remains a challenging research problem primarily due to the complex optical characteristics of underwater environments and the limitations of existing computer vision techniques when applied to degraded visual data. Environmental factors such as light absorption, scattering, turbidity, and uneven illumination significantly reduce image clarity, distort colors, and obscure important visual features required for accurate object recognition. Although deep learning-based detection models have demonstrated high performance in terrestrial environments, their accuracy declines considerably when used on underwater imagery because they are typically trained on clear datasets that do not reflect real underwater conditions. Traditional image enhancement techniques provide only partial improvements since they rely on fixed parameter settings that cannot adapt to changing environmental conditions. Consequently, their effectiveness varies widely across different underwater scenarios. More advanced deep learning-based enhancement approaches have been introduced to address complex distortions and improve visual quality; however, these models often increase computational complexity and processing time, which limits their practical use in real-time underwater applications such as robotic exploration and surveillance. Integrated enhancement and detection frameworks show promising results by combining image restoration and detection processes within a unified system, improving feature consistency and detection performance. Despite these advancements, many existing solutions lack adaptability and computational efficiency when deployed in dynamic underwater environments. Therefore, there is a clear need for adaptive and lightweight detection frameworks capable of dynamically adjusting preprocessing strategies while maintaining real-time performance. Such approaches can improve detection accuracy, enhance robustness against varying visibility conditions, and support the practical deployment of underwater object detection systems in real-world applications.

5.0 RECOMMENDATIONS AND FUTURE WORK

Future research should emphasize the development of lightweight and adaptive enhancement modules that can dynamically respond to varying underwater visibility conditions while preserving real-time processing capability and computational efficiency. Efforts should also focus on constructing larger and more diverse underwater datasets that capture a wide range of environmental variations, including differences in turbidity, lighting, depth, and object types, to improve model robustness and generalization. The incorporation of attention mechanisms and multi-scale feature extraction techniques may further strengthen detection performance by enabling models to concentrate on relevant object regions even under severe visual degradation. In addition, exploring domain adaptation, transfer learning, and semi-supervised learning strategies can help overcome the scarcity of labeled underwater data and enhance performance across unfamiliar environments. Future work should also prioritize the optimization of detection systems for deployment on resource-constrained platforms such as autonomous underwater vehicles and embedded robotic systems, ensuring efficient energy usage and low latency. Finally, extensive real-world testing under diverse operational conditions is essential to validate the practicality, reliability, and scalability of proposed underwater detection frameworks.

6.0 Acknowledgement

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