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Smart Underwater Monitoring Through Image Enhancement and Object Detection using AI

Prof. Archana Kotakar
Department of Computer Engineering
JSPM's Jayawantrao Sawant College of Engineering Pune, Pune

Pallavi Gawai
Department of Computer Engineering
JSPM's Jayawantrao Sawant College of Engineering Pune, Pune

Kajal Shelke
Department of Computer Engineering
JSPM's Jayawantrao Sawant College of Engineering Pune, Pune

Priyanka Gujale
Department of Computer Engineering
JSPM's Jayawantrao Sawant College of Engineering Pune, Pune

Dnyaneshwari Suke
Department of Computer Engineering
JSPM's Jayawantrao Sawant College of Engineering Pune, Pune

Abstract - This literature survey examines the rapid advancement of Artificial Intelligence (AI) techniques for underwater image enhancement and object detection. It covers a wide range of approaches, starting from traditional methods such as manual feature extraction and histogram equalization to advanced deep learning models, including Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Transformer-based architectures. Recent studies indicate that one-stage detectors, particularly the You Only Look Once (YOLO) family, offer an effective balance between detection speed and accuracy, achieving up to 96–99% mean Average Precision (mAP) in several applications. In addition, GAN-based enhancement techniques combined with attention mechanisms have significantly improved image quality by restoring color and contrast in challenging underwater conditions. Despite these advancements, several challenges remain, including high computational complexity, which limits real-time deployment on resource-constrained Autonomous Underwater Vehicles (AUVs). Moreover, issues such as limited dataset availability, lack of standard evaluation benchmarks, and poor generalization across different underwater environments continue to affect performance. Future research should focus on developing lightweight and explainable AI models to improve efficiency, reliability, and adaptability in real-world underwater applications.

Keywords - Underwater Computer Vision, Deep Learning, Image Enhancement, Object Detection, YOLO, Generative Adversarial Networks (GANs).

I. INTRODUCTION

The underwater environment plays a significant role in supporting marine life, natural resources, and scientific exploration. However, capturing clear and informative images underwater is a challenging task due to factors such as light absorption, scattering, low contrast, and color distortion. Traditional image processing techniques, including histogram equalization and manual feature extraction, have been used in the past, but they often fail to provide accurate results in complex underwater conditions [1].

With the advancement of Artificial Intelligence (AI) and Deep Learning (DL), underwater image processing has improved significantly. Modern approaches based on Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Transformer-based models are capable of automatically learning complex features from raw data. These models have shown better performance in enhancing image quality and detecting underwater objects compared to traditional methods [2], [6]. In particular, object detection algorithms such as the You Only Look Once (YOLO) series have gained popularity due to their ability to provide real-time detection with high accuracy [3].

AI-based underwater vision systems have a wide range of applications, including marine life monitoring, underwater waste detection, aquaculture management, and inspection of underwater infrastructure such as pipelines and cables. These systems are also used in Autonomous Underwater Vehicles (AUVs) to improve navigation and decision-making in deepsea environments [4], [8]. The ability to automatically detect and classify underwater objects plays a crucial role in improving efficiency and reducing human effort in such applications.

Despite these advancements, several challenges still exist in underwater image enhancement and object detection. The availability of high-quality datasets is limited, and models often struggle to generalize across different underwater environments due to variations in lighting, water depth, and turbidity. Additionally, many deep learning models require

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high computational resources, making real-time implementation difficult on resource-constrained devices [2], [7]. Therefore, there is a need for efficient, lightweight, and robust AI models that can perform accurately under diverse underwater conditions.

II. LITERATURE REVIEW

Wang et al. [1] analyzed traditional feature-based methods and deep learning models such as Mask R-CNN and YOLOv3, showing improved recognition accuracy but limitations due to poor image quality. Elmezain et al. [2] reviewed CNN, GAN, and Transformer models, highlighting their improved performance but high computational cost.

Walia et al. [3] evaluated YOLO models and reported accuracy up to 96%, making them suitable for real-time applications. Tarekegn et al. [4] combined image enhancement with YOLO models and achieved 99% mAP, showing the importance of preprocessing. Rao [5] used machine learning and deep learning models for underwater analysis and emphasized the need for Explainable AI.

Sugunapriya and Markkandan [6] compared traditional and AI-based methods, concluding that deep learning models perform better but still face challenges such as motion blur. Khan et al. [7] classified detection methods and highlighted the trade-off between accuracy and computational cost. Reddy et al. [8] demonstrated real-time garbage detection using YOLOv8 with high speed but limited by hardware constraints. Walia and Pavithra [9] emphasized lightweight YOLO models for real-time performance.

Recent studies focus on improving detection under challenging conditions. Sarkar et al. [10] proposed enhancement-based detection methods, while Cao et al. [11] introduced a bidirectional YOLO model for improved performance. Chen and Er [12] focused on small object detection, and Ding et al. [13] developed lightweight models for low-light conditions. Liu et al. [14] proposed unsupervised enhancement techniques to improve image quality.

III. METHODOLOGY

The proposed system uses AI and deep learning techniques for underwater image enhancement and object detection. First, underwater images are collected and preprocessed using noise removal, resizing, and color correction techniques. Then, enhancement models such as CNN and GAN improve image quality. After enhancement, YOLO-based object detection models are used to identify underwater objects .

The proposed AI-Based Underwater Monitoring System begins with collecting underwater images and videos from different datasets and sources. The collected data is preprocessed using techniques such as noise removal, resizing, and color correction to improve image quality and reduce underwater distortions caused by low light and turbidity.

After preprocessing, deep learning models such as CNN, GAN, and YOLO are applied for underwater image enhancement and object detection. CNN and GAN models help improve image clarity and restore colors, while YOLO-based models detect and classify underwater objects like marine species, waste materials, and obstacles in real time with high accuracy.

Finally, the system performs depth mapping and stores the processed information in a database or repository. The enhanced images, detected objects, and depth analysis results are displayed to the user for effective underwater monitoring, navigation, and environmental analysis.

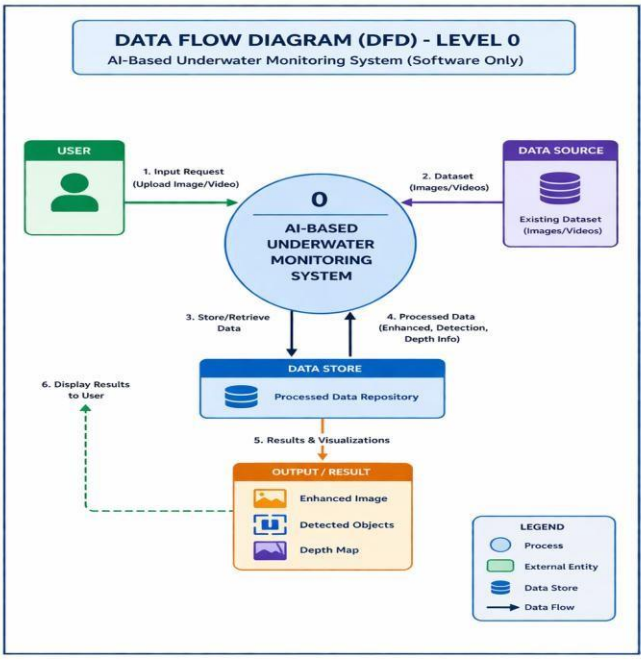

Fig 3.1 Data flow for AI based underwater monitoring system

The Data Flow Diagram (DFD) represents the overall working of the AI-Based Underwater Monitoring System. The user uploads underwater images or videos, and the system processes the data using AI techniques for image enhancement, object detection, and depth mapping. The processed data is stored in the data repository, and the final results such as enhanced images, detected objects, and depth maps are displayed to the user.

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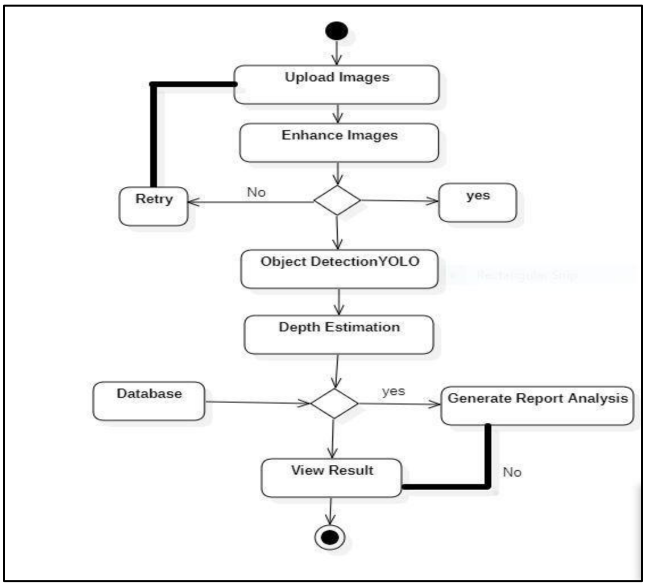

Fig 3.2 workflow

IV. COMPARATIVE ANALYSIS

COMPARISON OF UNDERWATER IMAGE ENHANCEMENT AND OBJECT DETECTION

Different approaches for underwater image enhancement and object detection can be compared based on performance, accuracy, computational cost, and limitations. One-stage detectors, particularly the YOLO family, are widely used for real-time applications due to their high processing speed and balanced accuracy. Studies report that YOLO-based models achieve detection accuracy between 96% and 99% while maintaining real-time inference, making them suitable for Autonomous Underwater Vehicles (AUVs) [3], [4], [8]. However, these models often struggle with detecting small, overlapping, or camouflaged objects in complex underwater environments [7].

Two-stage detectors such as Faster R-CNN and Mask R-CNN provide higher localization accuracy compared to one-stage detectors. Wang et al. [1] demonstrated that Mask R-CNN improves recognition performance when combined with transfer learning. However, these models are computationally expensive and introduce higher latency, which limits their real-time applicability [3].

Generative Adversarial Networks (GANs) are mainly used for image enhancement tasks. These models improve image clarity by correcting color distortion and reducing haze, thereby indirectly improving object detection performance [2], [10]. Despite their effectiveness, GANs require high computational resources and may generate artificial features that do not perfectly match real-world underwater conditions [14].

Transformer-based models have recently shown promising results due to their ability to capture global contextual information. These models perform better in complex scenes and improve detection of small objects [2], [12]. However, they require high memory and computational power, making them less suitable for real-time underwater deployment.

Recent research focuses on lightweight and optimized models. Ding et al. [13] proposed a lightweight YOLO-based model for low-light environments, while Cao et al. [11] introduced a hybrid approach combining enhancement and detection. These models aim to balance accuracy and computational efficiency, but challenges such as dataset limitations and environmental variability still remain.

V. RESEARCH GAP

Despite significant advancements in Artificial Intelligence (AI) for underwater image enhancement and object detection, several critical research gaps remain unresolved. One of the major challenges is the lack of large-scale, standardized datasets, which limits fair comparison and benchmarking of different models. Most existing studies rely on small or custom datasets, leading to biased evaluation and reduced generalization across different underwater environments [1], [6].

Another important issue is **domain shift**, where models trained in one underwater condition fail to perform effectively in different environments due to variations in water depth, salinity, lighting, and turbidity. Current approaches lack adaptive mechanisms to handle such variations dynamically, which affects real-world deployment [2], [7].

The **high computational complexity** of modern deep learning models such as CNNs, GANs, and Transformers is another major limitation. While these models achieve high accuracy, they require significant memory and processing power, making them unsuitable for real-time applications on

Additionally, existing detection models struggle with **small, overlapping, and camouflaged objects**, which are common in underwater environments. One-stage detectors like YOLO offer high speed but often compromise accuracy in such complex scenarios, while two-stage detectors provide better precision at the cost of slower performance [7], [8].

There is also a growing concern regarding the **lack of interpretability in AI models**. Most deep learning systems operate as “black boxes,” making it difficult to understand their decision-making process. This lack of transparency reduces trust and reliability, especially in critical applications such as marine exploration and defense [5].

Furthermore, many approaches are heavily dependent on **image enhancement techniques**, which may not perform well under extreme conditions such as low light, high turbidity, or motion blur. This dependency limits the robustness of the overall system [4], [6].

Finally, a persistent challenge is the **trade-off between accuracy and real-time performance**. Models that achieve high detection accuracy are often computationally expensive, while lightweight models suitable for real-time processing tend to

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compromise precision. Addressing this balance remains an open research problem in underwater vision systems [3], [8].

VI. CONCLUSION

This literature survey highlights the rapid advancement of Artificial Intelligence (AI) techniques in underwater image enhancement and object detection. The transition from traditional image processing methods to deep learning approaches such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Transformerbased models has significantly improved detection accuracy and visual quality in challenging underwater environments. Among these, the YOLO series has demonstrated an effective balance between speed and accuracy, making it suitable for real-time applications, while GAN-based models have enhanced image clarity by addressing issues such as color distortion and low contrast [3], [4].

Despite these advancements, several challenges persist. The high computational requirements of advanced models, lack of standardized datasets, and poor generalization across diverse underwater conditions continue to limit practical deployment. Additionally, issues such as detection of small or camouflaged objects and the lack of explainability in AI systems remain open problems [2], [7].

Overall, it can be concluded that while AI has significantly improved underwater vision systems, further research is required to develop lightweight, efficient, and explainable models. Future work should focus on improving real-time performance, enhancing robustness under extreme conditions, and creating standardized datasets to enable fair comparison and reliable deployment in real-world underwater applications [1], [6].

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