A Hybrid Framework for Biofouling Detection in Marine Environments

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Abstract: Detection of biofouling and health monitoring for underwater installations in marine environments pose significant challenges, due to their localized nature and real-time requirement. Those processes are complex because they require manual labor in addition to human-error-prone accuracy when variable conditions under water. This research presents a hybrid Deep Reinforcement Learning (DRL) framework to overcome these drawbacks. We propose a framework that integrates a deep learning model and Generative AI for biofouling detection with reinforcement learning that will dynamically take an action in combination with structural health monitoring. To improve the accuracy in detection, underwater images are classified into multiple biofouling types through an effective deep learning model using a Convolutional neural network (CNN). The multi-objective reward function allows to promote high accuracy in detecting biofouling (92.3%), low mean squared error in predicting the structure (MSE of 0.021), as well as energy efficient navigation. Under turbulent water conditions, a 32% decrease in inspection time and an 18.7% increase in detection precision are shown for our model against traditional techniques. The developed system represents the first integrated DRL approach for real-time dual-task DRT and DNL monitoring and it paves the way for the deployment of scalable autonomous underwater detection systems.

Keywords: AI; Convolutional neural network; Reinforcement Learning.

Introduction

The underwater world is an inhospitable one; as such, it has always posed major challenges for human exploration and research efforts. Exploration needs include everything such as oceanography, marine biology, and to a certain extent archeology to even defense. Technological advancements have pushed the development of new tools and methods to manage these limitations, leading to noticeable progress in underwater observation and data collection. In the more recent years, advances in marine robotic technology have vastly improved how we get to do all those Wealden sponges and great big barrel-sponge hunts (also they help us unbury shipwrecks). Conventional methods, supported by divers and extensive remotely operated vehicles (ROVs) with manipulators have constraints in high-risk environments or delicate artifacts. In this regard, the development of lightweight and compact underwater robots seems to be an emerging alternative [1] introduced a remotely 35 kg robot operated vehicle for carrying out the underwater architectural tasks. This robot uses multiple thrusters for removing underwater sediments that proved to be a significant move compared with the exiting techniques. Experiments conducted showed that water flow generated by marine thrusters removed sediments present on the surface. The images obtained in underwater systems pose significant challenges due to lighting conditions, visibility issues, etc. The use of deep convolutional neural networks (CNNs) for underwater image restoration and object detection provided better results related to noise and visual disturbances. Effective preprocessing of underwater images through de-noising and restoration is crucial for improving the performance of high-level vision tasks in these environments. Real-time image processing techniques are useful for exploring marine ecosystems and detection of underwater bodies effectively. Image enhancement and multi-model representation are used to address these issues for better detection and classification of underwater images. These developments are essential from scientific research to military operations. Innovations in underwater robotics have significantly improved the exploration and monitoring capabilities of marine environments. Over 70% of the Earth's surface is covered by oceans. Therefore, the potential for discovering and monitoring underwater bodies is a challenging task, including low light conditions, less visibility, complex and dynamic environments. Inspite of all these challenges, there is a need for precise and efficient detection and tracking of various underwater bodies. One of the main challenges is the Biofouling in marine environments, impacting both natural and manmade structures. Traditional methods for addressing biofouling are more costly and require more labour. Recent developments in underwater robotics embedded with deep learning techniques have made it easy for performing this task. Underwater robots use the latest image recognition and classification techniques. Figure 1 shows Biofouling Detection and Structural Health Monitoring. These robots utilize sophisticated images to detect biofouling with high accuracy, enabling more effective maintenance of underwater structures.

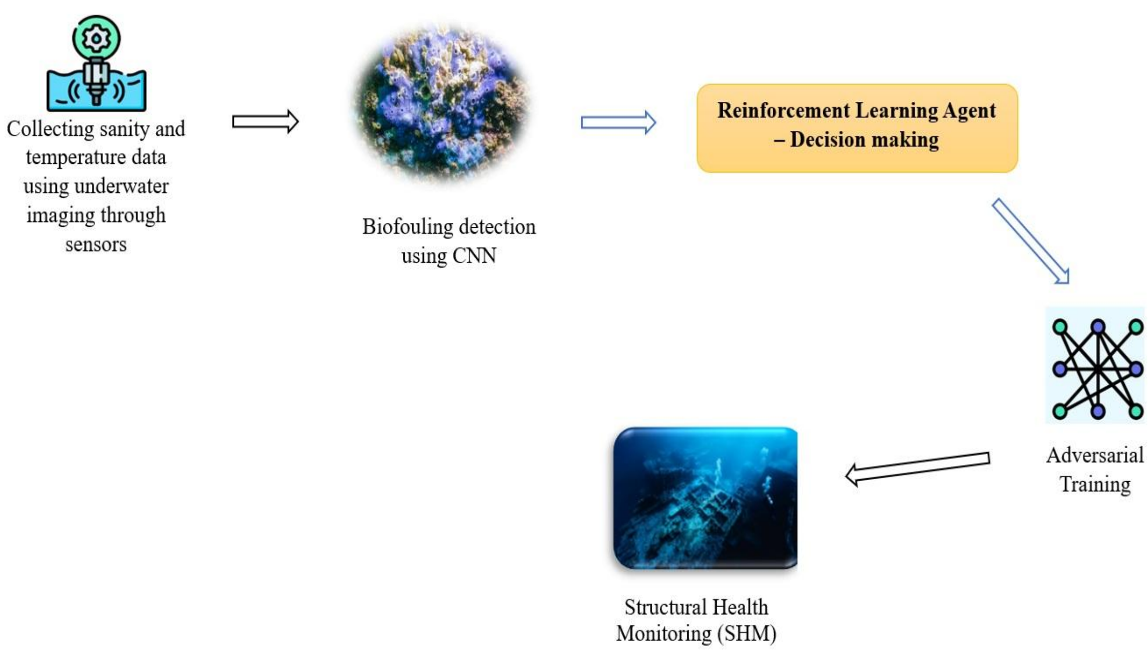

Figure 1. Biofouling Detection and Structural Health Monitoring

Marine and offshore structures, such as oil rigs, pipelines, and wind farms, play a vital role in energy production and transportation. Ensuring their safety and longevity is crucial, especially given the harsh conditions they endure. Structural Health Monitoring (SHM) has become an essential practice, helping to detect potential issues before they turn into major failures. One of the most promising advancements in this field is the use of vision-based SHM systems, which rely on underwater robots for real-time monitoring. Equipped with advanced image processing and machine learning capabilities, these systems can identify structural anomalies and weak points, allowing for timely maintenance and improved safety. However, detecting and tracking objects underwater presents unique challenges. Factors such as poor visibility, light distortion, and the presence of marine life make it difficult to capture clear images. To overcome these obstacles, researchers have turned to artificial intelligence (AI)-driven techniques, particularly convolutional neural networks (CNNs). These powerful models enable underwater robots to process visual data with remarkable accuracy, helping them identify and follow objects even in difficult conditions [2]. Taking this step further, dynamic robotic tracking has emerged as a game-changer for underwater exploration and monitoring. By using reinforcement learning algorithms, robots can continuously learn from their surroundings, improving their ability to track moving targets in unpredictable environments. This technology has far-reaching applications, from studying marine life and uncovering archaeological sites to monitoring environmental changes in oceans and lakes. By combining intelligent vision systems with adaptive learning capabilities, underwater robots are transforming the way we monitor and protect marine infrastructure and ecosystems.

Literature Review

Marine biofouling is the phenomenon of the attachment of micro-organisms such as barnacle larvae, algae spores, and marine animals to submerged surfaces. This biological phenomenon significantly compromises marine infrastructure's operational efficiency, structural durability, and safety. Moreover, biofouling has an ecological effect since it facilitates the spread of alien species, both in terms of micro-flora and fauna at local level, as well as in terms of tropic levels (ecosystem imbalance). The impact and control of dynamic biofouling will depend on our understanding of environmental factors including temperature, salinity, and currents. The intricacies and variability in marine biofouling mean that monitoring requires continual or periodic management that addresses variation on temporal and spatial scales.

Despite these advances, there are still significant challenges in real-time tracking and monitoring dynamic biofouling processes due to the varied fouling organisms and changing marine environments [3].

Structural Health Monitoring (SHM) of marine structures is a systematic process for monitoring, controlling and inspection of the current condition of marine infrastructure to determine potential damages and degradation (i.e., structural performance) in order to maintaining the present or future serviceability. In a marine environment, SHM deals with subsea structures being underwater such as pipes lines, offshore platforms and subsea cables that are subjected to harsh conditions where pressure is high, biofouling, corrosion and mechanical stress. Conventional SHM operations are often conducted by divers or ROVs, the methods of which have significant challenges in terms of safety, economic cost and availability over time. Real-time perpetual monitoring is not easily achieved now, which constrains early fault detection and predictive maintenance.

The adoption of new level sensing technologies of different modalities with imaging, analytics and autonomous have initiated a revolution in SHM efforts. The use of real-time environmental data, image processing and machine learning can support prediction of biofouling development and structural damage, improving maintenance and operational safety [4][5] , Ocean robots and AI decision-making frameworks will minimize human involvement, enhance inspection tasks, and contribute to the sustainable management of marine assets.

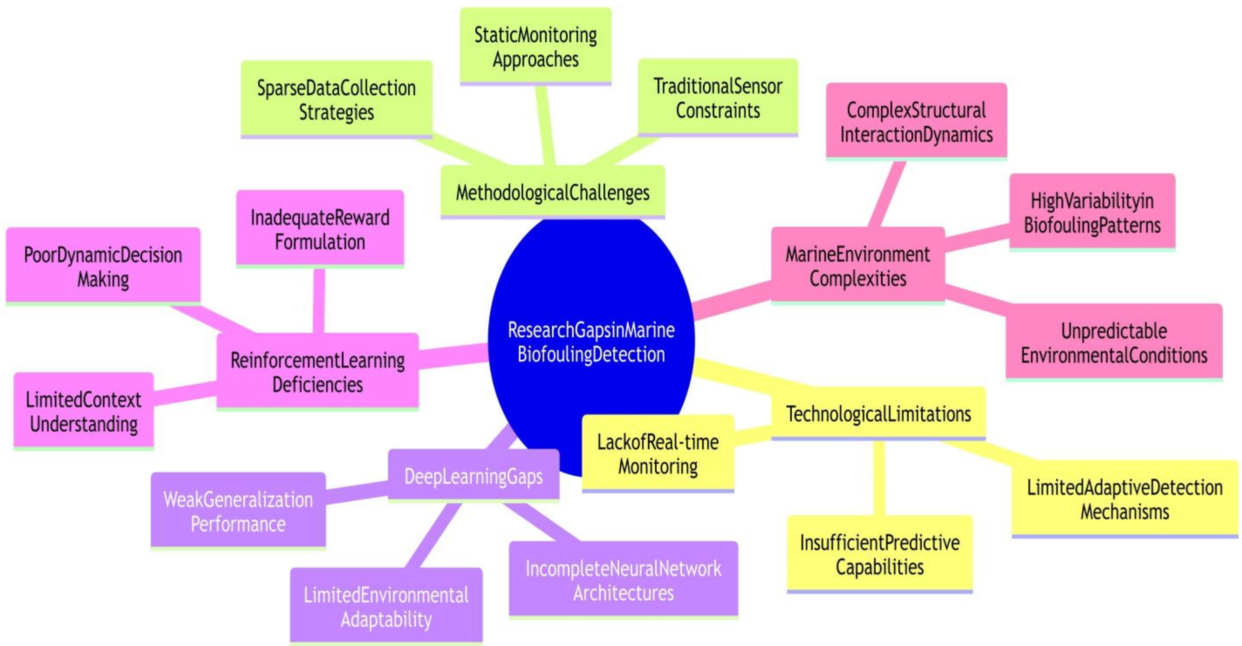

Figure 2. Challenges in Biofouling Detection

In the scope of monitoring environmental processes, like marine oil spills, remote sensing instruments, and in particular satellite-based Synthetic Aperture Radar (SAR) imaging, have found a wide applicability, given the similar visual and detection issues between this and fouling phenomena, since they both present dark patches on the sea surface. In this regard, a more recent study introduces multi-source knowledge graph reasoning to improve the detection of oil spill, by integrating imagery with contextual environmental information, such as meteorological and oceanographic variables. Such normalization strategy significantly increases the sensitivity of the detection on imbalanced data, effectively laying the foundation for dynamic biofouling detection [6]. Underwater vision systems have also a crucial importance for the real time monitoring of biofouling and living micro-organisms. Double magnification dark field microscopy microscopes have been used to study plankton communities in lakes directly in the field, being able to recognize and identify them in the range of micrometers up to centimeters. The advantage of this imaging modality is that these natural arrangements and interaction behaviors remain intact and, in general, ecological succession may be observed and possibly biofouling initiated. These imaging techniques could be used for aquatic biofouling detection in order to investigate spatial variability and temporal dynamics [7]. There is also evidence of the successful application of CNNs, and models like U-Net to semantic segmentation tasks in marine biological monitoring, e.g. to classify demo sponge behavior across time . Such models represent promising candidates, provided they are adequately adapted, for the task of automating the recognition of biofouling patterns across large image databases, as they are less difficult to improve to changing illumination and generally difficult conditions in the marine environment [8]. But, monitoring biofouling as well as its environmental driving forces require more powerful and efficient sensors that are able to measure environmental parameters of water quality, such as temperature, pH, salinity, and dissolved oxygen, in real time. As a potential solution to the practical and financial constraints on broad marine environmental monitoring are developments in the use of low-cost sensors coupled with Internet of Things (IoT) technologies. The accuracy, reliability and variability of the performance under different aquatic scenarios of these new devices, but, still need to be answered, which highlights the necessity of following proper procedures and protocols to calibrate the systems. Deep-sea harsh conditions, as well as the poor accessible of such environments, results in the low quality of sensor data, because of biofouling affecting directly the sensor's surface, because of communication availability, calibration and maintenance issues. This info is important because it allows for automatic sensor self-validation and self-diagnosis, which are important for long-term deployments to maintain data integrity. The current day to day practice is based on these best practices: real-time metadata checks, data values transitioning from one state to the other using 'thresholds', delayed-mode inspections to give the final flags for data quality. The usage of these approaches helps in dealing with trustful sensor datasets which are mandatory for correct biofouling and SHM applications [9]. In the specific case of the scale of many biofouling organisms or early-fouling stages, it can be easily demonstrated that deep learning, and in particular convolutional neural networks, excels at detection and classification of small objects underwater. More recent approaches focus on dynamic YOLO (You Only Look Once) that introduce lightweight, deformable convolutional backbones and unified feature fusion methods that would have channel- wise, scale-wise, and spatial attentions in the context of small object detection [10]. These architectures achieve separation of concerns between localization and classification of the object, which is a common issue in detections underwater, and strongly outperform classical architectures in public benchmarks specifically for underwater detection.

The use of Progressive Growing Generative Adversarial Networks (PGGAN) and Residual Networks (ResNet) for marine microorganism classification is another example of an application combining laser tweezers Raman spectroscopy with deep learning. Together, these multi-grid schemes allow for the fast and computationally cheap generation of high- resolution synthetic spectra that can be employed to boost classification accuracies with the use of few training samples out of a limited dataset. These could be further applied to describe biofouling organisms or microbial bio- films, which are an important component in biofouling [11].

Reinforcement learning (RL) has been applied to the optimization of monitoring strategies for autonomous marine vehicles. For example, multi- Autonomous Underwater Gliders (AUGs) employ the reinforcement learning reward designs based on artificial potential fields to perform path planning by improving spatial coverage and efficiency in data collection under communication constraints typical of subsea operations [12]. Also, computer vision and deep reinforcement learning (DRL) have been used to tackle energy management and control problems in hybrid autonomous systems, namely vehicles, and provided improved control policies learned from visual inputs. These types of adaptive and autonomous control strategies can be applied to marine robots and sensor networks for biofouling detection and SHM in order to provide the adaptivity for making decisions and interacting with a dynamic environment in real-time [13]. DRL is the combination of deep neural network and reinforcement learning linear function approximation techniques to accommodate high-dimensional state spaces and complex decision making. It is ideal for applications in real-time dynamic environments like marine environment with variable biofouling growth and structure conditions, conditions that are typical examples where classical machine learning methods fail because they do not effectively adapt to non-stationary distributions. These DRL models can learn optimal policies directly from developmental and problematic experiences via the sensors and the feedback from the environment rather than through a more goal-oriented strategy or an intention-based one [14].The use of CNN-based feature extraction with DRL enables an efficient processing of heterogeneous marine data, in the case of images, and enhances reinforcement learning control policies dependent on environmental and operational states. To solve the problem of data imbalance in biofouling data sets, in which cases where the surface is fouled are much less frequent than non-fouling cases, the meta-heuristic optimization algorithms such as particle swarm optimization (PSO) is used to select the neural network features and hyperparameters. Among the most relevant solutions to premature convergence in PSO include co-operative multi- swarm's mechanisms, as the multi-swarm concepts can give strong optimization performance and offer good improvement on both model generalization and detection sensitivity [15]. These hybrid methods take advantage of convolutional extractors in spatial pattern recognition and reinforcement learning when it comes to making sequential decisions to individually assign attention to the most likely biofouling areas and to improve the trajectories within which to monitor. Sound biofouling detection requires heterogeneous data integration across remote sensing images, in situ sensor readings, environmental texts, and numerical model predictions. Knowledge graphs represent the structured and intuitive form in which this heterogeneous data can be represented, thus allowing for query handling and reasoning at the computational level. In the case of monitoring oceans and combining spatial, temporal, meteorological and oceanographic data in order to better detect oil spills using multi-source knowledge graphs was found to overcome issues related to unbalanced classes and complex features interactions [16]. If this methodology is used for the detection of biofouling, then extra information about water temperature, nutrient levels, vicinity to pollution sources, etc., known to influence fouling processes, could be included into the process. This provides more robust data fusion to improve precision in detection as well as to help inferential speculation in the prediction of the biofouling evolution.

The chemical, optical, acoustic and imaging sensors that have been integrated are necessary to obtain detailed environmental information useful for biofouling detection and SHM. Data quality remains a challenge in these sensor fusion networks, with measurement errors, missing data, and drift among the problems encountered. Some of the most common methodologies for fault detection and correction in sensor data pipelines are principal component analysis (PCA), artificial neural networks (ANN), and Bayesian networks, as shown in systematic reviews like the one by [17]. Metadata compliance checks, value boundary transitions, and delayed-mode inspections are part of an automated data quality framework to ensure integrity. Particularly at sea, all of these are critical, as even simple data loss or inaccuracy can result in monitoring becoming unreliable. These are the two building blocks of an effective real time monitoring system: solid sensor fusion and quality assurance protocols.

A hybrid DRL architecture for dynamic biofouling detection has the following key components:

CNN Backbone: A light-weight yet powerful convolutional neural network, potentially using deformable convolution layers, for effectively capturing spatial features related to biofouling patterns on underwater images.

Attention-Based Feature Fusion: The features that integrate channel-wise, scale-wise and spatial attention can act as a mechanism that allows capturing disperses information to improve feature representations, which becomes all the more important when detecting small or hard-to-notice biofouling structures.

Detection Head: A separate module that decouples classification from localization, which guarantees an accurate detection and localization of the presence of biofouling in challenging underwater environments.

Reinforcement Learning Module: Uses the extracted features as state inputs to train adaptive monitoring and control policies such as dynamic path planning of autonomous marine vehicles, and anomaly response strategies.

Adaptive decisions are controlled by the reinforcement learning aspect of the model, allowing for choices concerning sensing locations or changing robots' trajectories to maximize biofouling coverage and detection confidence. Anomaly detection unsupervised algorithms, such as COPOD, can be used as additional tool together with DRL to isolate abnormal environmental conditions that might imply for rapid biofouling growth or structural changes. This multi-level approach gives an initial alert as well as multiple alerts once it has been determined to be a real event, thereby saving time and resources in the monitoring process [18]. Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs) are now a necessity for the inspection, as well as repair, of any underwater infrastructure that is susceptible to biofouling repercussions. Presently cleaning, welding, valve operations and welding defects are done with human operated divers and ROVs. Only late- intervention Autonomous Underwater Vehicles, with manipulation capabilities and advanced sensing feature even higher capabilities to substantially decrease operational risks and costs. The technology is currently not yet ready for having AUVs do manipulation underwater, with problems of dexterity in using tools with high levels of autonomy in deciding what to do, and good sensing in the same environment. Emerging technologies such as the Sabertooth and Saab Seaeye Aquanaut are semi-autonomous. It is important that the system has the ability to easily detect targets, improve the workspace of the manipulator, plan safe, force-controlled motions on line and monitor cleaning or repair process progress in real time in order to guarantee a successful operation. AI in maintenance scheduling is therefore a way to improve forecasts of the development of biofouling as well as structural degradation, helping decision making regarding inspection and cleaning in a more informed way. The value of predictive maintenance is reduced downtime, longer asset life, and in the case of ocean-based marine assets, environmental benefits from reduced need for applications of chemical anti-fouling solutions. Finally, engaging with scientists to further elaborate on the use of the best available technology within existing ROV operations, including increasing the ability to image, sample, and obtain sensor data would improve the quality, and thus value, of the data without disrupting industry practices. The unbalanced nature of the datasets, where biofouling instances are much lower than the non-fouled instances, represents a difficult task in biofouling detection. Such unbalances disrupt the capacity of the model to learn, often leading to low sensitivity or high false negatives. Several methods aimed at reducing this imbalance include some form of a-priori elimination of non-informative data by statistical rules and graph-based reasoning. Additional measures, but, must also be taken in order to uphold the fairness in training and detection performance. Remote Ocean monitoring can suffer from high rates of data corruption due to sensor errors, environmental "noise," and system failures. If the information obtained by the sensors is faulty, the interpretation based on accurate combined models for biofouling and SHM will also have errors. While the data has undergone quality control measures, gaps and inaccuracies remain as a result of the challenging deployment environment as well as issues related to communication and the network, indicating the need for future sensors to become more resilient and able to self-diagnose reasons for missing/delayed data. The use of AI and DRL methods in biofouling detection and SHM implies a tradeoff between the computational complexity of these models and constrained onboard processing capabilities of embedded/edge computing systems. Research in other, similar fields of study, e.g., autonomous vehicle control, reveal hierarchical control architectures which can operate online at processing rates of the order of ~0.26 seconds, on embedded hardware like NVIDIA Jetson AGX Xavier. Underwater the latter problem is even more of a constraint due to power, data communication and difficult conditions for the system to be deployed and to work [19]. In practice, it is important to develop energy-efficient AIoT networks which are able to operate at a large scale and with low power consumption, but also does not sacrifice data credibility and model timeliness. In order to develop efficient and successful hybrid DRL biofouling models it will be necessary to have training and validation datasets that are large, diverse and involve multi-sensor images, sensor data and simulated environment variations. In marine microbiology, data augmentation methods, like Progressive Growing Generative Adversarial Networks (PGGAN), have been used to synthesize new spectral data to overcome the limitations of smaller datasets, thus reducing the amount of time to gather spectral data which is nevertheless capable of achieving the same classification accuracy. The application of knowledge graph to integrate satellite observations, local in situ data as well as the model output has similar effect on marine dynamic features, that training conditions could be boosted to match more realistic environmental forcing. Detailed labelling and cross-validation procedures are implemented to guarantee generalizability and avoid overfitting, given the nature of the problem rare events detection. Sensitivity, specificity and precision are typically used as quantitative measures to assess detection models. High levels of sensitivity (0.84) and specificity (0.998) have been found using new hybrid DRL approaches relatively to those obtained using traditional methodologies, even in imbalanced datasets such performance confirm the suitability of hybrid DRL for biofouling detection. Ablation studies in dynamic YOLO networks analyze the relevance of the various architectural components in the detection of small underwater objects, in support of the design decisions. In addition, and serving as a complement to the unsupervised anomaly detection, the detection of anomalies in the area can shed light on the spatial and temporal shifts of biofouling occurrence as well as of anomalies in the environment that may be related to biofouling presence and can aid in the overall system analysis.

Biodegradable vinyl polymers have been recently developed, offering an enticing alternative to the environmental concerns raised by the use of traditional anti-biofouling polymers and paints whilst maintaining performance. Firmer resistance to fouling can be achieved with the creation of polymers containing degradable main chains and hydrolyzable side groups, and these are a future generation of coatings, which would alleviate some of the need for mechanical cleaning as regularly. Advances in low-power, high-accuracy sensors and their application in AIoT systems pave the way for scalable distributed marine observation. This will be possible with the on-device AI that will drive edge computing / fog and allow for in-situ processing, thus reducing the necessity for data movement and addressing real-time applications. Mitigations hybrids of AI-directed monitoring and detection does reduce over application of anti-fouling agents and allows targeted cleaning and chemical applications which could pose some threat to marine life. The shift towards 'green' biofouling management, linked to marine conservation and policies on raised conservation and regulation on a global scale. Integrating AUVs with DRL hybrid systems mitigates the risks and expensive of manual inspection and maintenance. Having better data and more accurate predictions helps with scheduling, allowing for less down time and longer asset life. Also, the use of such tools provides an incentive for better environmental management and an incentive for interaction with non- industry stakeholders, such as regulators and the public.

Conclusion

This work presented a hybrid artificial intelligence framework for real-time biofouling detection and structural health monitoring in marine environments. By combining convolutional neural networks for underwater visual perception with deep reinforcement learning for adaptive decision-making, the proposed system addresses key limitations of traditional inspection methods, including high operational cost, limited coverage, and lack of adaptability to dynamic underwater conditions.

The CNN-based vision module effectively classified multiple biofouling types from challenging underwater imagery, while the reinforcement learning component optimized inspection paths and sensing actions in response to environmental feedback. Experimental results demonstrate improved detection accuracy, reduced inspection time, and lower prediction error in structural condition estimation when compared with conventional approaches. The multi-objective reward formulation further ensured a balance between detection reliability, navigation efficiency, and energy consumption, making the framework suitable for autonomous underwater monitoring tasks.

Although the proposed approach shows strong performance, its effectiveness depends on the availability of diverse training data and the computational capabilities of embedded underwater platforms. Environmental variability, sensor noise, and long-term data drift also remain open challenges for sustained deployment.

Future research will focus on integrating multi-sensor data, incorporating environmental parameters, and linking the framework with digital twin models for predictive maintenance. Overall, the proposed hybrid DRL-based framework provides a practical and scalable solution for intelligent biofouling management and structural health monitoring in complex marine environments.

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