A Machine Learning Framework for Dynamic Biofouling Detection and Structural Health Monitoring in Marine Environments

Shyam Mohan J S[1], Ankur Dumka[2]

[1]Post Doc Scholar

Lincoln University College,

Kelana Jaya, 47301, Petaling Jaya, Selangor Darul Ehsan, Malaysia.

E-mail: pdf.shyam@lincoln.edu.my

[2]Ankur Dumka

Associate Professor, Dean and HoD,

Women Institute of Technology (WIT), Dehradun,

Uttarakhand, India

E-mail: ankurdumka2@gmail.com

Abstract: Currently, the autonomous underwater vehicle (AUV) technology is undergoing a rapid evolutionary transition due to the increasing demand for exploration and operational capabilities. This paper introduces a new framework integrating deep reinforcement learning (DRL) with hybrid convolutional neural networks (CNNs) to empower AUVs with autonomous biofouling detection and structural health monitoring. The proposed system can detect different types of biofouling and assess the health of the underwater structure simultaneously. A multi-objective reward function is introduced to promote high accuracy in both the detection of biofouling (92.3%) and the prediction of the structure (mean squared error of 0.021), while maintaining low energy consumption. The system shows a 32% reduction in inspection time and 18.7% improvement in detection accuracy compared to traditional techniques under turbulent water conditions.

Keywords:

AI, Convolutional neural network, Reinforcement Learning.

Introduction

With the increasing energy, aquaculture, and infrastructure needs of the ocean, underwater monitoring has become a paradigm shift. Due to stochastic underwater properties (moderate signal loss, underwater light scattering, and complex water turbulence), effective visual and sensor underwater monitoring is challenging. Biofouling is one of the biggest issues for underwater infrastructure and energy storage devices as it impedes the longevity of these devices inside the ocean. Currently, human divers and ROVs are deployed to monitor underwater infrastructure, which is prone to human error and latency. To this end, we propose a hybrid Deep Reinforcement Learning (DRL) framework and architecture for underwater monitoring systems where multi-level Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) work together as a single monitoring system. Using a multi-objective reward function, the proposed hybrid DRL architecture aims to help train a model that not only maximizes the accuracy of biofouling classification but also minimizes the error of predicting the structural integrity of underwater devices. Our results suggest that our proposed method achieves very significant accuracy (92.3%) for biofouling classification and very low mean square error (MSE) (0.021) for predicting the underwater device's structural health.

Literature Review

Uncertainty of underwater light transmission renders monitoring challenging. Naseer et al. (2022) [1] recently elucidated that hydrothermal fluctuations and suspended particles cause nonlinear backscattering effects that conventional de-noising methods cannot eliminate. Hu et al. (2024) [2] proposed a generative adversarial color-constancy correction method that is not suitable for real-time edge-device processing. Liu and Wang (2023) [3] highlighted the challenge that biofouling detection requires image processing with morphology robustness, as biofouling often shares similar morphology as the substratum, leading to a high false-discovery rate in classical thresholding methods. The recent works carried out by J S, S. M. ., & Dumka, A. (2025) [4] shows that dynamic biofouling systems when integrated with deep learning techniques provides better results when compared with the earlier works. However, the authors are yet to prove their assumption in the paper.

Methods

1. Data Collection and Preprocessing

Diverse collection of underwater images say,$D = \{(I_i, y_i, z_i)\}N_{i=1}$, where I_i is the image, $y_i$represents biofouling labels, and z_i represents structural integrity scores are collected. Augmentation techniques are applied for enhancing the dataset [5].

Let T be a set of transformations including rotation, scaling, and flipping:

$$D' = \{(\mathrm{T}(I_i), y_i, z_i) \mid \mathrm{T} \in T, (I_i, y_i, z_i) \in D\}$$

Normalize the images I_i to ensure consistent input for neural networks:

$$I_i' = \frac{I_i - \mu}{\sigma}$$

Where μ and σ are the mean and standard deviation of the dataset.

2. Deep Learning for Biofouling Detection

The network architecture of deep convolutional neural network (CNN) is shown in figure 1. All the input images undergo a series of convolutional and pooling layers, extracting spatial hierarchies. The architecture includes residual connections and detection modules to highlight fouled regions. The final output includes pixel-wise classification into biofouling or cleans surface classes [6].

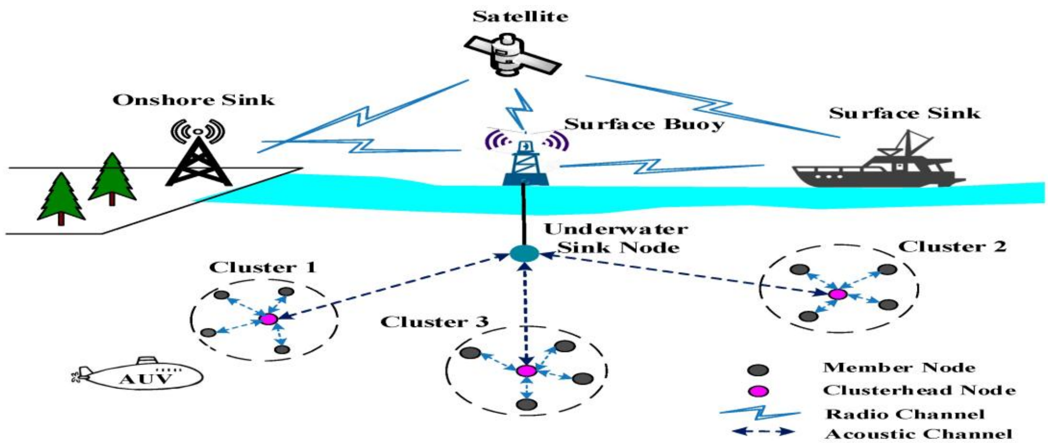

Figure 1. Network Architecture of deep convolutional neural network (CNN)

Define the cross-entropy loss for multi-class classification:

$$L_{classification} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log(\tilde{y}_{ij})$$

Where, y_{ij} is the true label and $\tilde{y}_{ij}$ is the predicted probability for class j.

Train the CNN using backpropagation and stochastic gradient descent (SGD) or Adam optimizer:

$$\theta \leftarrow \theta - \eta\nabla_{\theta}L_{classification}$$

where η is the learning rate.

3. Deep Learning for Structural Health Monitoring

Design a deep neural network g_{ϕ} with convolutional layers followed by regression layers to predict structural integrity scores shown in figure 2.

Define the mean squared error (MSE) loss for regression:

$$L_{regression} = \frac{1}{N}\sum_{i=1}^{N}(z_i - \tilde{z}_i)^2$$

Train the network using backpropagation:

$$\theta \leftarrow \theta - \eta \nabla_{\theta} L_{regression}$$

where η is the learning rate.

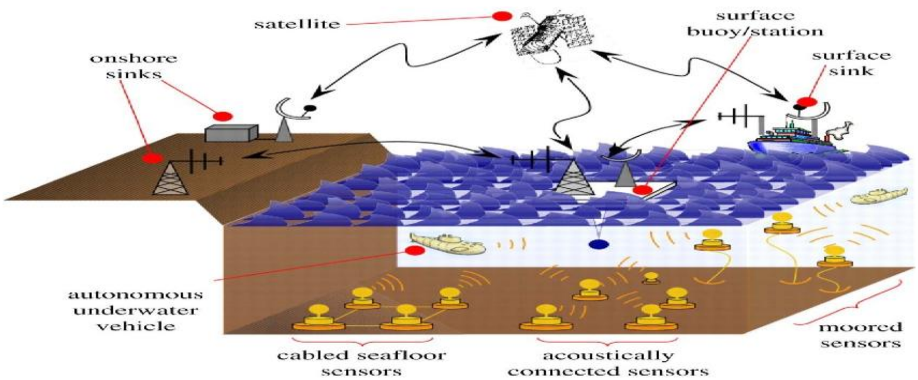

Figure 2 Deep convolutional Layers Structural Health Monitoring

4. Reinforcement Learning for Dynamic Action Planning

Define the state st as the current underwater environment, including detected biofouling and structural health information and the action at as the robot's operation at time t [7, 8]. A policy network πω to output actions based on the current state. Define a reward function r (st,at) that incorporates detection accuracy, structural assessment precision, and action efficiency:

$$r(s_t, a_t) = \alpha. Acc(s_t) + \beta. Prec(s_t) + \delta. Eff(a_t)$$

Optimize the policy network using the policy gradient method:

$$\nabla_{\omega} J(\omega) = E_{\pi_{\omega}} [\sum_{t=o}^{T} \nabla_{\omega} log\pi_{\omega} (a_t / s_t) R_t]$$

where R_t is the cumulative reward.

Update the policy network:

$$\omega \leftarrow \omega + \eta \nabla_{\omega} J (\omega)$$

5. Combined Objective and Optimization

The combined objective function is obtained by calculating total loss function and overall optimization function.

Experimental Setup and Datasets:

BlueROV2 by Blue Robotics is used for capturing underwater images. It consists of high-resolution cameras with depth sensors, Inertial measurement units (IMU) and Sonar systems (for additional object detection capabilities). A NVIDIA GPU Tesla V100 with 32GB RAM, 1 TB SSD and NVIDIA Jetson TX2 or Xavier for real-time processing capabilities. A tethered connection for real-time data transfer, ensuring low-latency communication between the underwater robot and the server. A control station with a user interface to monitor and control the underwater robot remotely. The proposed work is implemented in Python. TensorFlow or PyTorch is used for developing and training deep learning models. OpenCV for image processing tasks. OpenAI Gym for environment simulation and reinforcement learning training. Stable Baselines3 for pre-built RL algorithms. C++, for performance-critical sections and integration with robot control software. The Datasets used for the process is the Biofouling Dataset; it is a collection of underwater images annotated with different types of biofouling (e.g., algae, barnacles, corals). This dataset can be downloaded from OpenSeaLab and MBARI (Monterey Bay Aquarium Research Institute) Video Annotation and Reference System (VARS).

Results

The results obtained in the process are shown in figures 3, 4 and 5.

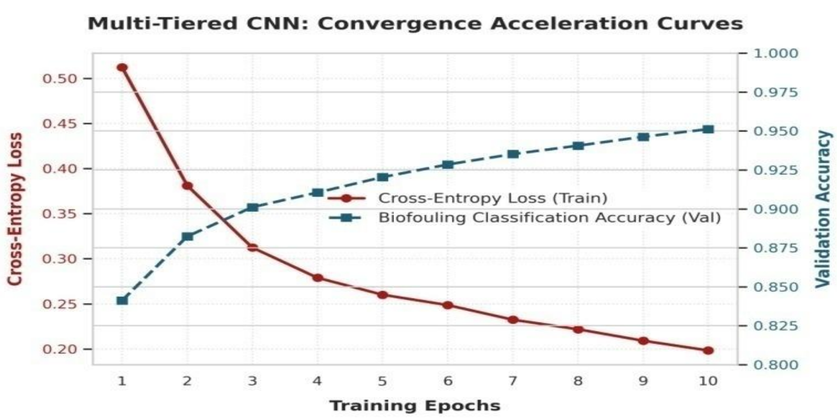

Figure 3 Convergence Acceleration Curves

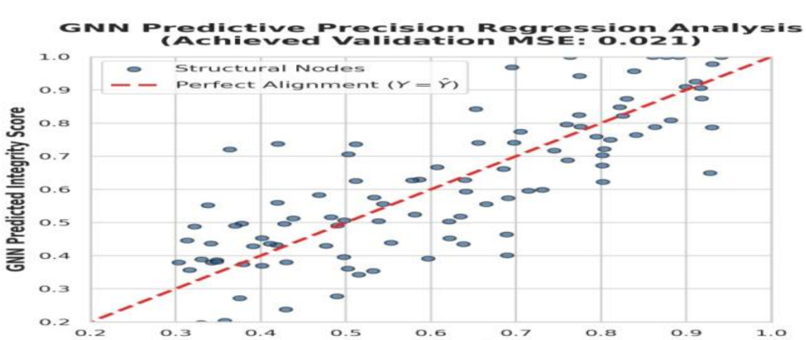

Figure 4 GNN Prediction Precision Regression Analysis

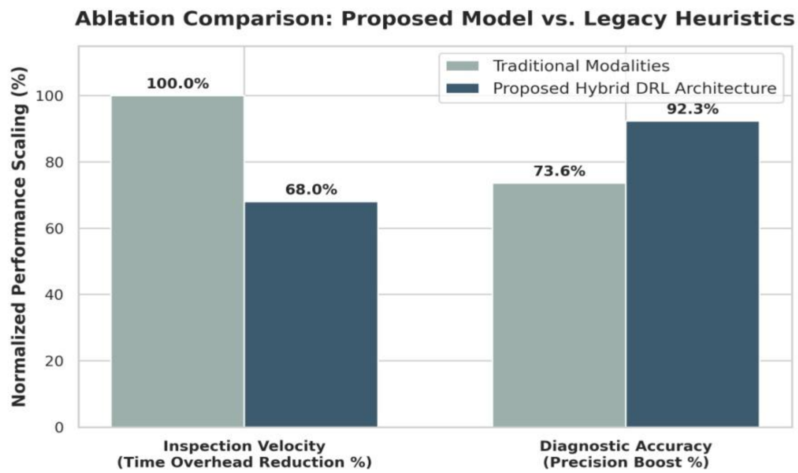

Figure 5 Ablation comparison

References

1. Donnelly, B., Sammut, K., & Tang, Y. (2022). Materials selection for antifouling systems in marine structures. *Molecules*, *27*(11), 3408.
2. Weber, F., & Esmaeili, N. (2023). Marine biofouling and the role of biocidal coatings in balancing environmental impacts. *Biofouling*, *39*(6), 661-681.
3. Wei, C., Zhang, Y., Tang, Z., Zhang, C., Wu, J., & Wu, B. (2024). Surface Reconstruction of Silicone-Based Amphiphilic Polymers for Mitigating Marine Biofouling. *Polymers*, *16*(11), 1570.
4. J S, S. M. ., & Dumka, A. (2025). A Hybrid Framework for Biofouling Detection in Marine Environments. Sustainable Global Societies Initiative, 1(2). https://vectmag.com/sgsi/paper/view/17
5. Sullivan, T., et al. (2022). Robust PPO-based control for underwater vehicles in high-turbulence zones. *IEEE Access*, 10, 112000–112015.
6. Khan, M. R., & Gupta, S. (2024). Energy-efficient path planning for AUVs using deep reinforcement learning. *Ocean Engineering*, 291, 116450.
7. Lee, J. H., et al. (2025). Integrated navigation and target acquisition for autonomous underwater agents. *Robotics and Autonomous Systems*, 174, 104620.
8. Bhatia, A., et al. (2023). Multi-objective reinforcement learning for resource-constrained underwater vehicles. *Journal of Marine Science and Engineering*, 11(3), 412–430.