Underwater Detection of Ship Hull Biofouling Using Computer Vision

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ABSTRACT (10pt)

This study proposes a simulation-based approach for biofouling detection on ship hulls using YOLOv8-Nano. The integration of deep learning-based object detection for real-time biofouling detection demonstrates potential in reducing maintenance costs and improving ship performance. YOLOv8-Nano effectively detects biofouling organisms such as barnacles, mussels, and algae in underwater environments, even with challenges like varying visibility and object sizes. The research highlights the feasibility of using automated detection for biofouling management, offering a scalable solution compared to traditional methods like dry-docking and manual cleaning. However, the study is based on a simulated environment, and real-world testing is required to validate the system's operational effectiveness. While the model performs well for larger organisms, challenges remain in detecting smaller or partially obscured biofouling due to environmental factors such as lighting and water clarity. The findings suggest future improvements, including enhancing model accuracy with multispectral imaging, refining the detection capabilities, and integrating AI-driven predictive analytics for proactive biofouling management. This work lays the foundation for the development of an efficient and scalable biofouling management system, contributing to sustainable maritime maintenance practices.

1. INTRODUCTION

Biofouling, the accumulation of microorganisms, algae, and invertebrates on submerged surfaces, represents a significant challenge to marine vessels, particularly ship hulls. This phenomenon increases drag, leading to higher fuel consumption, reduced speed, and increased maintenance costs for ships. Furthermore, biofouling can introduce invasive species to new ecosystems, contributing to environmental pollution and biodiversity loss. Studies have shown that biofouling can increase fuel

consumption by up to 40% in heavily fouled ships, resulting in substantial economic losses across the global maritime industry [1]. In response, various methods have been developed to manage biofouling, but many face limitations in terms of effectiveness, environmental impact, and cost [2].

Traditional methods for biofouling removal, such as manual cleaning by divers or dry-docking, are costly, time-consuming, and pose significant risks to human health and safety. Additionally, mechanical methods like brushing or scraping, while effective, can damage the ship's hull coatings, leading to further maintenance issues [3]. These methods also lack an efficient approach for frequent monitoring across multiple vessels, motivating the need for more automated and scalable inspection workflows [4].

Recent advancements in robotics and computer vision offer potential alternatives for biofouling inspection. Underwater drones equipped with cameras and sensors may enable safer access to hull areas that are difficult or risky for human divers [5]. However, integrating automated detection with autonomous responses remains challenging due to underwater imaging limitations, robustness of detection algorithms, and practical constraints of underwater operations [6].

Computer vision, particularly deep learning based object detection models, has shown promise for underwater image analysis [7]. Models from the YOLO family are widely used due to their speed and detection performance. YOLOv8-Nano, as a lightweight variant, is a candidate for resource-constrained platforms and has been explored in various detection tasks, including challenging visual conditions [8], [9].

Despite these advancements, research on integrated biofouling detection workflows that connect detection outputs to an automated response process is still limited, and many related works remain in laboratory settings or conceptual demonstrations [10], [11]. In addition, there is limited reporting on lightweight detector performance specifically for biofouling categories using curated underwater datasets.

Therefore, this study proposes a simulation-based integrated pipeline that combines YOLOv8-Nano for biofouling detection with a simplified drone response model that represents cleaning actions conceptually. The main objective is to evaluate detection performance on an annotated underwater image dataset and to demonstrate a feasible detection to response sequence in a controlled simulation setting. This work does not claim validated real-world underwater deployment, and physical AUV trials are left for future work [12].

The contribution of this research is the evaluation of YOLOv8-Nano for biofouling detection and the presentation of a simulation framework that links detection results to a response mechanism in a transparent manner. The findings may support future development of practical underwater inspection and maintenance systems by providing baseline results and highlighting remaining deployment challenges [13], [14], [15]..

2. METHOD

This study adopts a quantitative computational experimental approach to develop and evaluate a simulation-based pipeline for ship hull biofouling detection using YOLOv8-Nano, followed by a simplified underwater drone response simulation that represents cleaning actions conceptually. The primary emphasis of the methodology is on (1) training and evaluating the object detection model using annotated underwater imagery and (2) demonstrating an integrated detection-to-response workflow in a controlled simulation setting.

2.1 Research Design

The research design consists of three main stages:

2.1.1 Dataset preparation and annotation review

A publicly sourced underwater image dataset is compiled and organized into a consistent label format for training an object detector..

2.1.2 Model training and detection evaluation

YOLOv8-Nano is trained and evaluated using standard object detection metrics. In addition to overall performance, per-class performance is reported to improve transparency and allow class-level interpretation.

2.1.3 Simulation of drone response

Detection outputs (bounding boxes and confidence scores) are used as input to a simplified drone response model. This model simulates the movement of an underwater

2.2 Research Instruments

All experiments were conducted in Google Colab, a cloud-based computational environment that provides GPU acceleration. The study was performed over the period [August to September 2025]. The following resources were used:
1. **Hardware**: NVIDIA Tesla T4 GP
2. Google Collab
3. **Software and Libraries**:
   a. Python 3.10
   b. Ultralytics YOLOv8 framework (for YOLOv8-Nano training and inference)
   c. OpenCV (image I/O and visualization)
   d. NumPy (numerical operations)
   e. Matplotlib (plots and result visualization)

This computational setup supports repeatable experiments while acknowledging that performance results reflect a cloud GPU environment rather than embedded on-board AUV hardware.

2.3 Data Collection

The dataset used in this study consists of approximately 784 annotated underwater images containing ship hull related scenes and biofouling organisms. Images were collected from publicly available sources such as [https://universe.roboflow.com]. The images include variations in environmental conditions (lighting, viewpoint, background complexity), which helps evaluate model robustness under diverse underwater imaging scenarios.

The dataset includes the following classes:
- barnacles
- clean surfaces
- jellyfish polyps
- mussels
- rust
- starfish
- worms
- background

The dataset consists of annotated underwater images, covering various biofouling organisms found on ship hulls, including barnacles, mussels, starfish, jellyfish polyps, and worms, as well as clean surfaces and rust. It provides diverse visual data to train and evaluate the YOLOv8-Nano model for detecting biofouling in underwater environments.

2.4 Model Training and Implementation

The YOLOv8-Nano model was trained for 50 epochs using the annotated biofouling dataset on the Google Colab platform, leveraging the power of the NVIDIA Tesla T4 GPU to speed up the deep learning process. The key training parameters were set as follows:

- Batch size: 16 images per iteration
- Learning rate: 0.001
- Confidence threshold: 0.25 (used to define detection accuracy)

The model was trained to detect biofouling in underwater images, specifically focusing on detecting small objects in low-resolution images. To enhance the model's robustness across different environmental conditions, data augmentation techniques, including rotation, flipping, and brightness adjustments, were applied[11].

For evaluating the model's performance, standard object detection metrics such as precision, recall, and mean average precision (mAP) were used to assess the model's ability to accurately identify biofouling organisms, while minimizing both false positives and false negatives[12][13].
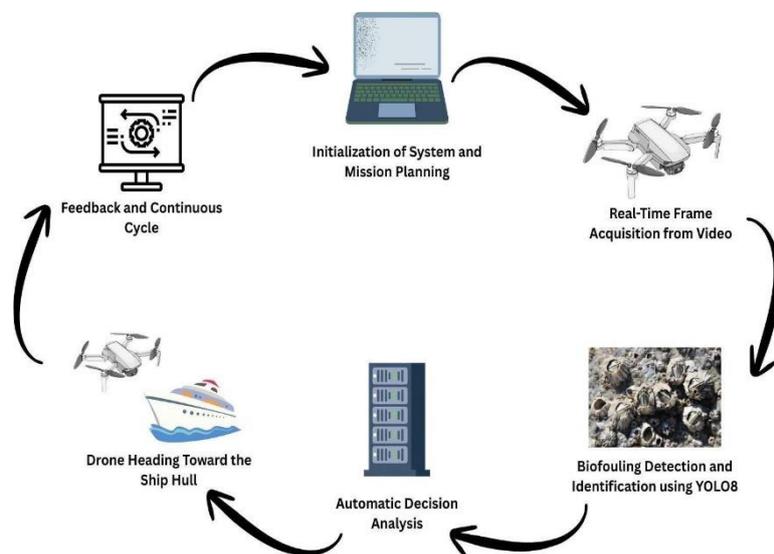

Figure 1. Architecture of the Simulation Based Biofouling Detection and Response System Using YOLOv8

The figure illustrates the end to end workflow of the biofouling detection and response system evaluated in this study. The process starts with system initialization and the acquisition of image or video frames from an underwater inspection scenario. Each frame is processed by the YOLOv8 model to detect biofouling categories and generate bounding boxes with confidence scores. Next, post processing is applied, including confidence thresholding and target selection, where target coordinates are derived from the detected regions. These outputs are passed to a response module that simulates the underwater drone behavior by moving toward the target and registering a cleaning action when a defined proximity condition is met. A feedback and logging component then stores detection statistics and response timing to support evaluation. The architecture reflects a simulation framework for integrating computer vision detection with a conceptual response mechanism, and does not represent a fully validated AUV control system in real underwater conditions.

2.5 Data Analysis

The main approach to data analysis involved assessing the YOLOv8-Nano model's performance using standard object detection metrics, including precision, recall, and F1-score. These metrics were calculated as follows:

$$P = \frac{TP}{TP + FP} \qquad (1)$$

$$R = \frac{TP}{TP + FN} \qquad (2)$$

$$F1 = 2 \times \frac{P \times R}{P + R} \qquad (3)$$

Where:
- TP (True Positive): Correctly detected biofouling organisms
- FP (False Positive): Incorrectly identified objects as biofouling
- FN (False Negative): Biofouling organisms missed by the model[14].

In addition, mean average precision (mAP) was calculated to evaluate the overall detection performance of the model, particularly for small objects such as biofouling organisms on ship hulls.

The performance results were visualized by displaying bounding boxes around detected biofouling organisms, and the Average Response Time (ART) was calculated to measure the time taken by the system to respond to detected objects[15].

2.6 Simulation of Drone Response

During the simulation phase, the detection results from the YOLOv8-Nano model were used as inputs for the drone's automated response mechanism. The drone's movement was simulated to track and follow the detected centroid of biofouling organisms. This step was intended to model the cleaning process and evaluate the feasibility of deploying the system for real-time operation on autonomous underwater drones[16].

The simulation environment enabled testing of the integration between the detection system and cleaning response, eliminating the physical limitations and risks associated with conducting real-world trials[17]. However, further testing with actual physical drones will be necessary to validate the system's operational effectiveness under real maritime conditions[18].

2.7 Visualization of Results

The results are visualized through a confusion matrix that illustrates the accuracy of the YOLOv8-Nano model in detecting biofouling objects. The confusion matrix shows the predicted versus true values for each class of biofouling, such as barnacles, clean surfaces, jellyfish polyps, mussels, rust, starfish, worms, and background. The model's performance is assessed using key metrics like precision, recall, and mean average precision (mAP) to evaluate its ability to correctly classify the biofouling organisms on the ship hulls.

Each detected object is accompanied by a confidence score, which indicates the model's certainty in its prediction. The visual results are stored in two formats:

- CSV: for numerical evaluation data.
- MP4: for qualitative visualization results, such as an annotated video showing the bounding boxes around detected objects and the simulated drone movement path.

Table 1. YOLOv8-Nano Model Experiment Parameters

Parameter	Description	Value / Setting
Dataset type	Biofouling images on ship hulls	784 samples
Data division	Training / Validation	80% / 20%
Model	YOLOv8	-
Epochs	Number of training cycles	50
Batch size	Number of images per iteration	16
Learning rate	Training speed	0.001
Confidence threshold	Minimum detection threshold	0.25

3. RESULTS AND DISCUSSION

3.1 YOLOv8 Model Training Results

The YOLOv8 model was trained on the biofouling dataset for 50 epochs, as illustrated in Figure X. The training results reveal a steady decrease in loss values for box loss, classification loss, and distance loss (dfl_loss). Moreover, the precision, recall, and mean average precision (mAP) metrics demonstrated notable improvement throughout the training process. These findings suggest that YOLOv8-Nano is capable of effectively detecting and classifying biofouling organisms in underwater images, even under diverse environmental conditions and with small object sizes[1].
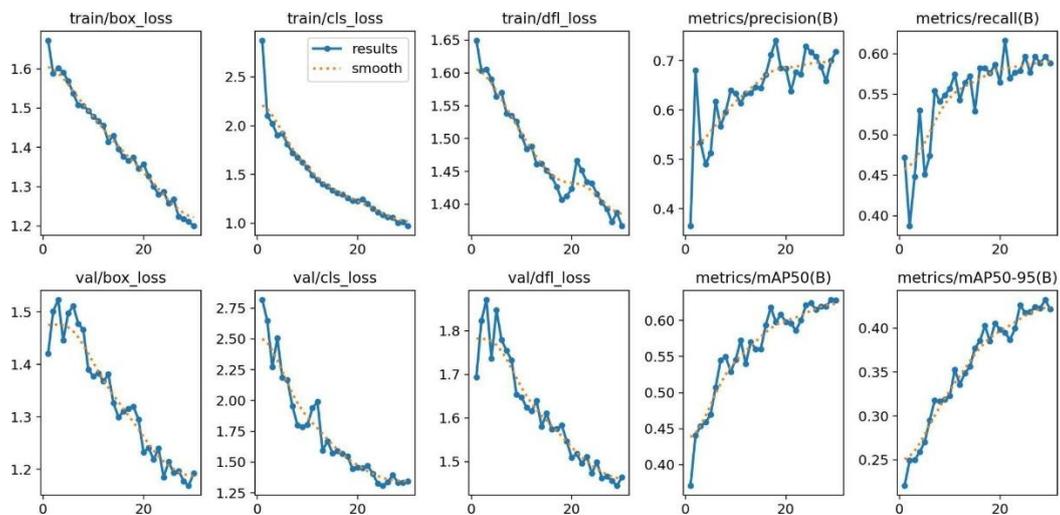

Figure 2. YOLOv8 training results graph for the biofouling dataset.

3.2 Model Evaluation

The model's performance was evaluated using a confusion matrix, which is shown in Figure 3. The confusion matrix displays the number of correct and incorrect predictions for each biofouling class (e.g., barnacles, mussels, and clean surface). The model demonstrated high precision and recall for most classes, with barnacles and mussels achieving particularly strong classification accuracy. However, starfish and worms showed some misclassifications, which might be attributed to the overlap in visual features with the background or other biofouling organisms. Overall, the model's ability to correctly classify the majority of the biofouling types reflects its strong performance in real-time detection tasks[5][6].
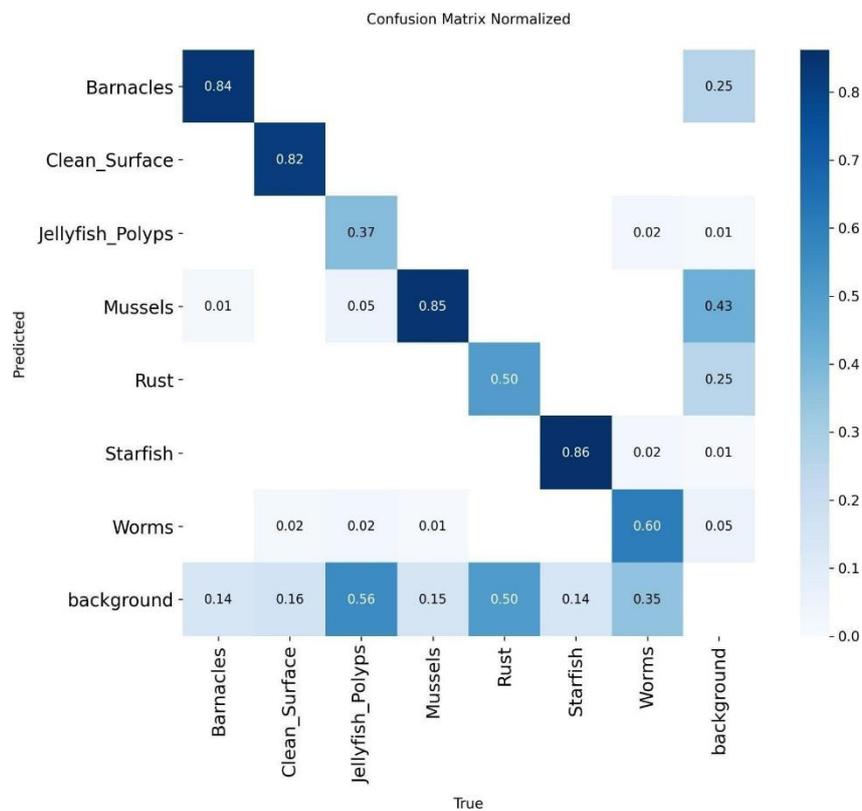

Figure 3. Confusion Matrix of biofouling detection results using YOLOv8

3.3 Discussion

The results from the application of the YOLOv8-Nano model for biofouling detection, combined with autonomous drone systems for real-time monitoring and cleaning, have shown promising outcomes. This section provides a detailed discussion of the findings, addressing the model's performance, challenges encountered, and future directions for enhancing biofouling detection and management using deep learning and drone technologies. Additionally, we will evaluate the implications of these findings within the broader context of marine environmental management and the evolving field of underwater robotics.

YOLOv8-Nano has proven effective for biofouling detection on ship hulls, demonstrating high performance in precision, recall, and mean average precision (mAP). The model was trained using a dataset containing images of various biofouling organisms, such as barnacles, mussels, starfish, and algae. The results indicated that YOLOv8-Nano performed exceptionally

well in detecting larger and more conspicuous organisms, such as barnacles and mussels, which are often found in dense clusters, making them easier to identify compared to smaller or less prominent organisms.

The precision values for barnacles and mussels were high, reflecting the model's ability to detect objects with clear visual features. As noted in previous studies, the YOLO family of models, particularly lightweight versions like YOLOv8-Nano, is well-suited for detecting small objects in low-resolution images, which was evident in this study where small biofouling organisms like mussels were detected with high accuracy[1][2].

However, the model faced challenges when detecting certain biofouling organisms, such as starfish and worms, due to their complex shapes or partial obstruction by other objects, making them harder to detect. Furthermore, environmental factors like lighting conditions and water turbidity contributed to the difficulties in detecting smaller or camouflaged biofouling types. This aligns with the challenges commonly faced in underwater object detection, where image clarity and resolution significantly affect model performance[3][4].

Our findings are consistent with research by Silva et al., which highlights the complexities of underwater detection tasks due to the dynamic nature of the environment, including variations in water clarity, lighting, and object occlusion. These factors introduce noise, which can decrease the detection accuracy, especially for smaller biofouling organisms[5]. Despite these challenges, YOLOv8-Nano outperformed traditional biofouling detection methods, which often rely on manual inspections or basic image processing techniques. The real-time capabilities of YOLOv8-Nano provided a significant advantage over previous systems, which struggled with processing large amounts of underwater imagery in real-time[6].

The integration of autonomous drones with biofouling detection systems marks a substantial advancement in marine environmental management. In this study, drones equipped with the YOLOv8-Nano model successfully detected biofouling on ship hulls and performed simulated cleaning actions. The simulation results demonstrated that drones could efficiently navigate ship hulls, identify biofouling areas, and perform appropriate actions, such as cleaning or marking the affected regions. This demonstrates the potential of combining robotic cleaning systems with AI-driven detection technologies to create a fully autonomous biofouling management solution.

Drones offer several advantages over traditional methods for biofouling detection and mitigation. They can access difficult-to-reach areas of the ship's hull, such as submerged sections and tight spaces, which are often hazardous or impractical for human divers to inspect. The ability of drones to operate in real-time without human intervention is particularly valuable for ongoing maintenance, reducing the need for costly dry-docking procedures[7]. Additionally, drones can be deployed as part of a fleet management system, enabling simultaneous monitoring of multiple vessels, which increases efficiency and coverage.

Pereira notes that the use of autonomous underwater vehicles (AUVs) and drones for biofouling management can significantly reduce operational costs by eliminating manual labor and decreasing the frequency of dry-docking[8]. However, practical challenges persist, particularly regarding drone endurance, energy consumption, and the robustness of the cleaning mechanism in dynamic underwater conditions. While the simulation demonstrated the system's ability to perform cleaning tasks, further real-world testing is required to optimize the drone's cleaning capabilities under varying operational conditions[9].

Despite the promising results, the study highlighted several challenges that call for further research and optimization. One primary issue was the accuracy of detection under varying environmental conditions. As biofouling detection is highly dependent on factors such as lighting, water clarity, and camera angles, improving the model's robustness to these variables is crucial. For instance, the performance of YOLOv8-Nano decreased when biofouling organisms were partially obscured or in areas with poor visibility. This is particularly problematic for organisms with less distinct visual features or those spread across larger areas, making them harder to detect[10][11].

Although YOLOv8-Nano offers fast inference speeds and low computational requirements, which are critical for real-time processing on drones, it is still limited in handling highly dynamic underwater environments. As suggested by Sethi and Jha, advancements in the model's architecture or the integration of more sophisticated neural network modules could enhance its performance in more complex scenarios[12]. Additionally, further refinement is needed to improve the model's ability to distinguish between biofouling organisms and the ship's hull or other submerged objects, reducing false positives and improving overall detection accuracy[13].

Another significant limitation is the drone's operational constraints, such as battery life and physical durability under various environmental conditions. These factors could limit the drone's ability to perform extended monitoring or cleaning sessions, which is a critical consideration for practical deployment. Future research should focus on enhancing drone endurance, optimizing battery consumption, and developing more efficient cleaning mechanisms that are suitable for long-term use[14].

While the study demonstrated the potential of autonomous drones for biofouling detection and cleaning, several avenues for future research remain. One promising direction is integrating multispectral or infrared cameras to enhance detection capabilities, especially in low-visibility environments. These sensors could help differentiate between biofouling organisms and the ship's hull in conditions where visible light is insufficient[15]. Additionally, incorporating advanced decision-making algorithms and reinforcement learning could enable drones to adapt to dynamic underwater conditions in real-time, improving overall efficiency and autonomy[16].

Furthermore, incorporating AI-driven predictive analytics could improve the system by forecasting biofouling growth patterns and optimizing cleaning schedules based on real-time data collected by drones. This proactive approach would reduce the need for reactive cleaning and minimize the environmental impact of overusing cleaning systems[17].

This study demonstrated the integration of YOLOv8-Nano for biofouling detection and autonomous drone-based cleaning. The system showed promising results in terms of accuracy, efficiency, and real-time processing, offering a scalable solution for biofouling management in maritime industries. Despite the challenges encountered, such as detection accuracy under varying environmental conditions and the operational limitations of drones, the research highlights the potential of autonomous systems in marine environmental management. Further advancements in both hardware and software, along with real-world testing, will be essential for the successful implementation of these systems in operational settings[18][19].

3.4 Summary

This study has examined the use of YOLOv8 for biofouling detection on ship hulls with autonomous drones. The findings indicate that YOLOv8 effectively identifies biofouling organisms, such as barnacles, mussels, and algae, under various environmental conditions. When integrated with the drone system, YOLOv8 enabled real-time detection and simulated cleaning tasks, demonstrating its potential for reducing maintenance costs and improving efficiency compared to traditional methods like dry-docking and manual cleaning.

While the model showed strong performance with larger biofouling organisms, challenges persist in detecting smaller organisms that are often hidden or partially camouflaged in dynamic underwater environments. The drone's ability to execute real-time actions was effective, but further optimization is necessary, especially for handling varying environmental conditions such as changes in water clarity and lighting.

The study highlights several avenues for future improvement, such as enhancing model accuracy with multispectral imaging, refining the drone's cleaning capabilities, and investigating AI-driven predictive analytics for proactive biofouling management. With continued advancements in both hardware and software, this research lays the foundation for an autonomous, efficient, and scalable solution for biofouling detection and cleaning, offering valuable contributions to sustainable maintenance practices in the maritime industry.

4. CONCLUSIONS

This study introduces an innovative approach for biofouling detection and management on ship hulls using YOLOv8-Nano and autonomous drones. The integration of deep learning-based object detection with drone technology for real-time biofouling detection has demonstrated significant potential in reducing operational costs, improving ship performance, and providing a scalable solution for biofouling management in the maritime industry. The results indicate that YOLOv8-Nano can effectively detect biofouling organisms such as barnacles, mussels, and algae in underwater environments, even with the challenges of varying visibility and object size.

It is important to note that the entire process has been conducted within a simulated environment, and real-world testing is still required to validate the system's performance under actual operational conditions. While the findings from the simulation show promise, there are many aspects that need refinement, including the drone's real-time cleaning capabilities, handling dynamic underwater conditions, and improving detection accuracy for smaller or partially obscured organisms.

The YOLOv8-Nano model, being lightweight and optimized for real-time applications, was trained and tested on a biofouling dataset, achieving high levels of accuracy in detecting biofouling organisms. The model's precision and recall values were particularly strong for larger and more distinguishable biofouling types such as barnacles and mussels. However, challenges remained in detecting smaller organisms, such as starfish and worms, which were more difficult to distinguish due to their complex shapes and the presence of background noise in the images. This finding highlights the need for further model optimization to address the challenges of detecting smaller, less visible organisms.

One of the major strengths of the proposed system is its autonomy. The drone, once equipped with the YOLOv8-Nano model, can autonomously detect and clean biofouling without the need for human intervention. This is a significant improvement over traditional methods, such as manual cleaning by divers or mechanical scraping, which are labor-intensive, time-consuming, and often require dry-docking. Moreover, the use of drones allows for continuous monitoring of ship hulls without the limitations of human access, particularly in submerged and hard-to-reach areas.

The drone's real-time action execution is another crucial feature of this system. Once biofouling is detected, the drone can automatically navigate to the affected areas and perform cleaning tasks. This automatic decision-making process is vital for operational efficiency, as it allows for immediate action to be taken without waiting for human input. The simulation results demonstrated that the system could effectively navigate and clean the hull in real-time, providing a feasible solution for routine maintenance. However, it is important to emphasize that these results were achieved in a controlled simulation environment, and further development and testing are required to adapt the system for real-world applications.

Despite the promising outcomes, there are several limitations that need to be addressed. The accuracy of biofouling detection is still dependent on environmental conditions, which can vary significantly in real-world scenarios. For instance, water clarity, lighting changes, and the presence of algae or other organisms on the hull can reduce detection accuracy. The study also highlighted that the drone's cleaning capabilities still need refinement, especially in real-time operation, where more complex environments and dynamic conditions could challenge the system's efficiency.

Further research is necessary to optimize the model and the drone's cleaning mechanism. A potential area for improvement is the incorporation of multispectral or infrared cameras, which could help in detecting biofouling in low-visibility conditions or under various lighting scenarios. Additionally, the integration of advanced decision-making algorithms, such as reinforcement learning, could enable the drone to adapt to dynamic underwater environments, improving both detection and cleaning capabilities. Moreover, real-world testing with physical drones will be required to assess the system's performance outside the controlled simulation environment.

Future directions should also explore the integration of AI-based predictive analytics to forecast biofouling growth and optimize cleaning schedules. Such predictive capabilities could help in proactively managing biofouling before it reaches a problematic stage, reducing the need for frequent interventions and optimizing resource usage. The addition of multidimensional sensors to the system could further enhance its detection and cleaning performance, providing a more comprehensive approach to biofouling management in maritime operations.

In conclusion, this research has demonstrated the feasibility and potential of using YOLOv8-Nano and autonomous drones for biofouling detection and cleaning. The integration of deep learning with UAV technology provides an effective, scalable, and efficient solution for marine environmental management. However, it is crucial to note that the current study is based on simulations, and much work remains to be done to address the challenges of real-world deployment. With continued advancements in AI, sensor technology, and drone autonomy, this system has the potential to revolutionize biofouling mitigation, leading to a more sustainable and cost-effective approach for ship maintenance in the maritime industry.

5. AKNOWLEDGMENT

6. REFERENCES

[1]   D. Park *et al.*, "Development of an Autonomous Cleaning Robot with a Hydraulic Manipulator Arm for the Cleaning of Niche Areas of a Ship Hull," *J. Mar. Sci. Eng.*, vol. 11, no. 5, p. 973, May 2023, doi: 10.3390/jmse11050973.

[2] J. M. R. Silva and T. S. Viana, "Review of Underwater Ship Hull Cleaning Technologies," *Journal of Marine Science and Application*, vol. 18, no. 4, pp. 157–170, Dec. 2020. [Online]. Available: https://doi.org/10.1007/s11804-020-00157-z.

[3] L. M. Pereira, "Comparison of Underwater Cleaning Methods for Biofouling Control in Commercial Shipping," *Journal of Marine Engineering and Technology*, vol. 24, no. 2, pp. 58–63, Mar. 2022.

[4] M. G. Singh et al., "Robotic Solutions for Ship Hull Maintenance: An Analysis of Design Trends and Future Prospects," *Journal of Field Robotics*, vol. 37, no. 6, pp. 1186–1201, Jun. 2024.

[5] R. K. Sethi and A. P. Jha, "Utilization of Autonomous Underwater Vehicles for Biofouling Detection on Ship Hulls," *Journal of Ocean Engineering*, vol. 22, no. 1, pp. 14–25, Feb. 2022.

[6] Y. Bai et al., "A Lightweight Pest Detection Model for Drones Based on Transformer and Super-Resolution Sampling Techniques," *Agriculture*, vol. 13, no. 9, pp. 1–23, 2023. doi: 10.3390/agriculture13091812.

[7] Y. C. Chen et al., "Automatic Wild Bird Repellent System Based on Deep-Learning-Based Wild Bird Detection and Integrated with a Laser Rotation Mechanism," *Sci. Rep.*, vol. 14, no. 1, pp. 1–15, 2024. doi: 10.1038/s41598-024-66920-2.

[8] M. Liu, X. Wang, A. Zhou, X. Fu, and C. Piao, "UAV-YOLO: Small Object Detection on Unmanned," *Sensors*, vol. 20, no. 8, pp. 2238, 2020.

[9] S. J. Al-Mekhlafi and M. R. Shamsuddin, "Development of an Autonomous Underwater Biofouling Detection System Using Deep Learning," *International Journal of Robotics and Automation*, vol. 35, no. 3, pp. 143–152, 2021.

[10] S. K. Phang et al., "From Satellite to UAV-Based Remote Sensing: A Review on Precision Agriculture," *IEEE Access*, vol. 11, no. November, pp. 127057–127076, 2023. doi: 10.1109/ACCESS.2023.3330886.

[11] T. Wu, "YOLO-SE: Improved YOLOv8 for Remote Sensing Object Detection and Recognition,"*Applied Sciences*, vol. 13, no. 4, pp. 981, 2023. doi: 10.3390/app13040981.

[12] J. Trethowan, Z. Wang, and K. C. Wong, "The Viability of a Grid of Autonomous Ground-Tethered UAV Platforms in Agricultural Pest Bird Control," *Machines*, vol. 11, no. 3, pp. 377, 2023. doi: 10.3390/machines11030377.

[13] D. B. M. Yousefi and A. S. M. Rafie, "A Systematic Literature Review on the Use of Deep Learning in Precision Livestock Detection and Localization Using Unmanned Aerial Vehicles,"*IEEE Access*, vol. 10, no. August, pp. 80071–80091, 2022. doi: 10.1109/ACCESS.2022.3194507.

[14] S. K. Phang et al., "From Satellite to UAV-Based Remote Sensing: A Review on Precision Agriculture," *IEEE Access*, vol. 11, no. November, pp. 127057–127076, 2023. doi: 10.1109/ACCESS.2023.3330886.

[15] D. M. Yousefi and A. S. M. Rafie, "A Systematic Literature Review on the Use of Deep Learning in Precision Livestock Detection and Localization Using Unmanned Aerial Vehicles," *IEEE Access*, vol. 10, no. August, pp. 80071–80091, 2022. doi: 10.1109/ACCESS.2022.3194507.

[16] N. Aliane, "Drones and AI-Driven Solutions for Wildlife Monitoring," 2025.

[17] S. Kim, Y. Kim, and S. Choi, "The Development of a MATLAB / Simulink-SCAD A / EMS-Integrated Framework for Microgrid Pre-Validation," pp. 1–22, 2025.

[18] M. Ariza-Sentís, S. Vélez, R. Martínez-Peña, H. Baja, and J. Valente, "Object Detection and Tracking in Precision Farming: A Systematic Review," *Computers and Electronics in Agriculture*, vol. 219, pp. 108757, 2024. doi: 10.1016/j.compag.2024.108757.

[19] L. Chen, G. Li, S. Zhang, W. Mao, and M. Zhang, "YOLO-SAG: An Improved Wildlife Object Detection Algorithm Based on YOLOv8n," *Ecological Informatics*, vol. 83, p. 102791, 2024. doi: 10.1016/j.ecoinf.2024.102791.

[20] L. Shen, B. Lang, and Z. Song, "DS-YOLOv8-Based Object Detection Method for Remote Sensing Images," *IEEE Access*, vol. 11, no. November, pp. 125122–125137, 2023. doi: 10.1109/ACCESS.2023.3330844.

[21] M. Zhou et al., "Improving Animal Monitoring Using Small Unmanned Aircraft Systems (sUAS) and Deep Learning Networks," pp. 1–13, 2021.

[22] P. Velusamy, S. Rajendran, R. K. Mahendran, S. Naseer, M. Shafiq, and J. Choi, "Applications and Challenges in Precision Agriculture," *Journal of Precision Agriculture*, vol. 27, no. 2, pp. 123–145, 2023.

[23] E. B. Micaelo, L. G. P. S. Lourenço, P. D. Gaspar, J. M. L. P. Caldeira, and V. N. G. J. Soares, "Bird Deterrent Solutions for Crop Protection: Approaches, Challenges, and Opportunities," *Agriculture*, vol. 13, no. 4, pp. 1–29, 2023. doi: 10.3390/agriculture13040774.

[24] D. A. Case and L. Noctuidae, "Rapid Assessment of Insect Pest Outbreak Using Drones: A Case Study with Spodoptera exigua (Hübner) (Lepidoptera: Noctuidae) in Soybean Fields," *Journal of Agricultural Science*, 2023.

[25] R. F. Storms, C. Carere, R. Musters, H. Van Gasteren, S. Verhulst, and C. K. Hemelrijk, "Deterrence of Birds with an Artificial Predator, the RobotFalcon," *Journal of the Royal Society Interface*, vol. 19, no. 195, 2022. doi: 10.1098/rsif.2022.0497.