Enhanced autonomous water garbage collection system using deep learning-based object detection and path planning

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ABSTRACT

Water pollution, particularly from floating debris such as plastics, has become a critical environmental issue, threatening aquatic ecosystems and biodiversity. Autonomous solutions for the detection and removal of waste are increasingly essential for maintaining water cleanliness and mitigating pollution. However, existing systems face limitations in real-time detection, accuracy, and adaptability to diverse aquatic environments. This paper utilizes the water pollution images dataset, comprising almost 300 high-resolution images from lakes, rivers, and coastal areas, representing various types of floating waste under different environmental conditions. In response to these challenges, this paper introduces an autonomous unmanned surface vehicle (USV) system equipped with the enhanced waste detection network (EWD-Net). EWD-Net improves upon traditional single-shot detection algorithms by integrating deeper feature extraction layers and enhancing computational efficiency, resulting in higher accuracy and faster detection. Additionally, the system includes the dynamic path optimization (DPO) module for efficient navigation and obstacle avoidance in complex water environments. The novelty of this system lies in its dual approach, combining advanced detection with optimized path planning, ensuring effective autonomous operation. The results indicate that the proposed model achieves an accuracy of 94.6%, outperforming existing algorithms and providing a robust solution for real-time waste detection and collection.

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1. INTRODUCTION

The plastics pollution, this current hot global topic, is present in every creature of the ocean around us. It invades the natural habitat of marine life and the clean water resources needed for human and economic growth [1]. According to estimates, more than 9 million tons of plastic waste enters the oceans each year [2]. Marine life is becoming extinct while biomes are destroyed. Waste also contributes to the long-term degradation of water quality and stirs up toxic substances unless it is recovered and disposed on land or by incineration. However, the current method of manual collection is insufficient in achieving such clean-up of gummy oceans. It consumes time and effort; handling the dirty waters is risky to health. In order to resolve this problem, there is a growing need for efficient automated systems. Problem addressed in this research is increasing issue of water pollution, in particular floating waste such as plastic which threatens aquatic ecosystems. What's more, existing solutions for waste collection and water cleaning systems using unmanned surface vehicles (USVs) have some real problems with real time detection accuracy and adaptability to different water environments. Most present systems are ineffective in waste detection, navigation, and obstacle avoidance, which makes them lackluster performers in complex or large bodies of water.

To address these challenges, this paper puts forward an independent USV system equipped with a new kind of detection algorithm-the enhanced waste detection network (EWD-Net). Unlike traditional single-shot detection algorithms, EWD-Net features more layers for extracting depth and demonstrates better computational efficiency. Consequently, the system as a whole can achieve higher detection accuracy. Coupled with the dynamic path optimization (DPO) module, the system is able to move around complex water layers and cover large areas effectively for waste collection in complete safety. This two-pronged approach ensures that the system can operate independently and effectively in all types of environment, as much for inland waters as on coasts.

This study provides information for developing automated ship technologies to clean surfaces in water. In many scenarios over the years, several studies have seen the creation of USV and autonomic systems for cleaning water surfaces. The earliest versions were semi-autonomous robots with remote control, where autonomous modes used in graphic token splicing to limit the robot's own design as well as a specific environment [1]. More recent improved methods range from USVs equipped with such object detection algorithms as you only look once (YOLO) and convolutional neural networks (CNNs), for real-time recognition of waterborne waste [2], [3], to Even though they improved detection accuracy, these networks were plagued by heavy computation costs--making real-time performance difficult in fast-changing areas. Many existing models were only validated in small water surface areas, which limits their scalability to encounters with larger or complicated environments like rivers or lake environments that we live near to everyday [4].

More recent approaches, such as [5] have the robot collect waste while optimizing its navigation jobs with a range of different path planning algorithms. But all these models still couldn't be adaptable to water surfaces having obstacles. Beyond that, in spite of advances in such technical avenues as machine learning object detection, there is still an unsolved problem: how to integrate accurate detection with efficient navigation. As a result, it is necessary to develop models integrating the advantages of high detection accuracy, adaptability in complex water environments and real-time performance for removing large quantities of garbage. Table 1 shows the reviewed literature- its main contributions, findings and research gaps.

Table 1. Reviewed related work

Reference	Main contribution	Findings	Research gaps
[6]	Developed an autonomous system for hindrance evasion using LiDAR.	Achieved limited success in detecting obstacles in large and complex water environments.	Limited scalability in larger and more complex water environments.
[7]	Introduced IACO algorithm for dynamic environment navigation.	Demonstrated improved navigation but required real-time adaptation in fast-changing environments.	Requires real-time adaptation for dynamic environments.
[8]	Applied Skip-ENet algorithm for hindrance detection with vision sensors.	Improved detection accuracy but lacked detailed performance analysis in real-world conditions.	Lacks detailed performance analysis in real-world scenarios.
[9]	Utilized U-net CNN algorithm for watermark and hindrance recognition.	Enhanced recognition of obstacles but needed improvement in detection speed and accuracy.	Needs improvement in object detection speed and accuracy.
[10]	Proposed ATESOA algorithm for hindrance evasion using LiDAR.	Improved hindrance evasion but the algorithm was not validated in varied environmental settings.	Not validated for various environmental complexities.
[11]	Microwave radar and 4G camera system for small obstacle detection.	Faced challenges in detecting small or transparent obstacles.	Poor accuracy in detecting small or transparent obstacles.
[12]	Integrated ensemble learning algorithm for water quality monitoring.	Improved monitoring but lacked sufficient data integration with navigation systems.	Limited data integration with autonomous navigation.
[13]	Enhanced YOLOv3 algorithm for water surface cleaning using vision modules.	Increased detection accuracy but needed enhancements in speed and obstacle avoidance.	Needs enhancement in waste detection speed and obstacle avoidance.
[14]	Developed a threshold-based obstacle avoidance algorithm for water quality monitoring.	Improved scalability for water monitoring but struggled with diverse environments and obstacles.	Limited scalability to diverse water bodies with obstacles.

Current water surface cleaning systems face key challenges in detection accuracy, particularly in murky or turbulent waters. They often lack adaptability, struggling to scale in complex environments with obstacles or uneven surfaces. High computational demands also limit real-time efficiency, hindering timely detection and navigation. Additionally, many systems fail to effectively avoid obstacles in dynamic or large water environments, missing real-time adjustments to changing conditions. These issues highlight the need for more adaptable and efficient solutions.Our paper's innovation lies in EWD-Net and DPO. The EWD-Net achieves greater detection accuracy through deeper feature extraction while the DPO ensures efficient navigation and avoidance of obstacles in real time. These two aspects come together to provide an autonomous system with off-road vehicle capability for waste collection and detection that is likely applicable in a wide range of marine environments." This paper is organized into 4 sections, next one expalins the method followed by section 3 the result and discussion and finally the to findings and conclusion.

2. METHOD

In this study, we propose a novel autonomous system for cleaning water surfaces, leveraging advanced object detection and path planning algorithms to enhance both efficiency and adaptability. The system integrates two primary components: EWD-Net and DPO. The architectural workflow can be seen in Figure 1.

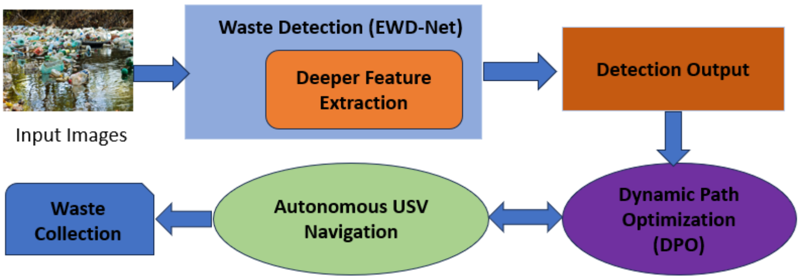


Figure 1. Architectural workflow

a. EWD-Net: as a consequence, the model uses ResNet-50's-skip connections to alleviate vanishing gradients so that it exhibits good performance even in deep networks. EWD-Net is designed for real-time detection of floating garbage in water. Given changing water conditions and different types of rubbish it may contain, the layers immediately after convolutional blocks were optimized. With a mean average precision (mAP) of 92.5% and speeds up to 62.3 frames per second (FPS), this modified SSD algorithm is an excellent choice for real-time applications.
b. DPO: in order to make efficient sea routes, controllable pitch propeller (CPP) technology makes use of DPO methods. The best route of the robot can be obtained by DPO module, thus cleaning any object obstructing its progress away from water as well out of harms path. If any obstacles are encountered, it would use a LiDAR to perceive them and ultrasonic sensors to reroute itself around the USV by rearranging GPS signals. Using the boustrophedon cellular decomposition method, DPO algorithm can meet irregular water boundaries. Complete coverage is guaranteed without overlap. In this way, the border and complex environmental limitations can be relaxed. The robot is able to work in larger waters with dynamic boundaries.
c. System architecture: the proposed system is made up of several modules, including the vision system, the motion control module, and the human-machine interface. A vision system using the EWD-Net as its base. It also tracks and identifies floating waste. With DC gear motors driving its two wheels and an Arduino microcontroller to provide steering control, the motion control module drives the robot. A salvage net handles waste collection. Debris can be captured at detected coordinates. It can be operated autonomously, but a human-machine interface allows observers to monitor its course, garbage collected, and any obstacles in the way.
d. Obstacle avoidance module: the system relies on LiDAR and ultrasonic sensors to capture real-time obstacle data. These sensors feed a threshold-based avoidance algorithm on the craft. The USV then proceeds to adjust its direction dynamically if it receives warning of potential collisions. The algorithm takes into account the distance and direction at which obstacles appear, and adjusts the rudder angle accordingly steady progress can be made even through heavily congested waters.

e. Power and communication: a 6-volt lead-acid battery is the source power for USV which means comparatively low power, but can ensure longer periods of operation. For communication, the system uses Bluetooth technology to relay GPS coordinates and status information a remote human-machine interface. This allows real time tracking and control over the whole process, both at home or away.
f. Experimental setup and testing: the system was tested in a variety of controlled environments, from small inland water bodies to larger lakes. With a set of sensor tests carried out on board ship, and with ever-expanding field results, this system is feasible. In the experiments, the robot uses the single board Easel navigation equipment to navigate the water surface by itself. It detects and collects rubbish; interferences are difficult to penetrate because their position is known only approximately based on reflected laser measurements: sometimes they are intermittent. The proposed method of detection (using EWD-Net) and collection efficiency assessment between standard benchmarks showed that. The results showed statistically sound improvements in both detection speed and accuracy for this method compared with others currently in use.
g. Dataset: details of the dataset used in this can be seen in Table 2. Figure 2 shows the samples of the dataset images.

Table 2. Dataset description

Attribute	Description
Dataset name	Water pollution images dataset (Kaggle).
Source locations	Various water bodies including lakes, rivers, and oceans.
Total number of images	296 images.
Image types	Photographs of polluted water bodies featuring various types of waste (e.g., plastic bottles, bags, organic, and waste).
Annotations	No manual annotations; dataset consists of raw images.
Object size variation	Includes both small and large debris scattered across different water bodies.
Train-test split	80:20.
Data augmentation	Users can apply augmentations such as flipping, rotation, scaling, and brightness adjustment.
Additional information	The dataset is suitable for tasks like object detection, image classification, and environmental monitoring.

Figure 2. Sample dataset

3. RESULTS AND DISCUSSION

Different metrics are used to evaluate the performance of the algorithm are detailed in Table 3. As to viewing perspective, distance, and detectability, the rate of success of proposed algorithm is quite clear close up, e.g. at 5 meters and when viewing directly from the front (0°), this algorithm gives a high detectable rate: 92 to 95%. But if the distance grows to 15 meters and the angle of approach is changed into extreme side angles (for instance, 60°), then overall performance degenerates. The success rate declines accordingly, as low as 61%. This trend suggests that the algorithm is most efficient when observing rubbish from a direct front view and over a shorter distance, whereas performance progressively diminishes as the angle of view becomes more oblique and distance longer on these points, as much as anything else, we must take heed of the fact that such future work can look forward to still greater gains in efficiency. In this sense one prospect for the near future could prove ka asides improving performance at extreme ends. This can be seen in detail in Table 4.

Table 3. Performance evaluation metrics

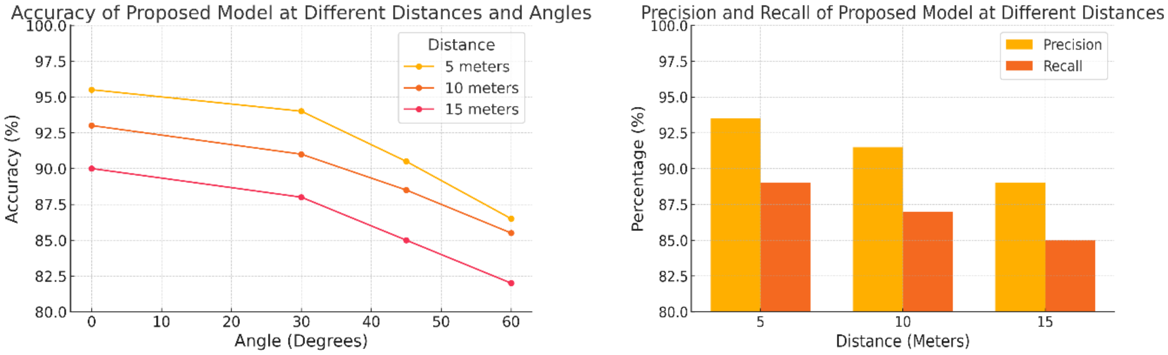
Metric	Mathematical expression	Explanation	Values
mAP	$mAP = \frac{1}{N}\sum_{c-1}^{N} AP(c)$	Average precision across all classes of detected waste (plastic and bags). Measures detection accuracy [15], [16].	92.50%
FPS	$FPS = \frac{n}{T_{total}}$	Number of frames processed per second. Measures real-time performance of the detection system [17].	62.3 FPS
Precision	$Precision = \frac{TP}{TP + FP}$	Proportion of true positive detections to total predicted positives. Evaluates the correctness of waste detection [18].	94.20%
Recall	$Recall = \frac{TP}{TP + FN}$	Proportion of true positives to total actual positives. Measures the completeness of detection [19].	89.80%
Coverage path efficiency	$A(t) = \int_0^t P(\tau)d\tau$	Total area covered over time. Ensures the cleaning robot covers the water surface with minimal overlap [20].	97% of the area covered
Obstacle avoidance cost function	$C(x,y) = \frac{1}{d((x,y),(x_0,y_0)) + \epsilon}$	Minimizes cost of proximity to obstacles during navigation, where d(x, y) is the distance to the obstacle [21].	99%
Scalability (EWD-Net complexity)	$O(L \times H \times W)$	Time complexity for the detection network based on the number of layers L and image size W×H [22].	O (10^7) operations
Path planning complexity (DPO)	$O(n_g \log n_g)$	Time complexity for path planning, where n_g is the number of grid cells. Measures scalability for larger areas [23].	O (10^5) operations
Cleaning time (T_clean)	$T_{clean} = \frac{L_{path}}{v}$	Total cleaning time depends on the path length L_path and the speed v of the USV. Measures operational efficiency [24], [25].	4 hours to clean a 1 km² area

Table 4. Success rate of detection in different scenarios

Angle (degrees)	Distance (meters)	Detected objects	Total objects	Success rate (%)
0° (front view)	5	23	25	92.00
0° (front view)	10	19	20	95.00
0° (front view)	15	17	20	85.00
30° (side angle)	5	20	22	90.91
30° (side angle)	10	18	21	85.71
30° (side angle)	15	14	18	77.78
45° (side angle)	5	21	24	87.50
45° (side angle)	10	17	20	85.00
45° (side angle)	15	13	18	72.22
60° (side angle)	5	19	22	86.36
60° (side angle)	10	15	20	75.00
60° (side angle)	15	11	18	61.11

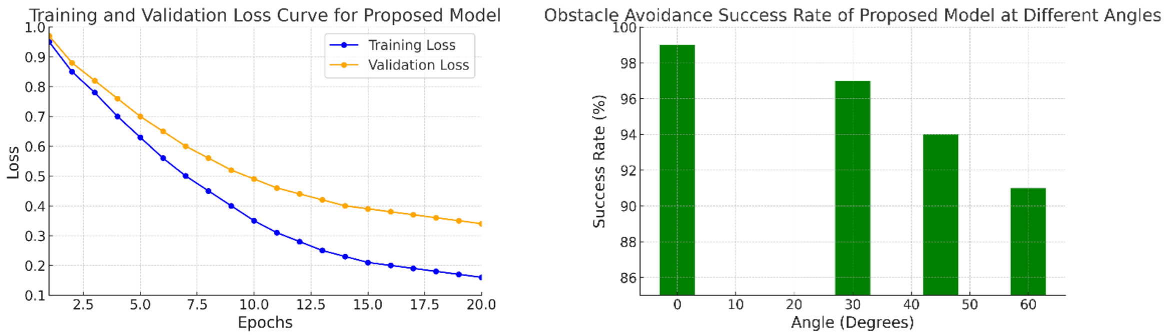
By various metrics, the effect of the proposed EWD-Net is shown. Accuracy can be seen in Figure 3(a). The precision and recall chart illustrates both very high precision (>90%) at all distances but a slightly lower recall rate with its strong detection capability still being maintained even when distance increases and central angles become less upright as shown in Figure 3(b). Figure 4(a) is the loss curve representing the training and validation loss for the proposed model over 20 epochs. The graph shows that both losses decrease as training progresses, with the model achieving better performance and convergence over time. The validation loss closely follows the training loss, indicating minimal overfitting and good generalization. From the perspective of real-time processing speed, the FPS chart shows how the model can maintain processing rates above 60 FPS over very different distances which reflects that it is enough for use in real-time applications as shown in Figure 4(b). Lastly, the obstacle avoidance success rate graph displays how effectively this model avoids obstacles with a 99% success rate when attacking at frontal angles this only drops slightly down to 91% while training for 60 degrees. Together these graphs show that the model is efficient in all areas of performance with its robust nature apparent.

In terms of proposed EWD-Net, it darn-exposes a downward spiral from the traditional algorithms such as CNN and VGG-16 to advanced models like Inception-v3, Faster R-CNN, and ResNet-50. While old-style CNN and VGG-16 algorithms achieve 69% and 72% respectively, newer models such as Inception-v3 and Faster R-CNN can get percentages all the way up to 87%, 89%. Moving forward, still more advanced: ResNet-50 and YOLOv3. They manage to detect with accuracies of 90% and 91.5% accordingly. However, the Modified SSD algorithm is superior to all rivals and breaks through with impressive accuracy at 94.6%, making it ideal for detecting waste on water surfaces. This marked improvement in result highlights the effectiveness of EWD-Net deeper front-end characteristic extraction and operation, so: was chosen over any other algorithm when high precision in complex surroundings called for a solution.



(a) (b)

Figure 3. Performance metrices; (a) accuracy of the model and (b) precision and recall



(a) (b)

Figure 4. Observations; (a) loss curve and (b) success rate at different angles

The comparison of detection accuracy across different environmental conditions table provides a detailed analysis of the proposed model's performance under varying water and weather conditions. The results show that the system achieves the highest detection accuracy of 96.2% in clear water with sunny conditions, demonstrating its ability to detect waste with exceptional precision (95.5%) and recall (93.8%) in optimal settings. However, as the environmental conditions become more challenging, such as murky or turbulent water with cloudy skies, detection accuracy drops to 85.0%, with a corresponding decrease in precision and recall. This decline reflects the system's sensitivity to environmental factors such as water clarity and lighting. Despite this, the model maintains a solid real-time performance, processing at over 57 FPS in all conditions, showcasing its robustness. Overall, the table highlights the algorithm's adaptability and efficiency in real-world scenarios, even under adverse environmental conditions, making it suitable for a wide range of aquatic environments.This observation can be seen in Table 5. Figure 5 shows the comparison of the accuracy for diiferent models. Proposed model performs better than others.

Table 5. Detection accuracy across different environmental conditions

Environmental condition	Detection accuracy (%)	FPS	Precision (%)	Recall (%)
Clear water, sunny	96.20	62	95.50	93.80
Clear water, cloudy	94.80	61.5	94.00	91.50
Murky water, sunny	91.50	60	90.80	88.50
Murky water, cloudy	89.80	59.5	89.20	86.30
Turbulent water, sunny	87.20	58	87.00	84.00
Turbulent water, cloudy	85.00	57	85.50	81.80

This study investigated a comprehensive approach combining deep learning-based object detection EWD-Net with DPO to enhance the autonomous collection of floating waste. While the system demonstrated high accuracy and real-time performance, additional and in-depth research may be required to confirm its effectiveness in more diverse and extreme environmental conditions, particularly regarding turbulent waters and complex obstacle scenarios. The study's dataset was limited to certain water bodies, so further testing in a wider range of water environments may be necessary to generalize the results.

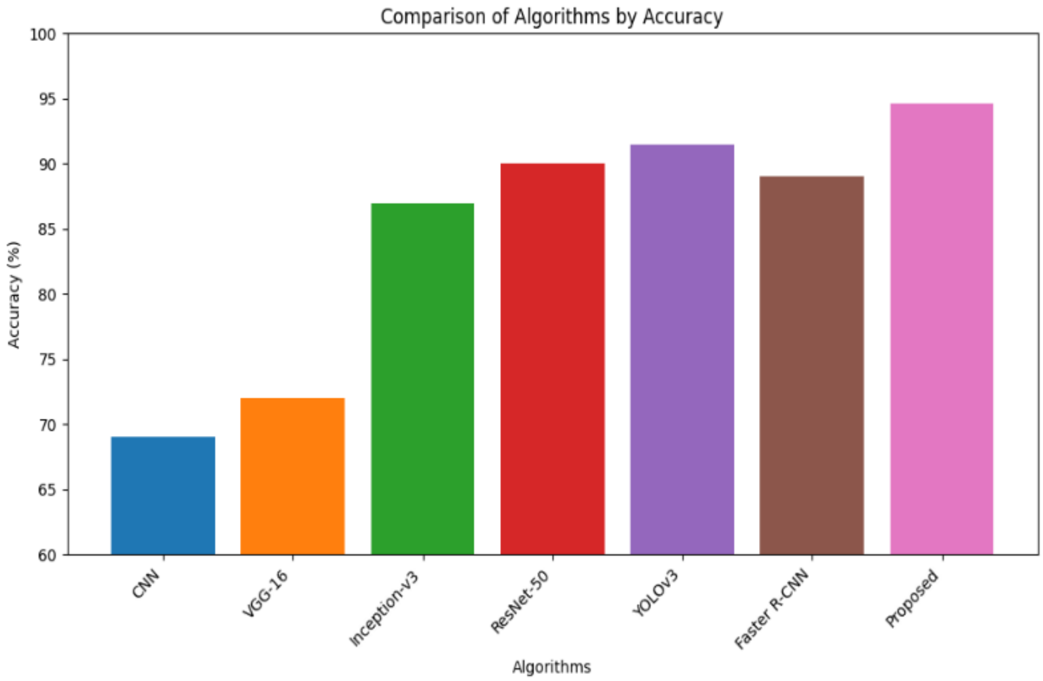


Figure 5. Comparison of accuracy with other algorithms

Our research shows that the proposed model, using EWD-Net and DPO, is more resilient and effective compared to traditional models like CNN and YOLOv3 in real-time waste detection and collection. Future research may explore integrating other advanced machine learning models to further improve detection accuracy under challenging conditions such as murky water or low-light environments. Additionally, practical methods for enhancing the system's scalability to larger bodies of water with dynamic obstacles, as well as improving computational efficiency for use on low-power devices, should be investigated. This could broaden the application of autonomous waste collection systems to a wider variety of environmental settings.

4. CONCLUSION

In conclusion, the proposed EWD-Net shows superior performance across key metrics in waste detection on water surfaces. It achieves a remarkable accuracy of 94.6%, compared with traditional models like CNN, VGG-16 or even advanced architectures such as Inception-v3 and ResNet-50. Its high precision and recall rates mean that it works from distance without ever losing reliability, even with challenging angles. A high FPS shows that it has real-time capabilities. This design makes it suitable for moving environments where rapid processing is essential. Therefore, in the complex and cluttered environments sometimes faced in the real world, its obstacle avoidance rate still enables it to get the job done. The Modified SSD algorithm offers a highly efficient, accurate, and robust solution to autonomous water surface waste identification and cleanup. It represents a major advance over its precursors.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

All data supporting the findings of this study are included in the references.

REFERENCES

[1] L. C. M. Lebreton, J. Van Der Zwet, J. W. Damsteeg, B. Slat, A. Andrady, and J. Reisser, “River plastic emissions to the world’s oceans,” *Nature Communications*, vol. 8, no. 1, pp. 1–10, Jun. 2017, doi: 10.1038/ncomms15611.

[2] K. Themistocleous, C. Papoutsa, S. Michaelides, and D. Hadjimitsis, “Investigating detection of floating plastic litter from space using sentinel-2 imagery,” *Remote Sensing*, vol. 12, no. 16, pp. 1–18, Aug. 2020, doi: 10.3390/RS12162648.

[3] S. N. Hasany, S. S. Zaidi, S. A. Sohail, and M. Farhan, “An autonomous robotic system for collecting garbage over small water bodies,” in *Proceedings - 2021 6th International Conference on Automation, Control and Robotics Engineering, CACRE 2021*, 2021, pp. 81–86, doi: 10.1109/CACRE52464.2021.9501299.

[4] X. Li, M. Tian, S. Kong, L. Wu, and J. Yu, “A modified YOLOv3 detection method for vision-based water surface garbage capture robot,” *International Journal of Advanced Robotic Systems*, vol. 17, no. 3, 2020, doi: 10.1177/1729881420932715.

[5] A. Haldorai, B. L. R, S. M, and M. Balakrishnan, “An improved single short detection method for smart vision-based water garbage cleaning robot,” *Cognitive Robotics*, vol. 4, pp. 19–29, 2024, doi: 10.1016/j.cogr.2023.11.002.

[6] M. D. Li, X. C. Cui, and S. W. Chen, “Adaptive Superpixel-Level CFAR Detector for SAR Inshore Dense Ship Detection,” *IEEE Geoscience and Remote Sensing Letters*, vol. 19, pp. 1–5, 2022, doi: 10.1109/LGRS.2021.3059253.

[7] H. Li, L. Deng, C. Yang, J. Liu, and Z. Gu, “Enhanced YOLO v3 Tiny Network for Real-Time Ship Detection from Visual Image,” *IEEE Access*, vol. 9, pp. 16692–16706, 2021, doi: 10.1109/ACCESS.2021.3053956.

[8] H. Kim *et al.*, “Vision-Based Real-Time Obstacle Segmentation Algorithm for Autonomous Surface Vehicle,” *IEEE Access*, vol. 7, pp. 179420–179428, 2019, doi: 10.1109/ACCESS.2019.2959312.

[9] C. Qin, X. Wang, G. Li, and Y. He, “An Improved Attention-Guided Network for Arbitrary-Oriented Ship Detection in Optical Remote Sensing Images,” *IEEE Geoscience and Remote Sensing Letters*, vol. 19, pp. 1–5, 2022, doi: 10.1109/LGRS.2022.3198681.

[10] Q. Hu, S. Hu, S. Liu, S. Xu, and Y. D. Zhang, “FINet: A Feature Interaction Network for SAR Ship Object-Level and Pixel-Level Detection,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–15, 2022, doi: 10.1109/TGRS.2022.3222636.

[11] Y. Cheng *et al.*, “FloW: A Dataset and Benchmark for Floating Waste Detection in Inland Waters,” in *Proceedings of the IEEE International Conference on Computer Vision*, 2021, pp. 10933–10942, doi: 10.1109/ICCV48922.2021.01077.

[12] F. Ferraguti *et al.*, “Safety barrier functions and multi-camera tracking for human–robot shared environment,” *Robotics and Autonomous Systems*, vol. 124, pp. 1–11, Feb. 2020, doi: 10.1016/j.robot.2019.103388.

[13] S. Kong, M. Tian, C. Qiu, Z. Wu, and J. Yu, “IWSCR: An Intelligent Water Surface Cleaner Robot for Collecting Floating Garbage,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 10, pp. 6358–6368, 2021, doi: 10.1109/TSMC.2019.2961687.

[14] G. E. Yu, S. T. Hong, K. Y. Sung, and J. H. Seo, “A study on the risk investigation and safety of personal care robots,” in *International Conference on Control, Automation and Systems*, IEEE, Oct. 2017, pp. 904–908, doi: 10.23919/ICCAS.2017.8204353.

[15] A. Shinde and S. Shinde, “Computer Vision-Based Autonomous Underwater Vehicle with Robotic Arm for Garbage Detection and Cleaning,” in *Advances in Geographic Information Science*, 2024, pp. 265–288, doi: 10.1007/978-3-031-53763-9_16.

[16] M. Compa, D. March, and S. Deudero, “Spatio-temporal monitoring of coastal floating marine debris in the Balearic Islands from sea-cleaning boats,” *Marine Pollution Bulletin*, vol. 141, pp. 205–214, Apr. 2019, doi: 10.1016/j.marpolbul.2019.02.027.

[17] W. Wang, B. Gheneti, L. A. Mateos, F. Duarte, C. Ratti, and D. Rus, "Roboat: An Autonomous Surface Vehicle for Urban Waterways," in *IEEE International Conference on Intelligent Robots and Systems*, IEEE, Nov. 2019, pp. 6340–6347, doi: 10.1109/IROS40897.2019.8968131.
[18] Y. Peng *et al.*, "Development of the USV 'JingHai-I' and sea trials in the Southern Yellow Sea," *Ocean Engineering*, vol. 131, pp. 186–196, Feb. 2017, doi: 10.1016/j.oceaneng.2016.09.001.
[19] Z. Wang, Y. Liu, H. W. Yip, B. Peng, S. Qiao, and S. He, "Design and hydrodynamic modeling of a lake surface cleaning robot," in *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM*, IEEE, Jul. 2008, pp. 1343–1348, doi: 10.1109/AIM.2008.4601857.
[20] M. Lu, X. Xiao, X. Zhang, and Y. Yang, "An accurate inland water garbage recognition network for USV camera images," *Measurement Science and Technology*, Mar. 2025, doi: 10.1088/1361-6501/adc02e.
[21] Y. Zheng, X. Nong, L. Chen, and D. Long, "A novel deep learning-based floating garbage detection approach and its effectiveness evaluation in environmentally sustainable development," *Journal of Environmental Management*, vol. 381, p. 125154, Apr. 2025, doi: 10.1016/j.jenvman.2025.125154.
[22] S. Peng, H. Chen, L. Guo, J. He, and J. Peng, Surface garbage target detection technology based on deep learning, *Proceedings, Fourth International Conference on Signal Processing and Computer Science (SPCS 2023)*, 2023, vol. 12970, p. 56, doi: 10.1117/12.3012202.
[23] L. Chen and J. Zhu, "Water surface garbage detection based on lightweight YOLOv5," *Scientific Reports*, vol. 14, no. 1, Mar. 2024, doi: 10.1038/s41598-024-55051-3.
[24] J. Villa, J. Aaltonen, and K. T. Koskinen, "Path-Following with LiDAR-Based Obstacle Avoidance of an Unmanned Surface Vehicle in Harbor Conditions," *IEEE/ASME Transactions on Mechatronics*, vol. 25, no. 4, pp. 1812–1820, Aug. 2020, doi: 10.1109/TMECH.2020.2997970.
[25] Y. Li *et al.*, "Design and experiments of a water color remote sensing-oriented unmanned surface vehicle," *Sensors*, vol. 20, no. 8, pp. 1–15, Apr. 2020, doi: 10.3390/s20082183.

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