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Autonomous Watercraft for Cleanup of Floating Waste in Water Bodies Using YOLO

S Ashok[1], V Anne Joan Venita[2], E Gowri Shankari[2], M Ranjana[2] and V Prabhu[3]

[1]Associate Professor, Dept of ECE Vel Tech Multi Tech Dr. Rangarajan Dr. Sakunthala Engineering College (Autonomous), Chennai, Tamil Nadu, India
[2]UG Scholar, Dept of ECE, Vel Tech Multi Tech Dr. Rangarajan Dr. Sakunthala Engineering College (Autonomous), Chennai, Tamil Nadu, India
[3]Professor Dept of ECE, Dept of ECE, Vel Tech Multi Tech Dr. Rangarajan Dr. Sakunthala Engineering College (Autonomous), Chennai, Tamil Nadu, India

Correspondence to: S Ashok, sashok@veltechmultitech.org

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ABSTRACT

The proposed work deals with the very pertinent issue of plastic waste within enclosed bodies through design and development of an innovative Unmanned Surface Vehicle (USV) targeted specifically towards effective debris gathering. The modular approach will draw upon a catamaran-like configuration, applying PVC hulls to provide added buoyancy and stability while introducing a modular debris collection system designed to improve capture and removal rates of floating waste. Actuated by DC motors, the controls are exercised through an ESP32 microcontroller that makes the USV equally functional in remote-controlled as well as autonomous modes. Thus, it is highly adaptable to various operational environments. In autonomous mode of operation, onboard camera has been installed so that the python-based computer vision algorithms can be utilized for real-time detection of debris and navigation accordingly to ensure that accurate collection of waste materials. It is agile yet eco-friendly solution that works efficiently under many conditions rather than just one for better plastic waste management. The USV addresses more robust automated and repeatable approaches to debris gathering, which reduce workforce intervention during remediating operations and support efforts aimed at preserving aquatic ecosystems.

Keywords: Catamaran USV, YOLOv8 debris detection, ESP32 motor control, Modular floating waste collector, Autonomous narrow-canal navigation

Introduction

Floating waste pollution has emerged as one of the most pressing global environmental challenges of the 21st century. It severely impacts biodiversity, disrupts fragile aquatic ecosystems, hampers the livelihoods of communities relying on water resources, and endangers public health. The problem is especially acute in urban and semi-urban regions where garbage often accumulates in narrow canals, lakes, and drainage systems. These water bodies, while small in size, play a critical role in water circulation and community sanitation but are frequently neglected due to the difficulty of accessing and cleaning them. Traditional methods for cleaning such polluted water bodies rely heavily on manual labour or bulky mechanical skimmers and nets. Manual cleaning exposes workers to harmful pathogens and chemicals found in contaminated water, posing serious health risks. Moreover, these efforts are time-consuming, labour-intensive, and not scalable. On the other hand, large mechanical solutions are not only expensive to deploy and maintain but also impractical for narrow or shallow water bodies due to their size and limited manoeuvrability. Although some autonomous robotic solutions have been developed to address the issue of floating waste collection, most are designed for open or large water bodies. These existing systems often face significant limitations in confined environments—they lack the agility to navigate tight spaces, the precision needed for obstacle avoidance in cluttered areas, or the ability to efficiently collect waste without obstructing their own movement. In some cases, their waste collection mechanisms are bulky, inefficient, or unable to adapt to varying water flow and waste patterns in constrained settings. Our project aims to bridge these gaps by designing and building a compact, remote-controlled watercraft with autonomous navigation capabilities specifically tailored for narrow and restricted water bodies. This watercraft is engineered for stability and agility, allowing it to move efficiently through tight spaces without losing balance or direction. Unlike conventional robots, our solution includes a built-in scooping mechanism that collects floating debris without interrupting the watercraft's movement. This design minimizes drag and prevents entanglement, ensuring continuous and efficient operation. The use of embedded systems, smart sensors, and real-time object detection using computer vision technologies (like YOLOv8) enables the craft to autonomously detect and avoid obstacles, recognize waste materials, and make navigation decisions dynamically. By automating the entire waste collection process, our solution reduces the need for human intervention, lowers the risk of exposure to harmful substances, and enables consistent cleanup operations in areas that are typically neglected due to their inaccessibility.

Earlier Works

Numerous efforts have been made to tackle the challenges of waste management, particularly in automating the processes of waste sorting and removal. One study proposed a hybrid approach that combines automated and manual techniques using Near-Infrared (NIR) and Visible (VIS) optical sorting systems. While this method improves sorting purity and efficiency, its performance heavily depends on system calibration, material composition, and other environmental factors, limiting its adaptability in complex, dynamic environments.[1] Another study introduced RWCNet, a deep learning model based on the TrashNet dataset, to classify recyclable garbage into six distinct categories. This demonstrated the growing potential of AI and machine learning in waste sorting, especially in handling the variability of waste characteristics. However, its primary focus remained on classification accuracy within controlled datasets, not on real-time application in water-based environments.[2] Further research addressed robotic systems for sorting mixed industrial waste, focusing on three technical aspects: adaptive

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end-effectors, high-accuracy sensing, and advanced planning algorithms. These studies made significant strides in improving robotic dexterity and object identification, but were largely designed for solid-ground industrial settings, not aquatic or floating waste collection.[3] Work in sustainable construction also explored reconfigurable systems using modular self-locking blocks (SL-blocks), offering insights into structural adaptability. Though innovative, this research remains in the construction domain and does not intersect with waste-cleaning robotics.[4] One of the most relevant works for our project introduced a floating robotic platform equipped with a conveyor belt and oil-water separation system for river cleanup. This early-stage concept illustrated a promising direction for aquatic waste collection. However, it lacked detailed implementation for narrow or highly restricted water bodies, and did not address dynamic navigation, debris detection, or integration of real-time computer vision.[5]

Proposed Methodology

The methodology of the autonomous watercraft is to develop a cost-efficient system to clean floating wastes from water bodies especially in constraints locations like canals and small rivers. This system is required to work autonomously, using computer vision and path planning for garbage detection and collection. The system must be able to operate in different environmental conditions while focusing on being ecofriendly, requiring low human maintenance intervention and reasonable cost.[6] The use of real time waste detection and path planning algorithms allows the continuous operation of the automated watercraft, which helps in promoting environment conservation with the help of technology. The hardware system of autonomous watercraft is designed to efficiently clean up floating waste in water bodies. The watercraft has a catamaran style frame made of light weight PVC pipe for durability, buoyancy and stability. Propulsion is driven by DC motors connected to propellers, their speed and direction is controlled by a L298N motor driver. The ESP32 microcontroller acts as a central processing device, integrating information from sensors and cameras, performing motion commands and managing wireless communications. The schematic diagram of the autonomous boat for collecting waste is shown in Figure 1.[7]

In Figure 1, the ESP32 microcontroller acts as a central unit for controlling all components. It uses Wi-fi and Bluetooth capabilities of the ESP32 for wirelessly controlling all the components of the system. Lithium cell holders are used for powering the ESP32, the DC motors, and the other components. L298N motor drivers enable speed and direction control of the four DC motors that drive the attached propellers for movement. The 3-inch pipes and caps form a buoyant or structural framework that holds up the buoyancy in keeping the system stable, and the square basket setup serves to collect debris or for other tasks, as need be. This all combines together to make it a module and efficient design, presumably for an autonomous or remotely operated watercraft.[8]

Figure 2 shows the working process of the autonomous boat, which first loads the YOLO object detection model, then connects the camera, establishes a WebSocket for communication purposes, and captures live video frames continuously. These live video frames are processed for the purpose of detecting waste in them using YOLO model. If no waste is detected, the system keeps processing the incoming frames. If it finds a waste, the boat counts the Euclidean distance of the waste from the boat. The boat sends all commands through the ESP32 microcontroller controlling the

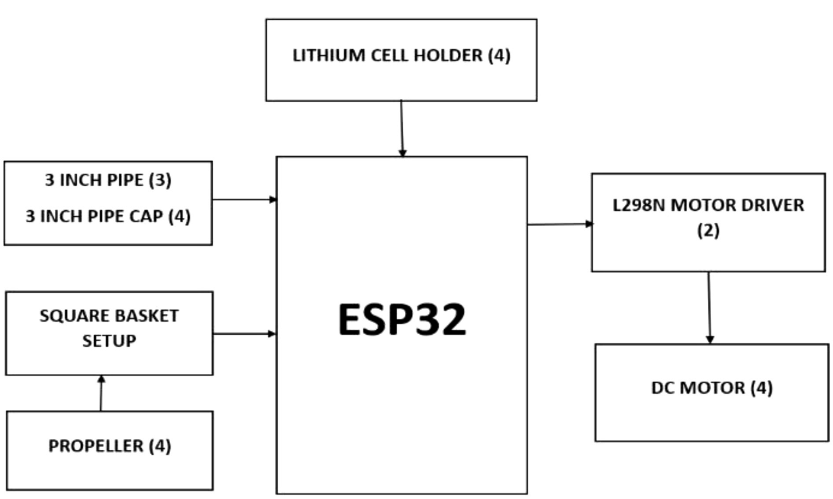

Fig 1 | Schematic diagram of the autonomous boat for collecting waste

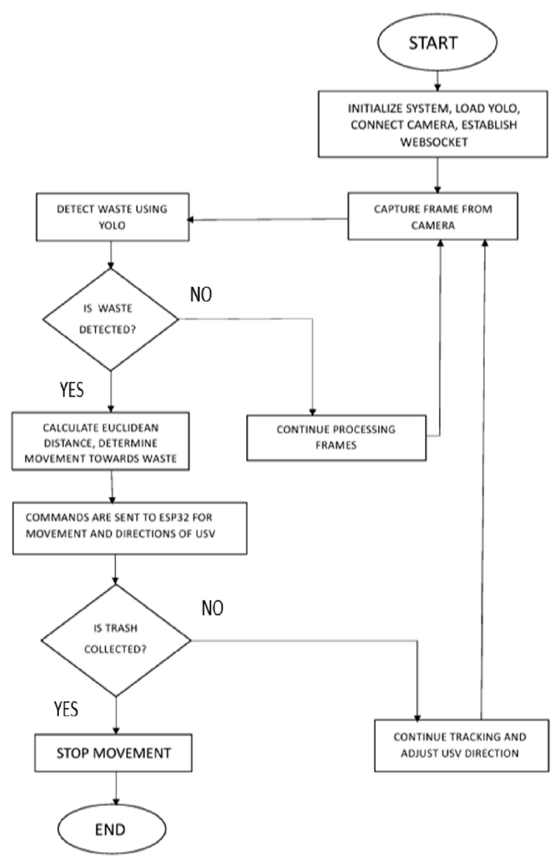

Fig 2 | Flowchart representation of the work flow of the autonomous watercraft using YOLOv8 motors by setting its direction for getting close to the waste. After aligning toward the waste, following the waste, it proceeds for picking up the waste. Once the waste is well-collected into the basket, movement of the boat will come to a stop. However, if the waste is still in water, then the system dynamically reiterates directions and moves accordingly until the task is well done.[9]

Result and Discussions

The watercraft that is designed to be independent and self-driven in this study applies computer vision for identifying and retrieving floating debris within an aquatic ecosystem. The current system uses the YOLO-based framework and has accuracy has reached up to 92% for detecting surface debris, which are plastics and other waste materials under different environmental conditions.

Figure 3 shows the hardware setup of the autonomous boat used for collecting waste which has integrated proximity sensors and navigation algorithms for obstacle avoidance, hence assuring dependability even in highly confined aquatic systems like canals and narrow rivers.[10,11] Hardware is made of a PVC catamaran style frame, with DC motor propulsion controlled by an ESP32 microcontroller. It not only automates the process of waste cleanup but also minimizes human intervention towards sustainable water resource management, which further improves the health of the aquatic ecosystem.

Figure 4 demonstrates YOLO-based object detection model applied to identify and classify different kinds of waste. Each object like bottles, brushes and containers appears inside a bounding box with a class label and its corresponding confidence score. This model analyses the scene, localizes multiple objects even when they are overlapped.

Figure 5 represents the training and validation progression of our YOLOv8 model regarding floating debris detection. The box_loss and cls_loss depicts a trend of gradually decreasing loss, meaning the model learns to predict a right bounding boxes, classify debris and localization of objects. In the same way, the validation metrics such as precision and recall boxes increase progressively, meaning it has a good generalization for unseen data. In other words, increased precision means that the model becomes more accurate at pinpointing actual debris, whereas increasing recall indicates that the model is correctly detecting more and more floating debris. This denotes the general effectiveness of the model in detecting and locating debris with high precision and reliability.[12,13]

Table 1 depicts the training history of the YOLOv8 model over 35 epochs, showing key metrics for both training and validation.Training losses, box_loss, cls_loss and dfl_loss, are all declining, indicating that the model is getting better at predicting accurate bounding boxes, classifying debris, and locating objects. Validation losses also tend to follow a downward trend, indicating good generalization to unseen data. Metrics such as precision and recall indicate how well the model is doing in detechting true positives and minimizing false negatives.[14,15] Further the learning rates for different parameter groups decrease step by step to ensure fine tuning with training.

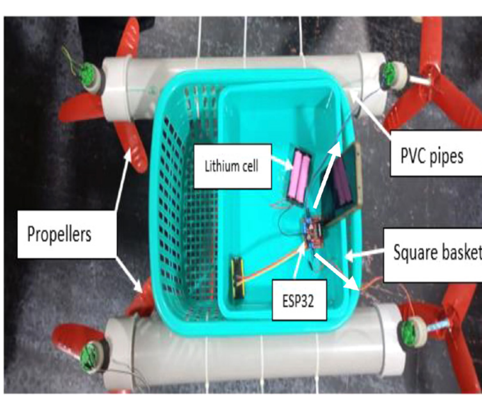

Fig 3 | Hardware setup of the autonomous boat used for collecting waste

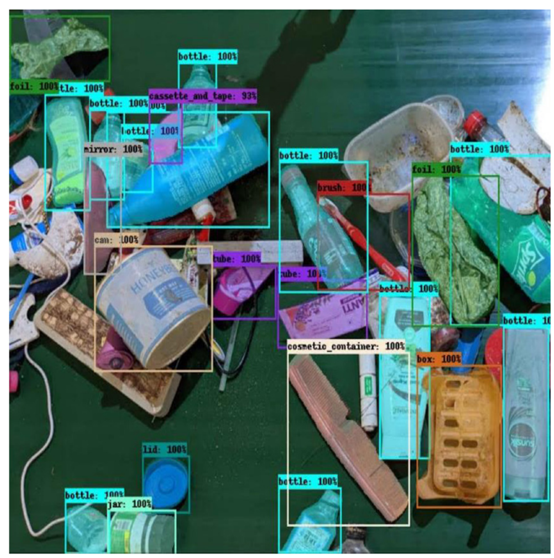

Fig 4 | Visual representation of waste detection and classification using YOLOv8

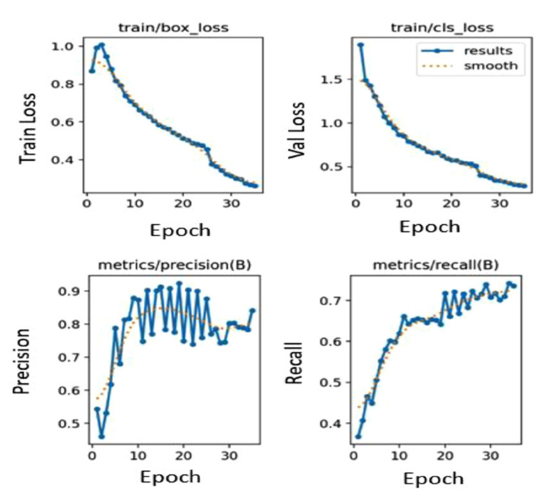

Fig 5 | Detection accuracy versus scale metrics of the trained YOLOv8 model

Table 1 | Training and validation metrics from the testing optimization of the YOLOv8 model

S. No	train/ box_loss	train/ cls_loss	train/ dfl_loss	metrics/pre-cision(B)	metrics/ recall(B)	metrics/ mAP50(B)	metrics/ mAP50-95(B)	val/ box_loss	val/ cls_loss	val/ dfl_loss	lr/pg0	lr/pg1	lr/pg2
1	0.86832	1.8963	1.4268	0.5437	0.36758	0.385138	0.22156	1.3113	2.611	1.9672	0.000255	0.000255	0.000255
2	0.99207	1.4881	1.5159	0.46	0.40753	0.361938	0.21568	1.3179	1.9743	1.9173	0.000497	0.000497	0.000497
3	1.0091	1.4252	1.5522	0.53095	0.46609	0.409931	0.27141	1.1884	1.591	1.5972	0.000724	0.000724	0.000724
4	0.94573	1.3029	1.4467	0.61742	0.40943	0.429511	0.34066	0.99779	1.5138	1.5929	0.000704	0.000704	0.000704
5	0.87881	1.1988	1.4226	0.78834	0.50579	0.609746	0.34915	1.0369	1.2697	1.6996	0.000682	0.000682	0.000682
6	0.81641	1.1097	1.4452	0.5128	0.552	0.387346	0.32945	0.94654	1.2847	1.6188	0.000662	0.000662	0.000662
7	0.74164	0.9971	1.3475	0.81303	0.5802	0.682933	0.35371	0.78115	0.95851	1.3164	0.000637	0.000637	0.000637
8	0.73875	0.94551	1.295	0.81909	0.61411	0.691162	0.36176	0.70689	0.91412	1.384	0.000617	0.000617	0.000617
9	0.70927	0.86547	1.2857	0.87931	0.59844	0.749034	0.6087	0.66538	0.82743	1.2789	0.000595	0.000595	0.000595
10	0.69069	0.85253	1.271	0.87355	0.61984	0.705898	0.58454	0.61765	0.75923	1.2222	0.000573	0.000573	0.000573
11	0.68632	0.78908	1.2435	0.74821	0.66196	0.681902	0.54009	0.61803	0.71931	1.2135	0.000551	0.000551	0.000551
12	0.6447	0.76846	1.2339	0.76995	0.62253	0.684673	0.56453	0.61994	0.69437	1.2315	0.00053	0.00053	0.00053
13	0.60653	0.7142	1.2098	0.90191	0.72174	0.772803	0.75807	0.63872	0.69376	1.255	0.000508	0.000508	0.000508
14	0.5855	0.675	1.198	0.78955	0.60034	0.671593	0.65807	0.63879	0.67395	1.229	0.000486	0.000486	0.000486
15	0.57202	0.65889	1.1789	0.78338	0.64587	0.68871	0.67513	0.54675	0.62129	1.1466	0.000443	0.000443	0.000443
16	0.56275	0.64614	1.1689	0.73862	0.64565	0.670156	0.65758	0.53836	0.59921	1.1567	0.000421	0.000421	0.000421
17	0.54307	0.62712	1.1572	0.77577	0.64456	0.685806	0.69082	0.54836	0.59921	1.1567	0.000399	0.000399	0.000399
18	0.53164	0.59858	1.153	0.92937	0.64187	0.78645	0.78645	0.50232	0.54711	1.1081	0.000377	0.000377	0.000377
19	0.51416	0.578	1.134	0.92119	0.71787	0.78645	0.78645	0.50329	0.55647	1.1181	0.000356	0.000356	0.000356
20	0.50436	0.57356	1.1277	0.93078	0.71698	0.79542	0.79542	0.49177	0.55558	1.1003	0.000334	0.000334	0.000334
21	0.48775	0.56036	1.1096	0.72123	0.70048	0.72123	0.70048	0.50368	0.55558	1.1003	0.000312	0.000312	0.000312
22	0.48336	0.54022	1.1162	0.89957	0.66901	0.7952	0.7952	0.4917	0.54238	1.0923	0.00029	0.00029	0.00029
23	0.47529	0.53429	1.1023	0.91776	0.70694	0.83048	0.75306	0.46452	0.51651	1.0631	0.000269	0.000269	0.000269
24	0.45589	0.51191	1.0982	0.87713	0.68308	0.84585	0.74317	0.47591	0.49128	1.0882	0.000248	0.000248	0.000248
25	0.37746	0.40325	1.0423	0.77715	0.70046	0.77023	0.83499	0.46452	0.51651	1.0631	0.000225	0.000225	0.000225
26	0.3647	0.39237	1.0243	0.78517	0.70046	0.77023	0.83499	0.42631	0.48437	1.0381	0.00018	0.00018	0.00018
27	0.34487	0.37477	1.0101	0.74345	0.77056	0.79362	0.82993	0.42631	0.48437	1.0381	0.000162	0.000162	0.000162
28	0.31551	0.33927	0.98727	0.80184	0.70831	0.84776	0.76596	0.40212	0.46618	1.0042	0.000138	0.000138	0.000138
29	0.30228	0.32856	0.97748	0.79178	0.70835	0.84628	0.75956	0.4166	0.47328	1.0143	0.000116	0.000116	0.000116
30	0.29649	0.31335	0.97101	0.79717	0.795	0.84628	0.75956	0.4166	0.47328	1.0143	0.0000947	0.0000947	0.0000947
31	0.28664	0.29155	0.94969	0.78387	0.74271	0.84329	0.74329	0.40457	0.47546	1.0073	0.0000729	0.0000729	0.0000729
32	0.26844	0.29155	0.94969	0.78387	0.74271	0.84329	0.74329	0.40457	0.47546	1.0073	0.0000729	0.0000729	0.0000729
33	0.26346	0.29155	0.94969	0.78387	0.74271	0.84329	0.74329	0.40457	0.47546	1.0073	0.0000729	0.0000729	0.0000729
34	0.26274	0.29155	0.94969	0.78387	0.74271	0.84329	0.74329	0.40457	0.47546	1.0073	0.0000729	0.0000729	0.0000729
35	0.26274	0.28261	0.94172	0.84074	0.73638	0.84248	0.73659	0.38568	0.44934	0.99912	0.0000294	0.0000294	0.0000294

Conclusion and Future Scope

The proposed work focuses on the development of an autonomous watercraft to address the increasingly major problem of floating waste within water bodies, especially in narrow canals and small rivers. Equipped with smart hardware and intelligent software, this watercraft can identify wastes in real time, navigate efficiently and collect debris effectively. The module design allows it to adapt to different environments, but autonomous features minimize the level of human intervention. It presents a practical solution to water pollution, which helps in the protection of aquatic ecosystems and contributes towards clean water bodies.

In the future, AI watercraft can be used for the better detection and classification of waste. The system can be made even more useful by adding environmental sensors that can monitor the water quality parameters, such as pH and turbidity. With improvements in solar panel efficiency, it would increase the time of operation and the design could be scaled up for larger water bodies or modified for specific tasks like cleaning up oil spills. Incorporating IoT technology for remote monitoring and management would give better control and data insights. Such upgrades might make the watercraft and essential tool in addressing global water pollution.

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