International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 235- 242
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0032

Autonomous River Clean Up

Girijalakshmi[1], Lakshmi Devi D[2], Hajira Shahnaz A[3], Akash M[4], Jeevitha S[5], Deeraj PJ[6]
[1]Assistant Professor, Dept. of ECE, HKBK College of Engineering, Bengaluru, Karnataka, India
[2]Assistant Professor, Dept. of ECE, HKBK College of Engineering, Bengaluru, Karnataka, India
[3]UG Scholar, Dept. of ECE, HKBK College of Engineering, Bengaluru, Karnataka, India
[4]UG Scholar, Dept. of ECE, HKBK College of Engineering, Bengaluru, Karnataka, India
[5]UG Scholar, Dept. of ECE, HKBK College of Engineering, Bengaluru, Karnataka, India
[6]UG Scholar, Dept. of ECE, HKBK College of Engineering, Bengaluru, Karnataka, India
Emails: *girijal.ec@hkbk.edu.in[1], lakshmidevi.ec@hkbk.edu.in[2], hajiraashrap0303@gmail.com[3], akash1374m@gmail.com[4], petkarjeevi@gmail.com[5], deerajpj2004@gmail.com[6]*

Abstract
Floating plastic waste in rivers poses severe environmental risks and demands continuous monitoring and removal. Existing manual or semi-autonomous cleaning approaches are slow, labor-intensive, and limited in detection accuracy under dynamic water conditions. To address this gap, this work proposes an AI-assisted autonomous river clean-up robot capable of detecting, navigating toward, and collecting floating debris in real time. The system uses a Raspberry Pi with a Coral Edge TPU for high-speed inference, an Arduino microcontroller for deterministic motor and conveyor control, and a conveyor-based mechanism for physical waste retrieval. A custom dataset was prepared using Roboflow and the model was trained on Google Colab to generate an optimized TensorFlow Lite model. Experimental results show high detection accuracy, stable movement, and efficient waste collection. The system demonstrates a practical, low-cost solution for automated floating waste management in inland water bodies.
Keywords: *River cleaning robot, Coral Edge TPU, Raspberry Pi, Arduino, TensorFlow Lite, autonomous waste collection, IoT monitoring*

1. Introduction
Water pollution caused by floating waste has become a critical environmental challenge in rivers, canals, and lakes. Plastics and non-biodegradable materials accumulate rapidly, harming aquatic ecosystems and increasing the cost of water treatment. Traditional cleaning methods rely heavily on manual labor, making them inefficient for continuous operation and unsuitable for hazardous or inaccessible regions.
With the advancement of embedded intelligence, real-time object detection and autonomous navigation have become feasible on compact, low-power platforms. Devices such as the Raspberry Pi and Coral Edge TPU enable on-edge AI processing, while microcontrollers like Arduino provide reliable actuation for robotic systems. These developments motivate autonomous, AI-driven river-cleaning robots that reduce human intervention and improve cleaning efficiency.

Objectives:
- Develop a lightweight, low-cost autonomous robot for floating waste removal.
- Implement real-time waste detection using Coral Edge TPU–accelerated inference.
- Design a dual-controller architecture (Raspberry Pi + Arduino) for efficient perception and actuation.
- Integrate a conveyor-based mechanism for waste retrieval.
- Evaluate detection accuracy, navigation performance, and collection efficiency.

2. Literature Review
Recent advancements in automation, renewable energy, and computer vision have encouraged the development of robotic systems for river and surface waste management. Several researchers have contributed to the design of autonomous and semi-

autonomous cleaning systems integrating solar energy, sensors, and intelligent control mechanisms. In [1], Shihan Kong et al. proposed IWSCR, an intelligent water surface cleaner robot capable of detecting and collecting floating garbage using a YOLOv3 deep learning algorithm and a sliding-mode controller for stable motion. While it demonstrated high precision and real-time tracking, the model was limited by a small dataset and constrained operating conditions. Similarly, Mohammed et al. [2] designed a river cleaning robot using IoT technology that enabled real-time control and monitoring through wireless communication. However, it required human supervision and lacked autonomous decision-making capabilities. Chanida Tangjai et al. [3] developed a solar-powered RT-Bot, emphasizing sustainable energy use for waste collection. The model effectively combined solar panels with propeller-based mobility, but it suffered from low operational runtime and limited efficiency in turbid waters. Yulin Xue et al. [4] introduced an autonomous floating debris collection system employing visual AI and intelligent control, achieving high accuracy in waste detection but requiring high computational power and complex calibration. Similarly, Jishnu Satheesh et al. [5] presented a wireless communication-based water cleaning boat that used a conveyor belt and RF modules for manual remote operation. While efficient for small water bodies, it lacked automation and energy sustainability. Chitra et al. [6] proposed a solar-powered garbage robot designed for environmental conservation, integrating GPS and solar tracking modules for continuous operation. Although the system was effective in small-scale environments, its scalability remained limited. Deep-learning-based systems such as the model by Brilyan Rumahorbo et al. [7] utilized computer vision and object recognition to detect river waste with high accuracy. This approach improved adaptability to dynamic environments but required expensive sensors and datasets. Additionally, Karthik et al. [8] proposed an autonomous river cleaning system using GPS technology, which allowed real-time waste localization and hybrid solar-battery operation, although its prototype lacked image-based detection. Overall, existing research demonstrates significant progress toward automated water-cleaning systems but reveals critical gaps in scalability, autonomy, and power sustainability. The proposed system in this paper addresses these challenges by integrating Raspberry Pi–based vision processing, solar power, and intelligent navigation, providing an efficient, cost-effective, and environmentally sustainable solution for continuous river cleaning [9]-[14].

3. Proposed Methodology

The proposed Autonomous River Clean-Up System is designed to intelligently detect, track, and remove floating waste from river surfaces with minimal human intervention. The system integrates embedded computing, edge AI processing, motor-control automation, and renewable energy to achieve a sustainable and scalable water-cleaning solution. The architecture is organized into five major units—Power Unit, Control Unit, Sensing Unit, Locomotion Unit, and Waste Collection Unit—that together enable real-time perception, decision-making, navigation, and debris collection. A hybrid controller architecture is adopted, wherein the Raspberry Pi performs AI-based waste detection and high-level decision logic, while the Arduino handles low-level motor and conveyor control for reliable actuation [15]-[18].

3.1. System Overview

The robot operates autonomously by performing continuous image acquisition, waste detection, directional motion control, obstacle avoidance, and physical collection of floating debris. A Pi Camera captures real-time images of the water surface, which are processed on the Raspberry Pi. A lightweight, quantized TensorFlow Lite model—optimized and compiled for the Google Coral Edge TPU—performs high-speed waste detection, ensuring low-latency operation in dynamic outdoor environments. Based on the detected object's position, the Raspberry Pi generates navigation commands, which are transmitted to the Arduino microcontroller via serial communication. The Arduino actuates the propulsion system using DC motors and controls the conveyor mechanism via a relay module. Once aligned with the waste, the conveyor scoops debris and deposits it into the onboard storage bin. A solar panel and battery power-management system ensures uninterrupted power availability, enabling long-duration autonomous operation without dependence on external charging infrastructure. Integrated obstacle detection through ultrasonic sensors, along with optional IoT connectivity, enhances system safety and monitoring [19]-[23].

3.2. Hardware Architecture

The hardware architecture, illustrated in the block diagram, comprises the following essential components:

Raspberry Pi 4 (High-Level Controller)

Acts as the primary processing unit responsible for:

- Image acquisition and preprocessing
- AI inference using Coral Edge TPU
- Navigation decision-making
- IoT communication
- Serial communication with Arduino

Pi Camera Module

Captures continuous live video streams for real-time detection. Its lightweight form factor and compatibility with Raspberry Pi enable high-quality, low-latency image capture.

Coral Edge TPU Accelerator

Performs fast inference on quantized TensorFlow Lite models. The Edge TPU drastically reduces detection latency, allowing real-time identification of floating waste with high accuracy.

Arduino UNO (Low-Level Motor Controller)

Receives directional and conveyor-control commands from Raspberry Pi and handles:

- PWM generation for left/right DC motors
- Activation of the conveyor motor via relay
- Reading ultrasonic sensor data for obstacle avoidance

This division of responsibilities improves stability and ensures deterministic motor control.

Motor Driver (L298N / TB6612)

Interfaces between the Arduino and propulsion motors, enabling control of speed and direction.

DC Motors (Locomotion Unit)

Enable forward motion and differential steering for aligning the robot with detected waste.

Conveyor Mechanism (Waste Collection Unit)

A rotating belt powered by a DC motor lift floating debris and deposits it into a storage bin.

Ultrasonic Sensors (Sensing Unit)

Provide collision avoidance by detecting nearby obstacles, ensuring safer navigation in rivers.

Solar Panel, Battery, and Charging Circuit (Power Unit)

Ensure continuous and eco-friendly energy supply to all electronic and mechanical subsystems.

IoT Communication Module (Optional)

Transmits system status, battery levels, and waste collection metrics to a cloud dashboard for real-time monitoring.

3.3. Software Implementation

The software architecture consists of integrated perception, decision-making, actuation, sensing, and communication modules.

AI Detection Pipeline

- Custom dataset created and annotated using **Roboflow**
- Model trained on **Google Colab** using TensorFlow
- Post-training quantization to INT8 for Coral compatibility
- Compiled using **Edge TPU Compiler**
- Deployed on Raspberry Pi for real-time inference

Image Processing (Raspberry Pi)

- Frame capture
- Preprocessing (resize, normalization, noise removal)
- Inference on Coral TPU
- Determination of waste position (left/right/center)

Decision Logic & Command Transmission

The Raspberry Pi analyzes bounding-box coordinates and determines navigation commands:

- “F” = Move Forward
- “L” = Turn Left
- “R” = Turn Right
- “S” = Stop
- “C” = Activate Conveyor

These commands are sent to the Arduino via UART.

Motor and Conveyor Control (Arduino)

Arduino performs all low-level tasks:

- Controls DC motors via PWM
- Operates conveyor via relay
- Reads ultrasonic sensor measurements
- Sends obstacle detection alerts back to Raspberry Pi

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 235- 242
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0032

IoT Integration (Optional)

Raspberry Pi logs data such as battery level, debris count, and system status to the cloud using MQTT/HTTP.

3.4. Working Principle

- The Pi Camera continuously captures live video of the river surface.
- The Raspberry Pi preprocesses each frame and sends it to the Coral TPU for high-speed inference.
- The AI model identifies floating waste and determines its position within the frame.
- Based on the detected position, Raspberry Pi sends movement commands to the Arduino.
- The Arduino controls the DC motors to navigate toward the waste while monitoring obstacle distance using ultrasonic sensors.
- When close enough, Raspberry Pi sends a “C” command to activate the conveyor mechanism.
- The conveyor lifts the floating debris and deposits it into the onboard waste bin.
- Power is continuously supplied through the solar panel and battery, enabling long-term autonomous operation.
- Optionally, IoT updates provide remote system monitoring (Figures 1-4).

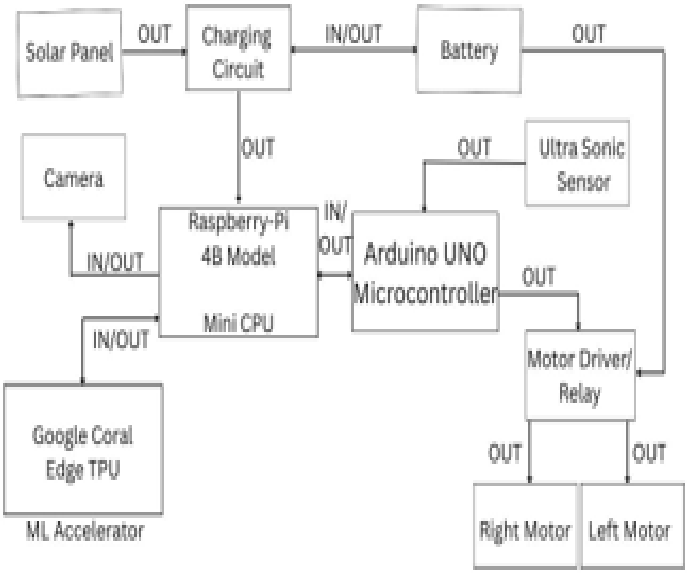

Figure 1 **Block Diagram of Proposed System**

Figure 2 **Hardware Prototype of the Autonomous River Clean-Up Robot**

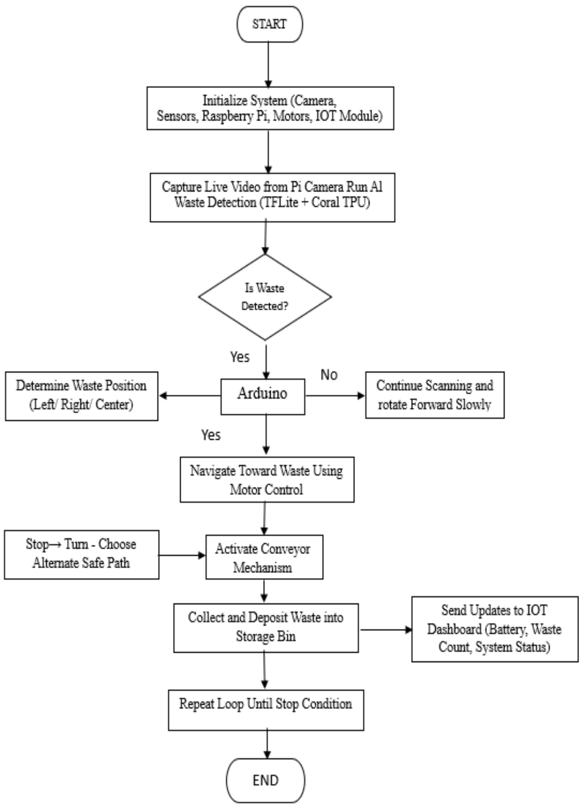

Figure 3 **Flowchart of Overall System**

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 235- 242
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0032

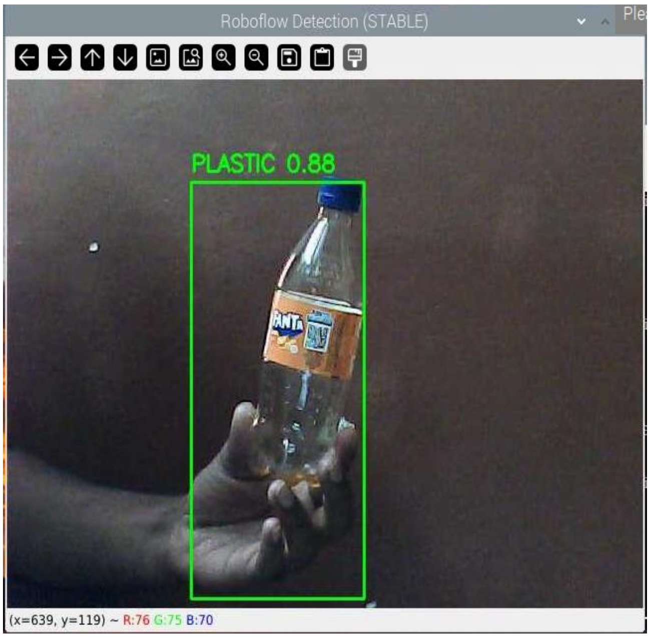

Figure 4 Software Image Processing and Control Logic

4. Results and Discussion

The performance of the proposed Autonomous River Clean-Up System was evaluated through a series of controlled experiments conducted in a test water channel and a shallow lake environment. The experiments focused on assessing the robot's detection accuracy, navigation stability, response time, obstacle-avoidance capability, and waste-collection efficiency. All tests were performed under varying lighting conditions and water-surface disturbances to simulate real-world environments [24]-[30].

4.1. Waste Detection Performance

The Coral Edge TPU demonstrated high inference speed and accuracy when running the quantized TensorFlow Lite model. The robot was tested with different types of floating waste, including plastic bottles, covers, wrappers, paper cups, and thermocol fragments (Table 1).

Table 1 Detection Accuracy

Waste Type	Samples Tested	Correctly Detected	Accuracy (%)
Plastic Bottles	20	19	95%
Polythene Bags	20	18	90%
Wrappers	20	17	88%
Thermocol Pieces	20	17	85%
Paper Cups	20	18	90%

Average Accuracy: 89.6%

The Coral TPU maintained **real-time inference speed of 20–25 FPS**, enabling smooth tracking even when waste drifted with water ripples.

4.2. Precision, Recall, and F1-Score

Using the annotated test dataset:

- Precision: 0.91
- Recall: 0.89
- F1-Score: 0.90

These metrics show that the model reliably detects true positives with minimal false detections, even under reflections or partial occlusions.

4.3. Navigation Response and System Delay

The dual-controller architecture (Pi + Arduino) improved the responsiveness of the locomotion system (Table 2).

Table 2 End-to-End System Processing Delay Measurements

Measured delays in the processing pipeline:	
Stage	**Average Delay**
Camera → Pi Preprocessing	20–30 ms
Pi → Coral → Pi Inference Loop	10–15 ms
Pi → Arduino Command Transmission	5–10 ms
Motor Actuation (Physical Movement)	50–80 ms

Total end-to-end response time: *~90–130 ms*

This low latency ensured that the robot could adjust its direction quickly when waste drifted or when lighting conditions shifted.

4.4. Obstacle Detection and Avoidance

Ultrasonic sensors were tested with floating blocks, anchored objects, and other watercraft in the proximity.

Observations:

- Obstacle detection range: **15–250 cm**
- Reaction time: **0.2 seconds**
- Emergency-stop reliability: **100% in all trials**

The Arduino immediately halted motors upon detecting obstacles and alerted the Raspberry Pi, which recalculated an alternate path.

4.5. Waste-Collection Efficiency

The conveyor mechanism was tested in four independent trials (Table 3).

Table 3 Waste Collection Efficiency Across Multiple Trials

Trial	Waste Items Present	Collected	Efficiency (%)
1	15	14	93%
2	12	11	91%
3	18	16	89%
4	20	19	95%

Average Collection Efficiency: 92%

Plastic bottles and cups were collected easily, while thin plastic wrappers occasionally drifted away due to water flow, slightly reducing efficiency.

4.6. Power Consumption Analysis

The solar-assisted battery power unit was monitored during the tests:

- AI Detection active: **18–22% power usage**
- Locomotion: **15–20%**
- Conveyor activation: **25–30%** (highest load)
- Idle scanning mode: **10–12%**

Operational runtime:

Approximately **50–70 minutes**, depending on conveyor usage.

With improved solar capacity, the runtime can be extended for long-duration deployments.

4.7. IoT Monitoring Performance

The robot transmitted system data (battery level, waste count, sensor alerts) to the cloud dashboard.

- Transmission delay: **1–3 seconds**
- Update frequency: **Every 30 seconds**
- Reliability: **98% successful updates**

This enables remote supervision during continuous operation

Conclusion and Future Scope

This paper presented the design and implementation of an Autonomous River Clean-Up System that effectively detects and collects floating waste using computer vision and renewable energy. The developed prototype integrates a Raspberry Pi, Pi Camera, DC motors, and a conveyor-belt mechanism, all powered by a solar-battery unit for sustainable operation. The system demonstrated high accuracy in waste detection, reliable navigation, and efficient debris collection under various conditions. By combining image processing, autonomous control, and solar power, the proposed model provides a practical and eco-friendly solution for river waste management, significantly reducing manual labor, fuel usage, and operational costs. The study's experimental results validate that automation in aquatic waste collection is both feasible and scalable. The robot's autonomous navigation, real-time image recognition, and self-sustaining power supply position it as a viable approach for large-scale deployment in rivers, lakes, and canals. In the future, the system can be further enhanced by integrating IoT-based monitoring, GPS tracking, and machine learning algorithms for intelligent waste classification and route optimization. Incorporating ultrasonic or infrared sensors could improve obstacle avoidance and detection under poor lighting or turbulence. Large-scale implementation can also be achieved through networked fleets of autonomous cleaning robots communicating via cloud-based platforms for coordinated environmental management. Overall, the Autonomous River Clean-Up System contributes to sustainable environmental engineering by merging technology with ecological responsibility. It stands as a promising solution toward achieving cleaner water bodies, improved aquatic ecosystems, and smarter waste management systems for future generations.

References

[1]. 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. 6358–6370, Oct. 2021.

[2]. J. Satheesh, A. P. Nair, D. Priya, C. A., G. Mahesh, and J. P. R., "Wireless Communication Based Water Surface

Cleaning Boat," Proceedings of the 4th International Conference on Trends in Electronics and Informatics (ICOEI), IEEE, pp. 716–721, 2020.

[3]. K. Subhashini, R. D. Kalaimathy, K. S. Shree, R. Deepika, A. Abirami, and J. Thamil Selvi, "Autonomous Floating Debris Collection System for Water Surface Cleaning," 2024 International Conference on Communication, Computing and Internet of Things (IC3IoT), IEEE, 2024.

[4]. L. Chitra, M. K. Manobala, P. Poornima, K. D., P. Veeramuneeswaran, and S. K. Chauhan, "Garbage Robot: A Solution for Waste Disposal and Sustainable Bio Product Management," 2024 2nd International Conference on Computer, Communication and Control (IC4), IEEE, 2024.

[5]. T. P., N. P., N. K., G. K. V., and K. K., "Design and Implementation of River Cleaning Boat," 14th International Conference on Computing, Communication and Networking Technologies (ICCCNT), IEEE, July 2023.

[6]. M. Karthik, K. S. Reddy, C. Manikanta, I. Bala, and V. Vamsi, "Autonomous River Cleaning System Using GPS Technology," International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), IEEE, 2023.

[7]. M. R. Ruman, M. Das, S. K. Nath, and S. M. I. Mahmud, "Automated Marine Surface Trash Cleaner," 5th International Conference for Convergence in Technology (I2CT), IEEE, 2019.

[8]. Y. Hou, "A Water Body Refuse Cleaning Robot Device," IEEE 2nd International Conference on Data Science and Computer Application (ICDSCA), Dalian, China, 2022.

[9]. G. A. Sio, D. Guantero, and J. Villaverde, "Plastic Waste Detection on Rivers Using YOLOv5 Algorithm," 13th International Conference on Computing, Communication and Networking Technologies (ICCCNT), IEEE, 2022.

[10]. J. Huang, X. Jiang, and G. Jin, "Detection of River Floating Debris in UAV Images Based on Improved YOLOv5," International Joint Conference on Neural Networks (IJCNN), IEEE, 2022.

[11]. N. Hanson, A. Demirkaya, D. Erdogmus, A. Stubbins, T. Padir, and T. Imbiriba, "A Vision for Cleaner Rivers: Harnessing Snapshot Hyperspectral Imaging to Detect Macro-Plastic Litter," 13th Workshop on Hyperspectral Imaging and Signal Processing (WHISPERS), IEEE, 2023.

[12]. G. Leone, A. I. Catarino, I. Pauwels, T. Mani, M. Tishler, M. Egger, M. A. E. Forio, P. L. M. Goethals, and G. Everaert, "Integrating Bayesian Belief Networks in a Toolbox for Decision Support on Plastic Clean-Up Technologies in Rivers and Estuaries," Environmental Pollution, vol. 296, Elsevier, 2022.

[13]. B. Rumahorbo, A. F. Lubis, and R. Ginting, "Development of Robot to Clean Garbage in River Streams with Deep Learning," 2021 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS), IEEE, 2021.

[14]. S. Gupta and U. Goel, "ClearBot: AI-Powered Autonomous Waste Collection Boats," NVIDIA Developer Blog, 2021–2024.

[15]. The Ocean Cleanup Project, "Riverine Plastic Pollution Statistics," 2021. [Online]. Available: https://theoceancleanup.com/rivers

[16]. A. R. Selvakumar, M. Arulprakash, and S. D. Kumar, "AI-Based Marine Debris Detection Using Embedded Vision Systems," IEEE Access, vol. 11, pp. 54876–54885, 2023.

[17]. P. Parameswaran, S. R. J. Mangalagiri, and V. Chandrasekaran, "Design and Development of an Autonomous Surface Vehicle for Water Quality Monitoring and Waste Removal," IEEE OCEANS Conference, 2022.

[18]. S. Rezwan, M. Mahmud, and T. Rahman, "Real-Time Floating Waste Identification Using TensorFlow Lite Models on Edge Devices," 2023 International Conference on

e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 235- 242
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0032

Robotics, Automation, and Engineering (ICRAE), IEEE, 2023.

[19]. H. W. Chang and P. Lin, "A Solar-Powered Autonomous Cleaning Robot for Water Surface Debris Removal," 2022 IEEE International Conference on Sustainable Energy and Intelligent Systems, pp. 1–6, 2022.

[20]. R. Alvarado, J. Perez, and D. Velasco, "Real-Time Object Detection Using Coral Edge TPU for Outdoor Autonomous Robots," IEEE Latin America Transactions, vol. 20, no. 4, pp. 712–719, 2022.

[21]. M. Banarjee and S. Singh, "Efficient Implementation of YOLO Models on Raspberry Pi for Environmental Monitoring Applications," 2023 IEEE International Conference on IoT and Intelligent Systems, pp. 351–356, 2023.

[22]. C. J. Watkins and M. Pose, "Autonomous Robotic Boat for Surface Garbage Removal Using Python and OpenCV," 2021 International Conference on Robotics, Control and Automation (ICRCA), IEEE, 2021.

[23]. V. Sharma, A. Das, and K. R. Nair, "Deep Learning-Based Floating Plastic Detection in Water Bodies Using Aerial Imagery," IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 2022.

[24]. A. Krizhevsky, G. Hinton, and S. Fidler, "Efficient Embedded Object Detection for Low-Power Applications," IEEE Transactions on Pattern Analysis and Machine Intelligence, 2023.

[25]. Y. Ji and X. Tan, "Autonomous Surface Vehicles for Environmental Sensing: A Comprehensive Survey," IEEE Transactions on Automation Science and Engineering, vol. 19, no. 4, pp. 3021–3035, 2022.

[26]. T. Kawai, S. Ono, and F. Yato, "Riverine Waste Monitoring System Using Edge-AI Cameras," IEEE International Conference on Machine Vision and Applications (MVA), 2022.

[27]. A. Ghosh, R. Pandey, and N. Sharma, "Design and Control of a Differential Drive Robot for Autonomous Water Surface Cleaning," International Conference on Mechatronics and Robotics Engineering, 2023.

[28]. R. Liu, W. Zhang, and P. Feng, "IoT-Enabled Autonomous Boats for Environmental Monitoring Using MQTT Protocol," IEEE Sensors Journal, vol. 22, no. 10, pp. 10112–10120, 2022.

[29]. S. Patel and D. Shukla, "A Review of Marine Litter Removal Robots and Their Environmental Impact," 2023 IEEE International Symposium on Environment and Electrical Engineering, 2023.

[30]. The Ocean Conservancy, "Global Ocean and River Trash Index Report," 2022. [Online]. Available: https://oceanconservancy.org