AquaNova: An AI-Powered, CNN-Based Aquatic Trash Collector with Whale-Inspired Suction, Solar-Battery Operation, Using Arduino, Waypoint Navigation, and Dijkstra's Algorithm

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DOI: https://doi.org/10.51584/IJRIAS.2025.10100000173

Received: 10 November 2025; Accepted: 17 November 2025; Published: 20 November 2025

ABSTRACT

Mismanaged solid waste, especially plastic, remains a major ecological threat, with the Philippines contributing heavily to marine pollution due to its sachet-driven consumption and highly contaminated river systems. This study responds to the need for an automated solution that reduces environmental and health risks caused by floating waste.

The research developed and evaluated AquaNova, an autonomous, solar-powered floating robot equipped with an AI vision system, GPS waypoint navigation, and a whale-inspired suction mechanism for efficient waste detection and collection. Built using the Prototype SDLC, the system integrates CNN-based detection through YOLOv8 and OpenCV on a Raspberry Pi, with performance assessed through quantitative metrics on detection accuracy, navigation, and operational reliability.

The AI detection model achieved 80 percent overall accuracy, including 100 percent precision for plastic and correct identification of non-trash items in 8 out of 10 cases. Reliability tests showed 92.6 percent system availability, confirming stable operation and dependable GPS waypoint navigation.

AquaNova's successful implementation demonstrates the feasibility of autonomous, sustainable aquatic waste cleanup. By combining accurate AI-based detection with reliable navigation, it reduces waste accumulation and helps prevent blockages. Future improvements should enhance metal detection performance and add night vision to support continuous operation.

Keywords: Trash Collection, Autonomous Robot, AI Detection, Water Pollution Robot, Autonomous Navigation

INTRODUCTION

Mismanaged solid waste, especially plastic, remains a major ecological burden in the Philippines, where millions of tons of waste are generated annually and an estimated 20 percent enters the ocean. With over 7,600 islands and a heavy dependence on single-use sachets, the country contributes significantly to global marine pollution. These plastics break down into microplastics that threaten marine life, while clogged waterways and outdated drainage systems worsen flooding and increase health risks. Other waste types such as food, paper, metal, clothing, rubber, and glass also harm ecosystems. Studies show that more than a quarter of the world's top plastic-emitting rivers are in the Philippines, including the Pasig River and 18 others among the top 50 most polluting globally.

AquaNova was developed as an autonomous solution to address this waste problem. It detects and collects floating solid waste using Arduino Nano–based control, AI-powered CNN detection, and a dual power system combining a 40W solar panel with lithium-ion batteries. Its vision system, powered by a Raspberry Pi running YOLOv8, OpenCV, and CNN models, identifies debris in real time. Inspired by whale-like movement and a mouth-style intake mechanism, AquaNova glides across water surfaces and gathers trash efficiently.

The robot navigates via the NEO-M8N GPS module and GY-271 HMC5883L compass, with AI-driven adjustments when trash is detected. Movement is supported by dual propellers, and waste is collected through a submerged whale-inspired chamber whose lifting "lip" secures debris inside two separate internal chambers.

AquaNova operates in three modes: Cycling Waypoint Mode for continuous GPS-based patrolling, Trash Collection Mode for automatic deviation when trash is detected, and Trash No Waypoint Mode for manual or IR-sensor-triggered collection. The IR sensor also determines when the chambers are full and directs the robot back to its home waypoint. The Raspberry Pi handles AI processing and sends detection data, including trash type and location, to the Arduino for navigation.

Its range is extended through LoRa technology for long-distance control and telemetry. A monitoring device displays real-time data such as battery voltage, IR alerts, propeller status, servo angle, heading, GPS coordinates, satellite count, HDOP, and mouth activity. The AquaNova Control software enables manual adjustments to modes, throttle, steering, and intake functions.

For optimal performance, AquaNova requires open-field operation for accurate GPS signals and sufficient lighting for visual detection. It performs best within 9V to 12.6V, with peak efficiency at 12.6V. Navigation is guided by a waypoint algorithm supported by Dijkstra's Algorithm for efficient targeting. A Windows interface provides real-time video, navigation data, and detection logs for operator monitoring.

With AI-driven detection, a whale-inspired intake design, dual-chamber segregation, precise GPS-compass navigation, and long-range communication, AquaNova presents an autonomous and eco-efficient solution for mitigating floating solid waste in Philippine waterways. Its development supports ongoing advancements in the HydroSent project, enhancing waste collection efficiency, detection accuracy, and navigation performance for sustainable water pollution management.

Statement of the Problem

Through an assessment of floating waste and its impact on water pollution, the researchers identified critical challenges in waste management. This study aims to address the following issue:

How can an autonomous system ensure waste collection without interfering with freshwater species?

Objective of the Study

To implement an AI-powered detection system using YOLOv8, OpenCV, and CNN on a Raspberry Pi for real-time recognition of floating solid waste, ensuring accurate trash detection while preserving freshwater species.

LITERATURE REVIEW

A. Review of Related Literature

The Philippines is the world's third-largest ocean plastic polluter, discarding about 2.7 million tons of plastic annually. Daily waste generation further highlights the scale of the problem, with over 163 million sachets, 48 million shopping bags, and 45 million thin-film plastic bags disposed of each day (Gorecho, 2024). Cleanup efforts reflect this severity: the International Coastal Cleanup collected 352,479 kilograms of trash across 250 coastal sites, dominated by plastic bags, food wrappers, bottles, and sachets (Abreo & Kobayashi, 2024). Even localized initiatives, such as Romblon's floating trash traps made from recycled bottles, gathered 285.76 kg of waste composed of 68 percent biodegradable, 14 percent recyclable, 12 percent residual, and 6 percent special waste (Gacu, 2023). These figures emphasize the need for scalable, automated, and energy-efficient cleanup solutions.

To address this need, the Department of Science and Technology – Metals Industry Research and Development Center developed a barge-type garbage collector capable of removing large quantities of floating debris in Metro Manila's waterways. Although effective on a large scale, its fixed-path, non-autonomous design limits responsiveness to shifting waste patterns. AquaNova overcomes this by combining YOLOv8-based AI detection, Convolutional Neural Networks, and Arduino-controlled autonomous navigation, enabling real-time waste recognition and dynamic path adjustments.

A related development is the solid waste filtering robot by Lecitona, Gamboa, Songco, and Abuan (2020), which filtered contaminated water, detected full capacity through sensors, and transmitted data wirelessly. While demonstrating autonomous waste filtration in shallow waters, its design focused on water purification rather than targeted solid waste retrieval. AquaNova extends this concept through targeted suction, AI-powered detection, Dijkstra's Algorithm for optimized pathfinding, and onboard waste segregation, allowing operation in broader and more variable aquatic environments.

Together, these technologies show the shift from manual and static systems toward intelligent, sensor-driven aquatic waste management. AquaNova integrates these advancements into a fully autonomous, energy-efficient platform capable of real-time detection, adaptive navigation, and efficient waste segregation, supporting sustainable environmental management efforts locally and globally.

B. Review of Related Studies

The increasing challenge of aquatic waste pollution has led researchers to develop advanced, technology-driven approaches for cleaner waterways. From mechanical collectors to AI-powered autonomous systems, recent studies highlight how robotics, microcontrollers, and machine learning can improve waste detection, collection, and overall environmental response. These works form the technological foundation of AquaNova by demonstrating innovations in control systems, navigation, energy management, object recognition, and sustainable aquatic design.

To address waterway pollution in Metro Manila, the Department of Science and Technology–Metals Industry Research and Development Center developed a barge-type garbage collector capable of removing solid waste and water hyacinth. Its mechanical rakes and conveyors allow large-scale debris removal, but it follows fixed routes and cannot adapt to shifting waste patterns. While effective for bulk collection, its lack of autonomy limits coverage. AquaNova builds on this by integrating YOLOv8 and CNN-based visual detection for real-time recognition and route adjustments, and its compact design enables operation in narrow or shallow waterways where large barges cannot.

UN-Habitat Philippines (2023) introduced an AI-assisted waste mapping system using satellite imagery and drones to identify plastic waste hotspots. Although effective for high-level assessment, it relies on post-processing and human evaluation before action can be taken. AquaNova removes this delay by embedding AI detection directly onboard, allowing immediate identification and retrieval of floating debris and merging data collection with rapid cleanup capability.

Lecitona, Gamboa, Songco, and Abuan (2020) developed a solid waste filtering robot for shallow waters that filtered contaminated water, separated debris, and returned cleaner water to the environment. With tactile sensors, wireless modules, and real-time monitoring, it demonstrated efficient localized filtration. AquaNova advances this model through targeted suction, YOLOv8-based visual detection, optimized navigation using Dijkstra's Algorithm, and bin-level sensing for intelligent decision-making, enabling operation in wider and more dynamic environments.

Overall, previous systems show strong progress in waste collection, filtration, and sensing but often lack adaptive navigation, onboard AI decision-making, or integrated waste segregation. AquaNova addresses these gaps by combining AI-based detection, optimized routing, hybrid solar-battery power, capacity monitoring, and dual-chamber segregation in a single autonomous platform, enhancing operational efficiency and supporting long-term waterway rehabilitation.

METHODOLOGY

The research methodology of this study ensures the systematic development and implementation of AquaNova, an AI-powered, whale-inspired aquatic trash collector. It follows a methodical approach that integrates Convolutional Neural Networks with a Raspberry Pi vision system running YOLOv8 and OpenCV for real-time trash detection. Navigation is guided by Dijkstra's Algorithm, with hardware and software components calibrated for efficiency and reliability. This section outlines the processes for data gathering, processing, and analysis of detection accuracy, navigation performance, and waste collection efficiency. Additionally, it facilitates the evaluation of system standards through quantitative metrics and expert validation, ensuring its effectiveness in autonomous waste removal.

A. Research Design

The research design of this study revolves around the Software Development Lifecycle Model applied to AquaNova, an AI-powered aquatic trash collector. It follows a systematic approach that incorporates the key principles of the Evolutionary Prototype SDLC to ensure efficient development, testing, and deployment. Additionally, the researchers conducted an interview and presentation with the Department of Environment and Natural Resources –National Capital Region (DENR-NCR) to validate the project's environmental relevance and gather expert insights.

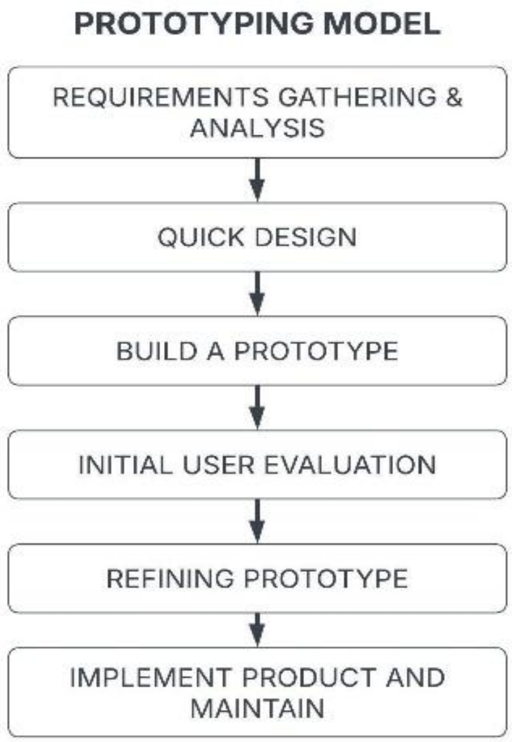


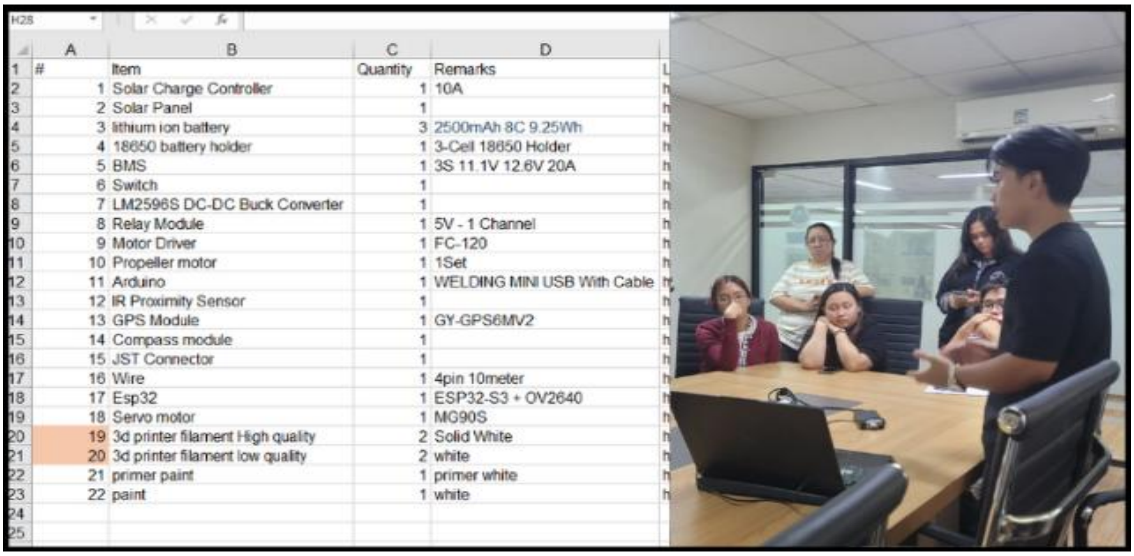
Fig. 1 Prototype SLDC as AquaNova's systematic Approach

The development of AquaNova, an upgraded aquatic trash collector, follows the Prototype Software Development Life Cycle (SDLC). This model allows researchers to build a working prototype early in the development stage, test its features with stakeholders, and refine the system through iterative feedback before final deployment. Unlike the Agile model, which emphasizes adaptability across sprints, the Prototype model emphasizes early visualization, evaluation, and user involvement. This ensures that AquaNova meets both technical requirements and environmental objectives. As shown in Fig. 1, there are six stages: Requirement Analysis, Quick Design, Prototype Development, Customer Evaluation & Refinement and Final System Development & Deployment.

Requirement Analysis:

This phase involves brainstorming sessions, consultations, and data gathering to clearly define the project's objectives and requirements. The researchers analyzed both the existing problems and the goals that AquaNova must accomplish within the given timeframe, while also addressing the shortcomings of its predecessor, HydroSent.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue X October 2025



#	Item	Quantity	Remarks
1	Solar Charge Controller	1	10A
2	Solar Panel	1	
3	lithium ion battery	3	2500mAh 8C 9.25Wh
4	18650 battery holder	1	3-Cell 18650 Holder
5	BMS	1	3S 11.1V 12.6V 20A
6	Switch	1	
7	LM2596S DC-DC Buck Converter	1	
8	Relay Module	1	5V - 1 Channel
9	Motor Driver	1	FC-120
10	Propeller motor	1	1Set
11	Arduino	1	WELDING MINI USB With Cable
12	IR Proximity Sensor	1	
13	GPS Module	1	GY-GPS6MV2
14	Compass module	1	
15	JST Connector	1	
16	Wire	1	4pin 10meter
17	Esp32	1	ESP32-S3 + OV2640
18	Servo motor	1	MG90S
19	3d printer filament High quality	2	Solid White
20	3d printer filament low quality	2	white
21	primer paint	1	primer white
22	paint	1	white

Fig. 2 List of required materials and interview conducted with DENR-NCR

Fig. 2 presents an interview conducted by the researchers with the Department of Environment and Natural Resources – National Capital Region (DENR-NCR).The discussion addressed key environmental concerns, including the identification of the main types of trash commonly found in bodies of water, and determined the specific features and functionalities required to be implemented in AquaNova. In addition, the researchers compiled a comprehensive list of the materials needed for the system and sourced reliable links for their procurement, thereby finalizing the goals and objectives of this study. The inputs for this stage were categorized into three areas: Knowledge Inputs – Artificial Intelligence (AI) Navigation, Machine Learning techniques, Object Detection using YOLOv8, and Waypoint Algorithms. Hardware Inputs – Raspberry Pi, Arduino Nano, GPS modules, environmental sensors, a dual-chamber waste collection system, and solar panels. Software Inputs – OpenCV, PyTorch, Arduino IDE, and Visual Studio Code, which served as the primary platforms for system development and testing.

The process involved defining the project goals, specifying the required features, and identifying system constraints, which formed the foundation for AquaNova's design. The outputs of this stage were consolidated into a draft list of functionalities, which included the whale-inspired suction mechanism, improved navigation capabilities, and optimized trash collection efficiency.

Quick Design:

At this phase, researchers created conceptual sketches and system architecture diagrams of AquaNova. It involves creating the initial design of AquaNova, a crucial step in establishing the foundation for development. The researchers utilized GrabCAD to develop the detailed illustration and 3D model of the system, ensuring that the design is both functional and feasible for implementation. This stage also focuses on aligning the model's features with the project's objectives to guarantee its effectiveness in real-world application

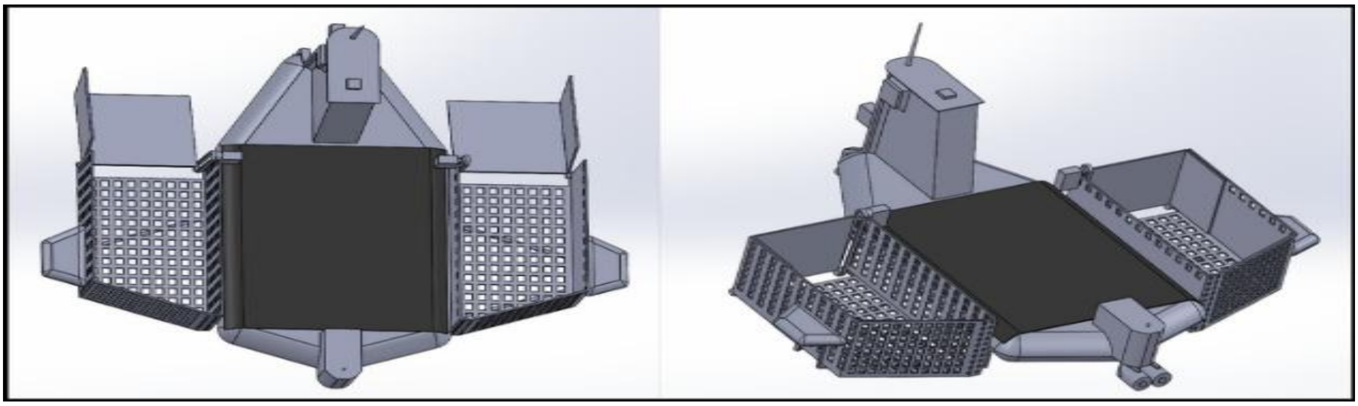


Fig. 3 3D Model of AquaNova

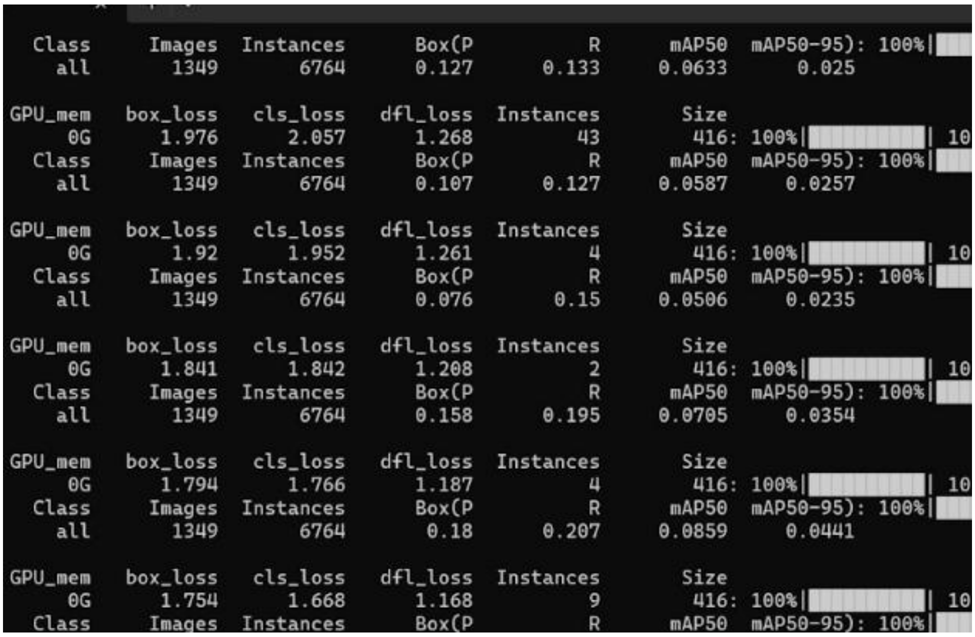
ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue X October 2025

Fig.3 showcases the quick design stage of the Evolutionary Prototyping Model for AquaNova involved the creation of initial conceptual sketches and system architecture diagrams that served as the blueprint for the prototype. This stage emphasized translating the identified requirements into preliminary visual and structural representations, allowing the researchers to outline the system's essential components and their interconnections before physical development.

The design primarily focused on four core aspects: the whale-inspired suction mechanism to enhance waste intake efficiency, the integration of solar-powered energy systems to improve sustainability and operational longevity, the dual-propeller maneuvering system for stability and adaptability in aquatic environments, and the implementation of AI-based trash detection to optimize real-time identification and collection of debris. These conceptual designs provided the foundation for building the initial prototype and guided subsequent refinement through stakeholder feedback and iterative development.

Development:

The development of AquaNova started with an extensive data-gathering phase, which focused on collecting relevant information, identifying key problems, setting clear objectives, and outlining the necessary hardware and software requirements. These well-defined requirements served as a strong foundation for the system's creation. During the development process, the researchers conducted continuous testing to detect and resolve bugs, ensuring that AquaNova met the established requirements and performed efficiently in collecting and managing waste from aquatic environments.



```
  Class     Images  Instances      Box(P          R       mAP50  mAP50-95): 100%|
    all       1349       6764      0.127      0.133      0.0633      0.025

GPU_mem   box_loss   cls_loss   dfl_loss  Instances        Size
     0G      1.976      2.057      1.268         43        416: 100%|          | 10
  Class     Images  Instances      Box(P          R       mAP50  mAP50-95): 100%|
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GPU_mem   box_loss   cls_loss   dfl_loss  Instances        Size
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GPU_mem   box_loss   cls_loss   dfl_loss  Instances        Size
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GPU_mem   box_loss   cls_loss   dfl_loss  Instances        Size
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  Class     Images  Instances      Box(P          R       mAP50  mAP50-95): 100%|
    all       1349       6764       0.18      0.207      0.0859     0.0441

GPU_mem   box_loss   cls_loss   dfl_loss  Instances        Size
     0G      1.754      1.668      1.168          9        416: 100%|          | 10
  Class     Images  Instances      Box(P          R       mAP50  mAP50-95): 100%|
```

Fig. 4 Developing Arduino Code for Maneuver

In Fig. 4, to support the functionality of the prototype, the researchers developed and integrated software using Visual Studio Code and the Arduino IDE. Visual Studio Code provided a scalable environment for managing project code, while the Arduino IDE enabled direct programming of the microcontroller for precise motor control and activation of detection triggers. This integration ensured communication between hardware and software components, allowing the prototype to maneuver in aquatic environments and respond to sensor inputs. Although limited in performance compared to the final system, the prototype served its purpose by demonstrating AquaNova's core mechanisms and establishing a working foundation for iterative testing and stakeholder evaluation.

Customer Evaluation and Refinement:

This phase focuses on testing AquaNova for potential bugs and errors. It involves evaluating the system's features and functionality to identify any gaps or unmet requirements. Through rigorous testing, the researchers ensure that AquaNova performs as intended, from maneuvering and detection to trash collection, while delivering optimal results in real-world conditions. A thorough assessment of the system's usability, functional suitability, performance, and dependability is conducted to verify its effectiveness in collecting waste from bodies of water. Testing guarantees a well-rounded and reliable aquatic trash collection system.

```
config.ledc_channel = LEDC_CHANNEL_0;
config.ledc_timer = LEDC_TIMER_0;
config.pin_d0 = Y2_GPIO_NUM;
config.pin_d1 = Y3_GPIO_NUM;
config.pin_d2 = Y4_GPIO_NUM;
config.pin_d3 = Y5_GPIO_NUM;
config.pin_d4 = Y6_GPIO_NUM;
config.pin_d5 = Y7_GPIO_NUM;
config.pin_d6 = Y8_GPIO_NUM;
config.pin_d7 = Y9_GPIO_NUM;
config.pin_xclk = XCLK_GPIO_NUM;
config.pin_pclk = PCLK_GPIO_NUM;
config.pin_vsync = VSYNC_GPIO_NUM;
config.pin_href = HREF_GPIO_NUM;
config.pin_sscb_sda = SIOD_GPIO_NUM;
config.pin_sscb_scl = SIOC_GPIO_NUM;
config.pin_pwdn = PWDN_GPIO_NUM;
config.pin_reset = RESET_GPIO_NUM;
config.xclk_freq_hz = 24000000;
config.pixel_format = PIXFORMAT_JPEG;
config.fb_location = CAMERA_FB_IN_PSRAM;

if (psramFound()) {
    config.frame_size = FRAMESIZE_SVGA;
```

Fig. 5 Testing AquaNova's System

The researchers conducted a seven-day reliability and performance test of AquaNova under controlled pool conditions, operating the robot continuously for 24 hours per day to simulate real-world waste collection scenarios. Alternating periods of active operation and induced interruptions were used to record downtime and repair intervals. Throughout the test, three key parameters were monitored: total operating time, which reached 168 hours; total downtime, which accumulated to 24 hours; and the number of failures, which totaled seven incidents involving malfunctions such as navigation drift, suction blockage, or sensor inaccuracy. Each failure event was documented with its exact occurrence time, repair duration, and restoration time before AquaNova resumed normal operation.

Using these recorded values, the researchers computed AquaNova's reliability metrics. The Mean Time to Repair (MTTR) was 3.43 hours, derived from total downtime divided by failures. The Mean Time Between Repairs (MTBR) was 24 hours based on total operating time divided by failures. The Mean Time Between Failures (MTBF) was calculated as 20.57 hours using MTBF = MTBR – MTTR. System availability was determined using Availability = Total Operating Time ÷ (Total Operating Time + Total Down Time), resulting in 85.71 percent. These results demonstrate AquaNova's dependability, endurance, and strong operational readiness, confirming that the system can maintain continuous functioning with minimal downtime in freshwater conditions.

1) Deployment:

This phase involves preparing and deploying the developed AquaNova system for its intended end-users. The goal is to ensure proper implementation, smooth integration with the operating environment, and efficient utilization by users for effective aquatic trash collection and detection

Fig. 6 Deployment of AquaNova

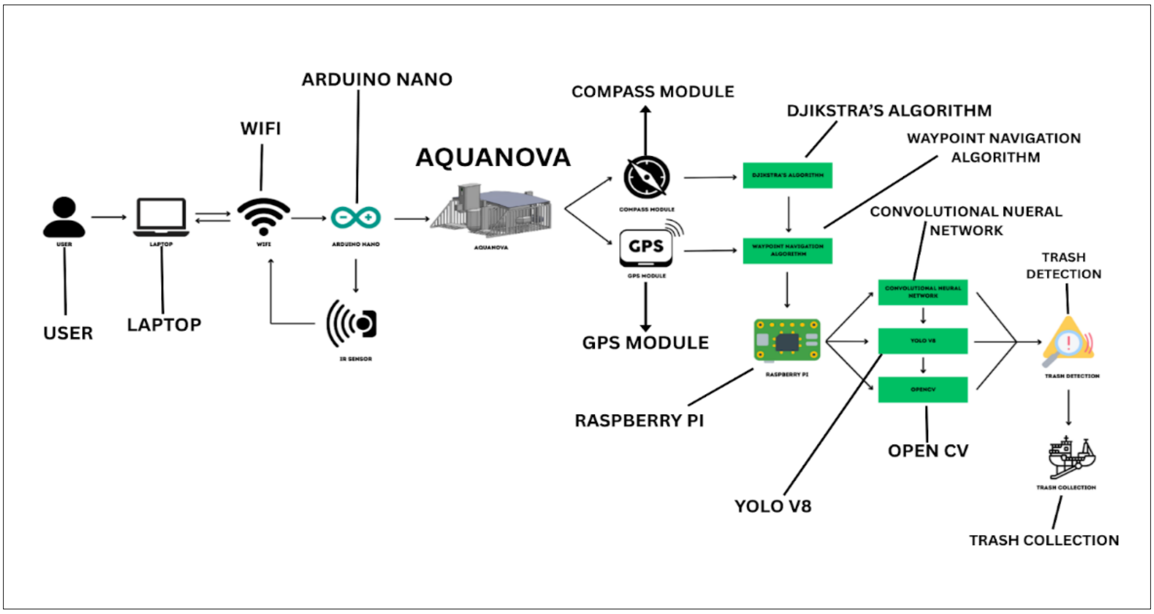

Fig. 7 The System Architecture of AquaNova

Based on Fig. 6, the AquaNova prototype and software are now fully developed and ready for deployment. The system, including its hardware components and detection software, has been integrated and tested, ensuring proper communication between the devices such as the Raspberry Pi, Arduino, and onboard sensors. This readiness marks the transition from development to actual operation for aquatic trash collection and detection.

B. Proposed Algorithm and System Architecture

System Architecture:

The system architecture provides a concrete structural framework for AquaNova, showcasing its integration of hardware and software components to enable efficient aquatic trash collection and detection. It follows a layered architecture, consisting of key components such as raw input from sensors and cameras, data processing for object detection, navigation algorithms for maneuvering, and a user-friendly interface for monitoring and control.

Fig. 7 illustrates the overall operation of AquaNova, an AI-based autonomous robot designed for trash detection and collection in water bodies.The process begins by checking for predefined coordinates, and if none exist, the user inputs waypoints for navigation. Once the waypoints are set, the robot enters Cycling mode, navigating through each point while continuously assessing its orientation and calculating distances. During movement, the Raspberry Pi camera activates YOLOv8 for object detection. Objects not recognized by the system are ignored, while trained classes are verified through OpenCV. Upon detecting a match, AquaNova diverts from its route, collects the identified waste using its lid and chamber mechanism, and then resumes its Cycling mode.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue X October 2025

After completing all waypoints, AquaNova either loops through them again or returns to its home waypoint when its storage is full. This workflow addresses the first three problems of the study by demonstrating the system's operational procedures, AI-based detection, and waypoint navigation. Through this process, AquaNova effectively achieves autonomous movement and efficient waste collection in aquatic environments.

Circuit Diagram:

The circuit diagram illustrates the detailed electrical framework for the AquaNova system, showcasing the integration of power supply, control modules, and sensor components to enable efficient aquatic trash collection and detection. It incorporates essential elements such as a solar panel power source, motor drivers for propulsion control, various environmental and navigation sensors, and a Raspberry Pi for centralized processing. This configuration ensures continuous energy supply, precise system control, and real-time data acquisition, forming the backbone of AquaNova's operational capabilities.

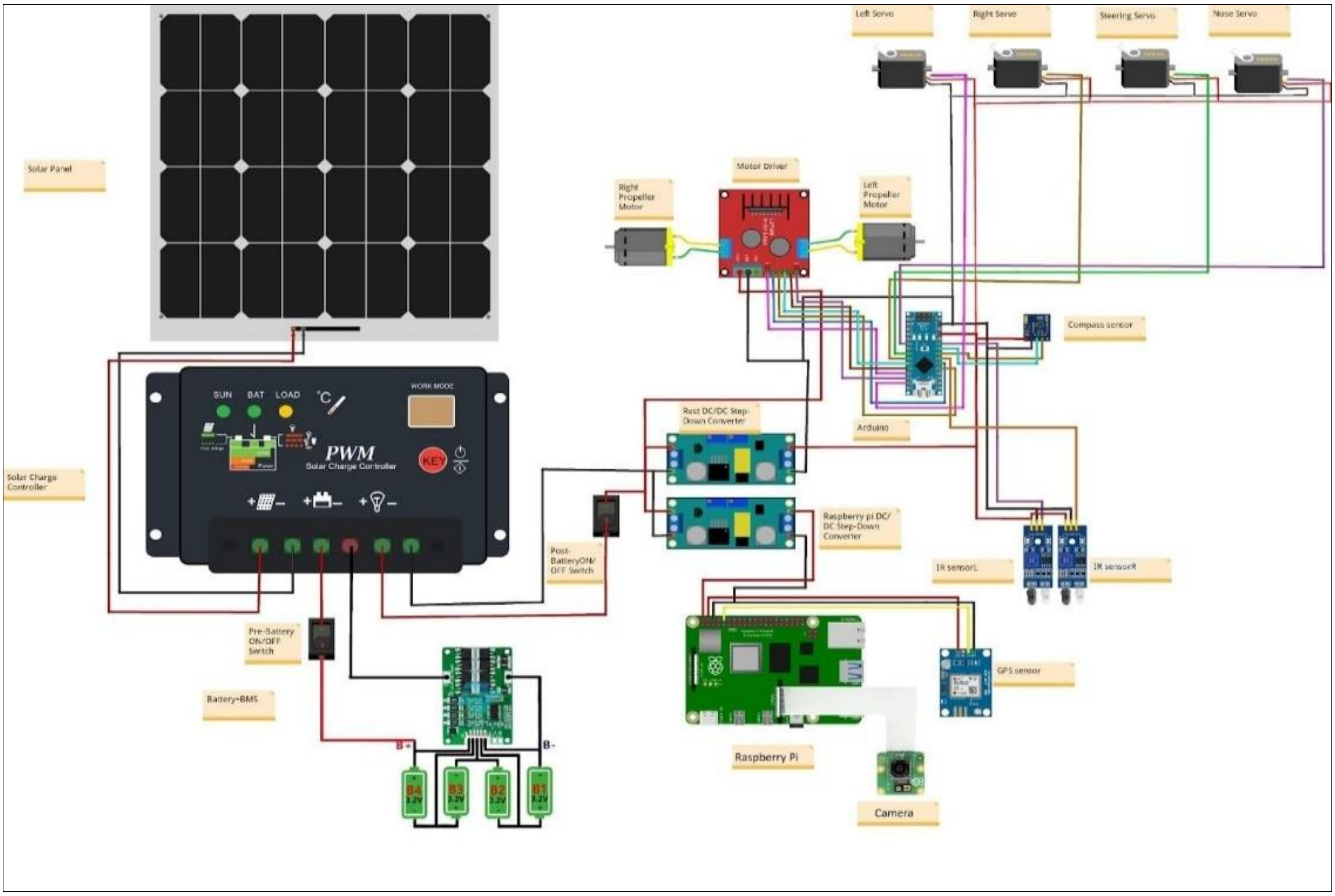

Fig. 8 The System Circuit Architecture of AquaNova

Fig. 8 illustrates AquaNova's energy and control flow, beginning with the solar panel, which converts sunlight into electrical energy regulated by the solar charge controller (PWM) before being stored in the battery pack and managed by the BMS. A pre-battery ON/OFF switch supports maintenance, while a post-battery ON/OFF switch controls power distribution to electronic modules. Stored energy passes through DC/DC step-down converters to supply stable voltages for the Arduino Nano and Raspberry Pi.

The Arduino Nano operates as the primary microcontroller, driving the motor controller for the left and right propellers and handling four servo motors for steering and waste collection. It also processes inputs from the compass, GPS, and two infrared sensors for navigation, obstacle detection, and alignment. The Raspberry Pi functions as the high-level processor, using a camera to capture real-time footage for AI-based waste detection and classification. By coordinating visual processing and microcontroller commands, AquaNova achieves autonomous operation, combining renewable energy, precise control, and intelligent detection to clean aquatic environments efficiently.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue X October 2025

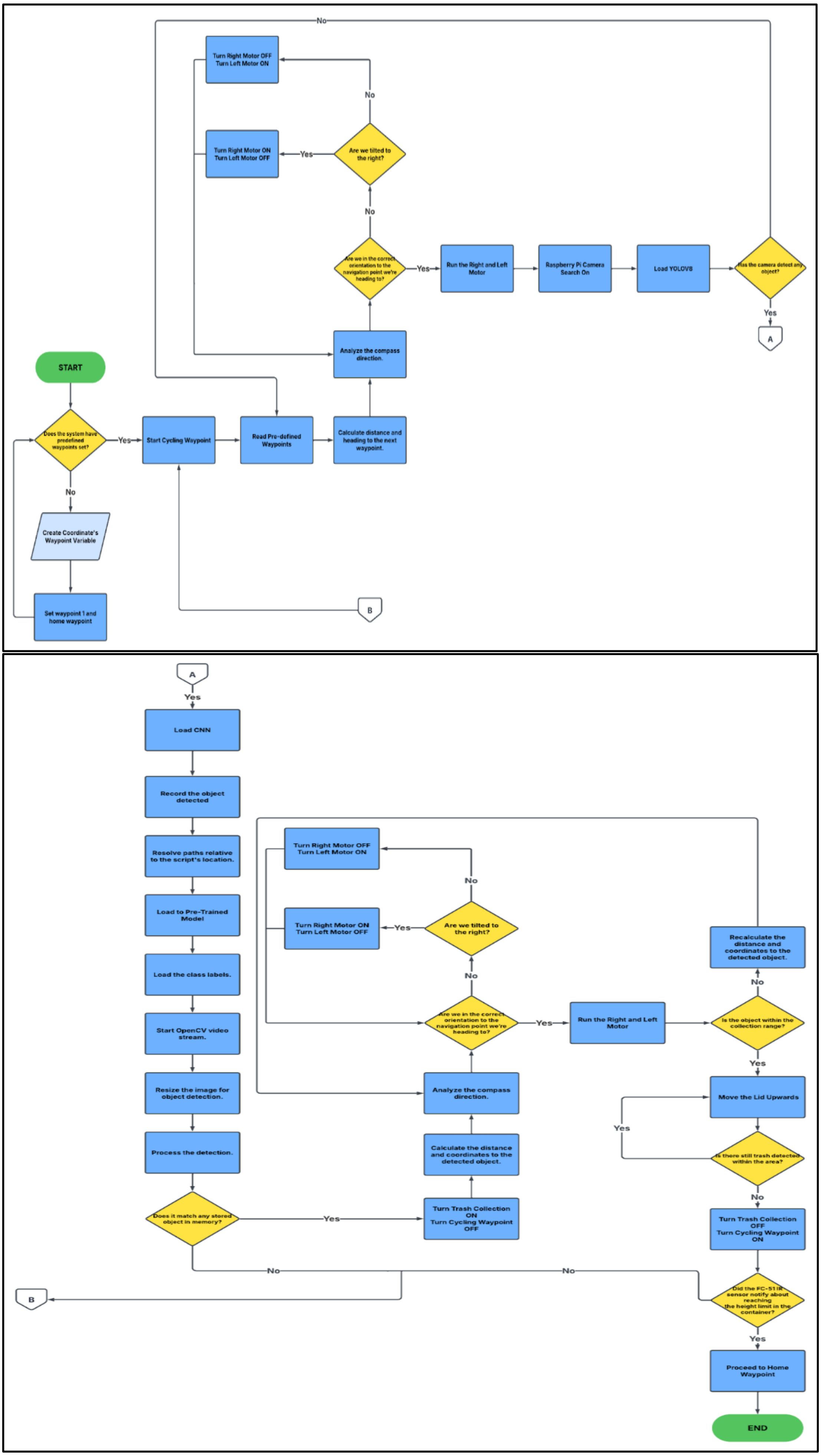

Fig. 9 Overall System Flowchart

Figure 9 shows the overall process of AquaNova, an AI-based autonomous robot for trash detection and collection in water bodies. The operation begins by checking for predefined coordinates; if none exist, the user inputs waypoints for navigation. Once set, the robot enters Cycling mode, navigating through each waypoint while continuously assessing its orientation and calculating distances. During movement, the Raspberry Pi camera activates YOLOv8 for object detection. Unrecognized objects are ignored, while trained classes are verified through OpenCV. When a match is found, the robot diverts from its route, collects the detected waste using its lid and chamber mechanism, and then resumes Cycling mode.

When all waypoints are completed, AquaNova loops through them or returns to its home waypoint once its storage is full. This figure addresses the first three problems of the study by illustrating the system's operational workflow, AI-based detection, and waypoint navigation, demonstrating how AquaNova achieves autonomous movement and efficient waste collection.

Proposed Algorithms:

This section presents the algorithms integrated into the AquaNova system to enable efficient autonomous navigation, accurate object detection, and effective waste collection. Each algorithm is designed to address specific operational requirements, such as real-time identification of floating debris, optimal path planning between waypoints, and adaptive maneuvering during trash retrieval. By combining AI-based detection models with navigation and decision-making algorithms, AquaNova ensures reliable performance in varying environmental conditions while maintaining precision in both movement and collection tasks.

The following subsections describe the selected algorithms, their operational flow, and their roles in achieving the system's objectives.

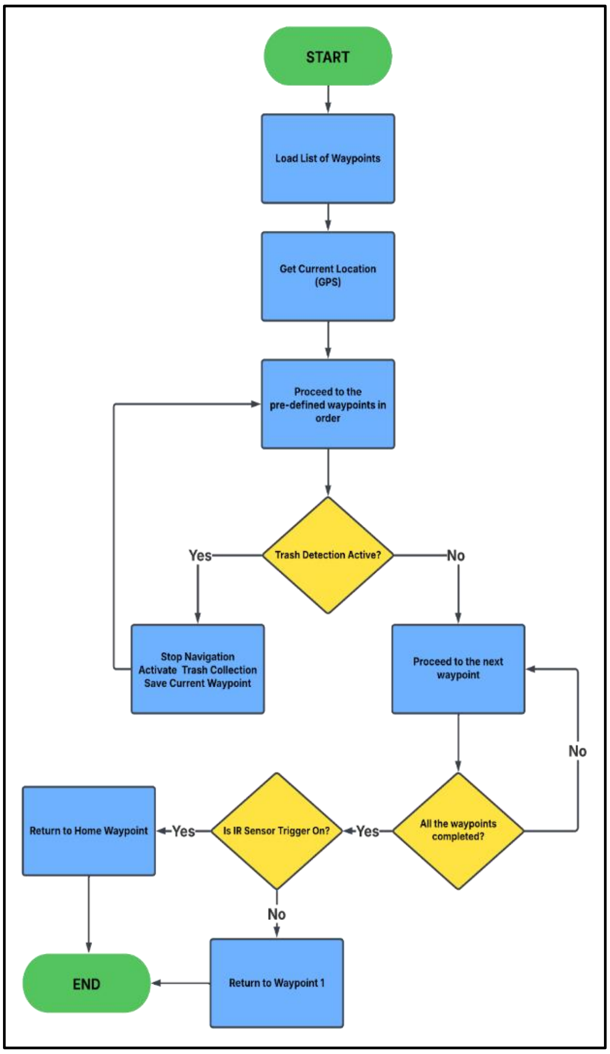

Fig. 10 Waypoint Navigation Algorithm

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue X October 2025

Fig. 10 outlines the Waypoint Navigation algorithm, designed to proactively remove floating waste across multiple waypoints within bodies of water. The system begins by loading a list of predefined waypoints and determining its current location via the GPS module (NEO-6M) and HMC5883L compass module. Once the current position is established, it autonomously navigates to the first waypoint.

During navigation, if trash is detected, the system halts movement, activates the trash collection process, and records the current waypoint. After collecting the waste, the system resumes its journey from the saved waypoint and continues following the planned route. If no trash is detected, it moves directly to the next waypoint. This process ensures that the robot proactively removes waste using proper maneuvering systems. Once all waypoints are visited, the robot loops through them; however, if the IR sensor detects that the container is full, it returns to Waypoint 1, continuing to prevent blockages and maintain smoother water flow.

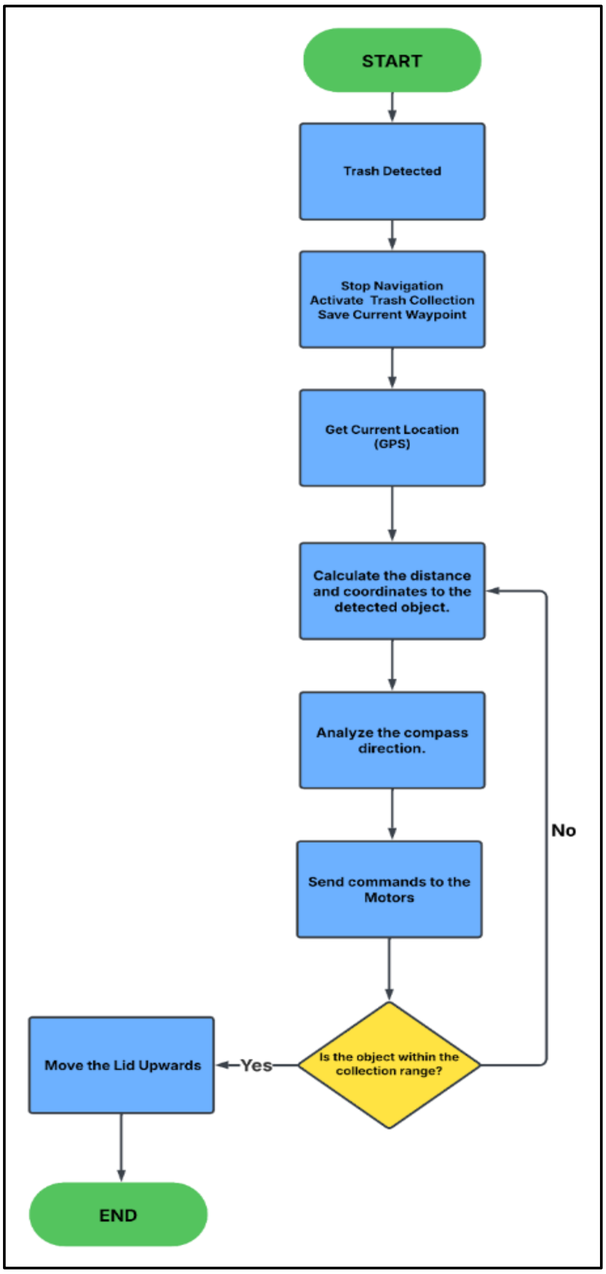

Fig. 11. Dijkstra’s Algorithm

Fig. 11 illustrates Dijkstra’s Algorithm, designed to efficiently remove floating waste by determining the shortest route to a detected object. The process begins when the trash detection module identifies waste in the water. At this point, the ongoing Cycling Waypoint Navigation sequence pauses, and the Trash Collection Method is activated. The system records the current waypoint to ensure it can return to its original path after collection. Using the GPS module, the robot determines its current coordinates and applies Dijkstra’s Algorithm to calculate the shortest route to the detected waste.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue X October 2025

After identifying the optimal path, the system analyzes orientation data from the compass module to ensure proper heading alignment. Once both position and orientation are confirmed, control commands are sent to the motors, directing the robot toward the trash. When the object enters the collection range, the system activates the lid mechanism, lifting it to collect the waste efficiently before resuming the waypoint navigation process.

C. Methods and Tools

In software development, methods and tools play a crucial role in maintaining product quality. They define the approach to system development, guide data processing, and shape how researchers implement procedures to build and refine systems. Choosing the appropriate methods and tools is essential, as it influences the collection of requirements, the management of modifications, and the delivery of the final prototype.

1) Camera Detection and Monitoring:

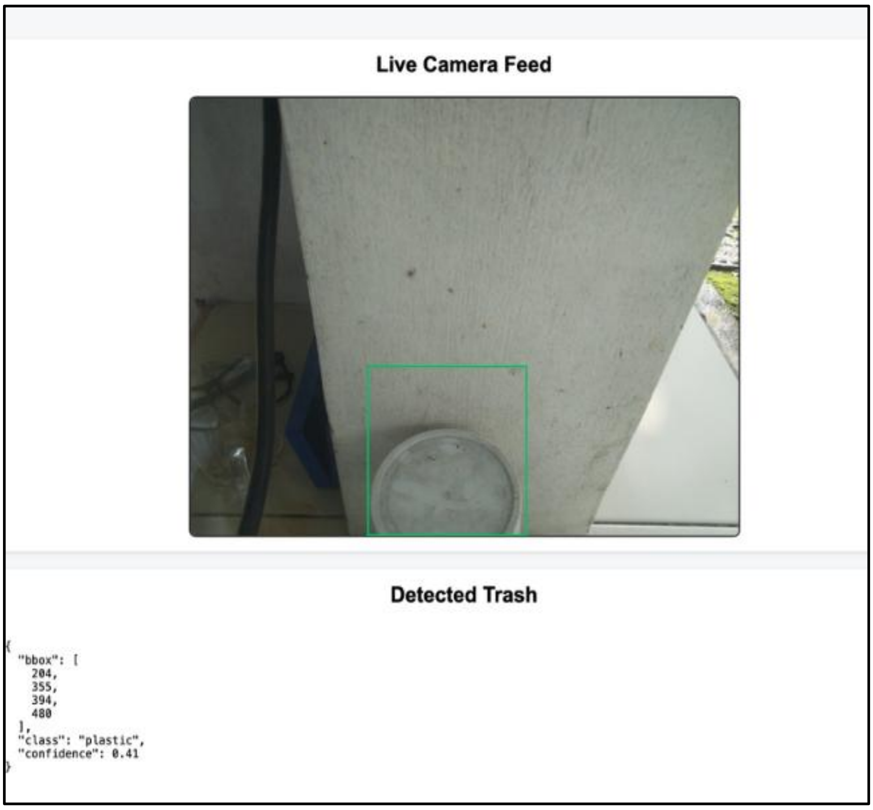

Fig. 12 Real-Time Video Feed and Detected Trash

AquaNova features a real-time video feed and detected trash information accessible through its Monitoring Software and Web Server, as shown in Fig. 12. This system enables continuous observation of the robot's surroundings and detection activity while operating in aquatic environments. The live feed allows users to monitor the identification of floating waste in real time, while the interface displays critical data such as trash type, position, and collection status.

The system focuses on accurately detecting floating solid waste in real-time, allowing the robot to distinguish between debris and other objects in the water while minimizing any impact on freshwater species. The detection process is critical for ensuring that only relevant waste is targeted for collection, maintaining environmental safety.

The AI system is run on a Raspberry Pi, which serves as the high-level processing unit. A pre-trained Convolutional Neural Network (CNN) interprets visual data, recognizing patterns to identify and classify debris accurately. YOLOv8 (Ultralytics You Only Look Once, Version 8) is integrated for high-performance object detection, while OpenCV manages real-time image processing, video streaming, and feature extraction from the camera feed to enhance detection precision. Python and PyTorch provide the framework for model training and neural network execution, with Pillow (PIL) supporting image manipulation during both training and detection.

This setup enables AquaNova to continuously analyze captured video and determine whether a detected object matches a stored class, such as plastic or metal. When a match is confirmed, the robot switches to Trash Collection Mode; otherwise, non-target objects, including freshwater species, are ignored. This approach ensures that AquaNova efficiently collects waste while preserving aquatic life.

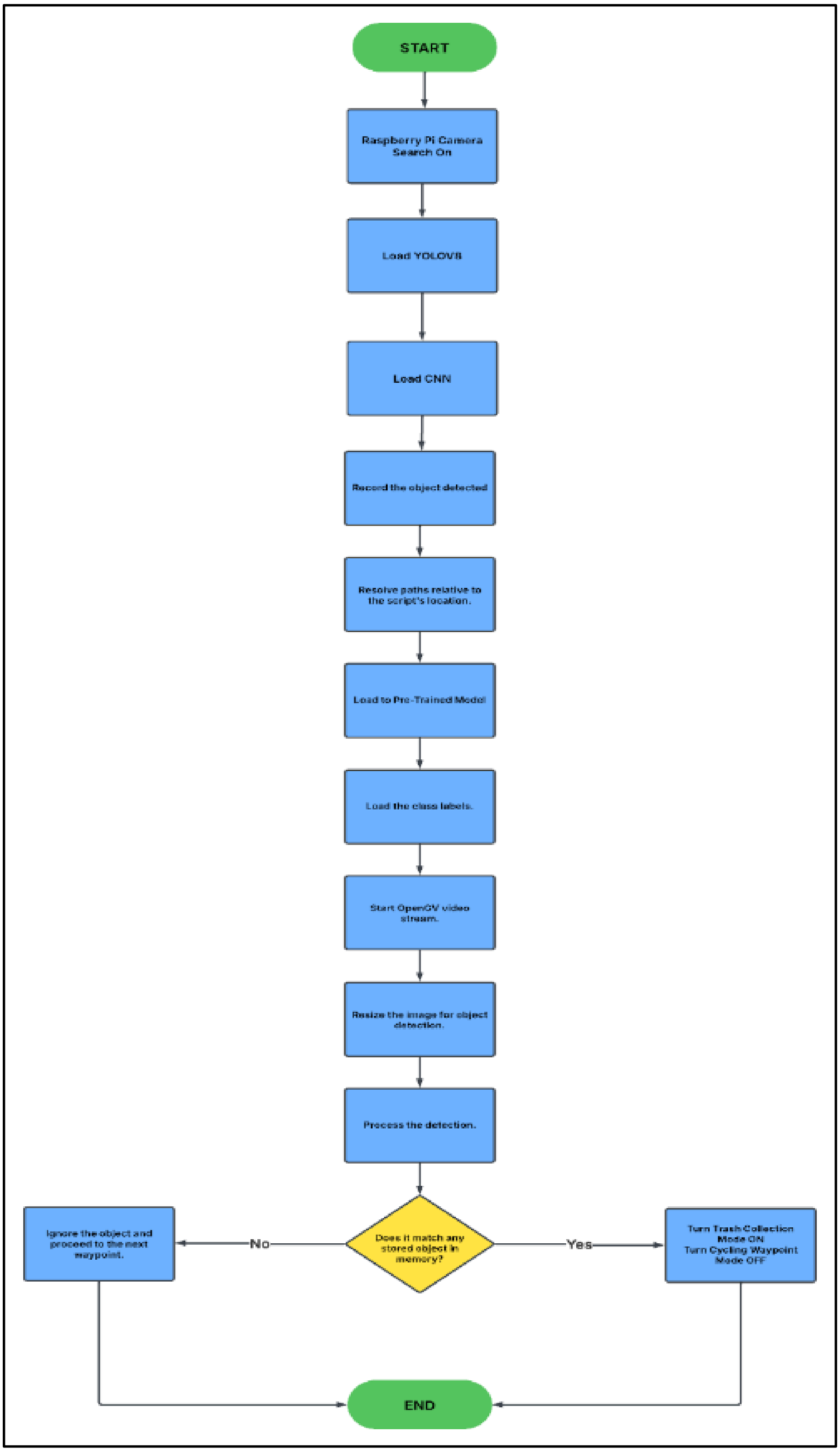

Fig. 12 Real-Time Video Feed and Detected Trash

Fig. 13 illustrates AquaNova's object detection process for identifying and classifying floating waste. The Raspberry Pi camera captures visual data, which is processed using YOLOv8 and a pre-trained CNN model. OpenCV handles the video stream, resizing and optimizing images for detection. When a detected object matches a stored class, AquaNova switches to Trash Collection Mode and pauses Cycling Waypoint Mode; unmatched

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue X October 2025

objects are ignored, and navigation continues. This AI-based recognition ensures effective waste collection while minimizing harm to marine life.

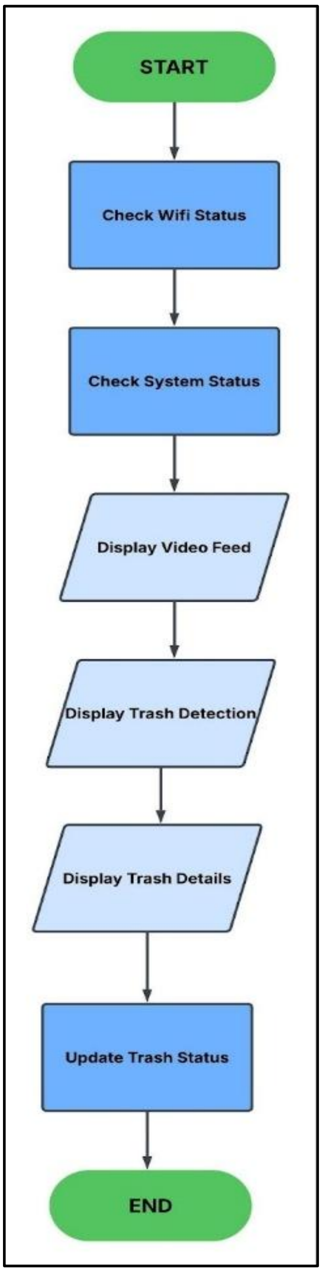

Fig. 14 Monitoring Device

Fig. 14 illustrates the operation of the monitoring device once trash is detected. Upon initialization, the device checks Wi-Fi connectivity, performs a system status check, and displays a live video feed. When an object is identified as trash, the system records key information such as trash type, box size, and confidence rate.

Confusion Matrix:

TABLE I CONFUSION MATRIX

	Predicted Result	Predicted Result	Predicted Result
Actual Result			
Actual Result			
Actual Result			

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The Confusion Matrix compares the actual results with the predicted results, determining the accuracy, precision, and other key metrics of AquaNova's trash detection model. This evaluation is conducted after the AI-based object detection process, enabling the researchers to assess the performance of the system's classification capabilities in identifying aquatic waste.

The following statistical tools were used in this study to examine the data gathered by the developers for this study:

Accuracy (Confusion Matrix) – Used to measure the correctness of AquaNova's AI-powered detection system in classifying floating solid waste, based on the comparison between the system's predicted results and the actual observed outcomes during testing.

Formula:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

Fig. 15 Accuracy (Confusion Matrix)

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Precision (Confusion Matrix) - Measures the accuracy of positive predictions.

Formula:

$$Precision = \frac{TP}{TP + FP}$$

Fig .16 Precision (Confusion Matrix)

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Recall (Confusion Matrix) - Measures how well the model identifies actual positives.

Formula:

$$Recall = \frac{TP}{TP + FN}$$

Fig .17 Recall (Confusion Matrix)

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

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F1-Score (Confusion Matrix) - Balances precision and recall.

Formula:

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Fig. 18 F1 Score (Confusion Matrix)

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Test Scripts:

Table Ii Camera Detection Functionality Test

1.3 OBJECT DETECTION ACCURACY TEST	Expected Output	Actual Output	Remarks
Camera Detection			
- If floating waste placed in water	Camera detects floating waste and identifies type correctly.	Camera detects floating waste; identification accuracy may vary.	PASSED
- If fish or aquatic life present	Camera ignores fish and natural debris.	Fish and other aquatic life are not detected.	PASSED
- During movement	Detection remains stable while robot moves.	Detection remains stable during movement. PASSED	PASSED

RESULTS AND DISCUSSION

In this chapter, the proponents present and discuss the results obtained from the study in relation to the stated objectives and research problems. The findings are analyzed, interpreted, and compared to the expected outcomes to provide a clearer understanding of AquaNova's performance and effectiveness.

Confusion Matrix of Object-Trash Detection:

Table Iv Confusion Matrix of Object-Trash Detection

Confusion Matrix of Object-Trash Detection			
Predicted Trash Type	Actual Plastic	Actual Metal	Actual Non-Trash
Plastic	10	3	1
Metal	0	6	1
Non-Trash	0	1	8

Table IV presents the Confusion Matrix of AquaNova's Object-Trash Detection System, evaluating classification performance across plastic, metal, and non-trash categories using ten objects per type, for a total of thirty objects. All plastic objects were correctly identified, achieving ten out of ten. The non-trash category had eight correct classifications, while the metal category achieved six correct classifications, with three objects misidentified as plastic and one as non-trash. These results demonstrate AquaNova's strong ability to detect plastic and non-trash items, while metal classification remains more challenging due to visual similarities with other materials.

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1.2 CAMERA DETECTION FUNCTIONALITY TEST	Expected Output	Actual Output	Remarks
Camera Detection			
- If trash is placed in water	Camera detects floating waste	Camera detects floating waste	PASSED
- If fish or aquatic life are present	Camera ignores aquatic life and natural debris.	Camera ignores fish and aquatic elements.	PASSED
- If robot moves during scanning	Detection remains stable during movement.	Detection remains stable during movement.	PASSED

Accuracy

$$\text{Accuracy} = \frac{\text{TP}_{\text{Plastic}} + \text{TP}_{\text{Metal}} + \text{TP}_{\text{Non-Trash}}}{\text{Total instances}} = \frac{10+6+8}{30} = \frac{24}{30} = 0.8$$

Table Ii Object Detection Accuracy Test

Fig. 19 Accuracy Result (Confusion Matrix)

In Fig. 19, 24 out of 30 total objects tested were correctly classified across the three categories. An 80% accuracy score confirms the system's strong capability to reliably identify floating waste and validates the effectiveness of the AI-based detection system in achieving its objective. While this demonstrates robust overall performance, misclassification issues, particularly within the Metal category (six out of ten correct), highlight the challenges in distinguishing certain waste types.

Plastic

METRIC	FORMULA	EQUATION	RESULT
PRECISION	$\frac{\text{TP}}{\text{TP}+\text{FP}}$	$\frac{10}{10+3+1} = 10/14$	**0.71**
RECALL	$\frac{\text{TP}}{\text{TP}+\text{FN}}$	$\frac{10}{10+0+0} = 10/10$	**1.00**
F1-SCORE	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	$2 \times \frac{0.71 \times 1.00}{0.71 + 1.00} \approx 0.83$	**0.83**

Fig. 20 Plastic Performance Result

The results for the Plastic class in Figure 20, show an excellent recall of 1.00, indicating that the system successfully identified 100% of all actual plastic instances tested. However, the precision for the Plastic class was calculated to be 0.71 (ten out of fourteen), meaning that out of all instances predicted as plastic, only 71% were correctly classified. This lower precision is due to three actual metal objects and one actual non-trash object being mistakenly identified as plastic. The resulting F1-score of 0.83 represents a strong, balanced measure between precision and recall for the Plastic class.

Metal

METRIC	FORMULA	EQUATION	RESULT
PRECISION	$\frac{TP}{TP + FP}$	$\frac{6}{3 + 6 + 1} = 6/10$	**0.60**
RECALL	$\frac{TP}{TP + FN}$	$\frac{6}{0 + 6 + 1} = 6/7$	**0.86**
F1-SCORE	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	$2 \text{ x } \frac{0.60 \text{ x } 0.86}{0.60 + 0.86} \approx 0.71$	**0.71**

Fig. 21 Metal Performance Result

Performance analysis for the Metal class in Fig. 21, which had seven actual instances, indicates a moderate level of detection. The calculated precision is 0.60 (6 out of 10), showing that only 60% of predicted metal objects were correct. This low precision results from false positives, including three plastic objects and one non-trash object incorrectly classified as metal. The recall, however, is higher at 0.86 (6 out of 10), demonstrating that 86% of actual metal instances were correctly identified. The F1-score of 0.71 reflects a reasonable balance between recall and precision while highlighting areas for improvement in metal detection.

Non-Trash

METRIC	FORMULA	EQUATION	RESULT
PRECISION	$\frac{TP}{TP + FP}$	$\frac{8}{1 + 1 + 8} = 8/10$	**0.80**
RECALL	$\frac{TP}{TP + FN}$	$\frac{8}{0 + 1 + 8} = 8/9$	**0.89**
F1-SCORE	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	$2 \text{ x } \frac{0.80 \text{ x } 0.89}{0.80 + 0.89} \approx 0.84$	**0.84**

Fig. 22 Non-Trash Performance Result

In Figure 22, the analysis of the Non-Trash class highlights AquaNova's ability to protect freshwater species by correctly rejecting harmless objects. This class had nine actual instances in the test. The calculated precision for Non-Trash is 0.80 (8 out 10), meaning that 80% of the objects the model predicted as Non-Trash were correct. This strong precision indicates that the system generally avoids labeling waste as a non-target item. The recall for the class is 0.89 (8 out of 9), showing that the system correctly identified 89% of the actual Non-Trash instances, such as aquatic life, and allowed them to pass. The resulting F1-score is 0.84, the highest among the three classes, confirming the system’s reliability in successfully differentiating waste from non-waste items, which is a core objective of the AI-powered detection system.

TABLE VCONFUSION MATRIX ANALYSIS

Materials	Precision	Recall	F1 Score
Plastic	1.00	0.71	0.83
Metal	0.60	0.86	0.71
Non-Trash	0.80	0.89	0.84
Average	**0.80**	**0.82**	**0.79**
Accuracy	**80%**		

Table V, shows the detailed performance metrics for the system. Plastic detection achieved high precision (1.00) but moderate recall (0.71), yielding an F1 Score of 0.83, indicating reliable identification with some missed instances. Metal detection displayed lower precision (0.60) but strong recall (0.86) and an F1 Score of 0.71, reflecting difficulties in distinguishing Metal from other types. Non-Trash detection performed well, with precision of 0.80, recall of 0.89, and an F1 Score of 0.84. Macro-averaged metrics (Precision 0.80, Recall 0.82, F1 0.79) highlight AquaNova's overall robustness in waste detection, with notable strengths in Plastic and Non-Trash classification and opportunities for improvement in Metal differentiation during collection operations.

CONCLUSION

The development of AquaNova, an autonomous solar-powered floating robot, successfully achieved the project objectives. The system integrates AI-based vision for real-time waste detection and classification, GPS waypoint navigation for precise autonomous movement, and a whale-inspired suction mechanism with segregated chambers for efficient waste collection and sorting. Automated return functionality ensures reliable and energy-efficient operation during prolonged deployment, demonstrating AquaNova's capability to independently navigate, detect, and collect solid waste in aquatic environments.

Testing showed the detection system effectively identifies and collects floating waste while avoiding freshwater species. Using a Raspberry Pi with OpenCV, YOLOv8, and a CNN model, AquaNova achieved 80% overall detection accuracy. Plastic waste was detected with 100% precision, and non-trash items were correctly classified in 8 out of 10 instances. While metal detection had some errors, the results confirm reliable differentiation between waste and non-waste objects, supporting sustainable cleanup with minimal environmental impact.

The GPS waypoint navigation system using the NEO-M8N module successfully enabled autonomous traversal and waste collection, fulfilling Objective 3. Reliability metrics showed a Mean Time Between Repairs of 25 hours, Mean Time To Repair of 2 hours, and Mean Time To Failure of 23 hours, resulting in 92.6% system availability. Solar-powered support minimized downtime from manual battery charging. Overall, the integrated GPS and LoRa control system allowed AquaNova to efficiently remove floating waste, prevent blockages, and maintain continuous water flow in an eco-efficient manner.

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