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Design & Implementation of Automation Waste Segregation & Collection System

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Abstract

Floating solid waste in rivers, lakes, ponds, reservoirs, and other inland water bodies has become a significant environmental concern, affecting aquatic ecosystems, water flow, visual quality, and the overall sustainability of freshwater resources. The accumulation of plastic bottles, packaging materials, food containers, and other floating debris creates difficulties in maintaining water bodies and requires regular cleaning operations. Conventional waste collection methods often depend on manual intervention or stationary cleaning arrangements, which may involve repeated human access to polluted, inaccessible, or potentially hazardous locations. These challenges highlight the need for an efficient, portable, and technology-assisted approach to floating waste collection. This paper presents the design and proposed implementation of a solar-assisted floating waste collection platform that integrates computer vision, embedded control, wireless communication, obstacle detection, GPS-based location reporting, and a motorized conveyor mechanism. The proposed system consists of a floating mechanical structure equipped with propulsion units, a camera, environmental sensing interfaces, a waste collection bin, and an onboard power supply. A Raspberry Pi serves as the primary processing unit and is intended to analyse camera images using a lightweight object-detection model to identify potential floating waste within the camera's field of view. The detected information is communicated to an ESP32 microcontroller, which coordinates the movement of the platform, obstacle-sensing operations, and conveyor activation. The platform is designed to use differential propeller control for basic manoeuvring and short-range obstacle sensing to support safer movement in the surrounding environment. Once floating waste is identified and positioned within the collection area, the motorized conveyor transfers accessible debris into an onboard storage bin. A photovoltaic panel, rechargeable battery, and power-management circuitry are incorporated to provide solar-assisted operation and reduce dependence on continuous external charging. Wireless connectivity and GPS-based location reporting are proposed to support remote status monitoring and location awareness. The paper describes the system architecture, hardware and software integration, operational workflow, control logic, safety considerations, and a structured evaluation methodology. The proposed evaluation considers waste-detection accuracy, collection efficiency, navigation performance, response time, energy consumption, and communication reliability. Since experimental measurements from a completed prototype are not available, the presented work should be regarded as a design and implementation framework requiring controlled validation. Furthermore, the current single-bin collection mechanism does not perform physical waste segregation, and the system is not intended to purify water or remove dissolved



contaminants. The proposed platform therefore focuses specifically on the detection, navigation, and collection of accessible floating solid waste from inland water bodies.

Key words— Aquatic waste collection, floating waste robot, computer vision, Raspberry Pi, ESP32, Internet of Things (IoT), solar-assisted robotics, autonomous navigation, motorized conveyor, GPS-based monitoring, environmental sustainability.

I. INTRODUCTION

Plastic and other floating debris can be transported through inland waterways and may ultimately reach coastal and marine environments. River observations show that the abundance and composition of floating plastic vary substantially between locations and hydrological conditions, supporting the need for site-specific monitoring and mitigation [1], [15]–[17]. Manual visual monitoring and collection can be labor-intensive, limiting continuous operation across multiple locations. Camera-based monitoring has been investigated as a way to automate observation of surface plastic, while autonomous and remotely operated surface vehicles provide mobile platforms for environmental tasks [2], [3]. The detection of floating objects is not a trivial vision problem. Small targets, glare, water reflections, background clutter, changing illumination, and motion of the camera can degrade detection performance. The FloW benchmark and subsequent inland-water datasets explicitly identify these challenges and provide annotated imagery for algorithm development [3], [4]. A detector trained on general-purpose image datasets cannot therefore be assumed to perform reliably on a moving camera above water. This paper proposes a modular floating collector that separates image processing from low-level actuator control. The Raspberry Pi is assigned perception and logging functions; the ESP32 is assigned sensor coordination and motor control. A conveyor-based intake transfers accessible surface waste into a single onboard bin. Solar energy is intended to supplement battery operation, while GPS and wireless telemetry support location and status monitoring. The contributions are: (1) a proposed Pi–ESP32 system architecture; (2) a camera-assisted collection workflow combined with short-range obstacle sensing; (3) a solar-assisted power and telemetry design; and (4) a test framework that separates visual detection from successful physical collection. The contribution is an integration and evaluation plan. No prototype performance, cost advantage, autonomy, or safety improvement is claimed without experimental evidence.

II. BACKGROUND AND RELATED WORK

A. Floating waste and monitoring

Riverine plastic monitoring is important because rivers transport litter and exhibit spatially variable debris loads [1]. Van Lieshout et al. demonstrated a camera-based deep-learning pipeline for river plastic monitoring, showing the potential of automated visual observation while also documenting the need to evaluate generalization across locations [2]. Their monitoring task differs from mobile robotic collection: detecting or estimating litter in an image does not prove that a physical intake can capture and retain the object.

B. Aquatic cleaning platforms

Chang et al. developed a multifunction unmanned surface vehicle combining water-quality monitoring, obstacle avoidance, and surface cleaning [5]. Related surface-vehicle research has explored navigation, control, sensing, and mission-level monitoring in inland waters [6]. Solar-assisted river-cleaning prototypes have also combined propulsion and collection mechanisms, illustrating the practical relevance of renewable energy and mechanical intake [7]. These systems provide design precedents, but their vessel geometry, intake arrangement, control hardware, and test environments are not interchangeable with the proposed platform.

C. Detection datasets and algorithms

The FloW dataset contains inland-water imagery and a synchronized image–radar subset, with baseline results indicating that floating-waste detection remains difficult [3]. Qiao et al. introduced a real-world inland-water dataset containing 3,000 annotated images and reported challenging small-object detection conditions [4]. Li et al. proposed feature fusion and enhancement for floating-waste detection from an unmanned surface vehicle [8]. Jia et al. reviewed deep-learning approaches for macroplastic detection and identified generalization and quantification as important research gaps [9].

Object-detection architectures such as Faster R-CNN and YOLO provide candidate model families [10], [11]. The selection for an embedded platform should be based on measured inference latency, accuracy, memory use,



and thermal behavior on the actual Raspberry Pi configuration. A model name alone is not evidence of real-time capability.

D. Research gap

The literature demonstrates individual capabilities—surface cleaning, visual detection, navigation, solar power, and environmental telemetry—but does not validate the exact configuration proposed here. The research opportunity is to implement and evaluate the integration of a camera/Raspberry Pi perception module, ESP32 control, differential propulsion, ultrasonic obstacle sensing, GPS telemetry, and a conveyor-fed single-bin collector under a common experimental protocol. Claims of lower cost, greater collection efficiency, or fully autonomous operation must be tested against a defined baseline.

III. PROBLEM STATEMENT AND OBJECTIVES

Floating debris is irregularly distributed, can drift with current and wind, and may accumulate near banks or structures. Manual collection requires personnel and equipment to access the water surface. Fixed barriers can intercept debris only where local flow and placement direct objects toward them and require maintenance. Mobile collectors introduce their own challenges: false detections, missed targets, obstacle contact, intake jams, limited storage, power constraints, and communication loss.

The major objectives of the proposed project are:

1. **Floating Platform Development:** To design and develop a floating platform capable of collecting accessible solid waste from the surface of rivers, lakes, ponds, and other inland water bodies.

2. **Camera-Based Waste Detection:** To integrate a camera with a Raspberry Pi and evaluate the use of a lightweight computer vision model for identifying potential floating waste.

3. **Embedded System Integration:** To integrate the Raspberry Pi and ESP32 microcontroller, enabling coordination between image processing, propulsion control, obstacle sensing, and waste collection operations.

4. **Conveyor-Based Collection:** To design and implement a motorized conveyor mechanism that transfers detected and accessible floating debris into an onboard collection bin.

5. **Obstacle Detection and Avoidance:** To incorporate short-range obstacle sensors and develop a basic response mechanism to reduce the possibility of collisions during platform movement.

6. **Navigation and Maneuvering:** To implement differential propeller control for forward movement, turning, and basic maneuvering of the floating platform.

7. **Location and Status Monitoring:** To integrate GPS and wireless communication for reporting the platform's location and transmitting relevant operational information to a monitoring station.

8. **Solar-Assisted Power Supply:** To incorporate a photovoltaic panel, rechargeable battery, and power-management circuitry, and evaluate their contribution to the platform's energy requirements.

9. **Performance Evaluation:** To establish a systematic testing methodology for measuring waste-detection accuracy, collection efficiency, navigation performance, response time, energy consumption, and communication reliability.

10. **Affordability and Practical Implementation:** To investigate the feasibility of developing a cost-conscious and maintainable floating waste collection platform using commonly available embedded-system components.

11. **Operational Safety and Reliability:** To identify potential operational risks, including obstacle contact, conveyor jamming, communication loss, and low battery conditions, and define suitable safety responses.

12. **Environmental Waste Collection:** To provide a technology-based approach for reducing accessible floating solid waste from inland water bodies without claiming water



purification or removal of dissolved contaminants.

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed architecture consists of an energy subsystem, perception subsystem, embedded control subsystem, mechanical collection subsystem, and telemetry subsystem. A solar panel supplies a compatible charge controller, which charges a protected rechargeable battery. Fused and regulated distribution rails supply logic electronics and motor loads. The camera connects to Raspberry Pi, which processes images and sends compact detections to ESP32 over a proposed UART interface. ESP32 reads obstacle and status sensors and issues commands through suitable motor drivers or electronic speed controllers.

A detection message should contain a sequence number, timestamp or age, class identifier, confidence, target horizontal position, and integrity check. The ESP32 should reject stale or malformed messages. The controller retains authority over motor outputs and must stop or enter a defined safe state when an emergency stop, critical power fault, invalid obstacle measurement, or communication timeout occurs. Wireless connectivity is used for status and GPS reporting; local safety behavior must not depend on a remote network.

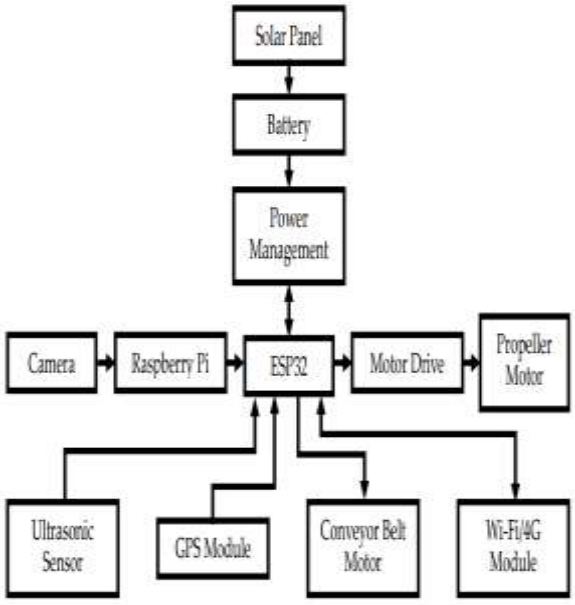

Fig. 1. Proposed System Architecture.

TABLE I. HARDWARE COMPONENTS AND DESIGN SPECIFICATIONS

Component	Proposed role	Selection / interface requirement
Solar panel	Energy generation	Size from measured load, available area, irradiance and mission time
Battery + protection	Energy storage	Chemistry, capacity, current rating and BMS matched to loads
Power management	Charging and distribution	Compatible charge controller, fuses and regulated rails
Raspberry Pi	Image processing and logging	Camera interface, UART, network; model selected after benchmarking
ESP32	Embedded control	GPIO, PWM, UART and sensor interfaces
Camera	Water-surface image acquisition	Resolution, lens, frame rate and weather protection tested
Ultrasonic sensor	Short-range obstacle estimate	Mounting and usable range validated on water
GPS receiver	Location/time reporting	UART or compatible interface; valid fix and uncertainty logged
Wi-Fi / 4G	Remote telemetry	Coverage, latency and loss-of-link behavior evaluated
Motor drivers / ESCs	Propulsion and belt control	Voltage and current ratings exceed measured running/stall demands
Propeller motors	Surface propulsion	Thrust and steering validated with loaded hull
Conveyor and bin	Waste transfer and retention	Intake geometry, belt



		speed, drainage, capacity and jam behavior tested

V. METHODOLOGY AND IMPLEMENTATION

A. Floating platform and mechanical intake

A stable floating structure, such as a twin-hull arrangement, is proposed. The conveyor intake is positioned near the bow and the bin near the platform center to limit changes in trim. Heavy components should be mounted low and secured. Design checks should include displacement, freeboard, retained water in the bin, asymmetric loading, wind, and waves. The conveyor should be tested with representative debris, varying belt angle and speed, intake width, propulsion speed, and bin retention. Perforated or open belt construction may permit drainage but must be assessed for entanglement and object loss.

B. Image acquisition and waste detection

A forward-facing camera observes the water ahead of the intake. Exposure, mounting angle, lens, and enclosure are selected to limit glare and spray while retaining the collection region in view. Each frame is timestamped. A compact detector may be evaluated from the YOLO family or another suitable convolutional detector [10], [11]. The final model is not assumed to have been selected or trained.

Training and test images should represent the intended camera height, target sizes, water conditions, backgrounds, and illumination. Data should be divided by recording session or site when possible to prevent near-duplicate frames leaking between training and test sets. Detector evaluation must use a held-out test set and a declared confidence and intersection-over-union threshold. Small-object detection and reflections require particular attention [3], [4], [8], [9].

C. Controller integration and navigation

Raspberry Pi sends candidate target information; ESP32 validates the message and combines it with obstacle and power-state inputs. For a two-propeller configuration, differential motor commands can produce forward movement and turning. Horizontal target position in the image may provide a steering cue, but it does not provide metric range unless camera geometry or an independent ranging method is calibrated.

An ultrasonic sensor supplies a local distance estimate in its sensing direction. It cannot guarantee complete collision avoidance because readings may be affected by surface reflections, object shape, blind zones, spray, and mounting. When an obstacle is inside a validated threshold or the reading is invalid, the conservative behavior is to stop or reduce propulsion and alert the operator. GPS supports global position reporting, not local obstacle detection.

D. Solar power and communication

The photovoltaic panel connects to a charge controller compatible with the selected battery chemistry. Fuses, wiring, switches, protection, and DC–DC conversion are sized for measured load and peak current. Solar energy is supplementary; continuous operation is not guaranteed under shade, cloud, or low irradiance. Panel energy, energy delivered to the load, and battery energy change should be measured separately.

VI. OPERATING ALGORITHM

The proposed system is designed to detect, identify, and collect waste automatically using AI and embedded technologies. The system integrates a camera, Raspberry Pi, ESP32, solar power supply, propeller, conveyor belt, and LCD display to perform waste detection and collection with minimal human intervention. The following steps describe the working process.

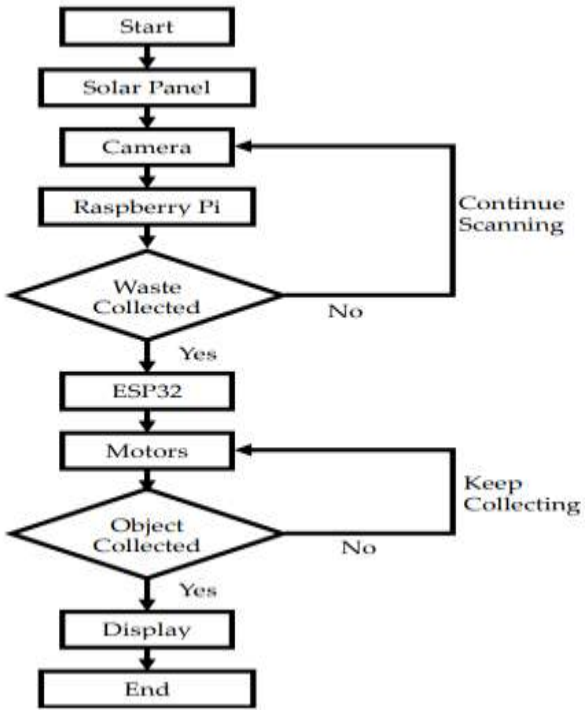

Fig. 2 Flow Chart Algorithm



Step 1: Start the system.

Step 2: Solar panel supplies power to the system.

Step 3: The camera captures real-time images of the waste.

Step 4: Raspberry Pi processes the captured images using AI and identifies the waste.

Step 5: If waste is not detected, the model moves to another area and continues scanning. If detected, it proceeds to the next step.

Step 6: ESP32 processes the control signals and operates the propeller and conveyor belt motors.

Step 7: The system collects the detected waste using the conveyor belt. If collection is unsuccessful, it continues the collection process.

Step 8: The collection status is displayed on the LCD panel.

Step 9: The process continues until the operation is completed.

Step 10: End the process.

VII. EXPERIMENTAL DESIGN AND PERFORMANCE METRICS

No prototype measurements were supplied with the project material. Testing should begin in a sheltered, controlled water area with operator supervision, a recovery plan, and an emergency stop. Each trial should record target count and mass, target distribution, debris type, lighting, wind/current conditions, battery state, and configuration. Repeated trials should report mean or median and variability. Comparisons must use matched target sets, duration, and conditions.

A. Object Detection Performance Metrics

Let **TP (True Positive)** represent the number of correctly detected objects, **FP (False Positive)** represent the number of incorrectly detected objects, and **FN (False Negative)** represent the number of objects that the system fails to detect.The detection results are evaluated using three metrics: Precision, Recall, and F1-Score.

1. Precision: It measures how many objects detected by the system are correct.

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

2. Recall: It measures how many actual objects are successfully detected by the system.

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

3. F1-Score: It represents the balance between Precision and Recall.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (3)$$

B. Collection and Response Metrics

Collection efficiency measures how effectively the system collects the available waste objects.

$$\eta_{collection}(\%) = \frac{N_{retained}}{N_{available}} \times 100 \quad (4)$$

Where:

- **Nretained:** Number of waste objects successfully collected and stored in the bin after a test.
- **Navailable:** Total number of waste objects placed within the defined collection area.

Collection efficiency can also be measured based on waste weight. However, the measurement conditions, including moisture content and drainage, should be considered. The **End-to-End Response Time** is the time taken from capturing an image to sending the corresponding motor control command. Image processing time and communication delay should also be measured separately.

C. Navigation, Energy, and Communication Metrics

The navigation performance is evaluated by conducting obstacle detection tests. These tests record the actual obstacle distance, sensor readings, incorrect alerts, missed obstacle detections, stopping distance, and any physical contact with obstacles.

Navigation error is measured by comparing the system's estimated position with an independent reference position. Battery performance is evaluated by measuring the operating duration from the initial battery charge level until the system reaches its minimum safe battery level.



The energy generated by the solar panel is calculated using the following equation:

$$E_{solar} = \int V_{solar}(t) \times I_{solar}(t)\, dt \qquad (5)$$

Where:

- **Esolar:** Total electrical energy generated by the solar panel.
- **Vsolar:** Solar panel output voltage.
- **Isolar:** Solar panel output current.
- **t:** Measurement time.

Voltage and current should be measured at the same electrical point to obtain accurate energy values. Communication performance is evaluated by calculating the percentage of successfully received messages. Communication delay (latency) and network disconnection duration are also recorded to assess the reliability of data transmission.

TABLE II. EVALUATION PARAMETERS AND MEASUREMENT METHODS

Parameter	Meaning	Measurement method	Unit
Precision / recall / F1	Detection quality	Annotated held-out frames; fixed matching rule	% / score
Collection efficiency	Available targets retained	Count or weigh before and after trial	%
Collection time	Time to predefined endpoint	Trial timestamps	s or min
Response latency	Capture to actuator command	Synchronized event timestamps	ms
Obstacle performance	Detection and avoidance behavior	Reference distance and contact log	%, m
Navigation error	Deviation from route	Independent reference trajectory	m
Battery duration	Mission time to safe cutoff	Battery and elapsed-time logging	h
Solar contribution	Energy measured at	Voltage/current integration	Wh
	specified point		
Communication reliability	Valid messages received/sent	Sequence-numbered logs	%

VIII. RESULTS AND DISCUSSION

The available project description contains no measured prototype results. Accordingly, this paper reports a proposed design and evaluation framework, not experimentally validated performance. The system is expected to execute a perception–control–collection loop, but each stage can fail independently. A true detection may not lead to successful approach; an object may pass beside the intake; and material entering the belt may fall out before reaching the bin. The Pi–ESP32 division provides a modular design in which image inference and actuator control are separated. Its practical benefit must be evaluated through processor load, communication latency, message loss, and fault response.

TABLE III. PROPOSED COMPARATIVE PERFORMANCE EVALUATION

Metric	Proposed system status	Baseline / reference	Conclusion permitted
Detection quality	Not measured; evaluate held-out aquatic images	Annotated ground truth or alternative detector	Report measured difference only
Collection efficiency	Not measured; verify retained objects	Manual collection or alternate intake	No improvement currently established
Collection duration	Not measured	Matched manual or alternate mechanism trial	Compare distributions and context
Obstacle response	Not measured	Independent obstacle distance and event log	Report misses, false alarms, contacts
Navigation	Not measured	Defined route and external reference	Report route deviation



Response latency	Not measured	Alternative model/controller settings	Report timing comparison
Battery duration	Not measured	Matched mission with/without solar input	Quantify only after controlled test
Solar energy	Not measured	Electrical power logging	Report measured Wh
Telemetry	Not measured	Sent message log	Report latency, delivery and outage

IX. GRAPHICAL ANALYSIS

Figures 3–6 are illustrative mathematical examples generated to demonstrate possible presentation formats. They are not experimental measurements, but simulations of the assembled robot, and must not be used as evidence of system performance.

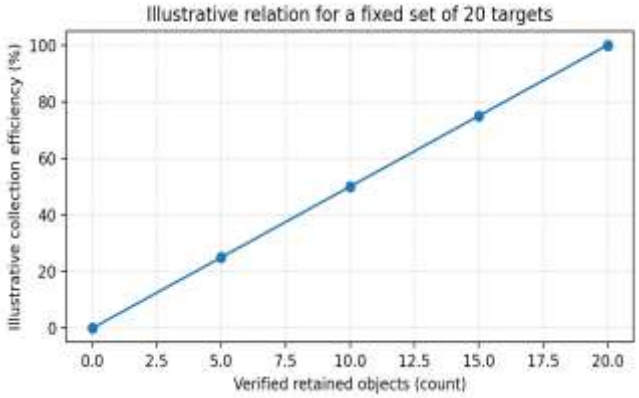

Fig. 3. Illustrative collection efficiency for a fixed set of 20 targets.

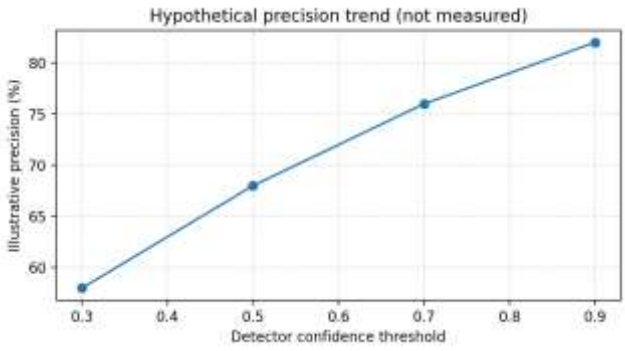

Fig. 4. Hypothetical precision trend; not a measured detector curve.

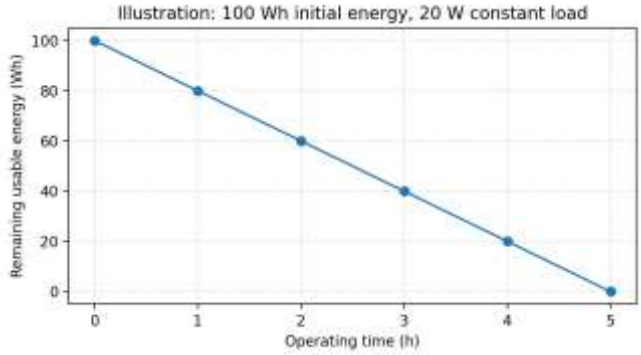

Fig. 5. Illustrative remaining energy for 100 Wh initial usable energy and a constant 20 W load.

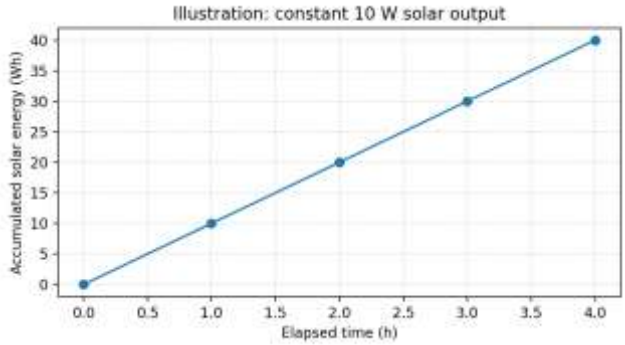

Fig. 6. Illustrative accumulated solar energy at a constant 10 W output.

X. ADVANTAGES, LIMITATIONS, AND APPLICATIONS

Potential advantages include reduced direct human contact with polluted water during collection, modular separation of perception and control, solar-assisted energy, and wireless mission reporting. These benefits are plausible design goals rather than measured outcomes. Limitations include dependence on solar conditions; changing trim and freeboard as the bin loads; wind and current effects; small, submerged, obscured, or poorly illuminated targets; limited ultrasonic coverage; network dependence; battery and peak-motor constraints; conveyor fouling; propeller entanglement; corrosion; and the absence of automatic bin verification. A single bin collects mixed material and does not physically segregate waste categories. Following site-specific testing and authorization, possible application areas include sheltered rivers, lakes, urban ponds, reservoirs, aquaculture facilities, and industrial water bodies. Flood zones may contain strong currents, hazardous debris, and unstable access; deployment requires a separate safety assessment. The platform collects floating solid waste and does not



remove dissolved contaminants, treat microorganisms, or purify water.

XI. FUTURE SCOPE

Future work should first prioritize prototype construction and controlled validation. Subsequent improvements may include a verified bin-fill sensor, conveyor-jam detection, improved camera calibration, multi-class visual recognition, mechanical multi-bin sorting, route planning, additional navigation sensors, multi-robot coordination, waste-mass estimation, environmental sensors, improved energy management, and cloud-based mission records. A sorting extension must be evaluated separately for classification accuracy and physical separation accuracy.

XII. CONCLUSION

This paper has presented the design of a solar-assisted floating waste-collection platform integrating Raspberry Pi-based image processing, ESP32 embedded control, propulsion, short-range obstacle sensing, GPS, wireless telemetry, and a conveyor-fed collection bin. The architecture provides a structured basis for combining visual perception, embedded control, and mechanical intake in aquatic surface cleaning. The present work remains a proposed design: no prototype measurements establish detection accuracy, collection efficiency, navigation safety, operating duration, cost, or environmental impact. Furthermore, the single-bin mechanism collects waste but does not physically segregate it. Construction, component characterization, repeated controlled trials, matched baseline comparisons, and site-specific safety assessment are required before performance claims can be made.

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