Swinburne University of Technology

Faculty of Science, Engineering and Technology

ENG30002- ETS Project

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Name of Assignment*: **Expected Research Outcome (Abstract)**

Project Title: **Sall-e: Autonomous Robot for Garbage Collection**

Group ID: **7.2**

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2. Executive Summary

Sall-e project is autonomous software-integrated robot systems for garbage detection, localization, and collection in Indonesia's most contaminated Citarum River. State-of-the-art computer vision (CV) and artificial intelligence (AI) models are integrated with real-time aerial video streams from drone-based sources for waste detection (YOLOv11l, YOLOv5, DETR), obstacle detection and riverbank detection (Mask R-CNN and DeepLabV3+), geospatial GPS localization and efficient pathfinding (A* and KNN), and a post-collection YOLOv11s classification model trained on custom garbage dataset for recycling and selective disposal.

The coordination signals are then integrated into coordinates in the real world through a geometric scaling process based on the drone altitude. The entire system runs on the AI edge device NVIDIA Jetson Orin, thus enabling low-latency onboard computation and no reliance on the cloud, hence improving field reliability. The Sall-e project seeks ecological sustainability, economic viability, and technical superiority against manual cleaning methods. The project is backed by detailed comparative analysis, prototype testing, and validation of scenarios in the real world for the potential scalability of application across polluted waterways.

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3. Statement of Problem

Citarum River in Indonesia is acclaimed as one of the most polluted rivers in the world, choking with heap upon heaps of plastic wastes, household wastes, and industrial wastes slipped into the river. The river daily admits wastage of nearly 20,000 tons and 340,000 tons of wastewater, which creates a very agitative barrier in the biodiversity of this part of the world, disturbing public health, local economies, and millions of them land down to this river to meet the daily needs [1][2].

Conventional cleanup operations employed by local authorities and NGOs are predominantly manual, labor-intensive, and costs the government and NGOs millions annually while failing to mitigate the crisis sustainably [5]. Workers often dredge waste with simple tools while facing severe pollution, toxic chemicals, and drowning hazards [29]. The situation underscore an urgent necessity for innovative, autonomous solutions capable of continuously detecting, localizing, and collecting floating debris while minimizing ecological disturbance.

Figure 1. Manual labour in action for Citarum river cleanup [29]

4. Introduction:

Project Overview

The Sall-e project aims to revolutionize waste management within the Citarum River through an advanced, autonomous robotic software solution. This system integrates robust CV and AI techniques for continuous, precise garbage detection and navigation optimization. Drone-captured aerial streams provide real-time data to the robot via wireless API communications.

Key Technologies:

- AI-Powered Detection: YOLOv11l (custom-trained from Garbage UAV Dataset), external YOLOv5, DETR models.
- GPS Localization: Real-time translation of drone-based pixel detections into real-world GPS coordinates using drone altitude data.
- Navigation Optimization: Path planning via A* and KNN algorithms.
- Drone Communication: Real-time wireless streaming of drone-captured ocean video feeds, including altitude data.
- Obstacle and Riverbank Detection: Mask R-CNN and DeepLabV3+ architectures.
- Post garbage-collection recycling: YOLOv11s model (custom-trained from self-collected garbage data [28])
- Simulation & Testing: Synthetic AI simulation validates real-world efficiency (with website demo).

Project Feasibility

Sall-e system is energy-efficient, scalable, and cost-saving and therefore an appropriate response to address large-scale pollution cleanup. The project leverages AI and autonomous technologies to break the limitations of traditional approaches and achieve a tangible effect in rescuing the river ecosystems.

Key Investigative Questions:

1. How can multi-model AI detection (YOLOv11l, YOLOv5, DETR) improve garbage detection accuracy in complex river environments?
2. How effectively can GPS scaling from drone altitude convert visual detections to real-world coordinates for robotic path planning?
3. What is the comparative financial impact of autonomous robotic cleanup versus traditional manual labor approaches in the Citarum River context?
4. How can AI-driven obstacle and riverbank detection (Mask R-CNN, DeepLabV3+) reduce environmental disruption and enhance system reliability?
5. What are the economic potentials of integrating garbage classification and recycling within this autonomous system for local community benefit?

5. Background:

5.1. Relevance of the Problem

The Citarum River's extreme pollution has severe ecological, economic, and social consequences, causing a massive health crisis, environmental damage, and economic loss through impacted fisheries and agriculture [3][4]. The Guardian reports "whole stretches of the river turned black and opaque" with human and industrial waste, where "fishermen haul in more plastic than fish" [29]. Thus, manual cleanup methods currently employed by the Indonesian government and NGOs are not sufficient to deal with the continuous influx of debris and typically have unsustainable costs of over millions annually [5]. Fusion of multiple CV models significantly improves the stability of debris detection, mitigating limitations of single model use [12].

5.2. Existing Systems and Limitations

System	Description	Limitation
The Ocean Cleanup (Interceptor)[6]	River-based passive garbage collection system	Requires human intervention, limited to river condition
Clear Blue Sea's Floating Robots[7]	Semi-autonomous marine debris collection prototype	Limited AI capabilities, lacks dynamic path optimization
WasteShark Drone[8]	Aquatic surface waste-collecting drone	Limited AI detection, manual control predominant
SeaClear Project (EU Funded)[9]	Underwater garbage collection using AI and robots	Focused underwater, limited floating debris handling
YOLOv5/DETR Models[10][11]	General AI model trained for waste classification	Not optimized specifically for river-centric debris scenarios

5.3. Literature Review

Mask R-CNN and DeepLabV3+ models can detect obstacles with good accuracy and differentiate between organic life and inorganic waste, enabling environmental sustainability [13][14]. Accurate GPS localization methods using drone altitude data through geospatial coordinate transformation [18] enhance navigation accuracy over traditional methods [14]. Jetson Orin is selected based on high embedded GPU performance proven in autonomous and robotics applications, enabling real-time CV-AI processing [23]. OpenCV libraries complement model integration and image processing tasks [24].

5.4. Integration of Model, Software and Dataset Evaluation

Model/Dataset	Description	Limitation
YOLOv5 Trash Detection [10]	Pretrained model for trash detection	Lacks aquatic / river-based environmental tuning
DETR Waste Model [11]	Transformer-based waste detection	Computationally intensive for real-time
Garbage UAV Dataset [19]	Labeled dataset for waste detection, used to self-train YOLOv11l [27]	Limited coverage of river-specific scenarios, focuses mostly on urban/waste station environments
A* Pathfinding Algorithm [21]	Heuristic-based navigation algorithm for optimal route planning	May require dynamic re-computation in fast-changing water flow conditions [20]
K-Nearest Neighbors (KNN) [22]	Spatial analysis algorithm for nearest garbage point selection	Sensitive to the density of garbage points, increasing computational load
Mask R-CNN [13]	CNN-based instance segmentation for obstacle or living being differentiation	Requires high computation; performance can degrade in low-contrast river environments
DeepLabV3+ [14]	Semantic segmentation for detecting riverbanks and obstacles	Sensitive to water reflection and lighting changes, needs fine-tuning on aquatic datasets
Garbage Classification YOLO[28]	Classified garbage types	Lack of garbage types and training volume

5.5. Legal, Environmental & Ethical Considerations

- AI-driven detection ensures minimal ecological disturbance.
- Compliance with AI ethics recommended by UNESCO [15].
- Optimized routes significantly reduce operational costs and energy consumption.

5.6. Limitations & Sustainability

Risks:
- Misclassification between organic life (fish, birds, weeds) and actual debris
- GPS drift impacting collection accuracy
- Model drift due to unseen debris types

Sustainability Contribution:
- Detection models reduce ecological impact by recognizing living beings [10][11].
- Continuous dataset expansion enhances precision over time.
- Onboard AI avoids fuel-based operations, maximizing environmental compatibility.

6. Strategy

Technical Scope:
- **Multi-Model AI Detection System:** Integrating YOLOv11l [27], YOLOv5, and DETR [10][11] to reliably detect diverse debris types.
- **Obstacle & Riverbank Detection**: Mask R-CNN [13] and DeepLabV3+ [14] provide accurate environmental perception, preventing collisions and minimizing ecological impact.
- **Real-time Localization:** Transforming detected object positions from pixel coordinates to precise GPS coordinates using drone altitude calibration [18].
- **Navigation Optimization**: A* and KNN algorithms reduce energy usage and operational expenses significantly compared to manual approaches [20][21][22].
- **Post-Collection Garbage Classification:** Custom-trained YOLOv11s model [28] using the Garbage Classification Dataset enables automated waste categorization for optimized recycling potential. This supports sustainability by segregating recyclables from organic, hazardous and other waste.

Justification of Approach
- Multi-model detection reduces false positives, improving classification accuracy [12], reducing the trade-off between speed and accuracy by singular model [17].
- Drone altitude and geometric scaling enable precise GPS localization.
- AI-driven route optimization reduces energy consumption [20].
- Edge computing ensures independence from unstable connectivity — vital for remote deployment.

Self-Expertise: Proven software engineering background, prior work in CV/AI model implementation and optimization of autonomous robotic navigation systems.

7. Project Management:

The Project Management section describes how the project will be managed, including a detailed timetable with milestones. Specific items to include in this section are as follows:

7.1. Description of task phases

Software development and design encompasses of 6 phases:

Phase	**Tasks**
Planning	Data collection and literature review, environmental analysis, system requirement analysis
Concept Development	AI model training and external selection, navigation algorithm, obstacle detection concept
System-Level Design	Software architecture definition, GPS localization modelling, altitude-based pixel coordination
Detailed Design	Python programming, multi-model integration
Testing & Refinement	Synthetic and testing, performance optimization, accuracy validation
Deployment	Field trials, system evaluation

7.2. Division of responsibilities and duties among team members

Team Member	**Role & Responsibilities**
Dang Khoa Le *(Software/AI Engineer)*	- Collected and processed dataset for AI training - Train and integrate existing AI model - GPS localization system, navigation algorithm development - Develop software pipeline for detection, navigation, control, demo - Detailed description of test procedures (Software component)
Masimiliano Bruno (*Robotics Engineer 1 - Movement*)	- Project economic analysis - Detailed description of test procedures (Robotics vision component)
Leah Griffiths (*Robotics Engineer 2 - Vision*)	- Physical Prototype - Detailed description of test procedures (Robotics hull component)
Harrison Ashford (*Robotics Engineer 3 - Collect*)	- Engineering analysis - Detailed description of test procedures (Robotics arm component)
Chamoda Mudiyanselage (*Electrical Engineer 1*)	- Electrical circuit diagrams - Data from experiments (Labview)
Hiruni Mendis (*Biomedical/Electrical Engineer 2*)	- Electric components (i.e., microprocessors and sensors) - Electrical circuit diagrams - Ethics and regulations

7.3. Timeline with milestones using Gantt chart

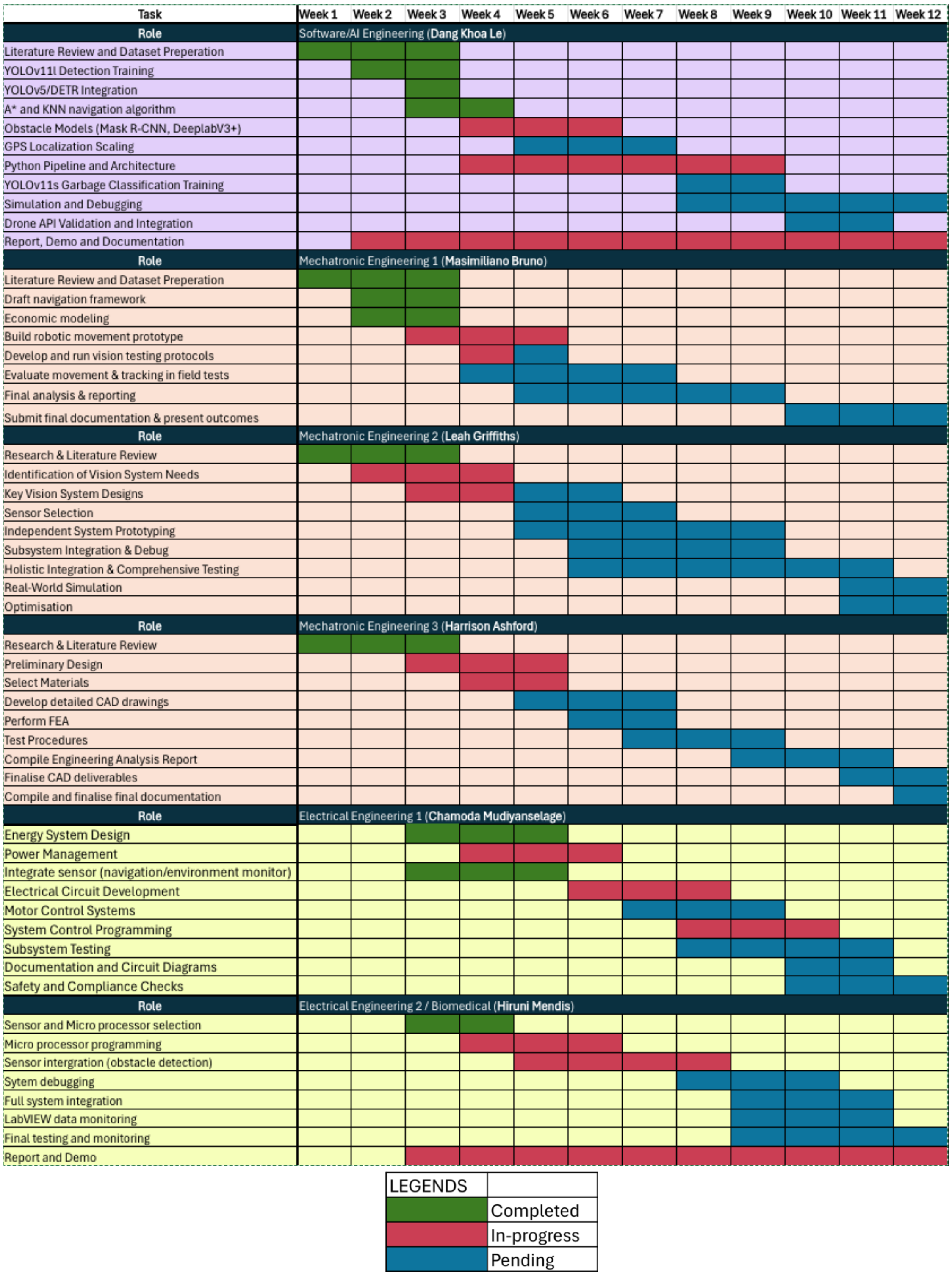

Figure 2. Group 7.2 timeline in Gantt chart

8. Finance

8.1. Cost of Implementation Evaluation:

Item	Justification	Cost (AUD)
NVIDIA Jetson Orin 64GB [23]	Real-time CV-AI execution without cloud reliance	$3,500
Software Development (100 hrs $40/hr)	Full pipeline dev, AI modelling, data processing	$4,000
Dataset Licensing and Model Training	Roboflow + YOLOv11 model training [19]	$1,000
GPS Receiver Module	Accurate mapping for geological localization	$250
Edge Storage & Testing	Data retention & tests	$500
Contingency	Miscellaneous	$500
Total Estimated Cost		**$12,150**

8.2. Financial Evaluation

Manual Cleanup Costs:
Recent studies indicate that Indonesia's government and local NGOs spend around AUD **2.5 million** annually on manual labor to collect garbage from the Citarum River [5]. This is labor-intensive, is a recurrent cost, and is ineffective for the waste collection due to the constant influx of garbage [4][5].

Sall-e Autonomous System Investment:
The initial estimated cost to develop and implement the Sall-e software - prototype system (inclusive to the development of the AI model and its implementation, hardware (NVIDIA Jetson Orin [23]), onboard integration, and field trials) will be **AUD 12,150**.

Unit Deployment Cost: Each additional operational unit — comprising one CPU (Jetson Orin), and one GPS module - is estimated at **AUD 3,750**. This modular cost allows scalable deployment based on operational needs.
This total investment represents **less than 1%** (estimate) of the annual manual labor cost and offers a significantly more sustainable approach [5][23].

Return on Investment (ROI) and Operational Efficiency:
- The autonomous system is projected to achieve **3–4 times greater operational efficiency** compared to manual collection, primarily due to *AI-driven optimized path planning (A, KNN)** and continuous 24/7 operation capability without fatigue [20].
- Reduced dependency on human labor dramatically lowers long-term operational costs and risks [5].
- Scalable deployment of multiple Sall-e units enables coverage expansion across wider river sections with minimal marginal cost per additional unit.

Projected Economic Impact:
By replacing or supplementing manual operations with the Sall-e system:
- The potential annual savings are estimated to be in the millions of AUD [5].
- Continuous operation enhances garbage removal efficiency while minimizing ecological disturbance through precision AI-based waste detection and classification [13][14].
- The scalable nature of this technology positions it as a viable, long-term solution for river and aquatic waste management across Indonesia and globally.

8.3. Economic Potential and Post-Collection Recycling Impact

Economic Revival through River Cleanup

The extreme pollution of the Citarum River has, for a long time, limited substantial local economic opportunities, especially for agriculture, fisheries, and tourism. According to studies, environmental degradation is an important impediment to tourism development in the region, thus dramatically reducing revenue streams that could have been earned through tourism [30].

By implementing the Sall-e autonomous system to restore the river's ecological health, the project is expected to create substantial economic value across multiple sectors:

Sector	Economic Potential After Clean-Up
Tourism	Reviving the river for ecotourism, water sports, and local tourism could generate up to AUD 4-6 million annually [30][31].
Recycling Economy	Post-collection garbage classification (YOLOv11s) enables separating recyclables, generating AUD 2-3 million yearly through plastic and metal recovery [32].
Fisheries/Agriculture	Cleaner water improves aquatic health, potentially restoring fishery yields by 30-50%, with an estimated AUD 1.5 million annual impact on local food markets [33].
Public Health Cost Savings	Reducing waterborne diseases from polluted river exposure could save AUD 800,000 annually in healthcare costs [34].

Recycling and Circular Economy Integration

The Sall-e system includes a post-collection waste classification model (YOLOv11s), allowing for the automated classification of waste collected. This system not only diverts waste from landfill, but also fosters the creation of a local recycling economy. The World Bank has indicated that if urban waste streams in Indonesia's cities are recovered in total, recyclable materials may generate **USD 4 billion** annually [32].

The floating plastic waste in the river, once collected and classified by Sall-e, can thus be recognized as part of this circular economy potential.

Long-term Economic Transformation

• **Tourism Rebirth**: Clean river banks and improved water quality attract domestic and international tourists, creating jobs in hospitality, guiding services, and recreational activities [30][31].
• **Sustainable Recycling Industry**: Local recycling plants can process Sall-e's classified waste, fostering green industry growth.
• **Fisheries Recovery**: Revitalized aquatic ecosystems boost fish populations, supporting small-scale fishing and aquaculture.

Projected Annual Economic Impact (Post Clean-Up)

Benefit	Estimated Annual Value (AUD)
Tourism Revenue	$4 – 6 million
Recycled Material Sales	$2 – 3 million
Fisheries/Agricultural Boost	$1.5 million
Healthcare Savings	$800,000
Total Potential Impact	$8.3 – 11.3 million per year

The Sall-e system takes river waste that was seen as environmental liability and turns it into economic opportunity generating millions in revenue while improving ecosystem health. Tourism, recycling and agricultural economy are the main beneficiaries, making Citarum a regional exemplar of sustainable river rehabilitation.

9. Deliverable Outcomes:

9.1 Engineering Analysis

- Performance comparison under varying conditions.
- GPS precision vs altitude scaling [18]
- Multi-model detection benchmarks
- Obstacle detection (accuracy, recall, precision)

9.2 Economic Analysis

- Manual vs Autonomous Cost Comparison: Current manual cleanup in the Citarum River costs over AUD 2.5 million annually [5].
- Projected Annual Savings: Autonomous operation reduces labor dependency, estimating AUD 2 million in annual savings.
- Energy Optimization: AI-driven efficient routing (A*, KNN) minimizes energy use, reducing operational costs [20][22].
- Recyclable Material Recovery: Post-collection classification enables material resale, adding potential AUD 2–3 million annually [32].
- Economic Impact: Clean river conditions support tourism, fisheries, and local economy growth, contributing an estimated AUD 5–7 million annually [30][31][33].
- Healthcare Savings: Pollution reduction lowers health risks, potentially saving AUD 800,000 annually [34].

Total Economic Benefit Potential: AUD 9.8 – 12.8 million annually.

9.3 Detailed Testing Procedures

- Synthetic dataset testing with controlled noise and debris variations.
- Navigation accuracy tests
- Obstacle detection precision tests.

9.4 Experimental Data Collection

- Precision, recall, and mAP and F1 scores for detection models.
- Path optimization metrics (distance, time).
- GPS localization error analysis and testing.

9.5. Software Deliverables:

- **Fully documented Python program** including:
    - Self-trained YOLOv11l detection model
    - Detection model YOLOv5, DETR integration
    - Obstacle model integration Mask R-CNN, DeepLabV3+
    - Garbage classification model (post-collection) with YOLOv11s
    - Custom garbage classification dataset supporting YOLO model training.
    - Detailed software architecture, flowcharts, and sequence diagrams.
    - A*, KNN pathfinding modules

- **Flowcharts and system architecture diagrams**

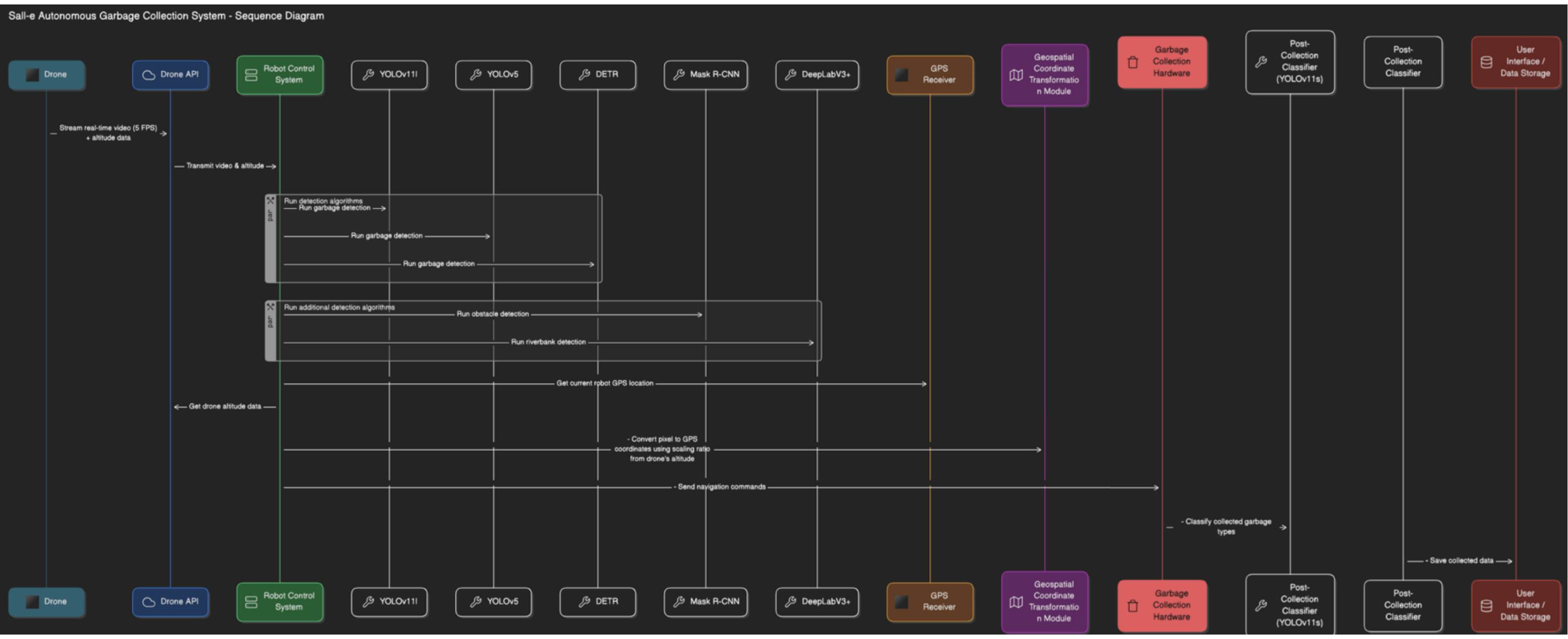

Figure 3. Python software sequence diagram visualization

- **Simulation videos and testing**

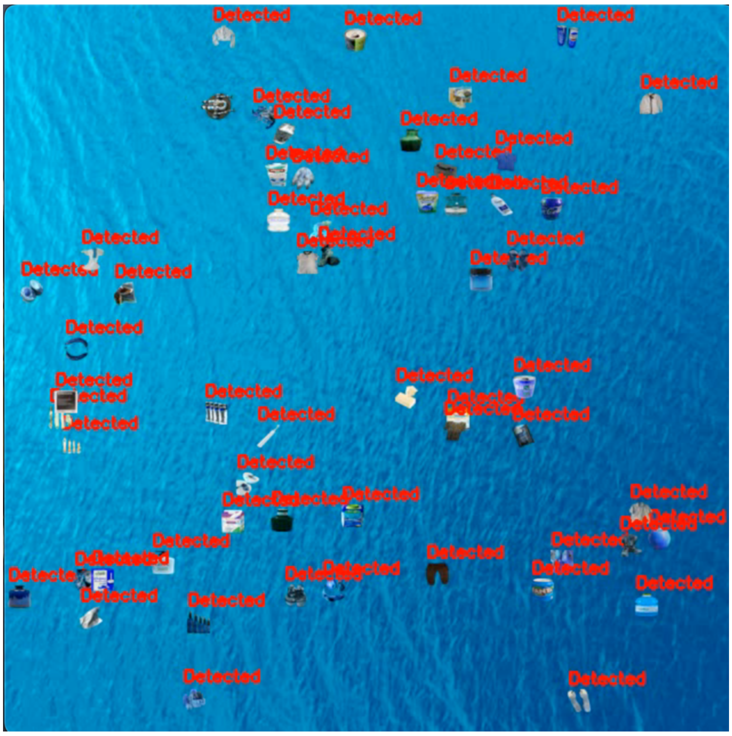

Figure 4. Simulation video (Download video) [25]

  - **Web-based demo** (FastAPI / Hugging Face) ready for supervisor interaction [26]
  - **Simulation video:** show garbage object detection and robot navigation using Python [25]
- **User and technical documentation** covering system design, APIs, maintenance guides

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