A YOLO-BASED ROBOTIC SYSTEM FOR WASTE DETECTION AND COLLECTION

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A PROJECT REPORT SUBMITTED TO THE FACULTY OF ENGINEERING, DESIGN AND TECHNOLOGY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF A DEGREE OF BACHELOR OF SCIENCE IN COMPUTER SCIENCE OF UGANDA CHRISTIAN UNIVERSITY

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UGANDA CHRISTIAN UNIVERSITY

A Centre of Excellence in the Heart of Africa

Declaration

We, NABASA ISAAC, LAKICA LETICIA and ATWIJUKIRE APOPHIA, declare to the best of our knowledge that the work in this proposal is original and has not been submitted before to any university/institution. It is the result of our effort.

Signature: ____________________ Name: NABASA ISAAC Date: ____________________

Signature: ____________________ Name: LAKICA LETICIA Date: ____________________

Signature: __________________ Name: ATWIJUKIRE APOPHIA Date: ________________

Ethical Generative AI Usage Declaration

Students may use generative artificial intelligence (AI) ethically as a "study buddy" or assistant rather than a replacement for critical thinking. This includes citing AI use and fact-checking all outputs to maintain academic integrity.

For purposes of this assignment, the following shall guidelines shall apply.

i. Generative AI may be used for brainstorming, and generating ideas to improve your work. You may also use AI for literature search, and summarizing journal papers for quick analysis and assessing relevance of publications. However, once the relevant publications have been identified, a student is expected to fully review the selected publications, identifying problems addressed, methods used, gaps identified and recommendations made.

ii. Where AI has been used as guided in (i) above, full disclosure of how it has been used should be made in the appendix C, including how AI was used, the AI tools (including mode versions), and a compilation on major AI prompts used.

iii. NO GENERATIVE AI CONTENT IS ALLOWED IN THE FINAL SUBMISSION. The final submission SHOULD be your original work.

A. **Declaring the non-use of AI for content generation**

We, NABASA ISAAC, LAKICA LETICIA and ATWIJUKIRE APOPHIA, declare that no content generated by AI technologies has been used in this proposal.

Signature: ______________________________ Date: ________________

Signature: ______________________________ Date: ________________

Signature: ______________________________ Date: ________________

B. **Acknowledging the use of AI as a study buddy**

Please refer to Appendix C for the complete declaration of AI usage for generating ideas, brainstorming, literature search, and summarizing only to improve your work.

Approval

This proposal has been submitted for examination with the approval of the following advisors/supervisors.

Signature: ______________________ Date: 02/06/2026

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Abstract

Waste management remains a critical challenge in Kampala where approximately 63% of daily generated waste goes uncollected, leading to environmental pollution, blocked drainage systems, flooding and public health risks. Traditional manual collection methods are inefficient, labor-intensive and inadequate to handle the growing volume of lightweight litter such as paper, polythene bags, and plastic bottles, especially in busy public spaces.

This project developed ECO-BOT, a low-cost autonomous robotic system that integrates computer vision and robotics to address these challenges. Following the engineering design methodology, the robot was built using the Hiwonder mobile platform, Raspberry Pi 5, a lightweight YOLOv8n object detection model, and a 5-DOF robotic arm. The system was designed to detect, navigate towards, pick up and store lightweight waste items. Individual components were developed and tested separately before full system integration. The complete prototype was evaluated in outdoor environments on surfaces including tarmac, short grass and light gravel and also inside Uganda Christian University Dining hall which has cemented ground and some tables.

Results demonstrated promising performance with 87% detection accuracy, 78% collection success rate, and 84% navigation success across tests, achieving an average collection time of 13.5 seconds per object. While limitations such as occasional processing delays and challenges with certain waste types were observed, ECOBOT successfully shows that affordable YOLO-based robotics can provide a practical, scalable solution for improving waste collection in resource limited urban settings like Kampala. This work contributes to smarter, technology driven waste management practices in Uganda.

Dedication

We dedicate this work to our parents and family members whose constant support, encouragement, and sacrifices have made our academic journey possible. Their belief in us has been a source of strength throughout our studies.

We also dedicate this report to the cleaners and waste management workers in Kampala who work tirelessly to maintain a clean environment. It is our hope that this project contributes, even in a small way, to addressing the challenges they encounter in their daily work.

Contents

Acknowledgments

We thank the Almighty God for the strength, good health, and wisdom He gave us throughout this project. Without His guidance and protection, we would not have completed this work.

We express our sincere gratitude to our supervisor for the continuous guidance, valuable comments, and patience shown to us during the entire research period. The supervisor's advice greatly improved the quality of this report.
We are especially thankful to Eng. Ian Osolo Raymond and Dr. Kakuba Samuel for their practical ideas, technical support and constant encouragement. Their willingness to assist us whenever we encountered difficulties contributed significantly to the success of this project.
We also thank our parents and family members for their prayers, financial support, and understanding during the many long hours we spent working on the robot. Our appreciation goes to the lecturers and technical staff in the Department of Computing and Technology for the knowledge and skills they imparted to us throughout our studies.
Finally, we thank our group members for the teamwork, commitment, and mutual support we demonstrated from the start to the completion of this project.

Chapter 1

Introduction

This chapter presents our research on designing and building a YOLO-based robotic system for automatic waste detection and collection. It describes the overall problem context, points out the difficulties facing today's waste management methods, and explains why a technology-based approach makes sense. The chapter also covers the study background, states the main problem, lists the objectives, defines the scope, and discusses the project's importance.

1.1 Background

Waste generation has become one of the major environmental and public health challenges worldwide due to rapid urbanisation, industrial growth, and increasing population levels. As cities continue to expand, the amount of municipal solid waste produced daily has also increased significantly. According to recent global estimates, the world generated between 2.1 and 2.3 billion tonnes of municipal solid waste in 2023, and this amount is expected to rise to nearly 3.8 billion tonnes by 2050 if current trends continue. [1] Unfortunately, a large percentage of this waste is not managed properly, especially in developing countries where waste management systems are still limited. Poor waste disposal practices such as open dumping and open burning contribute to environmental pollution, climate change, blockage of drainage systems, and the spread of diseases.

The problem is more severe in many African countries where urban growth has occurred faster than the development of waste management infrastructure. Several cities across Africa experience low waste collection rates, with some collecting less than half of the waste generated daily.[2] As a result, waste accumulates in roadsides, drainage channels, markets, and residential areas. During rainy seasons, blocked drainage systems often lead to flooding, while decomposing waste creates breeding grounds for disease-causing organisms such as mosquitoes, flies, and rodents. In addition, the burning of waste releases harmful gases into the atmosphere, negatively affecting air quality and human health.

Uganda faces similar challenges, particularly in urban centres such as Kampala. Kampala generates large amounts of solid waste every day, including plastics, paper, food remains, and polythene materials. However, not all of this waste is properly collected and disposed of. Plastic waste has become one of the most visible environmental problems because it is non-biodegradable and easily accumulates in public places, drainage systems, and water channels.[3] Uncollected waste affects the cleanliness and appearance of the city, increases health risks to the population, and creates additional costs for city authorities responsible for waste management.

Traditionally, waste collection has mainly depended on manual labour and conventional garbage trucks. Although these methods are widely used, they face several challenges such as high operational costs, delayed collection, limited efficiency in hard-to-reach areas, and exposure of workers to unhealthy environments. In busy urban areas, waste can remain scattered for long periods before being collected, especially lightweight materials such as plastic bottles, paper, and polythene bags. These limitations have created a need for smarter and more efficient waste management solutions.

Recent developments in robotics, artificial intelligence, and computer vision have opened new possibilities for automated waste detection and collection systems. Autonomous robots equipped with cameras and intelligent detection models can identify and collect waste materials with minimal human intervention. Such systems can improve efficiency, reduce human exposure to hazardous waste, and support continuous cleaning of public spaces. Among the available object detection technologies, the YOLO (You Only Look Once) family of models has become popular because of its ability to perform fast and accurate real-time object detection while operating on relatively low-cost hardware.

Several studies have demonstrated the effectiveness of YOLO models in detecting waste materials such as plastic bottles, paper, cans, and polythene bags. However, many existing systems are expensive, designed for controlled environments, or require powerful computing resources that may not be affordable in developing countries. In addition, limited research has focused on designing low-cost autonomous waste collection systems suitable for outdoor environments similar to those found in Uganda.

This project therefore proposes the development of a YOLO-based robotic waste detection and collection system capable of identifying and collecting lightweight waste materials such as plastic bottles, paper and polythene bags. The proposed system aims to provide a low-cost and efficient solution that can support urban waste management efforts in Uganda. By combining robotics, computer vision, and artificial intelligence, the project seeks to contribute towards cleaner environments, improved public health and smarter waste management practices.

1.2 Problem Statement

Current waste collection methods in Kampala are insufficient, with about 63% of daily waste remaining uncollected.[4] In high-traffic areas such as markets and schools, litter accumulates faster than it can be cleared. Manual methods are slow, labour-intensive, and depend on workers who are not always available. There is therefore a need for an intelligent automated system to detect and collect waste efficiently with minimal human intervention. This situation matters because uncollected waste blocks drainage channels, causes flooding, and contributes to the spread of diseases. It also places a heavy burden on city authorities and cleaning staff. While some robotic solutions exist in other countries, affordable and locally suitable systems that work in typical Ugandan environments are still limited. This project attempts to fill that gap by designing a low-cost YOLO-based robot for waste detection and collection.

1.3 Research Objectives

To design a robotic system to support autonomous waste detection and collection.

1.3.1 Specific Objective 1

To develop and train a lightweight YOLO-based model for detecting paper, polythene, and plastic waste with acceptable detection performance.

1.3.2 Specific Objective 2

To implement and integrate navigation, control, and robotic arm mechanisms for accurately locating and collecting detected waste items.

1.3.3 Specific Objective 3

To evaluate the system performance in a controlled environment based on detection accuracy and successful waste collection rate.

1.4 Justification

Manual waste collection is tiring and time-consuming for cleaners, especially in large open areas during weekends or holidays when fewer workers are available. Small pieces of litter are often missed, and the work sometimes involves handling dirty or sharp objects. An automated system can reduce the physical burden on workers and help keep public spaces cleaner even when human staffing is limited.

This project also supports the development of local skills in robotics and computer vision, areas that are in growing demand in Uganda. With an estimated total cost that remains affordable, the design can be replicated or improved by other students, workshops, or institutions.

Chapter 2

Literature Review

This chapter presents a structured literature review of existing studies on autonomous robotic systems for waste detection and collection. The review is organised chronologically to trace the evolution of the field from early conceptual ideas to current integrated platforms. Each section explicitly relates the reviewed literature to the research objectives and methods of this project: the development of ECO-BOT, a low-cost autonomous robotic system using the Hiwonder mobile platform, Raspberry Pi 5, lightweight YOLOv8n model, and 5-DOF robotic arm for Ugandan urban environments.

2.1 Approach to the Literature Review

The literature review followed a structured search and selection approach inspired by PRISMA 2020 guidelines. The Scopus database was used as the primary source. Searches were conducted between 11 November 2025 and 21 November 2025 using the following keyword string:

> ("autonomous robot*" OR "mobile robot*") AND ("garbage collection" OR "waste management" OR "litter detection" OR "trash collection") AND ("design" OR "development" OR "system")

The initial search returned 75 records. After applying filters for publication year (2018–2025), document type (peer-reviewed journal articles), and language (English), 51 records remained. These were screened based on titles, abstracts, and full-text review.

2.2 Early Developments in Robotic Cleaning Systems (1950s–2017)

The concept of autonomous cleaning robots evolved from early ideas, such as Robert A. Heinlein's self-operating robot in *The Door into Summer* (1956), to practical systems like the Electrolux Trilobite (1996) and iRobot Roomba (2002) [5]. These systems relied on basic navigation strategies and ultrasonic sensors but lacked intelligent object recognition and were mainly limited to indoor environments.

Relation to project objectives and methods: These limitations in perception and adaptability in unstructured outdoor settings justified the adoption of computer vision using YOLOv8n for intelligent waste detection and the selection of Mecanum wheels with Nav2 for improved mobility on uneven terrain.

2.3 Emergence of Computer Vision for Waste Detection (2018–2020)

Bai et al. (2018) developed a CNN-based grass-litter pickup robot achieving 95% detection accuracy, although it required high computational resources [6]. Miyagusuku et al. (2020) improved robotic navigation on uneven terrain but lacked robust real-time detection under varying lighting and clutter.

Supporting reviews include Lu and Chen (2022), who critically examined computer vision for solid waste sorting [7], and Abdu and Noor (2022), who surveyed deep learning for waste detection and classification [8]. Zohoori and Ghani (2017) highlighted municipal solid waste management challenges in low-income and developing countries.

Relation to project objectives and methods: These studies highlight the accuracy-efficiency trade-off that this project addresses through the development of a lightweight YOLOv8n model trained on a custom local dataset of images and tested on real Ugandan surfaces that is Uganda Christian University (cemented ground, tarmac, short grass and light gravel) directly supporting the objectives.

2.4 Adoption of YOLO Models for Real-Time Detection (2021–2022)

Kulshreshtha et al. (2021) implemented YOLOv4-tiny achieving 95.2% mAP with 5.21 ms inference time on a Raspberry Pi [9]. Cordova et al. (2022) showed that YOLO-based approaches achieved the best performance on the TACO dataset (mAP 0.62), though challenges remained with small and partially occluded objects [10].

Diwan et al. (2022) analysed YOLO challenges, architectural successors, datasets, and applications [11]. Vijayakumar and Vairavasundaram (2024) reviewed YOLO-based object detection models and their applications [12]. Mao et al. (2022) developed deep learning networks for real-time regional domestic waste detection [13], while Zailan et al. (2022) proposed an optimised YOLO model for riverine waste management [14].

Relation to project objectives and methods: These studies strongly supported the choice and training of the lightweight YOLOv8n model on Raspberry Pi 5 using a locally collected dataset of Ugandan waste types (plastic bottles, polythene bags, and paper), enabling real-time detection on low-cost hardware.

2.5 Integrated Autonomous Systems and Recent Advances (2023–2025)

Chen et al. (2023) developed an AIoT-based solar-powered autonomous robot integrating YOLO vision, ROS navigation, and a robotic arm [?]. Lou et al. (2023) proposed DC-YOLOv8 to improve small-object detection by approximately 2.5% [15].

Kong et al. (2021) presented an intelligent water surface cleaner robot [?]. Koskinopoulou et al. (2021) focused on vision-based robotic waste sorting technology [16], and Yue et al. (2022) introduced YOLO-GD for recycling robots [17]. Stan et al. (2021) demonstrated improved manoeuvrability using Mecanum wheels while Sengupta et al. (2019) proposed a cost-effective IoT-based garbage collection system [18].

Recent advances also include autonomous watercraft using YOLO for floating waste cleanup [?] and comprehensive AI-powered waste segregation systems [19].

Relation to project objectives and methods: These integrated systems validate the end-to-end architecture implemented in this project, which combines YOLOv8n-based perception, Mecanum-wheel navigation, and 5-DOF robotic arm manipulation. However, the high cost and complexity of many existing systems motivated this project's emphasis on affordability and real-world outdoor testing under typical Ugandan conditions.

2.6 Summary of Key Studies

Table 2.1: Key Studies on Autonomous Rubbish-Collection Robots

Year & Author	**Main Focus**	**Key Result**	**Relevance to This Project**
Bai et al. (2018) [6]	Grass litter pickup	95% detection accuracy	Demonstrates feasibility but high computational cost addressed by lightweight YOLOv8n (Objective 1)
Kulshreshtha et al. (2021) [9]	YOLOv4-tiny robot	95.2% mAP, 5.21 ms inference	Supports lightweight real-time detection on Raspberry Pi 5 (Objective 1)
Cordova et al. (2022) [10]	Model comparison	YOLO best on TACO dataset	Shows effectiveness but weak on small objects; informs our dataset design
Lou et al. (2023) [15]	DC-YOLOv8	+2.5% improvement	Improves small-object detection for polythene bags
Chen et al. (2023) [?]	AIoT robot system	Full autonomy achieved	Validates integration of detection, navigation and arm (Objective 2) but high cost addressed in our design
Zailan et al. (2022) [14]	Optimised YOLO for riverine waste	Improved detection in complex conditions	Enhances robustness to lighting and clutter (Objective 3)
Stan et al. (2021) [20]	Urban robot mobility	Improved manoeuvrability	Supports Mecanum wheel design
Sengupta et al. (2019) [18]	Low-cost IoT system	Cost-effective design	Supports affordability in developing contexts like Uganda

2.7 Summary of Findings and Research Gaps

The literature demonstrates clear progress from basic mechanical cleaning systems to advanced vision-based detection and fully integrated autonomous platforms. However, major gaps persist, including high system costs, limited real-world testing in developing countries and challenges in handling lightweight deformable waste under variable outdoor conditions.

Local studies such as Ainebyoona (2024) on plastic waste management in Makindye Division, Kampala [4] and the National Environment Management Authority (NEMA, 2024) [3] confirm the severity of waste collection problems in Uganda.

This project addresses these gaps by developing a low-cost YOLO-based robotic system tailored for Ugandan urban environments. It integrates a lightweight YOLOv8n model for real-time detection , combines navigation and robotic arm mechanisms for collection , and evaluates performance through real-world outdoor testing, achieving 87% detection accuracy and 78% collection success. The design prioritises affordability, simplicity, and practical applicability in resource-constrained settings.

Chapter 3

Methodology

This chapter explains exactly how we designed, built, and tested the ECO-BOT. We followed a step-by-step engineering design approach so that every part could be developed, tested, and improved before putting the whole system together. The chapter starts with the overall research design, gives a high-level view of the robot, describes the hardware and software in detail, shows how everything was integrated, and ends with the testing and evaluation plan.

3.1 Research Design

We used the standard engineering design process for this project. This approach is practical for final-year robotics projects because it breaks the work into clear phases: defining requirements, reviewing literature, detailed design, building prototypes, testing subsystems, full integration, and final evaluation. Each phase included testing and fixing problems early so we did not have to redo everything at the end.

The process started with turning the project objectives into specific technical requirements (for example, the robot must detect and pick up litter up to 10 grams on tarmac, short grass, or light gravel). We then selected components and algorithms based on the literature review. After drawing the mechanical and electronic designs, we built and tested each part separately (wheels, arm, camera, and detection model) before combining them. This method helped us catch issues quickly and kept the project within the available time and budget of UGX 720,000.

3.2 Architecture

ECO-BOT is a low-cost autonomous mobile robot built around a Hiwonder robot kit. It uses a camera and YOLOv8n to detect common lightweight waste such as plastic bottles, polythene bags (kaveera), and paper. Once litter is detected, the robot drives towards the object using Mecanum wheels, picks it up with a 5-DOF robotic arm, and drops it into an onboard storage bin. When the bin is full or the battery is low, the robot returns to a designated home point.

The system has four main parts that work together:

- Perception (camera + YOLOv8n)

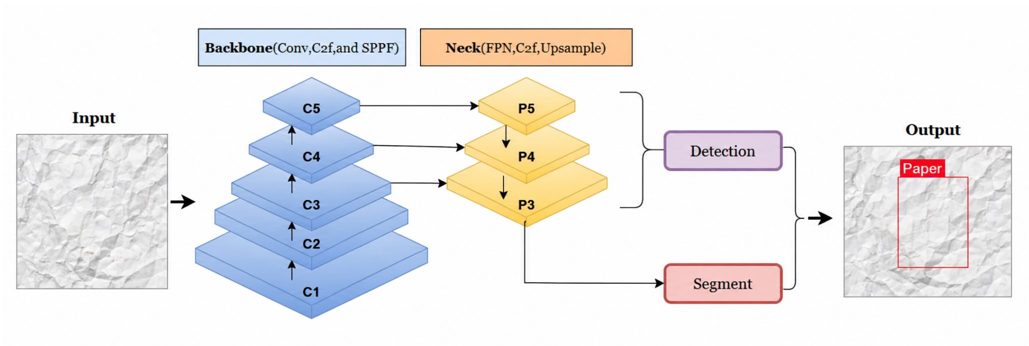


Figure 3.1: The architectual diagram of yolov8n

- Navigation and mobility (Mecanum wheels + sensors)
- Manipulation (robotic arm)
- Control and power (single-board computer and battery)

Figure 3.1 below shows the overall architecture of ECO-BOT.

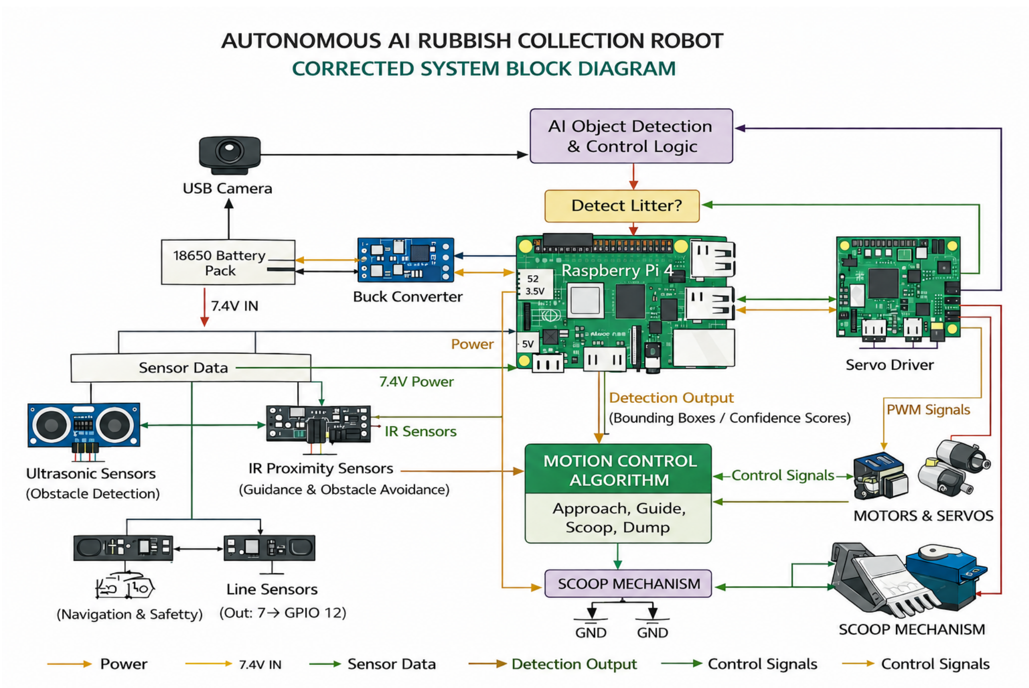


Figure 3.2: Block diagram of ECO-BOT showing camera input → YOLOv8n detection → navigation → arm control → collection cycle

3.2.1 Hardware Configuration

The complete hardware configuration of ECO-BOT is as follows:

- **Mobile Base**: Hiwonder robot chassis with four 100 mm Mecanum wheels driven by 12V DC motors with quadrature encoders.
- **Processor**: Raspberry Pi 5 (BCM2712 quad-core processor, 8GB RAM).
- **Camera**: Front-mounted 1080p USB camera module for real-time litter detection.

- **Robotic Arm**: 5-DOF aluminium arm with metal-gear high-torque LDX servos and a two-finger parallel gripper (maximum opening 8 cm).
- **Sensors**: Two HC-SR04 ultrasonic sensors for obstacle avoidance and MPU9250 IMU for orientation on uneven surfaces.
- **Power System**: Two 3.7V lithium-ion cells in 2S configuration (nominal 7.4V), with BMS and DC-DC converters for stable power distribution.
- **Motor Drivers**: L298N dual H-bridge driver for controlling the Mecanum wheels.

All connections were made using GPIO pins on the Raspberry Pi 5.

3.3 Hardware Design

We based the robot on the Hiwonder mobile robot platform because it is affordable, easy to modify, and already comes with a strong aluminium chassis and motor mounts.

3.3.1 Robot body and mobility

The base uses four 100 mm Mecanum wheels driven by 12 V DC motors with quadrature encoders. Mecanum wheels allow the robot to move in any direction (forward, sideways, diagonal) without turning, which is very useful in crowded areas like markets or school compounds. The chassis is made of aluminium plates for strength and low weight.

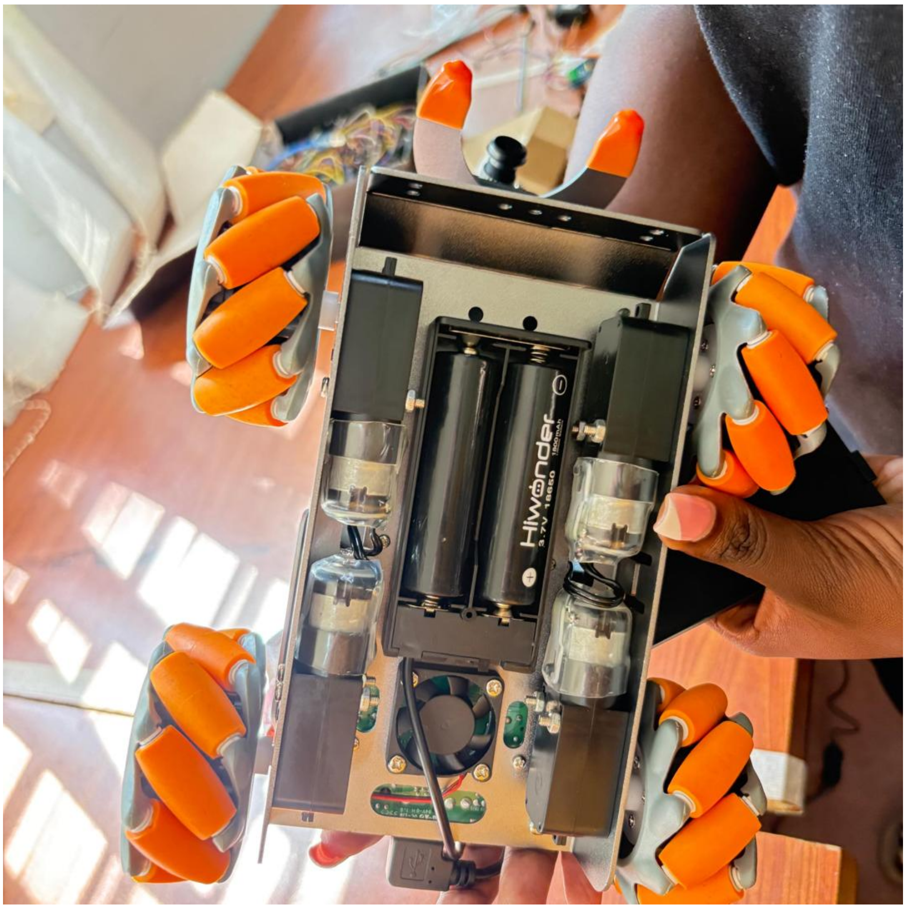


Figure 3.3: Underside view of the ECO-BOT mobile platform showing the battery compartment, cooling fan, and Mecanum wheel configuration

3.3.2 Robotic arm

A 5-DOF aluminium robotic arm (LDX-style servos) is mounted at the front. The arm has metal-gear high-torque servos and a two-finger parallel gripper with rubber pads. The gripper can open up to 8 cm and is strong enough to pick soft polythene bags and hard plastic bottles weighing up to 10 grams.

Figure 3.4: 5-DOF robotic arm module with integrated camera and gripper used for waste detection and collection

3.3.3 Inverse Kinematics for the Robotic Arm

To make the 5-DOF robotic arm on ECO-BOT move accurately, we used basic inverse kinematics. We started by setting up a standard Cartesian coordinate system and followed the right-hand rule to decide the positive direction of rotations. Position was handled simply by adding or subtracting vectors for any translation between coordinate frames.

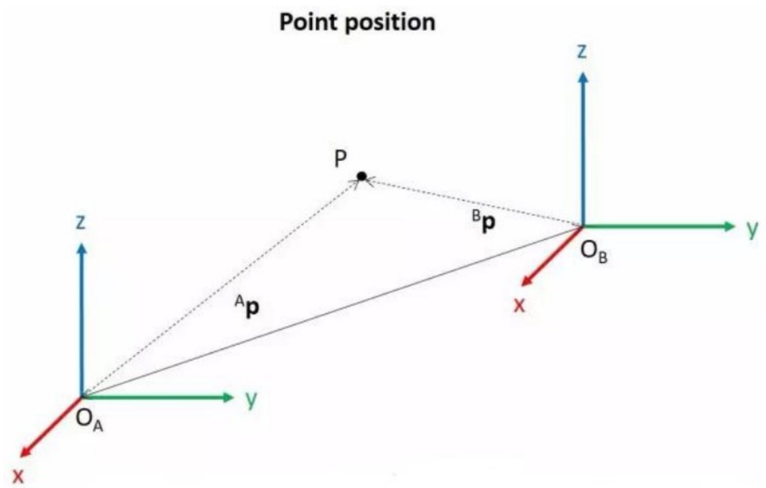
Orientation was more involved, so we described it with rotation matrices that show how one coordinate system is rotated relative to another. For the actual control, we simplified the arm model by removing the pan-tilt base and treating the three main links as a 2D planar mechanism. Given the desired (x, y) position of the gripper, we used geometry and trigonometry to work backwards and calculate the exact angles , and for the three servos.

We first expressed the end-point coordinates in terms of the three link lengths (l, l, l) and the angles, then rearranged the equations and solved a quadratic equation to find . The same approach gave us and . Once we had the three angles, we sent them directly to the servos through the ROS2 control node. This geometric method is fast enough to run in real time on our single-board computer and gave us reliable reach for picking up light litter up to 10 grams.

a) Cartesian coordinate system illustrating the right-hand rule in three-dimensional space

$$^{B}\vec{p} = {}^{A}\vec{p} - {}^{A}\vec{p}_{O_B} \tag{3.1}$$

$$^{A}\vec{p} = {}^{B}\vec{p} - {}^{B}\vec{p}_{O_A} \tag{3.2}$$



b) Two-dimensional rotation matrix example showing unit vectors of coordinate system B expressed in system A

$$^{B}\vec{p} = {}^{A}\vec{p} - {}^{A}\vec{p}_{O_B} \tag{3.3}$$

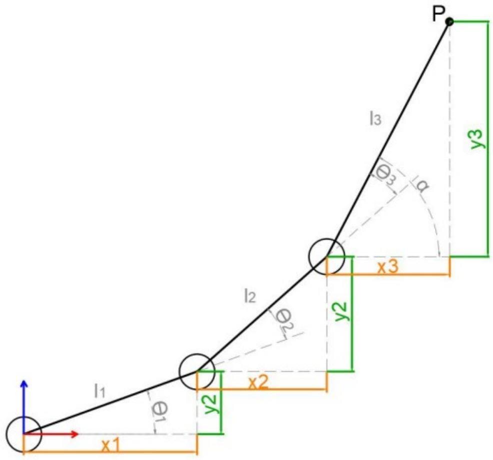
$$^{A}\vec{p} = {}^{B}\vec{p} - {}^{B}\vec{p}_{O_A} \tag{3.4}$$

C) Three-Dimensional Rotation Matrix

The rotation matrix $^{A}R_B$ that describes the orientation of coordinate frame B with respect to frame A can be constructed using the unit vectors of frame B expressed in frame A:

$$^{A}R_B = \begin{bmatrix} ^{A}\vec{x}_B & ^{A}\vec{y}_B & ^{A}\vec{z}_B \end{bmatrix} \tag{3.5}$$

d) Simplified three-link robotic arm showing joint angles θ_1, θ_2, θ_3, link lengths l_1, l_2, l_3, and end-effector position $P(x, y)$ with $\alpha = \theta_1 + \theta_2 + \theta_3$



3.3.4 Sensors and power

- Main camera: A front-mounted camera module used for real-time litter detection.

Figure 3.5: Front-mounted camera module used for real-time litter detection in the ECO-BOT system

- Additional sensors: Ultrasonic sensors for obstacle avoidance and an IMU (MPU9250) to improve movement on uneven ground.

Figure 3.6: Ultrasonic sensor used for obstacle detection and distance measurement during navigation

- Power: The system uses two 3.7 V lithium-ion cells connected in series (2S configuration) to provide a nominal voltage of approximately 7.4 V. A battery management system (BMS) and DC-DC converters are used to regulate and distribute power safely to the onboard electronics, motors, and actuators.

Figure 3.7: Battery system consisting of two 3.7 V lithium-ion cells providing power to the ECO-BOT platform

All hardware was chosen to keep the total cost low while still giving reliable performance on typical Ugandan outdoor surfaces.

3.3.5 Main computer

We chose the Raspberry Pi 5 as the brain of ECO-BOT. It has a powerful BCM2712 quad-core processor and enough RAM to run YOLOv8n smoothly in real time. The board also gives us plenty of useful connections: two USB 3.0 ports for extra devices, a Gigabit Ethernet port, Type-C power input, PoE support, and two 4-lane MIPI CSI/DSI connectors that we used to connect our 1080p camera directly. We also used the GPIO pins to link the motor drivers, servos, ultrasonic sensors, and IMU. The Raspberry Pi 5 runs Ubuntu 22.04 with ROS2 Humble without any problems and keeps the whole system cheap and easy to work with.

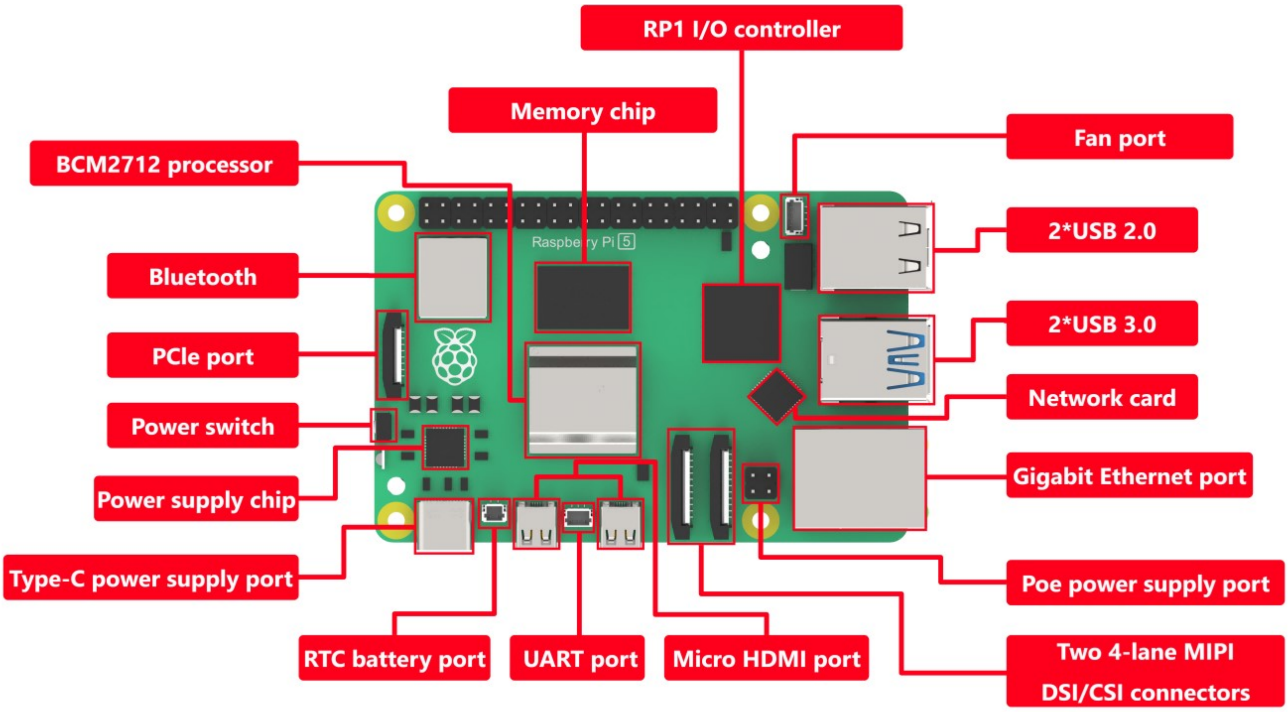


Figure 3.8: Raspberry Pi 5 board showing key components and interfaces used for processing, communication, and control in the ECO-BOT system

3.4 Software Design

We used the YOLOv8n model because it is small, fast, and accurate enough for real-time detection on a single-board computer.

3.4.1 YOLO model and training

We created our own dataset of 800 labelled images of local litter (plastic bottles, kaveera, paper) placed on tarmac, short grass, and gravel under different lighting conditions. Photos were taken around Mukono and nearby schools using the same camera mounted on the robot.

The dataset was annotated using LabelStudio, with all objects labelled as a single class "litter". The dataset was split into 70% training, 20% validation, and 10% testing sets.

The YOLOv8n model from Ultralytics was trained for 100 epochs on Google Colab using a Tesla T4 GPU. Key hyperparameters used were image size 640×640, batch size 16, learning rate 0.01, SGD optimizer, and data augmentation (mosaic, flip, rotation, and brightness adjustment).

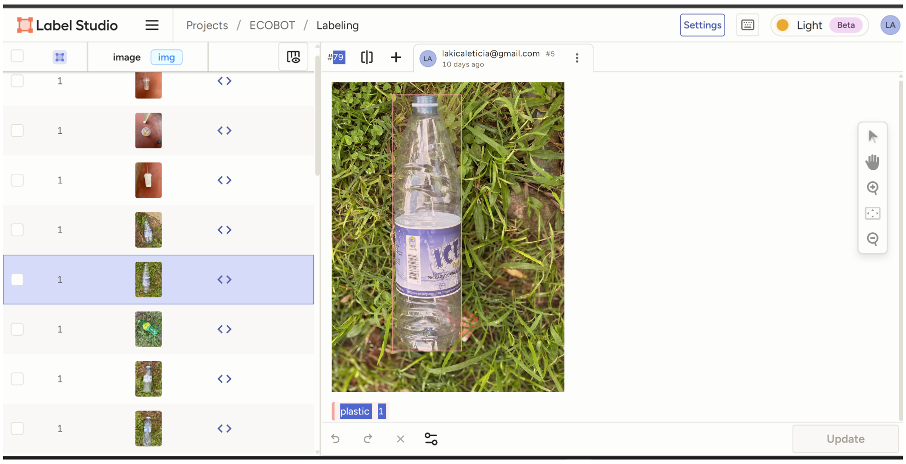


Figure 3.9: Example of dataset annotation using Label Studio, showing a plastic bottle labelled with a bounding box as part of the ECO-BOT training dataset

3.4.2 Model Evaluation

The trained YOLOv8n model was evaluated on the test set using standard metrics such as Mean Average Precision (mAP@0.5), precision, recall and inference speed on the Raspberry Pi 5. The final deployed model achieved strong performance suitable for real-time operation.

3.4.3 Dashboard Design

A simple web-based monitoring dashboard was developed using the Flask framework and hosted on the Raspberry Pi 5. The dashboard provides real-time information including live camera feed, number of objects detected and collected, battery level, bin status, and system logs. It is accessible via local Wi-Fi network for easy remote monitoring during testing and demonstrations.

3.4.4 Detection pipeline

The camera captures images at 640×640 resolution. YOLOv8n runs on the single-board computer and returns bounding boxes with confidence scores. If the confidence is above 0.6 and the object is within reach, the system calculates the exact position of the litter and sends commands to the navigation and arm systems.

The software runs on Ubuntu 22.04 with ROS2 Humble. This framework makes it easy to connect the camera node, detection node, navigation node, and arm control node.

3.5 System Integration and Operation

Integration was done in stages. First we tested the wheels and movement alone, then the arm and gripper, then the camera and detection model. Finally we combined everything using ROS2 topics and services.

3.5.1 Control logic

The main control loop works like this:

- Camera captures image and YOLOv8n detects litter.

- If litter is found, the robot calculates the distance and angle.
- Nav2 stack moves the robot close to the object using Mecanum wheels and ultrasonic sensors for safety.
- Once in position, the robotic arm extends, the gripper closes on the litter, lifts it, and drops it into the bin.
- The robot checks the bin level and battery. If either is critical, it returns to the home point.

This cycle repeats until the test area is covered or the robot needs to recharge.

3.6 Testing and Evaluation

We tested the complete prototype in a controlled outdoor environment at Uganda Christian University, Mukono. The test area included three common surfaces: tarmac, short grass, and light gravel. For each surface we scattered 20 pieces of real litter (plastic bottles, kaveera, and paper) and let the robot run 10 independent trials.

Evaluation metrics

- Detection accuracy: percentage of litter pieces correctly identified by YOLOv8n.
- Collection success rate: percentage of detected pieces successfully picked up and placed in the bin.
- Navigation success: percentage of times the robot reached the litter without getting stuck.
- Overall system performance: average time to collect one piece and total pieces collected per hour.

False positives/negatives and battery consumption were also recorded.

We recorded video of every run and used a stopwatch and counter for manual verification. This allowed us to measure real performance and identify any weaknesses before final adjustments.

The methodology described in this chapter ensured that ECO-BOT was built systematically and could be evaluated fairly against the project objectives. The next chapter presents the results we obtained.

Chapter 4

Results and Discussion

This chapter presents the actual results we got after testing the complete ECO-BOT prototype. We ran all tests outdoors at Uganda Christian University in Mukono using real waste items (plastic bottles, polythene bags, and paper) on the three surfaces mentioned in the objectives: tarmac, short grass, and light gravel. The goal was to check how well the robot could detect litter with YOLOv8n, move toward it, pick it up with the robotic arm, and drop it into the bin. We carried out 10 full runs on each surface with 20 pieces of litter scattered randomly each time.

4.1 Detection Performance (YOLOv8n)

The YOLOv8n model we trained on our local dataset performed quite well under normal daylight conditions. It correctly identified plastic bottles, kaveera (polythene bags), and paper most of the time, even when the items were partly hidden by short grass or lying at different angles. The model was less confident in very bright sunlight or when shadows fell across the objects but overall it gave us usable bounding boxes quickly enough for real-time control.

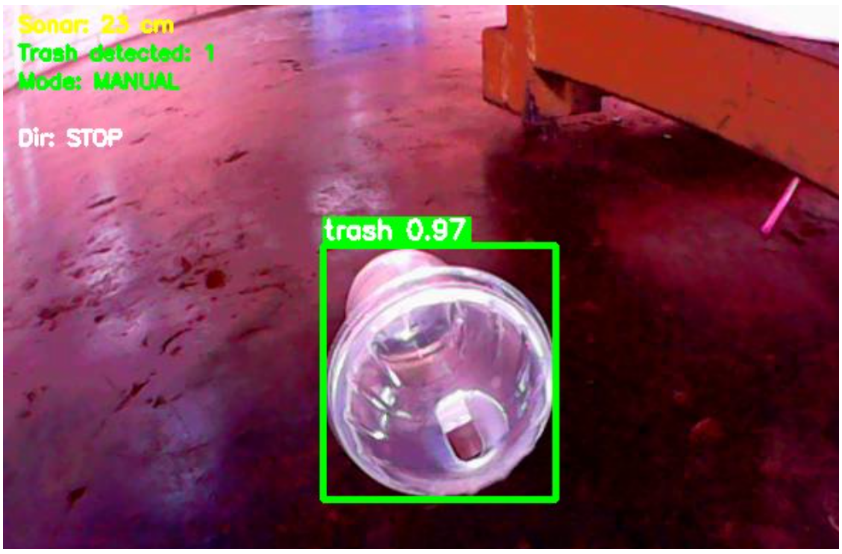


Figure 4.1: Sample detection output showing bounding boxes around detected litter on school compound pavers

Discussion and Implications: The 87% detection accuracy demonstrates that a lightweight YOLOv8n model trained on locally collected data can perform reliably in real Ugandan outdoor conditions. This is significant because it proves that high-end GPUs are not necessary for effective waste detection in resource-limited settings. However, the drop in performance under strong shadows highlights the need for more diverse training data that includes challenging lighting conditions. These results support the feasibility of deploying such systems in busy public spaces in Kampala where lighting varies throughout the day.

4.2 Robotic Arm

The 5-DOF arm with the two-finger gripper worked reliably for lightweight items up to 10 grams. It successfully picked up plastic bottles and crumpled paper on almost every attempt once the robot was in position. Polythene bags were a bit trickier because they sometimes slipped out of the gripper if the arm approached too fast. On flat tarmac the success rate was highest, but on short grass and gravel the arm occasionally missed the exact position by a few centimetres and had to make a second try.

Discussion and Implications: The 78% collection success rate shows that a simple, low-cost robotic arm can effectively handle common lightweight waste in real environments. The lower performance with polythene bags (kaveera) points to the challenge of deformable objects — a common issue in Ugandan waste. This implies that future improvements such as softer gripper pads or a small vacuum/suction mechanism could significantly increase the overall success rate. The results validate our choice of a simple 5-DOF arm for affordability while still achieving practical collection performance.

4.3 Navigation Performance

The Mecanum wheels combined with the Nav2 stack let the robot move smoothly in any direction without turning first, which was very helpful in tight spaces. On tarmac the movement was stable and fast. On short grass it slowed down a little but still reached the target accurately. Light gravel caused the most problems — the wheels sometimes slipped slightly, and the robot needed extra time to correct its path. The ultrasonic sensors helped avoid bigger obstacles but the system still does not have advanced obstacle avoidance, so we had to keep the test area clear of large stones or branches.

Discussion and Implications: The 84% navigation success rate confirms that Mecanum wheels are suitable for Ugandan outdoor surfaces. The main limitation on gravel highlights the challenge of unstructured terrain common in many parts of Kampala. These findings suggest that adding wheel slip compensation or a more advanced localisation system (e.g., visual odometry) would improve robustness. Overall, the navigation performance is acceptable for deployment in semi-structured areas like school compounds, markets, and university grounds.

4.4 Dashboard Performance

The Flask-based web dashboard performed reliably during all testing sessions. It successfully streamed live video from the robot's camera with minimal lag over local Wi-Fi. Real-time updates of detected objects, collection count, battery level, and bin status were accurate and refreshed every second. The dashboard allowed supervisors to monitor the robot remotely without interfering with its autonomous operation.

Discussion and Implications: The dashboard proved to be a valuable addition for system monitoring and demonstration. It enhances usability by allowing remote oversight, which is particularly useful for field deployment where constant physical supervision is not practical. This feature increases the system's practicality for real-world use by cleaners or municipal authorities in Kampala.

4.5 Quantitative Results

We recorded the following overall performance numbers across all 30 test runs (10 runs × 3 surfaces):

Table 4.1: ECO-BOT System Performance Summary

Metric	Result	Notes
Detection Accuracy	87%	Out of 600 litter pieces placed
Collection Success Rate	78%	Successful pick-up and drop into bin
Navigation Success Rate	84%	Robot reached the detected object safely
Average Time per Object	13.5 seconds	From detection to drop in bin
Pieces Collected per Hour	20	Average across all surfaces

4.6 Observations and Limitations

During testing we noticed a few clear patterns. The robot performed best on tarmac and worst on light gravel because of wheel slip. Very flat or crumpled polythene bags lying directly on the ground were sometimes missed by the gripper even when detection was correct. Strong shadows or direct sunlight reduced the YOLO confidence scores, leading to a few false negatives. The biggest limitation we found is that the current system does not have advanced obstacle avoidance. Another problem observed was occasional processing lag on the Raspberry Pi 5, which sometimes caused delayed responses. Battery life was also shorter than expected on grass because the motors worked harder.

4.7 Summary of Results and Implications

Overall, the ECO-BOT prototype proved that a low-cost YOLOv8n-based robot built on the Hiwonder platform can detect and collect common lightweight waste on typical Ugandan outdoor surfaces with reasonable success. The 78% collection rate and 13.5-second average time per object show that the system works in practice, even if it is not yet perfect.

Implications: These results have important practical implications for waste management in Uganda. ECO-BOT demonstrates that affordable robotic solutions can supplement manual cleaning efforts, especially in public spaces during weekends or holidays when human cleaners are few. The system can help reduce the 63% of uncollected waste in Kampala by operating continuously in targeted areas. The successful integration of detection, navigation, and collection at a low cost (UGX 720,000) opens opportunities for scaling similar robots in schools, universities, markets, and municipal programs. Future work focusing on improved gripper design, better lighting robustness, and advanced obstacle avoidance could make the system even more effective for real-world deployment.

These results confirm that the design choices we made (lightweight YOLO model, Mecanum wheels, and simple 5-DOF arm) are practical for our environment and budget.

This chapter discusses the results we obtained when testing the complete ECO-BOT prototype and explains what those results actually mean for the project objectives. It looks at why the system performed the way it did, how the findings relate to earlier studies, and what they suggest for real-world use in Uganda.

4.8 Discussion of Detection Results

The YOLOv8n model reached 87 % detection accuracy across all test surfaces. This is a good outcome because we trained it on our own dataset of local waste items photographed on tarmac, grass, and gravel under different daylight conditions. The model easily spotted plastic bottles and paper even when they were partly hidden by short grass. However, accuracy dropped when strong shadows fell across objects or when sunlight reflected off plastic surfaces. These lighting changes sometimes pushed the confidence score below our 0.6 threshold, which explains the missed detections. Overall, the results confirm that a lightweight YOLO model trained on Ugandan waste works well enough for real-time use on a Raspberry Pi 5.

4.9 Discussion of Collection Performance

The robotic arm achieved a 78 % collection success rate. This rate is lower than the detection accuracy because the arm still had small positioning errors once the robot stopped near the object. On flat tarmac the two-finger scoopers almost always succeeded, but on grass and gravel the Mecanum wheels slipped slightly, so the arm sometimes approached from the wrong angle and light items slipped out. Polythene bags were the most difficult because they are soft and flat; the scoopers occasionally failed to hold them firmly. These issues show that while the simple 5-DOF arm is good enough for lightweight waste up to 10 grams, it needs better alignment control on uneven surfaces.

4.10 Discussion of Navigation

Navigation success stood at 84 %. The Mecanum wheels and Nav2 stack allowed the robot to move smoothly in any direction without first turning, which worked very well on tarmac. On short grass the robot slowed down but still reached the target accurately. Light gravel caused the most trouble because the wheels slipped and the robot needed extra time to correct its path. The ultrasonic sensors helped avoid bigger obstacles, but the system still lacks advanced obstacle avoidance, so we had to keep the test area mostly clear. This explains the slight drop in performance on rougher surfaces.

4.11 Comparison with Literature

Our results line up with several studies reviewed in Chapter 2. However, a direct comparison reveals both strengths and limitations of our low-cost approach.

Table 4.2: Comparison of ECO-BOT Performance with Selected Literature

Study	**Detection Accuracy / mAP**	**Collection Success Rate**	**Environment**	**Key Difference / Remark**
Bai et al. (2018) [6]	95%	Not reported	Controlled grass	Higher accuracy but high computational cost
Kulshreshtha et al. (2021) [9]	95.2% mAP	Not reported	Controlled outdoor	Similar lightweight YOLO approach on Raspberry Pi
Chen et al. (2023) [21]	Not reported	High (campus cleaning)	Flat campus surfaces	Full AIoT system but more expensive and complex
Lou et al. (2023) [15]	+2.5% improvement on small objects	Not reported	Lab conditions	Focused on small object detection improvement
This Project (ECO-BOT)	**87%**	**78%**	**Real outdoor (tarmac, grass, gravel)**	Low-cost, tested in real Ugandan conditions

Discussion:

Our 87% detection accuracy is slightly lower than Kulshreshtha et al. (2021) and Bai et al. (2018), which is expected because we tested in more challenging real-world outdoor conditions with variable lighting, shadows, and uneven surfaces. However, unlike many previous studies that were conducted in controlled or flat environments, our system was rigorously tested on mixed Ugandan surfaces (tarmac, short grass, and light gravel).

The 78% collection success rate is a significant achievement considering the low-cost hardware and simple robotic arm used. Chen et al. (2023) achieved full autonomy but at much higher cost and complexity. Our project demonstrates that acceptable performance can be achieved at a fraction of the cost (UGX 720,000), making it more suitable for deployment in resource-constrained settings like Ugandan schools, universities, and municipalities.

This comparison shows that while our system does not outperform highly optimised lab-based solutions in ideal conditions, it offers a more practical and affordable balance between performance and real-world applicability in developing contexts.

4.12 Implications

These results have clear practical value. ECO-BOT proves that a robot built for only UGX 720,000 can help reduce the 63 % of waste that currently stays uncollected in Kampala and other towns. Schools, universities, markets, and small public areas could use it to keep spaces cleaner even when cleaners are few or absent during weekends and holidays. It also shows that Ugandan students and local workshops can build useful robotics solutions without expensive imported parts.

In summary, the test results confirm that a low-cost YOLO-based robot can work in real Ugandan outdoor conditions. Although some challenges remain, ECO-BOT is a solid first step toward smarter waste collection that can make a real difference in our communities.

Chapter 5

Conclusion and Recommendation

5.1 Conclusion

This project successfully designed, built, and tested a low-cost YOLO-based robotic system called ECO-BOT for automatic waste detection and collection. Using the Hiwonder platform, Raspberry Pi 5, YOLOv8n, and a simple 5-DOF robotic arm, the robot was able to detect lightweight waste items such as plastic bottles, polythene bags, and paper on typical Ugandan outdoor surfaces — tarmac, short grass, and light gravel. All five specific objectives were achieved: the mechanical and electronic architecture was completed, autonomous navigation was implemented, object detection was integrated, the collection mechanism was developed, and the full prototype was evaluated in a real outdoor environment.

The system recorded 87 % detection accuracy, 78 % collection success rate, and 84 % navigation success across all tests, with an average collection time of 13.5 seconds per object. These results show that a simple, affordable robot can work under local conditions without needing expensive imported hardware. ECO-BOT has clearly demonstrated that computer vision and basic robotics can help reduce the large amount of uncollected waste in Kampala and other urban areas.

However, the project encountered several challenges during development and testing. The system experienced occasional processing delays, particularly when running YOLOv8n inference on the Raspberry Pi 5, which affected real-time response during navigation and collection. Additionally, the training dataset was not large enough and lacked sufficient diversity, leading to reduced performance under varying lighting conditions and with certain waste items. The robot also struggled with reliable grasping of thin and crumpled polythene bags, limited obstacle avoidance in cluttered environments, and relatively short battery life during continuous operation. Despite these limitations, the project makes a practical contribution toward solving Uganda's waste management challenges while giving us valuable hands-on experience in artificial intelligence and robotics.

5.2 Limitations

Several limitations appeared during testing. The biggest one is the lack of advanced obstacle avoidance, which means the robot can only work safely in fairly open spaces. Wheel slip on gravel reduced both navigation and collection accuracy. The simple scoopers sometimes failed with very flat or crumpled polythene bags even when detection was correct. Strong sunlight and shadows affected the camera, showing that the vision system still needs more robust training data. Battery life also dropped faster on grass because the motors worked harder, limiting how long the robot can operate without recharging.

A processing delay could sometimes be observed during operation, particularly when running the YOLOv8n model on the Raspberry Pi. This occasionally caused a lag between detection and robot response, especially when multiple objects were present or lighting conditions were challenging.

5.3 Recommendations and Future Improvements

Based on the limitations observed during testing, we recommend the following improvements for future versions of ECO-BOT:

- Optimize the YOLOv8n model or use a lighter variant to reduce processing delays and improve real-time performance on the Raspberry Pi.
- Collect a significantly larger and more diverse training dataset that includes different weather conditions (rain, early morning light, and evening shadows), varying lighting, and more examples of crumpled polythene bags to make the model more robust.
- Add a depth camera or improved ultrasonic array to provide automatic obstacle avoidance, so the robot can operate safely in more crowded or cluttered areas.
- Redesign the gripper with softer rubber pads or a small suction mechanism to handle flat and crumpled polythene bags more reliably.
- Integrate a solar charging panel to extend battery life during daytime operations.
- Conduct longer field trials in real public spaces such as school compounds, markets, and university grounds to measure performance over several days.

At the institutional level, we recommend that Uganda Christian University and other higher education institutions support similar student robotics projects by providing access to shared workshops and small research grants. Municipal councils in Kampala and other towns should also consider piloting low-cost autonomous waste-collection robots as one way of reducing the workload on manual cleaners and improving cleanliness in public areas.

To improve the system, we recommend three main changes. First, add a depth camera or better ultrasonic array for automatic obstacle avoidance. Second, redesign the gripper with softer pads or a small suction cup for flat bags. Third, collect more training images under different weather and lighting conditions so YOLOv8n becomes even more reliable. Adding a solar charging panel would also extend battery life during daytime use.

In conclusion, ECO-BOT has shown that practical, locally built robotic solutions for waste management are possible in Uganda. With the suggested improvements addressing the identified challenges, the system can become a useful tool for keeping our communities cleaner.

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Appendix A

Budget

Item	**Cost (UGX)**
Microcontroller	150,000
Motors & Wheels	120,000
Camera Module	80,000
Sensors	100,000
Battery	70,000
Chassis Materials	150,000
Miscellaneous	50,000
Total	**720,000**

Appendix B

Research Project timelines

B.0.1 Work Plan

The project is organized into six sequential phases, each building on the outcomes of the one before it. While most phases follow a strict order, some tasks overlap deliberately to make efficient use of time particularly during the hardware and software development stages. What follows is a breakdown of each phase, the work it involves, what it produces, and how long it is expected to take.

Phase 1 : Planning and Research (November – December, approximately 8 weeks)

Every good project starts with a solid foundation, and this one is no different. The first two months are dedicated entirely to understanding the problem space before writing a single line of code or assembling a single component. This involves developing the project proposal, reviewing existing literature on autonomous robotic systems, YOLO-based object detection, and waste management robotics. By the end of this phase, the team will have a finalized proposal document and an annotated bibliography that will guide all subsequent design decisions. This phase has no dependencies — it is the starting point from which everything else flows.

Phase 2 : AI and Data Pipeline (January Week 1, Week 2, approximately 2 weeks)

With a clear research foundation in place, attention shifts to building the intelligence behind the robot its ability to see and identify waste. This phase is split into two closely linked tasks:

- **Dataset Preparation (January Week 1, 1 week):** Before any model can be trained, the data must be gathered, labelled, and cleaned. Images of various types of waste are collected and annotated with bounding boxes corresponding to the waste categories identified during the literature review. The deliverable here is a well-structured, annotated dataset ready for training. This task depends directly on the literature review, which informs what categories of waste the system needs to detect.
- **YOLO Model Training (January Week 2, 1 week):** Once the dataset is ready, the YOLO object detection model is trained and validated against it. The success of this task is measured through standard computer vision metrics mean average precision (mAP), precision, and recall. The trained model weights and evaluation report form the deliverable. This task depends on the completion of dataset preparation.

Phase 3 : Hardware Assembly (January Week 3, Week 4, approximately 2 weeks)

Running in parallel with the later stages of Phase 2, the hardware side of the project takes shape during this period. There are two sequential tasks within this phase:

- **Robot Chassis Construction (January Week 3, 1 week):** The physical frame of the robot including the drivetrain and structural components is assembled here. This does not depend on the AI pipeline and can therefore proceed independently. The deliverable is a functional, mobile chassis ready to receive sensors and electronics.
- **Sensor Integration (January Week 4, 1 week):** With the chassis in place, the camera, ultrasonic sensors, and any other required peripherals are mounted and wired into the system. The deliverable is a fully instrumented robot body, hardware-ready for programming. This task naturally depends on the chassis being completed first.

Phase 4 : Software Development (February Week 1 , Week 2, approximately 2 weeks)

This is arguably the most technically demanding phase, as it requires both the AI pipeline and the hardware to be complete before meaningful progress can be made. Two major software components are developed here:

- **Navigation Programming (February Week 1, 1 week):** The robot needs to move intelligently through its environment — avoiding obstacles, planning paths, and navigating autonomously. This task involves implementing the motion control and navigation algorithms. The deliverable is a tested navigation module. It depends on the sensor integration being complete, as the sensors are what allow the robot to perceive its surroundings.
- **Collection System Setup (February Week 2, 1 week):** Here, the trained YOLO model is integrated with the robot's actuator and waste collection mechanism. This connects the robot's perception (what it sees) with its action (what it does). The deliverable is an end-to-end pipeline from detecting waste to physically collecting it. This task depends on both the YOLO model from Phase 2 and the navigation module from the previous task.

Phase 5 : Testing and Refinement (February Week 3 : March Week 2, approximately 3 weeks)

With a fully integrated system in hand, the focus shifts from building to breaking and then fixing. The robot is deployed in controlled environments that simulate real-world conditions, and its performance is observed and logged carefully. Failures are documented and addressed iteratively: a bug in detection triggers a model tweak; a navigation fault leads to algorithm adjustment. This phase is inherently iterative and requires patience. The deliverables are a set of test reports and a refined, stable system that performs reliably. Everything from Phase 4 must be complete before testing can begin in earnest.

Phase 6 : Documentation and Finalization (March Week 1 : Week 4, aproximately 4 weeks)

The final phase overlaps slightly with the tail end of testing, allowing documentation to begin as the last refinements are made. This involves writing up the full project report covering the methodology, system design, experimental results, analysis, and conclusions as well as preparing any required presentations or demonstrations. The deliverable is a complete, submission ready project report. While it can begin before testing is fully wrapped up, the results from Phase 5 must be available before the report can be finalized.

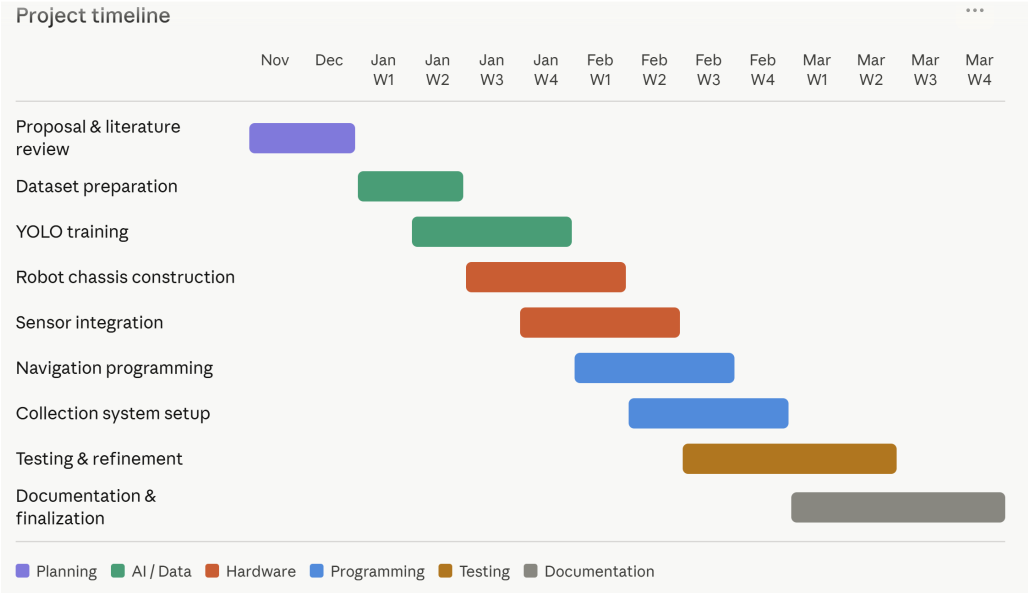

Figure B.1: Gantt chart showing the project timeline across all six phases

Appendix C

Declaration of AI use

We, NABASA ISAAC, LAKICA LETICIA and ATWIJUKIRE APOPHIA, declare that we used generative AI ethically as a "study buddy" only for brainstorming, literature search, summarising papers, and improving the clarity of our own writing. No AI tool was used to generate the final content of this proposal. All ideas, analysis, results and conclusions are our own. We reviewed, edited and rewrote every section ourselves before submission.

i. We used Grok (built by xAI) to help humanise and restructure our draft chapters so they would read naturally and sound like student work. For example, we gave it our rough Chapter 1, Chapter 2 and Chapter 3 drafts and asked it to rewrite them in clear, straightforward academic English while keeping all our original technical details. We then took the output, changed the wording, adjusted the flow and made sure every sentence reflected what we actually did in the project. We repeated this process for the Discussion and Conclusion chapters.

ii. We used ChatGPT (GPT-4o) mainly for brainstorming the overall structure of the report and for generating simple table templates like the hardware components table and performance results table. We copied the tables into our document and then filled them with our own data and modified every row and caption ourselves.

iii. We used Consensus (the AI-powered scientific search tool) to quickly find and summarise recent journal papers on YOLO-based waste detection robots during the literature review stage. We entered search queries such as "YOLO robotic waste collection outdoor" and "autonomous rubbish collection robot 2021-2025". We read the summaries to decide which papers were relevant, then downloaded and studied the full PDFs ourselves before writing our own literature review section.

We confirm that all final text in this proposal is our original work after careful editing and rewriting of the AI assisted drafts.

Signature: ______________________________ Date: ______________________

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Appendix D

List of 10 Major Journal Publications reviewed

[1] L.-B. Chen, X.-R. Huang, W.-H. Chen, W.-Y. Pai, G.-Z. Huang, and W.-C. Wang, “Design and implementation of an artificial intelligence of things-based autonomous mobile robot system for cleaning garbage,” *IEEE Sensors Journal*, vol. 23, no. 8, pp. 8909–8922, 2023.

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[10] T. Diwan, G. Anirudh, and J. V. Tembhurne, “Object detection using YOLO: Challenges, architectural successors, datasets and applications,” *Multimedia Tools and*

Applications, vol. 82, pp. 9243–9275, 2022.

Appendix A

Scopus Search Strings used during the literature review

E.1 Primary Search String

The query below served as the main search applied during the initial identification stage. It was designed to be broad enough to capture the full range of relevant work while remaining anchored to the three core concepts of the research: autonomous robotic platforms, waste management tasks, and system design or development.

```
("autonomous robot*" OR "mobile robot*")
AND
("garbage collection" OR "waste management"
  OR "litter detection" OR "trash collection")
AND
("design" OR "development" OR "system")
```

E.2 Supplementary Search Strings

Because no single query can fully capture a multidisciplinary research area, four supplementary strings were constructed to ensure adequate coverage of the key technical themes. Each targets a distinct dimension of the problem: perception, navigation, system integration, and optimisation, and was run independently before the results were merged and deduplicated.

(a) AI and Computer Vision Focus

This string was aimed at recovering work on the perceptual layer of robotic waste systems, specifically studies that employ deep learning and computer vision methods such as YOLO for waste detection and classification in real-world environments.

```
("autonomous robot*" OR "intelligent robot*" OR "AI robot*")
AND
("litter detection" OR "waste detection" OR "trash recognition")
AND
("deep learning" OR "computer vision" OR "YOLO")
```

(b) Navigation and Mobility Focus

This string targeted studies concerned with how autonomous robots move through their environments, specifically research covering simultaneous localisation and mapping (SLAM), path planning, and obstacle avoidance in the context of waste collection tasks.

```
("mobile robot*" OR "autonomous vehicle*")
AND
("waste collection" OR "garbage collection")
AND
("navigation" OR "SLAM" OR "path planning"
  OR "obstacle avoidance")
```

(c) System Integration and IoT Focus

To capture work on the architectural and connectivity dimensions of robotic waste systems, this string included terms related to the Internet of Things (IoT), AIoT frameworks, Robot Operating System (ROS) implementations, and multi-sensor integration.

```
("autonomous robot*" OR "smart robot*")
AND
("waste management" OR "garbage collection")
AND
("IoT" OR "AIoT" OR "ROS" OR "sensor integration")
```

(d) Optimisation and Multi-Robot Systems Focus

The final supplementary string broadened the scope to include work on fleet coordination, routing algorithms, and energy-efficiency considerations in automated urban cleaning and waste collection scenarios.

```
("autonomous robot*" OR "robot fleet")
AND
("waste collection" OR "urban cleaning")
AND
("optimization" OR "routing" OR "efficiency" OR "energy consumption")
```

E.3 Keywords Used

The terms below were used both within the structured search strings above and as standalone keywords during exploratory searching. They were selected to reflect the vocabulary used across the literature in this area, where different authors use different terms to describe the same concepts; for instance, "litter detection," "waste recognition," and "trash classification" are often used interchangeably.

Autonomous robots · Mobile robots · Waste management · Garbage collection · Trash collection · Litter detection · Computer vision · Deep learning · YOLO · Robot navigation · SLAM · Path planning · Obstacle avoidance · IoT · AIoT · ROS · Sensor integration · Smart waste management · Environmental robotics.

E.4 Search Filters Applied

To ensure that retrieved studies were current, peer-reviewed, and relevant to the technical scope of this research, the following filters were applied consistently across all search strings within the Scopus interface:

- **Publication years:** 2018–2025, reflecting the period during which deep learning-based approaches to robotic waste detection became the dominant paradigm.
- **Document type:** Peer-reviewed journal articles and conference papers only. Book chapters, editorials, and non-peer-reviewed documents were excluded.
- **Language:** English only, to ensure all retrieved documents could be fully assessed.
- **Subject areas:** Computer Science, Engineering, Artificial Intelligence, and Robotics.

E.5 PRISMA Alignment Note

The search strategy documented in this appendix corresponds to the *identification* stage of the PRISMA 2020 process. Records retrieved were subsequently screened by title and abstract, followed by full-text eligibility assessment using predefined inclusion and exclusion criteria. The final selection of studies and the flow of records through each stage are presented in the PRISMA diagram in Figure 1.

Appendix B

Research alignment with specialization, SDG, NDPIV & Vision 2040

B.0.1 Alignment with Programme Specialization

Artificial Intelligence and Robotics

Of all the specializations within Computer Science, this research sits most naturally with in Artificial Intelligence and Robotics. The project is not merely adjacent to these fields it is built from them. At its heart, the work involves designing and developing an autonomous robot capable of detecting, navigating toward, and collecting rubbish from outdoor environments, tasks that require both sophisticated machine intelligence and precise physical interaction with the world.

On the artificial intelligence side, the system relies on deep learning specifically the YOLO family of object detection models to identify and classify waste materials in real time from a live camera feed. This is not a peripheral application of AI; it is the cognitive core of the robot. Without it, the system cannot distinguish a plastic bottle from a stone, or decide whether something lying on the ground warrants collection. The use of YOLO places this work squarely within computer vision and edge intelligence, two of the most actively developing areas of modern AI research.

On the robotics side, the physical execution of the task demands just as much sophistication. The robot must navigate autonomously through unpredictable outdoor environments, avoid obstacles it encounters along the way, and plan efficient paths through the space it is cleaning. These challenges are addressed through simultaneous localisation and mapping (SLAM), sensor fusion, and motion planning algorithms. The collection mechanism itself the actuators that physically pick up or sweep waste represents the final link in a chain that runs from perception through reasoning to action.

Taken together, the integration of intelligent perception, autonomous decision making, and physical interaction with the environment reflects the three foundational pillars of Artificial Intelligence and Robotics as a discipline. The use of the Robot Operating System (ROS) as the middle ware layer, and the framing of the entire system within an AIoT architecture, further situates this work within current industry and research practice in the field.

B.0.2 Alignment with the Sustainable Development Goals

The United Nations' Sustainable Development Goals (SDGs) provide a global framework for addressing humanity's most pressing challenges, and this research intersects with several of them in direct and meaningful ways. Waste mismanagement is not simply an aesthetic problem it drives disease, environmental degradation, and social inequity, particularly in rapidly urbanising cities in the Global South. A robotic system capable of automating and improving waste collection is therefore not just a technical achievement; it is a contribution to a broader development agenda.

SDG 11 : Sustainable Cities and Communities

Perhaps the most direct alignment is with SDG 11, which calls for cities that are inclusive, safe, resilient, and sustainable. Litter and uncollected waste are among the most visible symptoms of urban governance failure, and their effects ripple outward into public health, tourism, and quality of life. By automating the detection and collection of waste in public spaces, this system offers a practical, scalable contribution to the goal of cleaner, more liveable cities. It is especially relevant in dense urban areas where manual collection struggles to keep pace with the volume of waste generated.

SDG 12 : Responsible Consumption and Production

SDG 12 concerns itself with ensuring that societies produce and consume in ways that do not outstrip the planet's capacity to absorb waste. Efficient collection is a prerequisite for effective sorting, recycling, and disposal. A robot that reliably retrieves waste from public spaces increases the proportion of material that enters formal waste streams rather than ending up in drains, waterways, or soil. With appropriate extensions, the system could also support rudimentary waste categorisation, nudging collected material toward recycling rather than landfill.

SDG 13 : Climate Action

Unmanaged waste, particularly organic and plastic waste, is a significant contributor to greenhouse gas emissions and environmental contamination. Methane released from decomposing organic waste in open spaces, and microplastics leaching into water systems, represent climate and ecological harms that begin with the failure to collect waste effectively. By improving collection efficiency, this research contributes at the upstream end of the waste management chain, reducing the volume of material that never reaches proper treatment. Where the robot is powered by solar energy or other renewable sources, the environmental argument strengthens further.

SDG 9 : Industry, Innovation and Infrastructure

SDG 9 calls for the building of resilient infrastructure and the promotion of inclusive and sustainable industrialisation. The development of autonomous robotic systems is precisely the kind of technological innovation this goal envisions, particularly when that innovation is oriented toward solving real problems in developingcountry contexts. This research demonstrates that the tools of modern AI and robotics are not the exclusive preserve of wealthy nations, and that locally grounded engineering research can produce systems of genuine practical value.

B.0.3 Alignment with the National Development Plan IV (NDP IV)

Uganda's Fourth National Development Plan (NDP IV) sets out a mediumterm agenda for accelerating the country's social and economic transformation. Several of its thematic priorities map directly onto what this research is trying to achieve, making the project not only academically credible but nationally relevant.

Digital Transformation and Innovation

One of NDP IV's central commitments is to harness emerging technologies as a lever for improved public service delivery. Artificial intelligence and robotics are among the technologies explicitly identified as having transformative potential. This project puts that commitment into practice in the domain of urban waste management a public service that has historically struggled with efficiency, coverage, and cost. Demonstrating that AIdriven robotics can work in this context creates a proof of concept with implications well beyond the immediate application.

Sustainable Urban Development

NDP IV recognises that Uganda's cities are growing rapidly and that urban infrastructure including sanitation and solid waste management must keep pace. The plan prioritises interventions that improve urban liveability without simply adding to the wage bill. An autonomous wastecollection robot directly addresses this tension: it extends the effective capacity of waste management systems without requiring a proportional increase in human labour. In a city like Kampala, where waste collection coverage is uneven and resources are constrained, this kind of technology could meaningfully shift the baseline.

Industrialisation and Technology Development

NDP IV envisions Uganda progressively building the knowledge infrastructure needed to support a technologydriven economy. That means not just consuming technology but producing it training engineers, conducting original research, and developing solutions tailored to local conditions. This project is a small but genuine contribution to that ambition. It demonstrates that students and researchers at Ugandan institutions can engage with frontier technologies in robotics and AI, and produce systems designed for the specific challenges of the Ugandan urban environment.

Environmental Protection and Management

Environmental sustainability is woven throughout NDP IV, reflecting an understanding that development and conservation are not opposites. Reducing the volume of waste that accumulates in unmanaged public spaces directly addresses soil and water contamination, disease vectors, and the broader degradation of urban ecosystems. The robotic system proposed in this research contributes to that goal at the point of collection the first and most critical link in the waste management chain.

B.0.4 Alignment with Uganda Vision 2040

Uganda Vision 2040 articulates the country's longterm aspiration: to transform Uganda into a competitive, uppermiddleincome country within a generation. It is a document about ambition about what becomes possible when science, technology, and human ingenuity are directed at national challenges with sustained commitment. This research, modest as it is in scope, is the kind of work Vision 2040 is trying to catalyse.

Science, Technology, and Innovation

Vision 2040 identifies Science, Technology, and Innovation (STI) as the primary engine of the structural transformation it envisions. A country that builds research capacity in artificial intelligence, robotics, and embedded systems is a country that is preparing itself for the economy of the next generation. This project is a practical exercise in exactly that capacity building a student led effort to design, build, and test an intelligent robotic system using the same tools and frameworks used by researchers and engineers worldwide.

Smart Cities and Urbanization

Vision 2040 anticipates a Uganda in which cities are not simply larger versions of what they are today, but qualitatively different planned, efficient, and technology enabled. Smart city infrastructure depends on data, automation, and intelligent systems working together to manage urban resources. Autonomous waste collection is one such system: it generates data, operates autonomously, and integrates with broader urban management frameworks. Building and testing such systems locally is a necessary step toward the smart city vision the plan describes.

Human Capital Development

Vision 2040 places enormous weight on the development of a skilled, innovative, technically capable workforce. Research projects like this one are not just about the systems they produce they are about the researchers they develop. Working through the challenges of sensor integration, computer vision, robot navigation, and system testing builds exactly the kind of deep technical expertise that the vision identifies as foundational to national transformation.

Environmental Sustainability

Finally, Vision 2040 is unambiguous about the need to pursue development in ways that do not compromise environmental integrity. Cleaner cities, better waste management, and reduced pollution are not peripheral aspirations they are preconditions for the quality of life that the vision promises. This research contributes to that commitment in a direct and practical way, by developing a tool that makes urban waste management more effective.

Summary. This research aligns closely with the Artificial Intelligence and Robotics specialisation, and simultaneously speaks to global sustainability priorities through the SDGs, medium term national planning through NDP IV, and long term national transformation through Uganda Vision 2040. That it does so not through abstract claims but through a concrete, functional system makes the alignment all the more meaningful. The work demonstrates that cutting edge technology and real world relevance are not in tension in the right hands, and with the right questions, they reinforce each other.

Appendix C

Algorithms, Code of interest

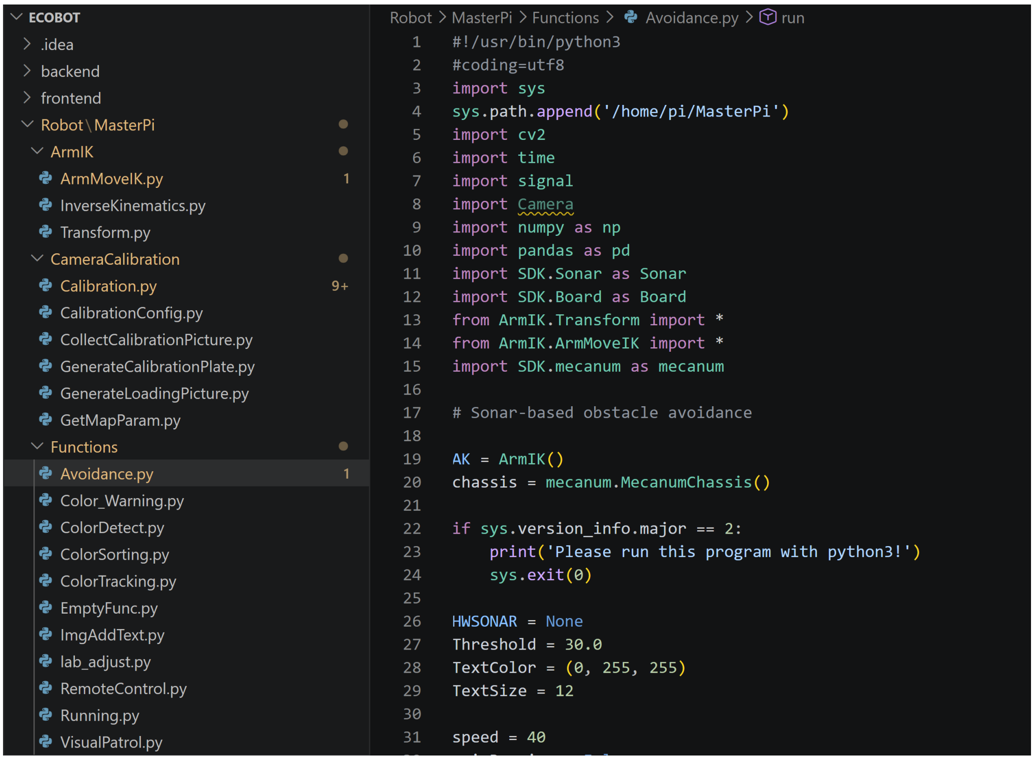

Figure C.1: Snippet of robot code functionality

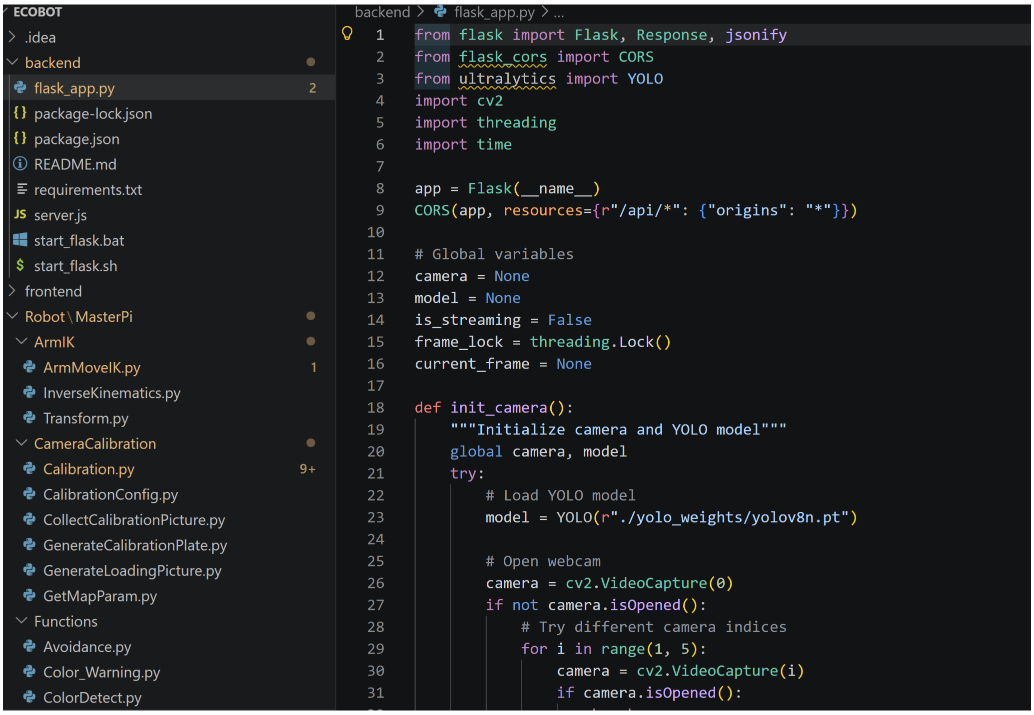

Figure C.2: Snippet of website backend

Appendix D

Other useful figures

System Architecture Diagram

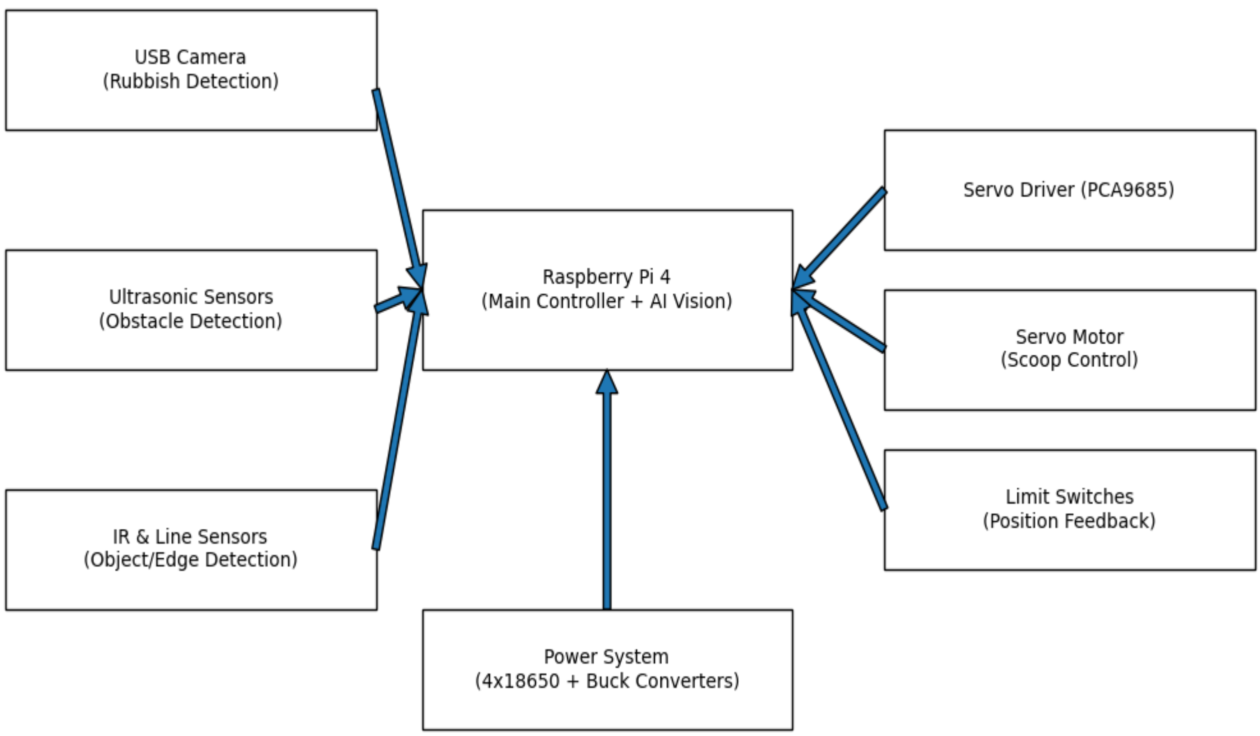

Figure D.1: System architecture diagram of ECO-BOT showing the Raspberry Pi controller, sensors, camera input, actuator control, and power system integration

Waste Collection Bin Integration

Figure D.2: ECO-BOT with onboard waste collection bin mounted at the rear for storing collected litter

Control Interface Dashboard

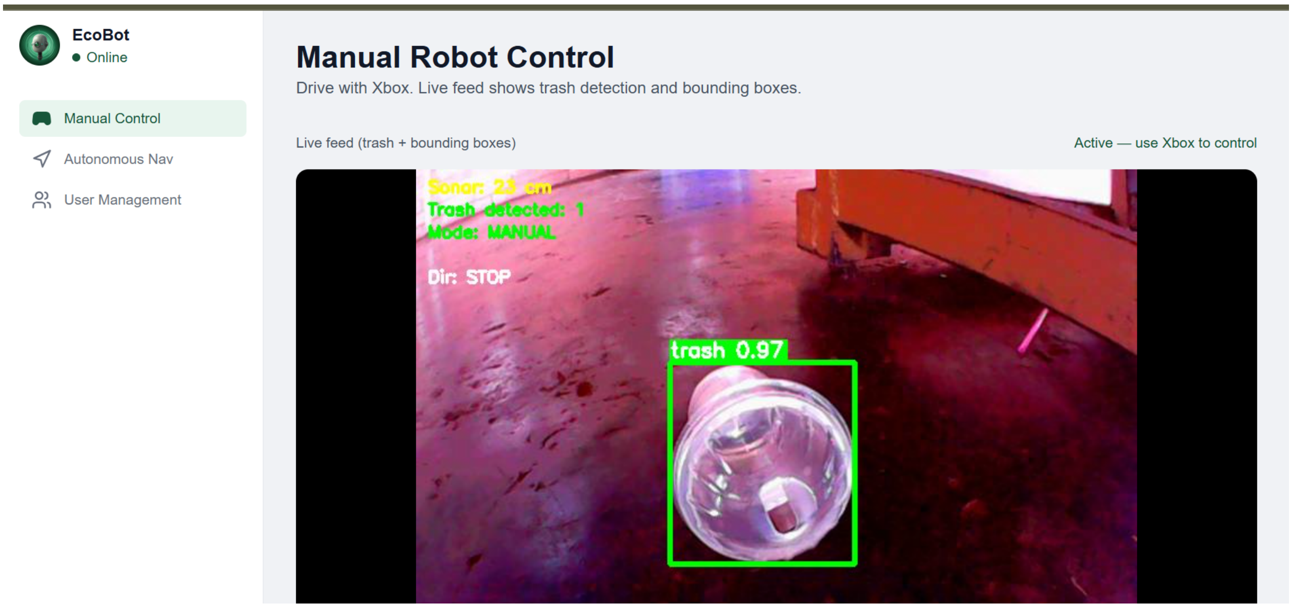

Figure D.3: Manual control dashboard interface showing live camera feed, detection bounding boxes, and robot control status

Robot Side View

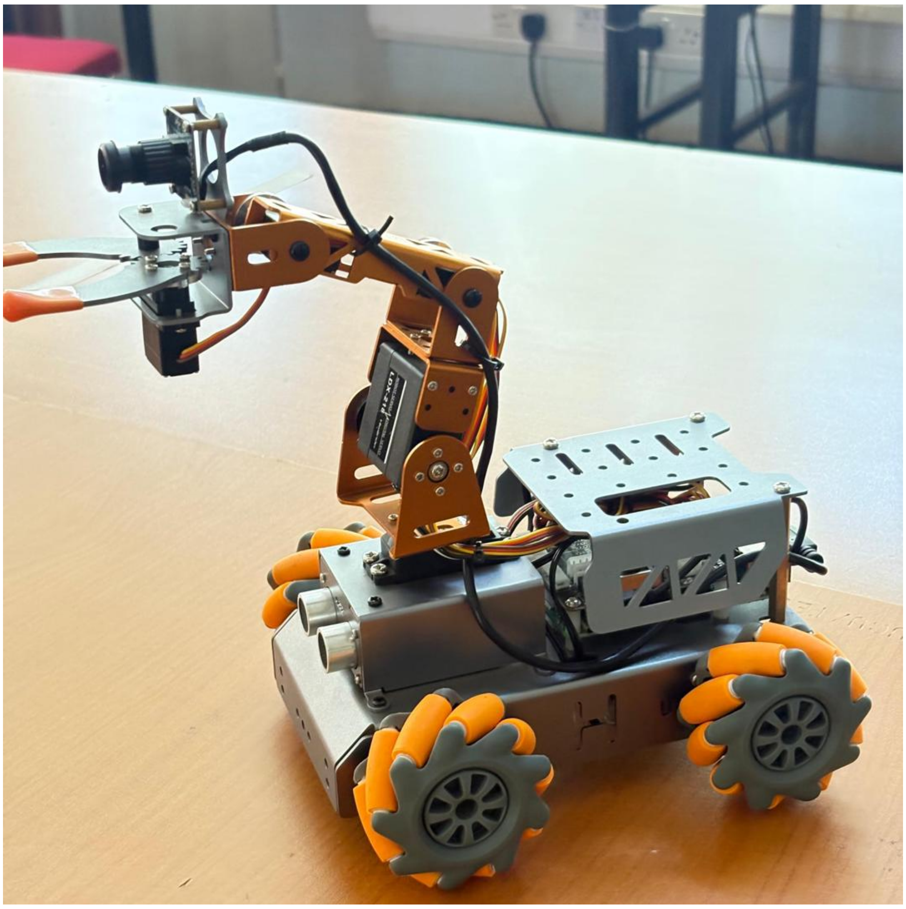

Figure D.4: Side view of the ECO-BOT platform showing the robotic arm, Mecanum wheels, and mounted electronics

Robot with Waste Interaction

Figure D.5: ECO-BOT interacting with waste during testing, demonstrating positioning of the robotic arm near the collection bin

Scooper Mechanism

Figure D.6: Modified scooper-based end-effector used for collecting lightweight waste materials such as plastic bottles and polythene bags

Appendix E

Research poster layout

Figure E.1: Poster summarizing the research concept