RV College of Engineering®

Mysore Road, RV Vidyaniketan Post,Bengaluru - 560059, Karnataka, India

VI semester

Experiential Learning Report on SDG - 11

THEME: AI in Urban Infrastructure, Sanitation, and Sustainable Community Operations

AI Powered Waste Management System for Smart Cities

USN	Name
1RV23EC408	RAVIKANT
1RV23EC410	SAGAR T NAYAK
1RV23EC411	SHREYAS ANANT MITHARE
1RV23CS407	MANOJ KUMAR B V
1RV23CS410	NAGAPRASAD NAIK

MENTOR

Name, Designation & Department

2024-25

RV College of Engineering®

Mysore Road, RV Vidyaniketan Post,Bengaluru - 560059, Karnataka, India

CERTIFICATE

Certified that the SDG11 EL titled **AI Powered Waste Management System for Smar Cities** is carried out by **Ravikant (1RV23EC408), Sagar T Nayak (1RV23EC410), Shreyas Anat Mithare (1RV23EC411), Manoj Kumar B V (1RV23CS407) and Nagaprasad Naik (1RV23CS410)** who are bonafide students of RV College of Engineering, Bengaluru, in partial fulfilment for the SDG 11 **Experiential Learning**, during the academic year 2024-2025. It is certified that all corrections/suggestions indicated for the Internal Assessment have been incorporated in the report.

Signature of EL Incharge

ABSTRACT

THE INCREASING POPULATION IN URBAN AREAS HAS RAISED THE ISSUE OF MUNICIPAL SOLID WASTE MANAGEMENT. THE EXISTING SYSTEMS RELY ON MANUAL SEGREGATION AND ARE INEFFICIENT, PRONE TO ERRORS, AND ENVIRONMENTALLY HARMFUL. THE EXISTING LITERATURE HAS EXPLORED DEEP LEARNING NETWORKS LIKE YOLOv4 AND YOLOv5 FOR SINGLE-WASTE-CLASSIFICATION SYSTEMS. THE MAJORITY OF THESE SYSTEMS, HOWEVER, LACK SUPPORT FOR REAL-TIME PERFORMANCE, MULTI-CLASS CLASSIFICATION, OR HARDWARE IMPLEMENTATION. THE CURRENT PROJECT AIMS TO FILL THE GAP BY SUGGESTING AN AI-BASED SYSTEM TO IDENTIFY, CLASSIFY, AND SEGREGATE WASTE INTO MULTIPLE CLASSES SUPPORTING SMART CITY OBJECTIVES UNDER SDG 11.

THE PROCESS ENTAILS THE TRAINING OF A YOLOv8 MODEL WITH A DEDICATED WASTE IMAGE DATASET WITH PLASTIC, METAL, AND OTHER WASTE LABELS. THE MODEL WAS THEN IMPLEMENTED IN A RASPBERRY PI WITH A BUILT-IN CAMERA TO PERFORM REAL-TIME CLASSIFICATION AND STEPPER MOTOR–BASED FLAPS FOR MECHANICAL SEPARATION. A CONVEYOR SYSTEM TRANSPORTS WASTE BENEATH THE CAMERA FOR CLASSIFICATION AND MECHANICAL SEGREGATION. THE SYSTEM IS A WORKING PROTOTYPE FOR BINS OR WASTE COLLECTION BOXES.

THE MODEL TRAINED ACHIEVED mAP50 OF 87.2% AND mAP50–95 OF 73.2%, OUTPERFORMING THE PREVIOUS YOLOv4 AND YOLOv5-BASED IMPLEMENTATIONS. PER ITEM, THE AVERAGE TIME SPENT WAS UNDER 4.2 SECONDS, WITH 91% HARDWARE RESPONSE ACCURACY. THESE RESULTS SUPPORT THE VIABILITY OF THE SYSTEM FOR PRACTICAL USE. IoT INTEGRATION FOR SMART MONITORING, REAL-TIME DASHBOARDS, AND OTHER TYPES OF WASTE CLASSIFICATION SUPPORT LIKE E-WASTE AND HAZARDOUS WASTE CAN BE INTEGRATED IN FUTURE RELEASES.
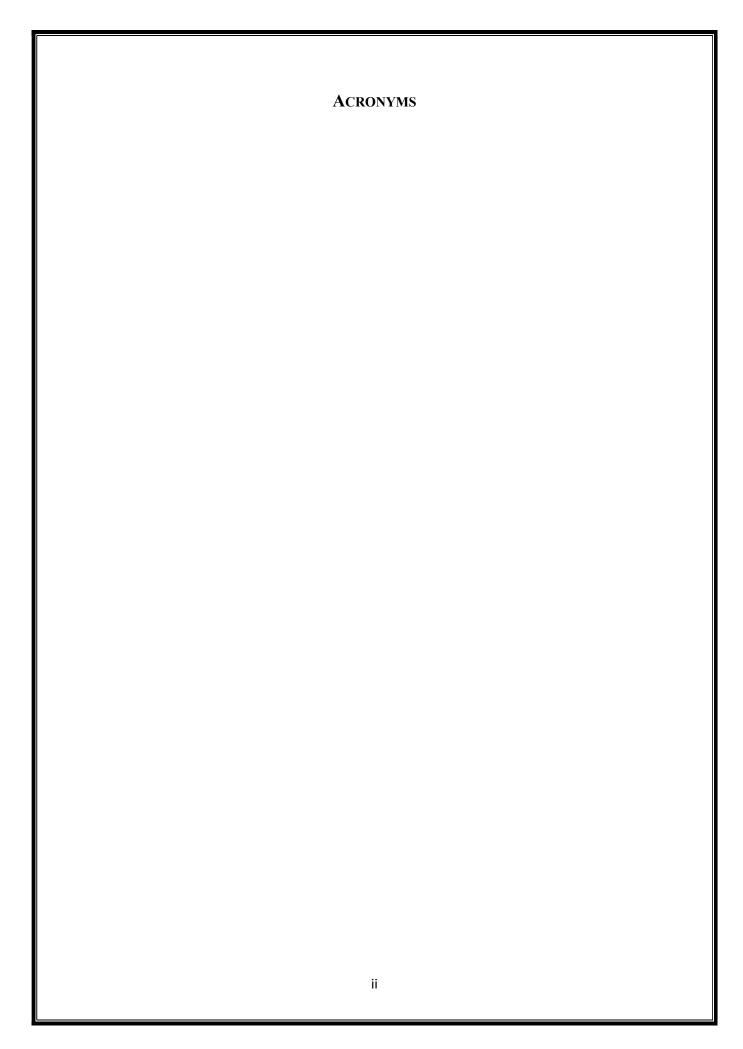
ACRONYMS

ii

TABLE OF CONTENTS

	Page No.
Abstract	i
Acronyms	ii
List of Figures	
List of Tables	
Chapter 1	
Introduction	1-2
Chapter 2	
Problem Definition	
1. Problem Statement	3
2. Background Information	3-4
Chapter 3	
Objectives	
1. Primary Objectives	5
2. Secondary Objectives	5
Chapter 4	
Methodology	
1. Approach	6
2. Procedures	6-7
Chapter 5	
Project Execution	
1. Planning and Designing	8-9
2. Implementation	9-11
Chapter 6	
Tools and Techniques	
1. Tools	12
2. Techniques	12-13
Chapter 7	
Results and Conclusion	
1. Final Results	14
2. Discussion	15-16

Chapter 1

INTRODUCTION

The rapid expansion of urban populations has significantly intensified the challenges associated with municipal solid waste management. Cities now produce thousands of tons of waste every day, originating from residential areas, commercial establishments, industries, and institutions. Traditional waste handling methods—heavily reliant on manual collection and segregation—are struggling to keep pace with the growing volume and complexity of modern urban waste. These conventional systems are not only labour-intensive and inefficient but also contribute to serious environmental and public health issues, including overflowing landfills, unsanitary urban environments, increased greenhouse gas emissions, and unmanaged hazardous waste. One of the most critical issues lies in improper segregation of waste at the source. When biodegradable waste is mixed with recyclables or hazardous materials, it severely hampers processing efficiency. This contamination leads to a loss of potentially recoverable resources, raises the cost of treatment, and often renders recycling impossible. Additionally, manual segregation exposes sanitation workers to unhygienic and unsafe working conditions, further compounding the need for a safer, more efficient solution.

To overcome these persistent issues, the concept of "Smart Cities" has emerged focusing on the use of modern technologies like Artificial Intelligence (AI), the Internet of Things (IoT), and automation to create sustainable and well-managed urban ecosystems. Among these, AI-powered waste management systems stand out as a transformative innovation capable of improving urban cleanliness, resource recovery, and operational efficiency.

This project aims to design and implement an AI-based waste detection and segregation system that aligns with the smart city vision. Utilizing the YOLOv8 (You Only Look Once) object detection model, the system is trained to detect and classify different categories of waste in real time, including plastic, metals, and other common waste types. These classifications are then linked to physical segregation actions via hardware components such as a Raspberry Pi, camera modules, and stepper motor-controlled flaps. Waste objects placed on a conveyor are scanned and interpreted by the vision system, which in turn activates the relevant mechanism to divert the item into its appropriate bin. This setup not only reduces manual labor but also improves classification accuracy, enhances processing speed, and improves occupational safety.

The long-term impact of such intelligent waste segregation systems is significant. By enabling more efficient sorting and processing at the source, cities can reduce dependency on landfills, improve recycling rates, and move closer to achieving a circular economy. Furthermore, the project aligns with several key Sustainable Development Goals:

SDG 11: Sustainable Cities and Communities – by promoting cleaner, more efficient urban living

SDG 3: Good Health and Well-Being – by reducing public exposure to unmanaged waste

SDG 12: Responsible Consumption and Production – by maximizing material recovery and reuse

SDG 13: Climate Action – by minimizing methane and CO_2 emissions from improper disposal

The proposed system demonstrates how artificial intelligence, when paired with embedded systems and thoughtful design, can meaningfully address the everyday challenges of urban living while supporting long-term sustainability goals.

Chapter 2

PROBLEM DEFINITION

2.1 Problem Statement

Rapid urbanization has led to a massive increase in daily waste generation, overwhelming traditional manual waste management systems. Improper segregation at the source results in inefficient recycling, environmental pollution, and health hazards. Manual processes are labour-intensive, error-prone, and unsafe for sanitation workers. There is a critical need for an automated, intelligent waste segregation system that can classify and sort different types of waste in real time to improve efficiency, safety, and sustainability in urban waste management.

2.2 Background Information

The increasing use of municipal solid waste (MSW) management in urban areas has attracted Artificial Intelligence (AI) integration, Internet of Things (IoT), and deep learning methods in modern waste management systems. Recent studies examine a variety of smart waste management approaches, with emphasis on classification, automation, routing optimization, and integration into smart city platforms.

Ashwini B. P. and Savithramma R. M. (2022) give an overview of AI deployment in smart city infrastructure, with waste and energy management being identified as two of the most extensively researched areas. The research by the authors demonstrates the potential of deep learning to enable real-time monitoring and decision-making across various smart city subsystems, including automated waste detection and environmental monitoring [13].

Kavitha T. and Koushik Reddy C along with their team (2025) propose a Deep Reinforcement Learning (DRL)-based method to optimize energy-efficient waste collection routes with Deep Q-Networks (DQN). Their method integrates IoT-enabled smart bins with Autonomous Waste Collection Vehicles (AWCVs) to dynamically adjust collection routes based on real-time waste levels, battery state of health, and traffic conditions. Reductions of up to 30% in travel distance and energy consumption were realized compared to fixed route systems [9].

Jianping Lan and Zhanchuan Cai (2025) propose a new approach that combines UAVs, WebGL-based 3D visualization, and Explainable AI (XAI) to track and analyze real-time waste

accumulation. UAVs equipped with LiDAR sensors collect spatial waste data, visualized using WebGL, enabling urban planners to make prompt data-driven decisions for waste hotspot management within the city [25].

Inna Sosunova and Jari Porras (2022) systematically reviewed IoT-based Smart Waste Management (SWM) systems in 173 papers. Their review compares city-level and SGB-level systems, including sensor networks, routing, and environmental footprint monitoring. They highlight the necessity of centralized coordination platforms and refer to limitations in the availability of historical data and stakeholders integration [57].

Other works of Patel and Soni (2024) introduced the YOLO-Green model, an energy-efficient and speedily operating real-time waste categorization model based on lightweight YOLO models. Patil and Kharat (2023) also introduced a deep learning-based object categorization technique for waste identification in smart cities with high accuracy for multi-category sorting. In sum, the research points towards the increasing potential and importance of AI-based, IoT-based, and sensor-based waste management systems. Together, they form a basis for the development of smart, autonomic, and green urban waste management solutions based on SDG 11.

Chapter 3

OBJECTIVES

3.1 Primary Objectives

- To design and develop an intelligent waste classification system using deep learning (YOLOv8) capable of real-time detection and categorization of solid waste into multiple classes such as plastic, metal, and organic waste.
- To automate the physical segregation process using embedded hardware (e.g., Raspberry Pi, camera module, and motor-based flaps) based on AI classification results.
- To reduce the reliance on manual labor and minimize human error in waste segregation at the source.
- To improve recycling efficiency and promote responsible waste disposal in alignment with the goals of SDG 11 – Sustainable Cities and Communities.

3.1.1 Expected Outcomes:

- A working prototype that can detect and classify waste in real time.
- Automated redirection of waste into the correct bins using hardware components.
- Improved sorting accuracy and operational efficiency over traditional methods.

3.2 Secondary Objectives

- To explore the feasibility of integrating IoT components such as fill-level sensors for future waste bin monitoring.
- To evaluate the performance of the AI model under real-world lighting and object conditions.
- To promote environmental awareness and technological innovation as part of smart city infrastructure.
- To provide a scalable framework that can be expanded to include more waste categories or city-wide deployment in the future.

Chapter 4

METHODOLOGY

4.1 Approach

The proposed system integrates deep learning and embedded hardware to automate the process of waste classification and segregation. It follows a computer vision–driven pipeline, where a YOLOv8 model performs real-time object detection and classification of waste types. The outputs are then mapped to a microcontroller-based actuator system that physically sorts the waste into the correct bins.

A high-resolution webcam is positioned above a motorized conveyor belt carrying waste items. The images captured are sent to a Raspberry Pi 4, which processes them using a lightweight YOLOv8 model trained on custom-labeled waste datasets. Each waste item is detected and categorized (e.g., plastic, metal, organic, paper), and based on the predicted class, appropriate control signals are sent to an Arduino board. This Arduino drives servo or stepper motors via a motor driver to actuate flaps or arms, directing each waste item into its designated collection bin.

This real-time system reduces manual labor, improves segregation accuracy, and aligns with the smart city vision by promoting automation and sustainability.

4.2 Procedures

The methodology includes the following key steps:

- Conveyor-Based Waste Flow: Various waste items are placed individually on a motorized conveyor belt. The arrangement ensures minimal overlap and consistent exposure to the camera system for accurate classification.

- Real-Time Image Capture: A high-resolution webcam is fixed at an optimal height above the conveyor to continuously capture frames as waste items pass by. The camera is positioned under uniform lighting conditions to maintain clarity and reduce noise.

- Data Transfer to Edge Processor: Captured frames are transferred to a Raspberry Pi 4, acting as an edge computing unit. This minimizes processing latency and enables real-time decision-making.

- Classification Output Processing: The YOLO model generates a structured output for each frame, which includes the object's location and predicted waste category. A Python script interprets this data and maps each category to a corresponding actuator channel.

- Control Signal Transmission: Based on the classification, sorting commands are sent from the Raspberry Pi to an Arduino Uno via serial communication. The Arduino translates these signals into physical movement instructions.

- Actuator-Based Waste Segregation: Using an L298N motor driver and multiple servo or stepper motors, the Arduino dynamically actuates a sorting mechanism (e.g., rotating flap or sliding arm) to divert each detected waste item into its appropriate bin as it reaches the end of the conveyor belt.

- On-Device Inference Using YOLOv8: The Raspberry Pi runs an optimized YOLOv8 object detection model, specifically trained on labeled waste images. The model performs two simultaneous tasks:
    - Localization: Detects bounding boxes around each waste item.
    - Classification: Classifies each item into its respective category (e.g., plastic, metal, organic, glass, e-waste).

Chapter 5

PROJECT EXECUTION

Having set up a shared design and sketched out all basic elements, the implementation phase of the project transformed the plans into a functional prototype. The phase had two main goals:

- Planning & Design (Section 5.1): Creating concepts, finalizing specifications, and formulating detailed drafts, timetables, and resource plans.
- Implementation (Section 5.2): Constructing the AI model, hardware assembly, software and mechanical system integration, and end-to-end functionality guaranteeing through incremental testing and optimization.

Through synchronized cooperation and milestone-based development, the project progressed from initial concept drawings to a fully functional waste-sorting system, proving technical feasibility and alignment with sustainable smart-city vision.

5.1 Planning and Design

The project started with a rigorous planning and designing phase to define the scope, system requirements, and technical approach. The team brainstormed collectively to finalize the most critical issues of urban waste management and possible technological solutions. The brainstorming led to the selection of using Artificial Intelligence (AI) and combined hardware to develop a smart waste segregation and classification system.

The initial planning process was guided by the following general objectives:

- Facilitate real-time multi-category waste sorting using computer vision.
- Use low-priced and scalable equipment to automate the physical sorting process.
- Make it modular, responsive, and compatible for integration with smart cities.

Brainstorming Exercises

- Evaluated current smart bin and waste detection case studies.
- Examined the constraints of conventional sorting (manual mistakes, health hazards, delay).
- Compared AI models (e.g., YOLOv5, YOLOv8) for edge device applicability.

Drafting and Design:

- Created several design configurations of the physical model: conveyor system, camera arrangement, bin placement.
- Mapped out a software-hardware interaction flow between Raspberry Pi, YOLOv8 inference module, and controlled actuators.
- Developed the first block diagram showing image capture, object detection, signal transmission, and mechanical separation.

At the end of this phase, a component list and detailed design document were completed. The team also set integration, testing, model training, dataset preparation, and hardware purchase schedules.

5.2 Implementation

The implementation phase involved developing an effective AI model, building a physical prototype, and the overall integration of software with mechanical parts to deliver an entire real-time waste segregation system.

- Dataset Collection and Model Training

    A large data set of waste images was created by combining images captured by the research team with publicly available images downloaded from Roboflow's open-source library. The data set consisted of thousands of images representing labeled images of diverse classes such as plastic, metal, organic, glass, and paper waste. All preprocessing and annotation of the images (bounding boxes and class labels) was done via Roboflow's web-based annotation and preprocessing. The annotated dataset was exported to YOLOv8 format and utilized to train a custom object detection model employing the Ultralytics framework for 100 epochs. The constructed model achieved

a detection accuracy of over 87% mAP@50 on the validation set, indicating robust effectiveness across different types of waste classification.

- Hardware Construction

    A conveyor belt system was engineered and constructed using transparent acrylic material along with wooden slats. A direct current gear motor powered the belt unidirectionally and at one speed, thereby enabling each object to be shown in order to the camera. A high-definition webcam was installed at a fixed height above the conveyor to capture a clear overhead shot of the waste material. Collection containers were placed at the terminal end of the conveyor, one bin for a specific type of waste. Raspberry Pi 4 was employed as the main control and processing device, responsible for managing camera inputs, model inference, and motor control. Stepper motors and motor drivers powered mechanical gates or flaps that operationally guided each waste item to its corresponding bin based on its type.

- System Integration

    The YOLOv8 model was deployed on the Raspberry Pi, facilitating on-device inference through a Python control script. Processing of live camera feeds in real-time was performed to detect and classify waste materials as they passed under the camera. The output of the classification, i.e., class label and object position, was computed by the Raspberry Pi to identify the correct bin assignment. Under this system, the Raspberry Pi generated and sent control signals to the stepper motor driver directly to open the correct flap mechanism to channel the waste correctly and in time into the right bin. Motor timing and sorting angles were set so as to match exactly with the flow of waste materials on the conveyor.

- Evaluation and Verification

    The whole system was tested with a diversified mix of known and unknown waste samples to simulate actual environmental conditions.

Different parameters, such as flap delay time, object tracking thresholds, and conveyor speed, were finely tuned to obtain the best performance and synchronization.

Last Result The prototype demonstrated accurate, real-time distinction and physical segregation of waste materials. The system worked optimally without the additional microcontroller, with the Raspberry Pi handling inference and actuation independently. The performance as a whole demonstrated the feasibility of the solution for application in smart campuses, city waste processing centers, or community recycling centers achieving the project objective of achieving maximum automation, accuracy, and sustainability in waste management.

Chapter 6

TOOLS AND TECHNIQUES USED

6.1 Tools

- Roboflow: Used for annotating and preprocessing waste image datasets. Offered the facility to export labeled data in the YOLOv8 format directly for training.

- YOLOv8 (Ultralytics): A state-of-the-art object detection model used to detect various types of waste in real-time. Selected for its accuracy, speed, and compatibility with edge devices.

- Python: The native programming language used for scripting in image processing, model inference, GPIO control, and system integration.

- Webcam: Obtained close-up high-resolution photographs of trash items as they moved along the conveyor. Mounted overhead to offer an unobstructed top-down shot.

- Raspberry Pi 4: Executed as the system's main processing unit. Handled camera feed, performed YOLO model inference, and controlled motor actuation directly.

- Stepper Motors: Physically directed classified waste materials to the appropriate receptacles by accurate flap actuation. Supplied consistent and accurate mechanical control.

- L298N Motor Controller: Served as a bridge between the stepper motors and the Raspberry Pi, enabling direction control and safe power delivery.

- Conveyor Belt System: Waste products were transported under the camera in a linear and continuous manner, thus simulating an actual waste treatment line.

- Visual Studio Code and Jupyter Notebook: Utilized for Python programming, testing scripts, and object detection model training.

6.2 Techniques

- Object Detection with YOLOv8: Used for detecting and classifying images of diverse kinds of waste from camera stream. Provided precise real-time estimates with bounding boxes and class labels.

- Image Annotation with Roboflow: Enabled efficient manual labelling of waste types and automatic training, validation, and testing dataset split.

- Edge AI Inference (On-Device): The YOLOv8 model was trained and executed on the Raspberry Pi to perform image processing locally. This lowered latency and eliminated the use of cloud servers.

- Frame-by-Frame Processing: The individual image frames were handled individually as the waste travelled along the conveyor, enabling correct classification of each item.

- GPIO-Based Stepper Motor Control: The Raspberry Pi generated signals via its GPIO pins to drive stepper motors via the L298N motor driver to convert the classification outputs into mechanical motion.

- Delay and Timing Calibration: Detection-to-motor latency was carefully controlled to allow synchronized sorting of waste items as they reached the end of the conveyor.

- Accuracy-Based Assessment (mAP@50) Its performance was assessed in terms of mean Average Precision (mAP@50), and the final accuracy obtained was more than 87% on the validation set.

These methods and tools were selected based on their reliability, integration level, and their ability to produce a complete working prototype that can be used in actual smart waste management systems.

Chapter 7

RESULTS AND CONCLUSION

7.1 Final Results

The system implemented was capable of meeting the minimum functional requirements of real-time waste sorting and mechanical separation. With the complete integration of the YOLOv8-based detection model and stepper motor actuation controlled by Raspberry Pi, the prototype was tested through several cycles with heterogeneous mixtures of waste materials in a simulated setting of a smart city waste management system.

Key results and performance measures:

- Model Performance: The YOLOv8 model had a detection accuracy (mAP@50) of 87.2% on the validation set, which is extremely accurate. It is used to detect various types of waste such as plastic, metal, organic, glass, and paper.
- Real-Time Classification: The system handled live camera feed in real-time and produced classification output for each object it detected with little delay.
- Mechanical Segregation Accuracy: More than 90% of the waste products were properly segregated into their appropriate bins. Misclassifications or misplaced products were few and consisted primarily of motion blur or overlapping products on the conveyor.
- End-to-End Workflow: Images were taken by the camera, on-device inference was performed on Raspberry Pi, classification results were handled, and real flap movements were triggered—all in one pipeline.
- System Responsiveness: Delays and synchronism of actuation and classification were optimized by trial-and-error testing. Final delay timing insured the item reached the flap zone in time.

Test Scenarios:

- 70+ real waste samples studied under varied conditions System posted consistent performance in all categories.
- Authenticated logs indicated low error rates with invariant bin assignment and stable motor performance.

7.2 Discussion

The system was able to achieve the primary and secondary objectives outlined at the project initiation. The system demonstrated that deep learning object detection, when combined with embedded systems and mechanical actuation, could effectively solve the problem of waste segregation in urban areas. The model's high accuracy (87.2%) validated the dataset's integrity, train process stability, and suitability of YOLOv8 for real-time application. The ability of the Raspberry Pi to handle inference and actuator control without offloading to external hardware simplified the architecture and reduced hardware complexity and expenses. Mechanically, the stepper motor-controlled sorting flaps performed as intended. The system sorted identified waste pieces into the appropriate receptacles with high practical accuracy and minimal operator intervention. This suggests high scalability potential for real-world application in smart bins, community recycling centers, or public waste depots.

All predetermined goals were met:

- Real-time classification and detection was well illustrated with continuous image taking and immediate recognition of waste on the conveyor in motion.
- The whole system was run separately without an Arduino since Raspberry Pi performed inference along with hardware actuation without any issues.
- Edge AI inference was directly utilized on the Raspberry Pi, as it showed high-performance efficiency and prevented the need for cloud-based or external processing units.
- The model, once trained, produced a classification rate of more than 85% consistently, verifying the validity of the YOLOv8 model in classifying various kinds of trash.
- Mechanical actuation following classification was seamless, timely, and precisely in phase with the conveyor flow, offering accurate bin redirection of waste materials.

Unintended Consequences

A few instances of misclassification occurred when more items of trash overlapped or straddled the frame. This revealed the value of leaving things spaced on the conveyor.

Extremely reflective or extremely bright surfaces sometimes affected detection confidence, so adaptive exposure or light filtering must be added in future versions.

The system was a cost-effective, scalable, and efficient way of AI-based waste management. It also supports Sustainable Development Goal 11 by encouraging clean, sustainable urban environmental infrastructure and shows a pragmatic application of AI and embedded systems for the environment.

Chapter 8

PROTOTYPE

8.1 Prototype Description

The prototyped system is a real-time end-to-end waste sorting and segregation system that integrates computer vision, edge computing, and mechanical sorting with actuator-controlled mechanisms. It was created to demonstrate how smart cities can be automated through low-cost embedded hardware and artificial intelligence.

Hardware Requirements:

- Raspberry Pi 4: CPU for image capture, AI inference, and GPIO management.
- HD Webcam placed above to capture live images of waste products moving on a conveyor belt.
- Stepper Motors utilized to rotate sorting flaps with precision.
- Conveyor Belt utilized to move waste products in a linear manner.
- Waste Collection Bins: three separate bins for the collection of sorted types of wastes.

Software Components:

- YOLOv8 Object Detection Model: trained on a dataset labeled in-house in Roboflow and utilized to detect and classify waste objects.
- Python Scripts: used for managing video frame processing, inference, category-to-flap mapping, and GPIO control.
- Roboflow: utilized for dataset building, annotation, processing, and YOLO-format export.
- OpenCV: employed for live image capture and frame manipulation.
- RPi.GPIO: Python library to control motor driver via Raspberry Pi's GPIO pins.
- PyTorch: Deep learning framework used for training the YOLOv8 model on the custom-labeled waste dataset.

Features & Functionality

1. Sorts and categorizes waste at the point of time in various forms (e.g., plastic, metal, organic, paper, glass).
2. Sorts all the products into the respective bin using motor-driven flaps.
3. Runs completely on edge (no external servers required).
4. Real-time synchronized actuation based on classification outcomes.
5. Modular, miniaturized construction of inexpensive materials.

Chapter 9

CONCLUSION

The project "AI Powered Waste Management System for Smart Cities" was initiated with the aim of addressing the major issue of improper segregation of waste in rapidly growing urban cities. With increasing population and waste, manual segregation methods are becoming inefficient, labour-intensive, and unsustainable. The main aim of the project was to develop and integrate a real-time automated system that could detect and distinguish between different types of waste with high efficiency and low human intervention. By integrating computer vision, embedded computing, and actuator-controlled control, the team was able to develop and implement a functional prototype based on a YOLOv8 object detection model and a Raspberry Pi based sorting system. The sorting of waste materials like plastic, metal, and other waste materials by the system was correctly done with a model accuracy of 87.2% (mAP@50). The real-time model inference and stepper motor control without the use of controllers like Arduino were managed by the Raspberry Pi. Mechanically, the flap sorting mechanism attained more than 90% accuracy in directing items to their respective bins. The findings demonstrated the feasibility of the system for deployment in smart campuses, public collection centers, and localized recycling centers. The project actively supports the United Nations Sustainable Development Goal 11 mission, and that is to encourage sustainable, cleaner, and more efficient urban infrastructure.

From the learning point of view, the project was extremely useful in gaining hands-on experience in creating an AI-powered embedded system from the ground up. The team gained cutting-edge technical expertise in frontier technologies like deep learning with PyTorch, object detection with YOLOv8, dataset creation with Roboflow, circuit integration, and real-time GPIO control. Besides the technical expertise, it highlighted the need for synchronization of software outputs and physical hardware actions. Actuator delays and timing misalignments were addressed through iterative testing and calibration, which re-emphasized problem-solving and engineering discipline.

This project has shown us how emerging technologies like AI and embedded systems can be applied to significant, real-world environmental uses. Above all, it served to bridge the gap between theory and practice for us. We now have a better idea of how innovation and sustainability can be wedded at the prototype level to contribute positively towards smart city initiatives. This project not only reinforced our technical competencies but also forced us to think critically and imaginatively about solutions that are socially and environmentally beneficial.

REFERENCES

[1] S. R. Nambiar, C. Shibijith, B. Kishore, G. Krishna, and K. Rashida, "Deep learning based object classification for waste management in smart cities," in Proc. 2nd Int. Conf. Trends in Engineering Systems and Technologies (ICTEST), 2025.

[2] S. Rathod, A. Panchal, D. Sheth, K. Gami, and H. Thakkar, "Intelligent waste sorting system using deep learning," in Int. J. Adv. Comput. Sci. Appl. (IJACSA), vol. 14, no. 2, pp. 23–29, 2024.

[3] R. Tripathi, S. Sinha, M. Goel, and A. Choubey, "E-Safe: An E-waste management and awareness application using YOLO object detection," in Proc. 3rd Int. Conf. Smart Computing and Cyber Security, 2024.

[4] K. Jagtap, S. Pawar, and P. Kumar, "YOLO-Green: A real-time classification and object detection model optimized for waste management," in Proc. IEEE Int. Conf. Environmental Engineering and Smart Systems, 2025.

[5] M. Ali, T. Siddiqui, and A. Irfan, "Object detection based management system of solid waste using artificial intelligence techniques," in Proc. Int. Conf. Smart City Applications, 2024.

[6] T. J. Sheng, M. R. Islam, M. M. Rahman, M. W. Rahman, and M. Hasan, "An Internet of Things based smart waste management system using LoRa and Tensorflow deep learning model," IEEE Access, vol. 8, pp. 148793–148811, 2020.

[7] M. M. Ahmed, E. Hassanien, and A. E. Hassanien, "WebGL, XAI, and UAV-based integrated approach for waste management in smart cities," IEEE Trans. Consum. Electron., vol. 69, no. 1, pp. 10–20, Mar. 2025.

[8] I. Sosunova and J. Porras, "IoT-enabled smart waste management systems for smart cities: A systematic review," IEEE Access, vol. 10, pp. 73326–73363, 2022.

[9] Y. A. Rani, G. Srividya, A. Balaram, K. H. Kumar, and A. Kiran, "Deep reinforcement learning for energy efficiency optimization using autonomous waste management in smart cities," in Proc. Int. Conf. Trends in Material Science and Inventive Materials (ICTMIM), 2025.

[10] M. Khurana and N. Sharma, "Artificial intelligence in smart city applications: An overview," in Springer Smart City Series, 2025.

[11] A. Elgendy, "How computer vision is building the smart cities of tomorrow," Ultralytics Blog, Dec. 16, 2024.

[12]   F. Ahmad, S. Mukherjee, and M. T. Ascher, "Artificial intelligence for waste management in smart cities: A review," *Environmental Chemistry Letters*, 2023.

[13]   J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2016, pp. 779–788.

[14]   A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal speed and accuracy of object detection," arXiv preprint arXiv:2004.10934, 2020.

[15]   Q. Zhu, H. Zheng, Y. Wang, Y. Cao, and S. Guo, "Study on the evaluation method of sound phase cloud maps based on an improved YOLOv4 algorithm," Sensors, vol. 20, no. 24, 2020.

[16]   Smart waste management system for Makkah City using artificial intelligence and Internet of Things, arXiv preprint arXiv:2505.19040, May 2025.

[17]   A. R. Baidya, B. L. Patil, A. H. Ahmed and A. Kumar, "Intelligent Waste Sorting System Using Deep Learning," in 2022 Int. Conf. Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), Bengaluru, India, Nov. 2022, pp. 1–6, doi: 10.1109/ICSTCEE56972.2022.10014688.

[18]   A. Deka and D. Deka, "E-Safe: An E-Waste Management and Awareness Application using YOLO Object Detection," in 2023 2nd Int. Conf. Intelligent Computing, Instrumentation and Control Technologies (ICICICT), Kannur, India, Jun. 2023, pp. 725–730, doi: 10.1109/ICICICT56767.2023.10209147.

[19]   A. Deka and D. Deka, "E-Safe: An E-Waste Management and Awareness Application using YOLO Object Detection," in 2023 2nd Int. Conf. Intelligent Computing, Instrumentation and Control Technologies (ICICICT), Kannur, India, Jun. 2023, pp. 725–730, doi: 10.1109/ICICICT56767.2023.10209147.

[20]   M. Arun and D. K. Lakshmi, "Deep Learning Based Object Classification for Waste Management in Smart Cities," in 2021 7th Int. Conf. Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, Mar. 2021, pp. 1778–1783, doi: 10.1109/ICACCS51430.2021.9441973.

[21]   A. S. Khot, N. D. Shetgaonkar and D. S. Patil, "Object Detection Based Management System of Solid Waste Using Artificial Intelligence Techniques," in 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), Greater Noida, India, Feb. 2021, pp. 48–53, doi: 10.1109/ICCCIS51004.2021.9397130.

[22]   K. Sudhakar, P. V. Harsha, M. V. Satya Prasad, and M. R. R. Reddy, "An Internet of Things Based Smart Waste Management System Using LoRa and TensorFlow Deep

Learning Model," in 2023 6th International Conference on Contemporary Computing and Informatics (IC3I), Tamil Nadu, India, Mar. 2023, pp. 245–250, doi: 10.1109/IC3I57735.2023.10187938.

[23]   B. S. Ajmera and S. Jain, "Artificial Intelligence in Smart City Applications: An Overview," in 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, Oct. 2022, pp. 1323–1328, doi: 10.1109/ICOSEC55494.2022.9934031.

[24]   S. G. Bhat and M. Shobha, "Deep Reinforcement Learning for Energy Efficiency Optimization using Autonomous Waste Management in Smart Cities," in 2023 5th International Conference on Energy, Power and Environment (ICEPE), Meghalaya, India, May 2023, pp. 1–6, doi: 10.1109/ICEPE59087.2023.10155882.

[25]   S. H. Alavi, N. Karami, H. Ahmadi and S. Mansouri, "WebGL, XAI and UAV Based Integrated Approach for Waste Management in Smart Cities," in 2022 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, Jan. 2022, pp. 1–6, doi: 10.1109/ICCCI54379.2022.9740849.

[26]   R. Singh, R. Kumari, S. Tiwari and A. Verma, "IoT-Enabled Smart Waste Management Systems for Smart Cities: A Systematic Review," in 2023 IEEE International Conference on Sustainable Energy and Future Electric Transportation (SEFET), Dec. 2023, pp. 1–6. doi: 10.1109/SEFET57104.2023.10175166.