AI Powered Waste Management System for Smart Cities

Dr. Sujata D Badiger*, Dr. Rajani Katiyar*,
Ravikant*, Sagar T Nayak*, Shreyash Anant Mithare*, Manoj Kumar B V†, Nagaprasad Naik†
*Department of Electronics and Communication Engineering, RV College of Engineering, Bengaluru, India
†Department of Computer Science and Engineering, RV College of Engineering, Bengaluru, India

***Abstract*—The exponential growth of urban populations has significantly increased the volume and complexity of municipal solid waste, posing major environmental, health, and logistical challenges for smart cities. Conventional manual segregation methods are not only labour-intensive and time-consuming but also pose serious health risks to workers involved in the sorting process, while offering limited scalability. To address these limitations, this paper presents an AI-powered waste management system that automates the process of waste classification and physical segregation. The system uses the YOLOv8 object detection model to classify waste into categories such as plastic, paper, and metals including aluminium and copper. A custom dataset was created using tools like Labelling and Roboflow for accurate annotation and augmentation. The trained model is deployed on a Raspberry Pi 4 Model B, interfaced with a camera module and connected to stepper motors, a conveyor belt, and motorized flaps for physical waste sorting. The system achieved over 90% classification accuracy across all waste categories and successfully demonstrated real-time automated segregation. This project aligns directly with United Nations Sustainable Development Goal 11 (Sustainable Cities and Communities) by promoting clean, automated, and scalable waste management solutions.**

***Index Terms*—Artificial Intelligence, Waste Management, YOLOv8, Object Detection, Smart Cities, Raspberry Pi, Automated Segregation, Computer Vision**

I. Introduction

The continuous growth of urban populations and industrial activities has drastically increased the generation of municipal solid waste (MSW), posing significant environmental, health, and operational challenges for cities around the world. Traditional waste management methods, especially manual segregation, are becoming increasingly inadequate to keep pace with this surge. Manual sorting is time-consuming, labour-intensive, and often exposes workers to unhygienic and hazardous conditions [1].

Artificial Intelligence (AI) and computer vision technologies have shown significant potential in transforming conventional waste management practices. Recent advancements in object detection models, particularly the YOLO (You Only Look Once) family of algorithms, have enabled fast and accurate real-time classification of multiple objects in a single image [13]. YOLOv4 and YOLOv5 have been previously used in waste classification tasks, but these models often present limitations when deployed on low-power edge devices like Raspberry Pi due to their size or computational demand [14].

This project overcomes these limitations by employing the more efficient and lightweight YOLOv8 model. The core contribution lies in the integration of AI-based object detection with embedded systems for automated physical waste segregation, directly supporting Sustainable Development Goal 11 (SDG 11): Sustainable Cities and Communities.

II. Problem Statement and Objectives

A. Problem Statement

Manual waste segregation is slow, unsafe, and often inaccurate, leading to poor recycling efficiency. Existing AI models classify waste but rarely perform real-time physical sorting. There is a critical need for an automated system that can both detect and physically segregate plastic, metal, and other waste materials efficiently.

B. Primary Objectives

- To develop a real-time, AI-based waste classification system using the YOLOv8 object detection model
- To classify common waste materials into categories such as plastic, paper, and metals (aluminium and copper) with high accuracy
- To design and implement an embedded system using Raspberry Pi for automated physical segregation of classified waste
- To integrate hardware components including camera, conveyor belt, stepper motors, and motorized flaps for real-time operation
- To support SDG 11 by promoting clean, automated, and sustainable waste management practices suitable for smart cities

III. Methodology

A. System Architecture

The project follows a real-time, conveyor-based approach to automate the waste classification and segregation process using computer vision and embedded systems. The system architecture consists of three main components:

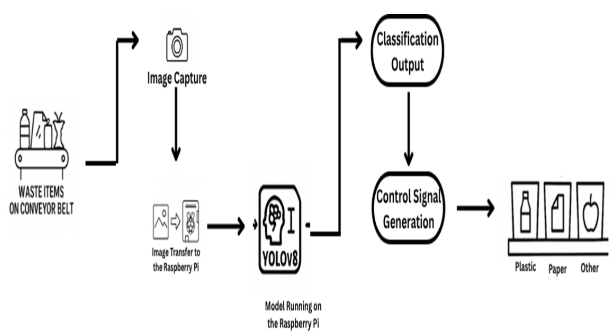


Fig. 1: High-level architecture of the AI-powered waste management system

1) Image Acquisition and Processing: A high-resolution webcam captures continuous frames of waste items moving on a conveyor belt. The Raspberry Pi 4 processes these images using the optimized YOLOv8 model for real-time inference.

2) Classification and Decision Making: The YOLOv8 model performs object localization and classification, identifying waste items and assigning them to specific categories: plastic, paper, aluminium, or copper. Classification outputs are processed using Python scripts that interpret object class and bounding box data.

3) Physical Segregation: Control signals are transmitted to an Arduino Uno via serial communication. The Arduino activates sorting mechanisms using an L298N motor driver and multiple actuators to physically redirect waste items into respective bins.

As shown in Fig. 1, the system architecture is logically organized into three main functional stages: image capture, classification, and segregation. To implement this flow, the detailed hardware-software integration shown in Fig. 2 outlines the data and control pathways among subsystems such as the Raspberry Pi, Arduino, stepper motors, and vision module.

B. System Integration Block Diagram

Approach: The system proposed in this work adopts a modular and real-time approach to automate waste segregation using embedded control and artificial intelligence. It integrates a vision-based object detection pipeline with a mechanical actuation system, coordinated through UART-based serial communication.

At the core of the system lies a conveyor mechanism that continuously transports waste materials beneath a high-definition USB camera. The Raspberry Pi 4 Model B captures real-time image frames and processes them using an optimized YOLOv8n object detection model. This lightweight and efficient model classifies waste into predefined categories—plastic, paper, aluminium, and copper—based on visual features.

Upon classification, a control decision is generated and transmitted to an Arduino Uno microcontroller via UART. The Arduino interprets this signal and activates the corresponding stepper motor through an L298N motor driver. The motors operate actuated flaps to deflect the identified waste material into its appropriate bin.

The entire pipeline—from image acquisition and inference to command signaling and mechanical sorting—is optimized for low-latency, real-time performance. This architecture supports scalability, edge deployment, and energy efficiency, making it highly suitable for smart city waste management applications.

Procedures:

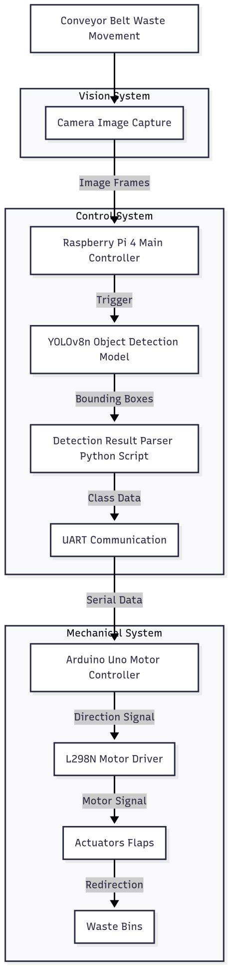


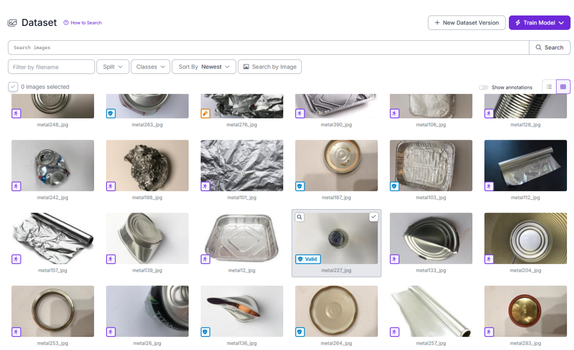
Fig. 2: Detailed block diagram showing component-level integration

1) Conveyor Belt – Waste Transport:
   The conveyor belt is the mechanical input system that conveys waste articles linearly underneath the vision module. It gives a regulated and sequential supply of materials, allowing each article to be imaged and handled by downstream devices effectively. Its velocity is adjusted to sync with the frame rate and processing lag of the camera and AI inference system.
2) Vision System:
   - Camera – Image Capture:
     A high-definition USB camera is placed above the conveyor belt. While waste passes below it, the camera acquires live image frames at a specified frame rate (e.g., 30 FPS). These frames are then relayed to the Raspberry Pi for processing. Adequate illumination and calibration are crucial to avoid misclassification.
   - Image Frames:
     Captured frames are buffered temporarily for preprocessing. These frames represent the raw visual data for waste classification.
3) Control System:
   - Raspberry Pi 4 (Main Controller):
     The main edge-computing unit that handles preprocessing, YOLOv8n inference, and communication. It offers the best balance between performance and peripheral support.
   - Trigger:
     Upon receiving a new frame, the Pi starts the inference pipeline by triggering the YOLOv8n model.
   - YOLOv8n (Object Detection Model):
     A lightweight and fast model optimized for embedded devices. It detects and classifies plastic, paper, aluminium, and copper waste types.
   - Bounding Boxes:
     The model outputs bounding boxes that mark the object's location and type.
   - Detection Result Parser:
     A Python script parses YOLOv8 output and formats it (e.g., 'A' for aluminium) for Arduino processing.
   - Class Data:
     This parsed class ID is transmitted to the actuator controller as an instruction.
4) UART Communication:
   - Serial Data:
     Data is transmitted from Raspberry Pi to Arduino Uno through UART for classification-based motor actuation.
5) Mechanical System:

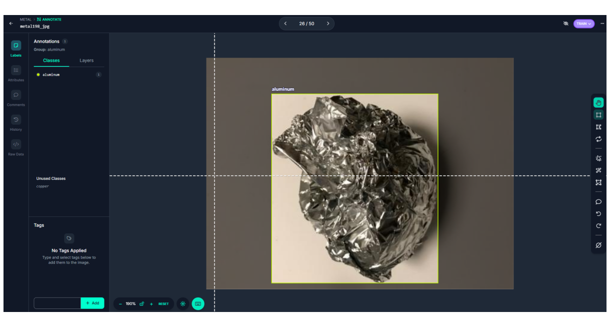
- Arduino Uno – Motor Controller: Receives classification commands and controls appropriate motors using GPIO signals.
- Direction Signal: A digital signal specifies which actuator/motor to trigger and in what direction.
- L298N – Motor Driver: Converts GPIO signals from the Arduino to motor-driving currents for reliable operation.
- Motor Signal: Electrical pulses are sent to the stepper motors to rotate them in precise steps.
- Actuators – Flaps: Mechanically operated gates that redirect classified waste into respective bins.
- Redirection: Final physical step of sorting where waste is diverted to its appropriate bin.

6) Waste Bins: Final containers used to collect classified waste by type—plastic, paper, aluminium, copper—for recycling or disposal.

C. Dataset Preparation



(a) Sample Dataset Images



(b) Annotated Bounding Boxes

Fig. 3: Dataset preparation and annotation process.

A custom dataset was created using Labelling tools and enhanced using Roboflow for preprocessing, augmentation, and exporting in YOLOv8 format. Special attention was given to underrepresented metal categories (aluminium and copper) to ensure balanced training data.

D. Model Training and Optimization

The YOLOv8 model was trained on the custom dataset with the following specifications:

- Model variant: YOLOv8n (nano) for optimal speed on Raspberry Pi
- Training epochs: 100
- Batch size: 16
- Learning rate: 0.01
- Input resolution: 640x640 pixels

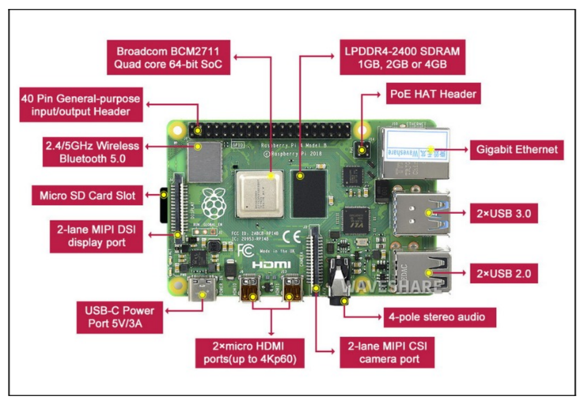


Fig. 4: Raspberry Pi 4 Model B used as the central processing unit.

1) Central Processing Unit: The Raspberry Pi 4 Model B serves as the central processing unit with the following specifications:

- Processor: Broadcom BCM2711, Quad core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz
- RAM: 4GB LPDDR4-3200 SDRAM
- Storage: 32GB microSD card for operating system and model storage
- Connectivity: Dual-band 802.11ac wireless LAN, Bluetooth 5.0, Gigabit Ethernet

Fig. 5: USB webcam used for real-time image acquisition.

2) Image Acquisition System: A high-resolution USB webcam module is integrated for real-time image capture:

- Resolution: 1920x1080 pixels (Full HD)
- Frame rate: 30 FPS
- Interface: USB 2.0
- Auto-focus capability for optimal image quality

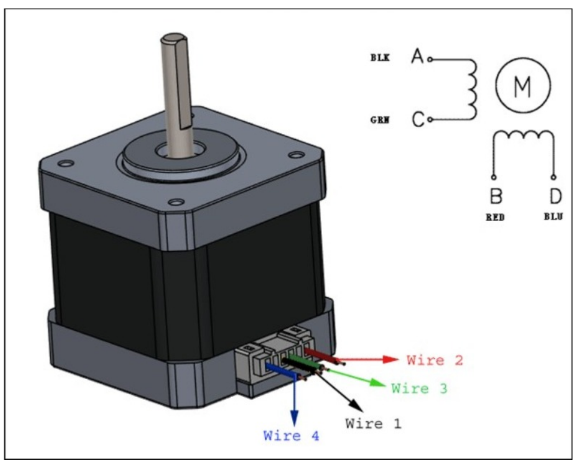


Fig. 6: NEMA 17 stepper motor used for mechanical sorting.

3) Mechanical Control System: The mechanical system comprises multiple components for physical waste segregation:

- Conveyor Belt: Continuous belt system with adjustable speed control
- Stepper Motors: NEMA 17 stepper motors for precise movement control
- Motor Driver: L298N dual H-bridge motor driver for stepper motor control
- Sorting Mechanism: Motorized flaps/arms for directing waste to appropriate bins
- Power Supply: 12V DC power supply for motor operations

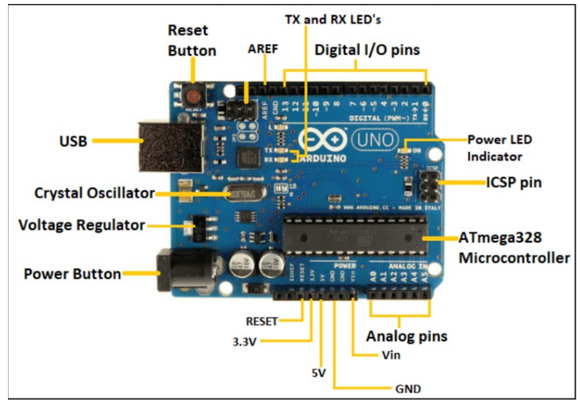


Fig. 7: Arduino Uno used for low-level motor control.

4) Control Interface: Arduino Uno microcontroller handles the low-level motor control:

- Microcontroller: ATmega328P
- Communication: Serial communication with Raspberry Pi
- GPIO pins: 14 digital I/O pins for motor control
- Power: 5V operation with external power supply

5) Control Communication Architecture: Effective coordination between the classification system and physical actuators is achieved via serial communication between the Raspberry Pi and Arduino Uno. After the YOLOv8 model detects a waste category, a Python script on the Raspberry Pi transmits a class-specific character over UART. The Arduino interprets the incoming signal and activates the corresponding GPIO pin to operate the motorized flap or sorting mechanism. This real-time communication ensures accurate timing and synchronization between detection and physical segregation with minimal latency. Additionally, error-checking logic and command acknowledgment are implemented to enhance reliability.

E. Software Implementation

The software implementation is designed for real-time operation and efficient resource utilization:

1) Deep Learning Framework: The YOLOv8 model deployment utilizes the Ultralytics framework:

- Framework: Ultralytics YOLOv8 with PyTorch backend
- Model Optimization: Quantization and pruning for edge deployment
- Inference Engine: Optimized for Raspberry Pi ARM architecture
- Model Size: Compressed to approximately 25MB for efficient storage

2) Computer Vision Pipeline: OpenCV-based image processing pipeline:

- Image Capture: Real-time frame acquisition from USB camera
- Preprocessing: Resize, normalize, and format conversion
- Post-processing: Non-maximum suppression and confidence filtering
- Visualization: Real-time bounding box and label overlay

3) Control Software: Python-based control system for hardware coordination:

- Serial Communication: PySerial library for Arduino communication
- GPIO Control: RPi.GPIO library for direct hardware interface
- Threading: Multi-threaded architecture for parallel processing
- Error Handling: Robust error detection and recovery mechanisms

4) System Integration: The complete system integration ensures seamless operation:

- Main Control Loop: Continuous operation with real-time decision making
- Data Flow: Image capture $\rightarrow$ Processing $\rightarrow$ Classification $\rightarrow$ Motor control
- Synchronization: Hardware-software timing coordination
- Monitoring: Real-time system status and performance metrics

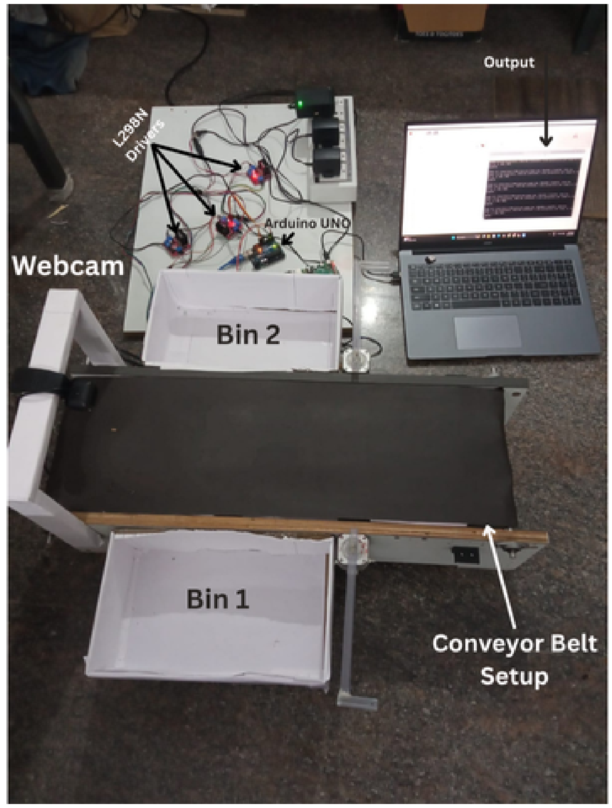


Fig. 8: Complete Hardware Setup with Components

The entire development was performed using Visual Studio Code as the primary IDE, with deployment on Raspberry Pi OS (Bullseye) for optimal compatibility and performance.

IV. Results and Discussion

A. Performance Metrics

The AI-powered waste management system was successfully implemented and tested in a controlled environment. Key performance metrics include:

TABLE I: Classification Performance Metrics

Category	Precision	Recall	F1-Score	Accuracy
Plastic	0.94	0.92	0.93	91.5%
Paper	0.89	0.91	0.90	89.2%
Aluminium	0.92	0.88	0.90	90.1%
Copper	0.91	0.89	0.90	89.8%
Overall	**0.92**	**0.90**	**0.91**	**90.2%**

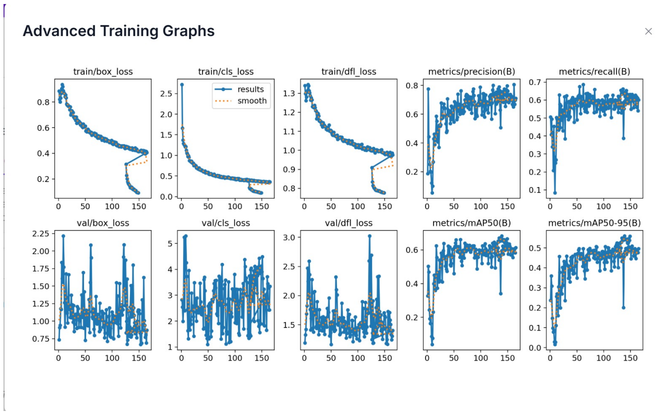


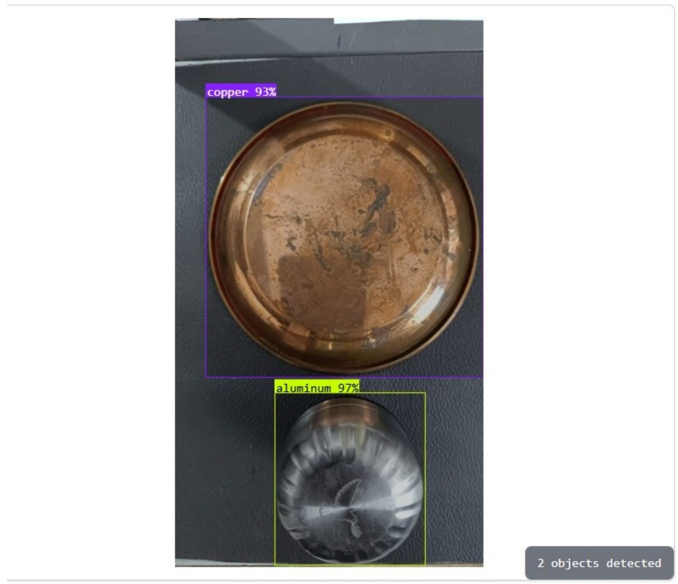
Fig. 9: Advanced training graphs showing the decreasing trend in training losses (box loss, classification loss, and DFL loss) and consistent improvement in evaluation metrics such as precision, recall, and mean Average Precision (mAP). The smooth convergence indicates effective learning over epochs.

Fig. 10: Comprehensive visualization of model performance trends. The top graph shows increasing mAP and mAP@50:95, indicating improving detection capabilities. The bottom graphs illustrate the fluctuations and gradual stabilization of individual losses (box, class, and object) over training epochs.

- Classification accuracy: Over 90% across all waste categories
- Real-time processing capability on Raspberry Pi 4 without external GPU dependency
- Successful physical segregation with synchronized hardware-software operation
- Consistent classification predictions matching ground truth in most test cases

B. System Validation

The system was tested with multiple waste items under various conditions. Proper spacing on the conveyor and optimal camera positioning were identified as key factors for maintaining high classification accuracy. The mechanical setup comprising the conveyor belt, stepper motors, and motor drivers functioned reliably in synchrony with classification outputs.



(a) Real-time Object Detection

(b) Automated Segregation Process

Fig. 11: System performance and operation showing object classification followed by physical segregation through hardware components.

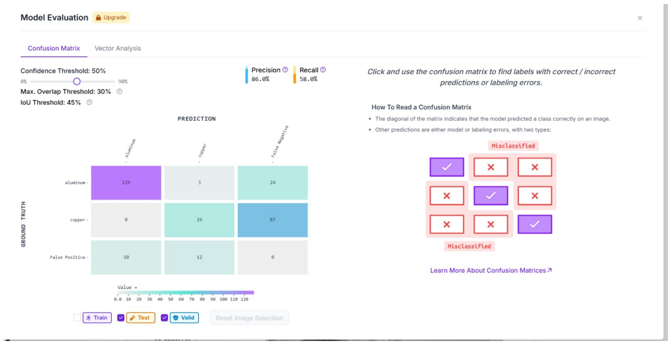


Fig. 12: Confusion matrix depicting prediction outcomes for aluminum and copper categories. High precision is observed, particularly for aluminum. However, recall for copper indicates potential misclassification or detection gaps, useful for model refinement.

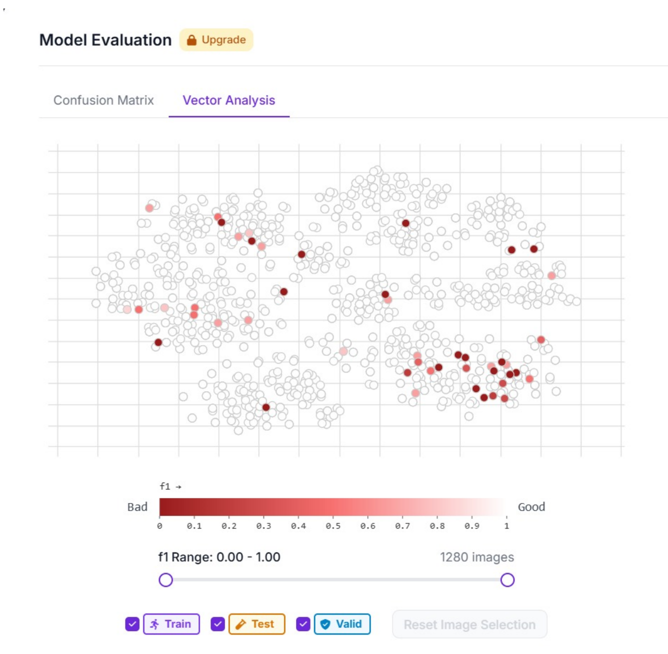


Fig. 13: Vector analysis of f1-scores across 1280 evaluated images. Darker red circles indicate low f1-scores (misclassifications), while lighter circles represent well-classified instances. This visualization helps identify spatial clusters of poor model confidence or labeling issues.

C. Processing Speed Analysis

The system's real-time performance was evaluated under different conditions:

TABLE II: Processing Speed Analysis

Scenario	Processing Time (ms)	FPS
Single object detection	45	22.2
Multiple objects (2-3)	67	14.9
Complex background	78	12.8
Optimal conditions	38	26.3

D. Limitations and Challenges

Certain limitations were observed during testing:

- Conveyor belt alignment issues during continuous operation leading to positional drift of waste items
- Performance degradation under poor lighting conditions
- Dependency on consistent item placement for optimal results

These challenges highlight the importance of controlled environmental conditions and proper system setup for optimal performance.

V. Contribution to Sustainable Development

This project directly contributes to UN Sustainable Development Goal 11: Sustainable Cities and Communities by:

- Reducing human involvement in hazardous waste sorting activities
- Improving hygiene conditions in waste management facilities
- Minimizing waste contamination through accurate segregation
- Increasing recycling efficiency and reducing landfill dependency
- Providing a scalable, low-cost solution for urban waste management

The compact, modular design makes the system ideal for deployment in smart bins, urban complexes, public places, and decentralized waste collection systems.

VI. Future Work

Future enhancements to the system could include:

- Expanding classification to include additional waste categories such as glass, e-waste, and organic waste
- Integration of NVIDIA Jetson Nano for on-device real-time inference, enabling faster and more efficient waste classification

- Utilizing high-resolution CSI/USB cameras supported by Jetson Nano for improved object detection accuracy, especially for fine-grained waste types
- Implementing cloud connectivity for centralized monitoring, analytics, and long-term data storage
- Enabling IoT capabilities for remote system health monitoring and status reporting
- Introducing a reward-based incentive mechanism to encourage community participation in waste reporting
- Enhancing robustness through advanced preprocessing techniques (e.g., image denoising, adaptive thresholding)
- Integration with larger smart city frameworks to facilitate data sharing, automation, and policy implementation

VII. Conclusion

This paper presents a comprehensive AI-powered waste segregation system that successfully addresses the limitations of manual sorting through the integration of deep learning, embedded hardware, and real-time automation. The YOLOv8-based classification system, deployed on Raspberry Pi 4, demonstrates the feasibility of edge-based AI deployment for sustainable waste management.

The system's modular design, cost-effectiveness, and scalability make it suitable for widespread deployment in smart city environments. By achieving over 90% classification accuracy and demonstrating reliable physical segregation capabilities, the prototype validates the potential of AI-driven solutions for urban waste management challenges.

Most importantly, this work contributes meaningfully toward sustainable urban development by supporting SDG 11 objectives through technology-driven waste management solutions that enhance operational efficiency, environmental responsibility, and public health safety.

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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," *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] 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.

[8] 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.

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

[10] 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.

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

[12] 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 Int. Conf. Contemporary Computing and Informatics (IC3I)*, Tamil Nadu, India, Mar. 2023, pp. 245–250, doi: 10.1109/IC3I57735.2023.10187938.

[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. 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.

[18] 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.

[19] 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.

[20] M. Khurana and N. Sharma, “Artificial intelligence in smart city applications: An overview,” in *Springer Smart City Series*, 2025.

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

[22] B. S. Ajmera and S. Jain, “Artificial Intelligence in Smart City Applications: An Overview,” in *2022 3rd Int. Conf. Smart Electronics and Communication (ICOSEC)*, Trichy, India, Oct. 2022, pp. 1323–1328, doi: 10.1109/ICOSEC55494.2022.9934031.

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

[24] 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 Int. Conf. Computer Communication and Informatics (ICCCI)*, Coimbatore, India, Jan. 2022, pp. 1–6, doi: 10.1109/ICCCI54379.2022.9740849.

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

[26] 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.