

CLEANTRACK: AN ARTIFICIAL INTELLIGENCE AND INTERNET OF THINGS (AIOT)-BASED SMART WASTE MANAGEMENT SYSTEM

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Abstract: Effective waste management requires timely monitoring, accurate waste classification, and efficient collection planning. Conventional waste collection methods mainly depend on fixed schedules and manual monitoring, which can result in overflowing bins, unnecessary collection trips, and inefficient use of resources. This paper presents CleanTrack, an Artificial Intelligence and Internet of Things (AIoT)-based smart waste management system designed for real-time waste monitoring and intelligent collection management. The proposed system uses an IoT-enabled smart bin equipped with an ultrasonic sensor for fill-level measurement, a load cell for waste-weight measurement, a temperature sensor for temperature monitoring, and a Global Positioning System (GPS) module for location tracking. The collected sensor data are transmitted for monitoring and analysis, enabling assessment of bin conditions and waste-generation patterns. For waste identification, a YOLOv8 Nano (YOLOv8n) classification model is integrated for image-based waste classification and achieved a Top-1 accuracy of 95.2% on the validation dataset. A Genetic Algorithm is further employed to optimize waste collection routes based on bin conditions and collection requirements. By combining IoT sensing, AI-based waste classification, data analysis, and route optimization, CleanTrack provides an integrated approach for improving the efficiency, responsiveness, and data-driven planning of waste collection operations.

Keywords: CleanTrack : Smart Waste Management; Internet of Things (IoT); Artificial Intelligence (AI); Real-Time Waste Monitoring and Waste Classification;

1. INTRODUCTION

Municipal solid waste management has become a major challenge with rapid urbanization, population growth, and changes in consumption patterns. In 2022, approximately 2.56 billion tonnes of municipal solid waste were generated worldwide, and this amount is expected to increase to 3.86 billion tonnes by 2050 under a business-as-usual scenario [1]. Poorly managed waste can lead to environmental pollution, public-health concerns, and inefficient use of available resources [2]. These conditions show the need for waste-management methods that can provide timely information and make better use of collection resources.

India faces a similar challenge because of its large population and continued growth of urban areas. According to CPCB data for 2023–24 reported by NITI Aayog, the country generates about 1.85 lakh tonnes of solid waste per



day. Around 1.79 lakh tonnes per day are collected, while approximately 1.14 lakh tonnes per day are processed or treated, leaving about 39,629 tonnes per day directed to landfills [3]. The Solid Waste Management Rules, 2026, which came into force on April 1, 2026, also place greater emphasis on segregation, monitoring, reporting, accountability, and digital tracking of waste-management activities [4]. These developments indicate the importance of improving the way waste is monitored and collected at the ground level.

In a conventional collection system, vehicles generally follow fixed schedules and predetermined routes. Such a method does not always consider the actual condition of individual bins. As a result, a vehicle may visit a partially filled bin while another bin may reach a high filling level before its next scheduled collection. IoT-based waste-management systems provide a way to overcome this limitation by using sensors to monitor bin conditions and transmit the collected information for remote monitoring [5]–[8]. Ultrasonic sensors have been widely used for estimating waste fill levels, while other sensing methods can provide additional information about waste accumulation [9]. Communication technologies such as LoRaWAN have also been investigated for connecting distributed smart bins [10]. The availability of bin-status and location information can further support route planning and optimization [13]–[19].

Along with monitoring and collection planning, identifying the type of waste is another important part of waste management. Recent studies have explored Artificial Intelligence (AI) and deep learning techniques for waste analysis and image-based waste classification

[21]–[24]. However, many existing approaches concentrate on one particular part of the waste-management process, such as bin monitoring, communication, classification, or route optimization. There is scope for combining these functions in a single practical system so that information collected from waste bins can be used directly for monitoring, analysis, and collection planning.

This paper presents **CleanTrack: An Artificial Intelligence and Internet of Things (AIoT)-Based Smart Waste Management System**. The proposed system combines sensor-based bin monitoring, wireless data communication, location tracking, waste-data analysis, AI-based waste classification, and Genetic Algorithm-based route optimization. The system uses the collected bin information to understand waste conditions and support collection decisions. By bringing these functions together, CleanTrack aims to provide a more responsive approach to waste collection, reduce unnecessary collection trips, and help identify bins that require timely attention.

1.1 Objectives

The main objectives of the CleanTrack system are focused on real-time monitoring, waste classification, data analysis, and collection planning.

- **Real-Time Bin Monitoring:** To monitor the fill level, weight, temperature, and geographical location of the waste bin using an ESP32-C-based IoT sensing unit.
- **Waste Data Analysis:** To record and analyze waste-level and weight measurements over time in order to observe waste accumulation patterns at monitored locations.
- **Route Optimization:** To use bin conditions and geographical locations with a Genetic Algorithm to plan suitable routes for waste-collection operations.
- **AI-Based Waste Classification:** To use an image-based AI model for identifying different categories of waste and providing information that can support waste segregation and analysis.

1.2 Applications

The CleanTrack framework can be used in different waste-management situations where timely information about bins can assist collection activities.

- **Smart Municipal and Community Bins:** The system can be installed on waste bins at municipal or community collection points to monitor their condition remotely and identify bins requiring attention.
- **AI-Assisted Waste Classification:** The classification module can be used to identify waste categories from images, providing additional information for segregation and waste-management activities.
- **Condition-Based Waste Collection:** Fill-level and weight information can help collection personnel decide which bins need to be serviced instead of depending only on a fixed collection schedule.
- **Intelligent Collection Route Planning:** The location and condition of monitored bins can be provided to the Genetic Algorithm-based module to assist in deciding an efficient sequence for collection visits.

2. RELATED WORK

Table 1 summarizes the existing literature and highlights the core technologies, key findings, and limitations of the selected studies. The comparison helps identify the research gap in integrating real-time IoT-based monitoring, waste-generation analysis, AI-based waste classification, location information, and Genetic Algorithm-based route optimization within a unified waste-management system.

Table 1: Literature Review Summary

Ref.	Study Title	Core Technology	Key Findings	Limitations
[5]	IoT-enabled smart waste management systems for smart cities: A systematic review	IoT, smart bins, communication and data analytics	Reviews major IoT applications and architectures for smart waste management	Review-based; does not present a unified experimental system
[6]	IoT-based solid waste management solutions: A survey	IoT, sensors, communication and cloud platforms	Identifies major IoT technologies used in solid waste management	Limited focus on integrated AI-based solutions
[7]	A proposed IoT-enabled smart waste bin management system and efficient route selection	IoT smart bin and route selection	Demonstrates smart-bin monitoring combined with route selection	Limited integration of AI-based waste classification
[9]	A LoRa-based IoT sensor node for waste management based on a customized ultrasonic transceiver	LoRa and ultrasonic sensing	Demonstrates wireless waste-level monitoring using ultrasonic sensing	Mainly focused on fill-level measurement
[10]	A multi-layer LoRaWAN infrastructure for smart waste management	LoRaWAN and distributed IoT architecture	Provides a multi-layer communication infrastructure for smart waste management	Infrastructure can be complex for deployment
[13]	The smart waste collection routing problem: Alternative operational management approaches	Dynamic waste-collection routing	Shows the importance of real-time waste information for collection-route planning	Primarily focused on routing rather than complete system integration
[15]	Dynamic routing for efficient waste collection in resource constrained societies	Dynamic routing and smart waste information	Improves collection planning under resource constraints	Limited integration with automated waste classification

[16]	Dynamic route optimization for IoT based intelligent waste collection vehicle routing system	IoT and dynamic route optimization	Considers waste amount, location, traffic, fuel and vehicle capacity	Evaluation relies on synthetic data
[19]	IoT-based smart bin allocation and vehicle routing in solid waste management	IoT, smart-bin allocation and VNS-ACO	Combines smart-bin information with vehicle-routing optimization	Does not integrate image-based waste classification
[21]	A survey of smart dustbin systems using the IoT and deep learning	IoT and deep learning	Highlights the integration of smart bins with AI-based waste analysis	Survey paper; no new integrated prototype

2.1 Research Gap Analysis of Existing Waste Management Approaches

1. Mainly monitor fill level or selected bin parameters [5]–[10]
2. Provides bin condition but does not identify waste type [21]–[24]
3. Mainly focus on route planning using location/bin conditions [13]–[19]

3. SYSTEM ARCHITECTURE and METHODOLOGY

3.1 Proposed System Architecture :

The proposed CleanTrack system combines IoT sensing, AI-based waste classification, data analysis, and route optimization for smart waste collection. The main components of the system are as follows:

- 3.1.1 Smart Bin Sensing:** The bin uses an HC-SR04 ultrasonic sensor to estimate the waste fill level, a load cell with HX711 to measure waste weight, an LM35 to record temperature, and a NEO-6M GPS module to obtain the bin location.
- 3.1.2 Embedded Processing:** An ESP32-C microcontroller collects the sensor readings, processes the data, and handles communication with the monitoring platform.
- 3.1.3 IoT Data Monitoring:** The collected sensor values are transmitted to the IoT platform for real-time visualization and storage. The recorded data can also be used to study changes in waste accumulation over time.
- 3.1.4 AI-Based Waste Classification:** An AI model analyzes input waste images and predicts their corresponding waste category. This provides additional information alongside the sensor measurements.
- 3.1.5 Route Optimization:** The bin locations and their current conditions are used by a Genetic Algorithm to generate a suitable collection route and prioritize bins that require attention.
- 3.1.6 Power Supply:** The system is powered by a 3S lithium-ion battery pack with a Battery Management System (BMS), supplying power to the ESP32 and connected sensing components.

Overall, these components work together to provide waste-bin monitoring, waste classification, data analysis, and intelligent collection-route planning within the CleanTrack framework.

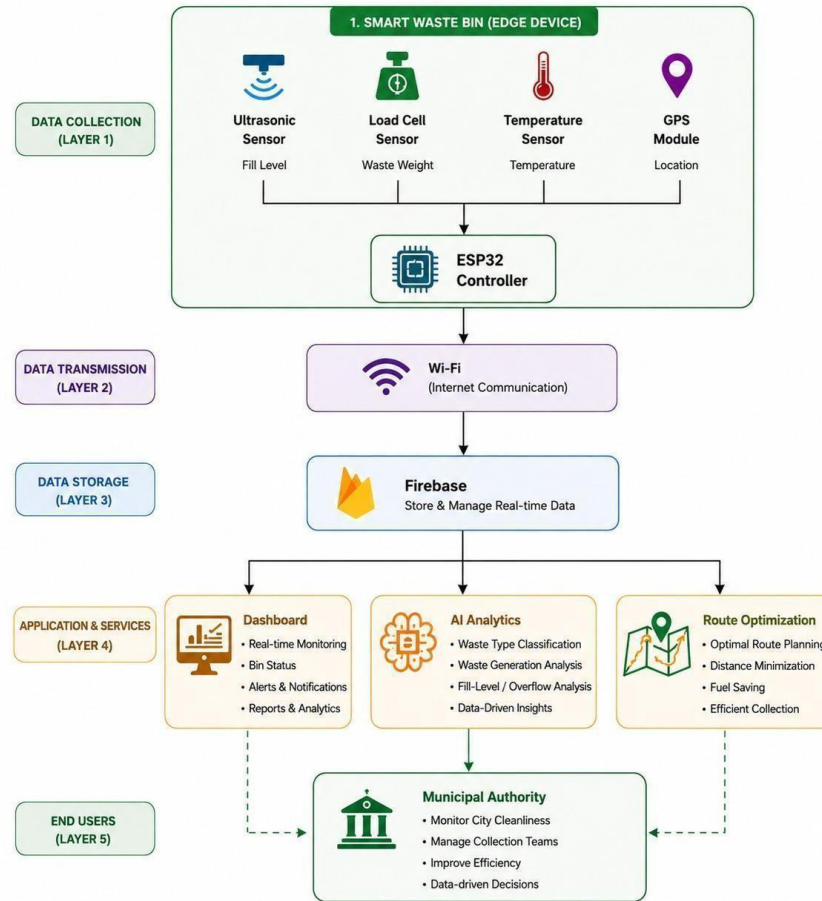


Fig. 1 – Proposed CleanTrack System Architecture

3.2 Hardware Components

Table 2 summarizes the major hardware components used in the CleanTrack smart-bin prototype.

Table 2: Hardware Components Used in CleanTrack

Component	Purpose / Function
ESP32-C	Acts as the central controller for sensor data acquisition, processing, and wireless communication.
HC-SR04 Ultrasonic Sensor	Measures the distance between the sensor and the waste surface to estimate the bin fill level.
Load Cell	Measures the weight of waste accumulated inside the bin.
HX711 Load Cell Amplifier	Amplifies and converts the low-level electrical signal from the load cell into digital data for the ESP32-C.
LM35 Temperature Sensor	Measures the temperature inside the waste-bin environment for monitoring changes in bin conditions.
NEO-6M GPS Module	Provides the geographical coordinates of the smart bin for location-based monitoring and route planning.
3S Li-ion Battery Pack	Provides the required electrical power to operate the smart-bin hardware.

3S BMS	Provides battery protection and management functions such as overcharge, over-discharge, and cell protection.
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3.3 IoT Data Acquisition And Communication

The CleanTrack smart bin collects sensor readings through the ESP32-C. The HC-SR04 measures the distance from the sensor to the waste surface to estimate the fill level, while the load cell and HX711 measure the waste weight. The LM35 records the bin temperature, and the NEO-6M GPS provides its geographical coordinates.

The ESP32-C processes these readings and sends the fill level, weight, temperature, and location data to the IoT monitoring platform through wireless communication. The data can then be stored and visualized for continuous monitoring.

The recorded fill-level and weight values are also used to study waste accumulation over time. Location data supports collection planning, while the sensor information and AI-based waste-classification results provide additional information for the route-optimization stage.

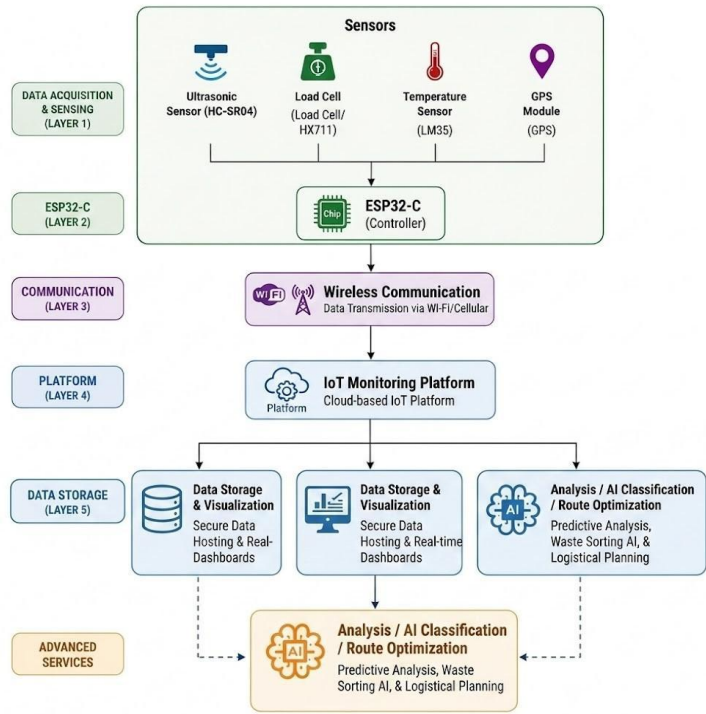


Fig. 2 – IoT Data Acquisition and Communication Flow of CleanTrack

3.4 Waste-Generation Analysis

As shown in **Fig. 3**, the waste-surface distance is monitored over different dates and times using the ultrasonic sensor. The measured distance helps estimate the amount of waste inside the bin. Changes in the distance indicate changes in the waste level. This data can be monitored over time to understand waste accumulation and support better collection planning.

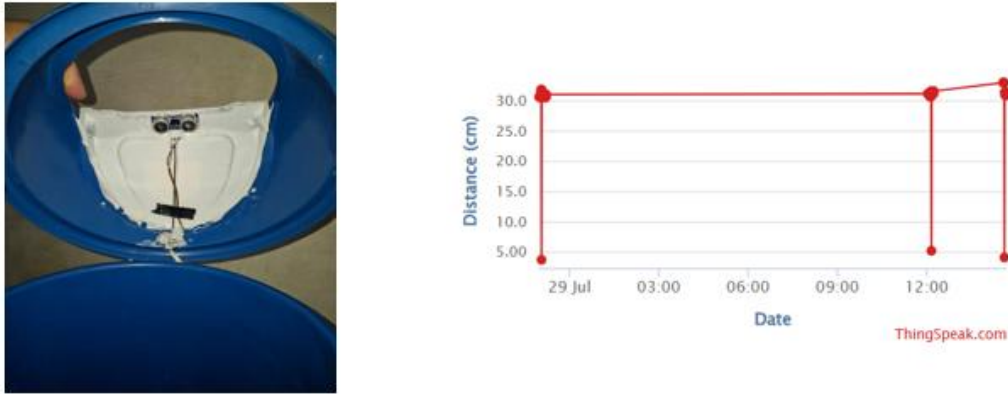


Fig. 3 – Variation of Waste-Surface Distance with Date and Time

3.5 Ai-Based Waste Classification

As shown in **Fig. 4**, the AI-based waste classification process starts with capturing an image of the waste. The image is given to the trained **YOLOv8 model**, which analyzes it and identifies the waste category. The classification result is then stored and displayed through the dashboard. The system can classify different types of waste such as **plastic, paper, glass, metal, and organic waste**. This information helps in understanding waste composition and supports better waste segregation and management.



Fig. 4 – AI-Based Waste Classification Process

3.6 Genetic Algorithm-Based Route Optimization

As shown in **Fig. 5**, the Genetic Algorithm-based route optimization starts by collecting **bin sensor data and GPS coordinates**. The system identifies bins that require collection based on their fill level and current condition. Possible routes are then generated and evaluated using factors such as **distance, time, and collection requirements**. The Genetic Algorithm applies selection, crossover, and mutation to improve the routes. Finally, the **optimal route** is generated and provided to the collection vehicle, helping reduce unnecessary travel and improve collection efficiency.

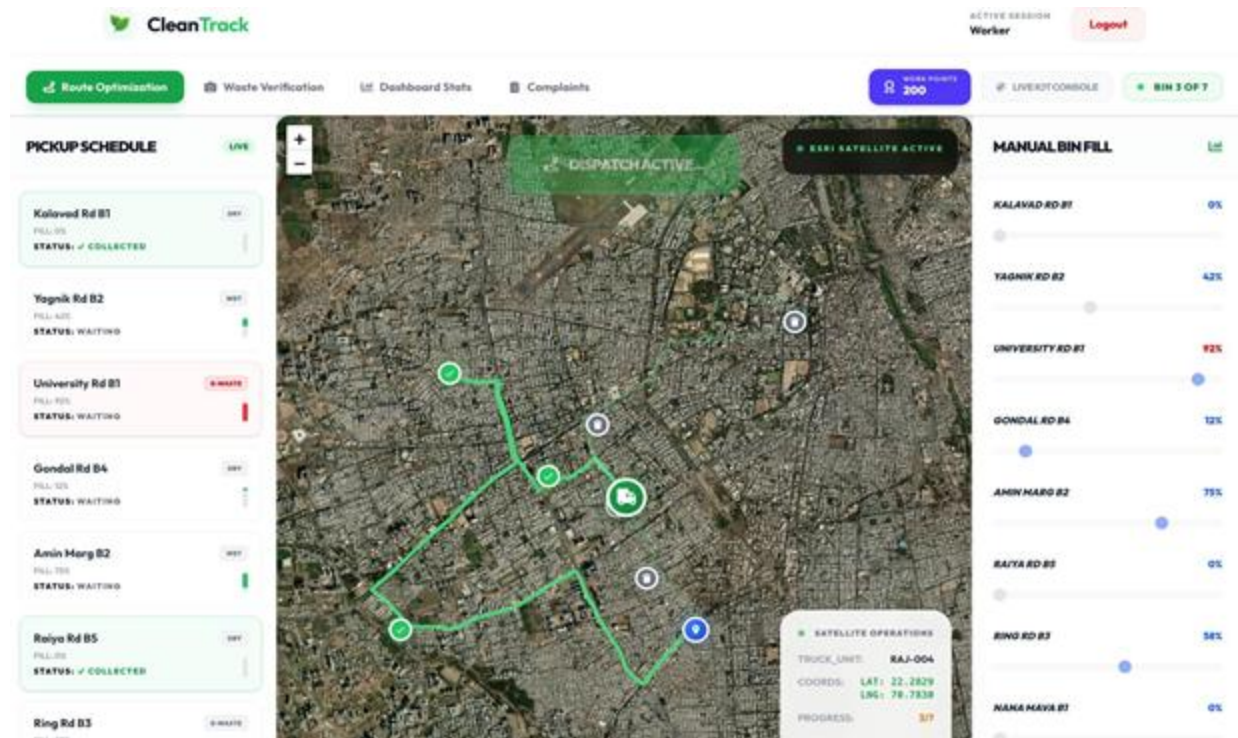


Fig. 5 – Genetic Algorithm-Based Waste Collection Route Optimization

4. RESULTS AND DISCUSSION

The CleanTrack prototype was evaluated using the data obtained from the implemented IoT sensing system and the developed AI-based waste classification module. The experimental observations demonstrate the capability of the system to monitor important waste-bin parameters, including waste-surface distance, waste weight, temperature, and geographical location. The collected data was transmitted to the ThingSpeak platform for real-time visualization and further analysis. The results obtained from the IoT monitoring system and AI-based classification module are discussed below.

4.1 IoT Sensor Monitoring Results

The smart bin was tested using different sensors to monitor its condition. **Fig. 6** shows the waste-weight readings collected using the load cell, while **Fig. 7** shows the temperature readings recorded by the LM35 sensor. **Fig. 8** presents the geographical location data obtained from the NEO-6M GPS module. These results show that the CleanTrack prototype can collect and monitor important bin parameters such as **waste weight, temperature, and location** for further analysis and collection planning.



Fig. 3.1 – Variation of Waste-Surface Distance with Date and Time

1. Ultrasonic Sensor — Waste-Surface Distance :

Formula: $D = (TxV)/2$ Where:

D = distance between sensor and waste surface (cm) T = echo time (μs)

0.034 cm/ μs



Fig. 6 – Waste Weight Variation with Date and Time

2. Load Cell — Waste Weight Formula : $W = (R - R_0)/(C)$

Where:

W = measured weight R = raw HX711 reading R₀ = tare/zero reading C = calibration factor

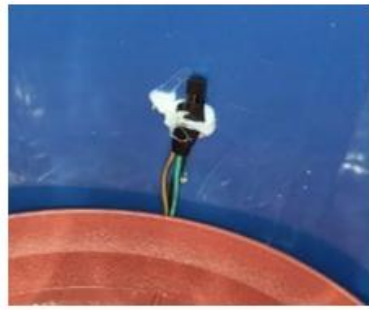


Fig. 7 – Temperature Variation with Date and Time

3. LM35 — Temperature Formula : $W = V_{out}(mv) / (10)$



Fig. 8 – Geographical Location of the Smart Bin

4. GPS — Latitude and Longitude $Latitude = GPS_{lat}$

Longitude = GPS_{long}

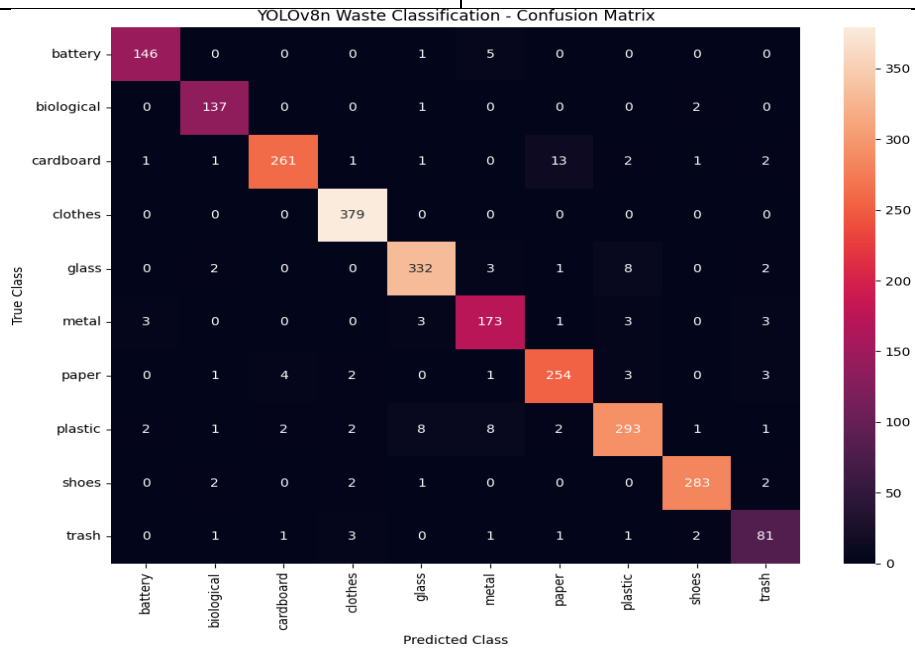
4.2 AI-Based Waste Classification Results

The CleanTrack system incorporates an AI-based waste classification module to identify the category of waste from an input image. The classification output provides information about the type of waste and can support waste analysis, monitoring, and future automated segregation. In the current implementation, the AI module performs image-based classification and does not physically segregate the waste.

Table 3: Experimental configuration and overall performance of the YOLOv8n waste classification model

Parameter	Value
Dataset	Garbage Classification v2
Number Of Classes	10
Training Images	9802
Validation Images	2457
Total Images	12259
Model Architecture	YOLOv8n Classification
Training Epochs	40
Input image size	224 × 224 pixels

Batch Size	32
Hardware	NVIDIA Tesla T4 GPU



Classification Report:

	precision	recall	f1-score	support
battery	0.9605	0.9605	0.9605	152
biological	0.9448	0.9786	0.9614	140
cardboard	0.9739	0.9223	0.9474	283
clothes	0.9743	1.0000	0.9870	379
glass	0.9568	0.9540	0.9554	348
metal	0.9058	0.9301	0.9178	186
paper	0.9338	0.9478	0.9407	268
plastic	0.9452	0.9156	0.9302	320
shoes	0.9792	0.9759	0.9775	290
trash	0.8617	0.8901	0.8757	91
accuracy			0.9520	2457
macro avg	0.9436	0.9475	0.9454	2457
weighted avg	0.9523	0.9520	0.9519	2457

Fig 9 : Confusion Matrix - YOLOv8n waste classification model

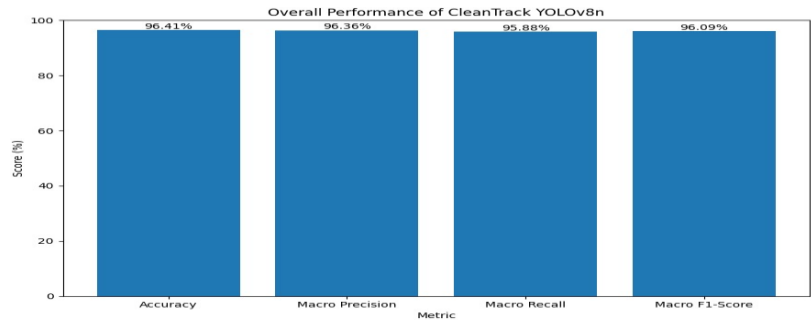


Fig 10

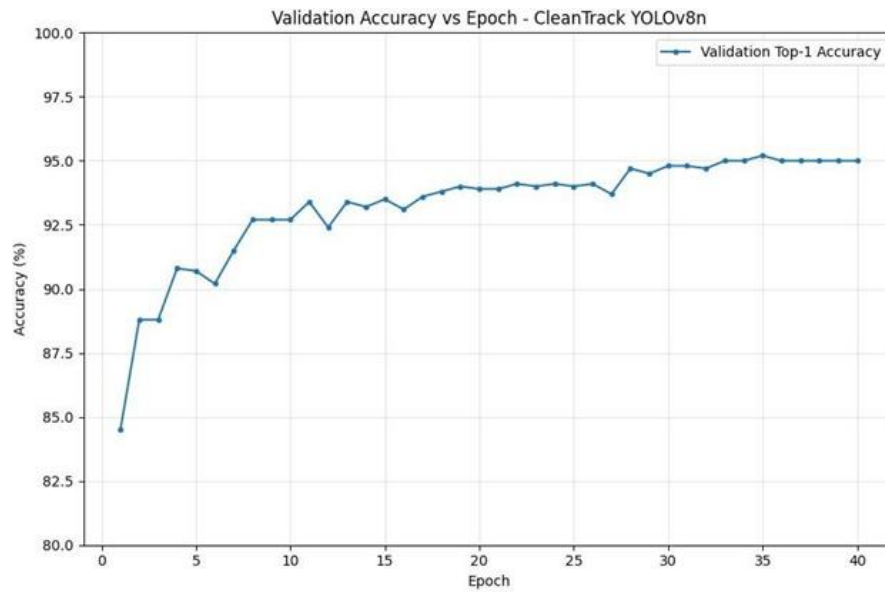


Fig 11

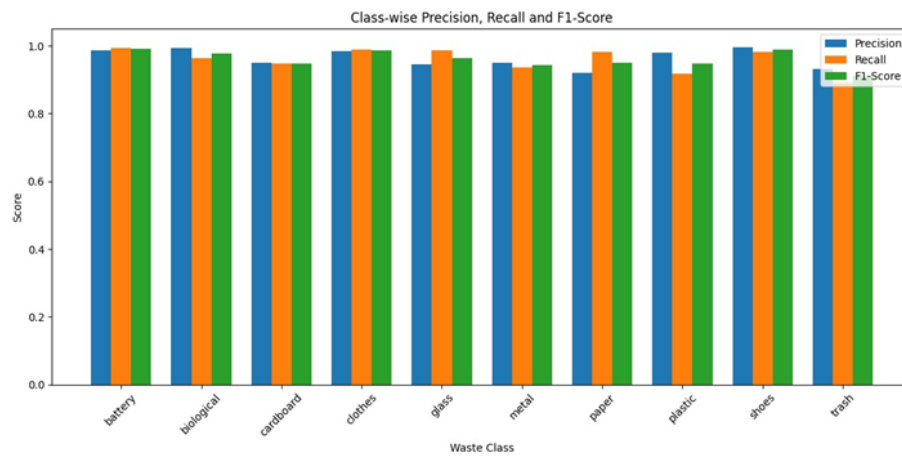


Fig 12

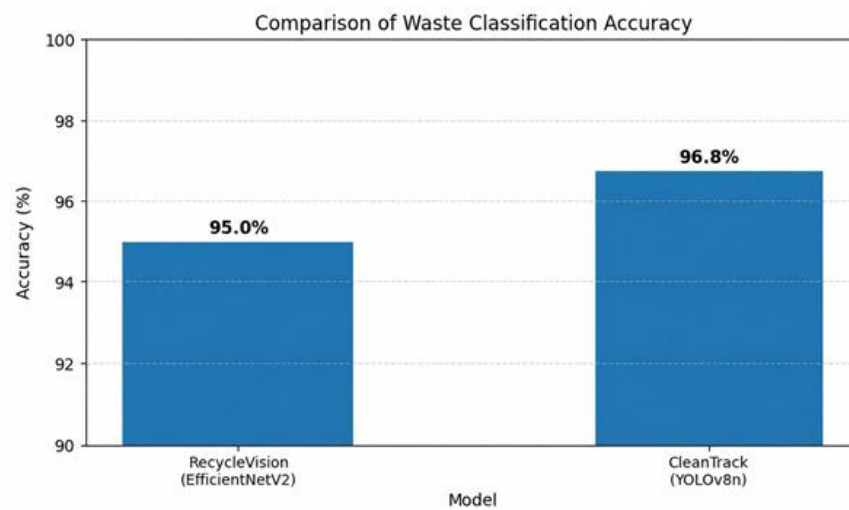


Fig 13

To evaluate the performance of the proposed CleanTrack waste classification model, its results were compared with the RecycleVision approach reported in [28]. RecycleVision uses the EfficientNetV2 architecture and was evaluated on the Garbage-Classification-V2 dataset, achieving a classification accuracy of 95%. In comparison, the proposed YOLOv8n model achieved a highest validation accuracy of 95.8%, showing a 0.8 percentage-point improvement over the reported result.

4.3 Sample Classification Results

To demonstrate the practical inference capability of the trained classification model, sample waste images were provided as input to the model. The model successfully classified the presented samples as **Plastic, Clothes, and Biological**, with prediction confidence scores of **100.0%, 89.8%, and 96.9%**, respectively.

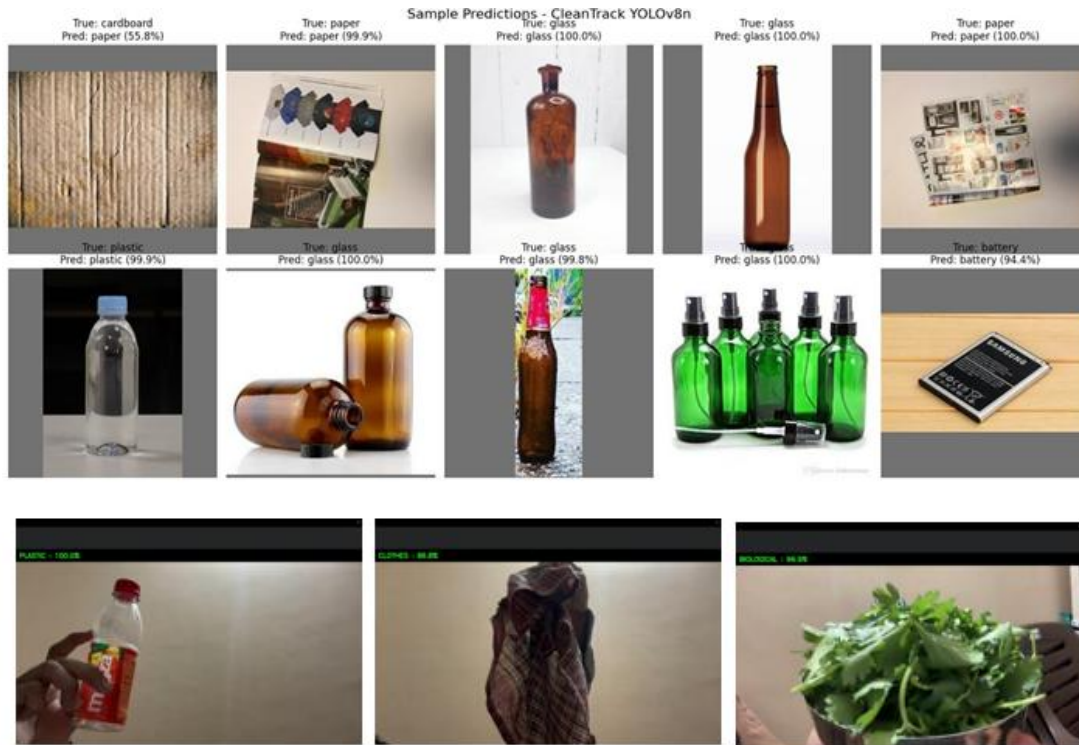


Fig. 14 – Sample outputs of the trained YOLOv8n classification model for different waste categories.

These results demonstrate that the trained model can identify different waste categories from input images and provide the corresponding prediction confidence. The individual confidence scores shown in the sample outputs represent the model's predictions for those particular images and are distinct from the overall Top-1 and Top-5 validation accuracies reported in the model evaluation.

4.4 Comparison of Different Route Optimization Algorithm

Table 4

Algorithm	Strength	Limitation for CleanTrack	Suitability
Nearest Neighbor	Very simple and fast	Can get trapped in poor routes; no global optimization	Medium
Dijkstra	Finds shortest path between two points	Not designed to optimize a complete multi-bin collection route	Low–Medium
Ant Colony Optimization (ACO)	Good for routing and combinatorial problems	Can require more iterations and parameter tuning	High
Particle Swarm Optimization (PSO)	Good global optimization capability	Less naturally suited to discrete routing problems without adaptation	High
Genetic Algorithm (GA)	Handles complex multi-point routing and large search spaces	Requires parameter tuning and multiple generations	High / Selected

5. CONCLUSION

The proposed CleanTrack system integrates IoT-based sensing, real-time monitoring, AI-based waste classification, geographical tracking, waste-generation analysis, and Genetic Algorithm-based route optimization into a single smart waste-management framework. The developed prototype successfully collected waste-surface distance, waste weight, temperature, and geographical location data using the implemented sensors. The recorded measurements shown in Figs. 3, 6, 7, and 8 demonstrate the ability of the system to monitor important bin parameters over time and transmit the data for further analysis.

For waste classification, the YOLOv8n classification model was trained on the Garbage Classification V2 dataset containing 10 classes, with 9,802 training images and 2,457 validation images. The model used 224×224 pixel images and was trained for 40 epochs. The highest validation Top-1 accuracy achieved during training was **95.8% at Epoch 36**, while the Top-5 accuracy reached **99.8%**. The classification module successfully identified different waste categories, with sample predictions demonstrating confidence scores of **100.0%, 89.8%, and 96.9%** for Plastic, Clothes, and Biological waste, respectively.

The Genetic Algorithm module uses bin conditions and GPS information to generate a suitable collection sequence and prioritize bins requiring collection. Overall, the results show that CleanTrack can combine physical bin monitoring with AI-based waste identification and route planning in one system. The proposed framework provides a practical foundation for condition-based, data-driven, and more responsive waste-collection management.

5.1 Future Scope

Future development of CleanTrack will focus on large-scale, real-world deployment through pilot testing in campuses and municipal areas. A dedicated mobile application can provide real-time bin status, alerts, waste reporting, and collection services. The AI module can be enhanced for automatic waste segregation using multi-compartment smart bins. Further integration with GIS, smart-city infrastructure, traffic data, and cloud platforms can enable centralized city-level monitoring. Additionally, carbon-footprint analysis and collaboration with municipalities, recyclers, and NGOs can support sustainable and scalable waste-management operations.

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