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Design and Validation of a Smart Waste Management System Integrating Internet of Things (IoT) and Artificial Intelligence (AI)

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Abstract. This paper presents the design, fabrication, and validation of an end-to-end smart waste management system that integrates AI, embedded IoT, and mechanical automation for real-time waste classification, sorting, and environmental monitoring. The system introduces a novel dual-stage AI pipeline, combining YOLOv5 object detection with a fine-tuned ResNet50 convolutional neural network architecture classifier that categorises waste into six classes: Plastic, Paper, Metal, Glass, Cardboard, and Organics. The AI model, deployed on an Intel NUC Mini-PC (Core i3-3217U), also functions as an IoT gateway, transmitting sensor data from an Arduino MEGA–controlled sorting module to a cloud dashboard. Integrated IoT components include an ultrasonic sensor for fill-level detection, a DHT22 sensor for temperature and humidity monitoring, and a GPS module for real-time geolocation data is extracted from $GPGGA NMEA sentences, ensuring precise tracking of system deployment. The proposed system achieved 90.44% accuracy at a fabrication cost of £1231.17, delivering a cost-effective, real-time AI-IoT waste management solution with strong performance across all categories for scalable smart city deployment. Future work will expand waste categories, enhance sorting speed, and integrate additional environmental sensors to improve scalability and adaptability in diverse municipal contexts.

1. Introduction

Waste is more than discarded material; it is a societal construct shaped by context and perception [1]. As urbanisation, industrialisation, and consumerism intensify, global waste generation is projected to rise by 70 percent, reaching 3.40 billion tonnes annually by 2050, compared to 2.01 billion tonnes in 2016 [2]. This surge places immense strain on waste management infrastructure, particularly in rapidly urbanising regions. Improper disposal, landfill saturation, and the absence of real-time waste data have escalated the waste crisis to a global scale [3]. Traditional systems, which are manual, static, and heavily reliant on human intervention, are increasingly inefficient, labour-intensive, and unsustainable [4].

Effective waste management requires optimisation across the entire lifecycle, including collection, classification, recycling, and treatment [5-6]. However, municipal waste systems often operate in isolation, which results in inefficiencies, delays, and underutilised recycling capacity.

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Unregulated dumping and cross-contamination further obstruct the achievement of a circular economy and hinder progress towards the United Nations Sustainable Development Goals [7-8].

This paper presents a fully working integrated AI, IoT, and mechanical waste management system that addresses these challenges through real-time waste classification, environmental monitoring, and automated sorting. The system design combines embedded AI with sensor-driven telemetry and modular actuation to provide a scalable, cost-effective, and deployment-ready solution for urban environments. The system addresses three critical gaps in existing waste management infrastructure: the absence of real-time insight, the lack of instant automated sorting, and limited interoperability between components.

In this paper, Section 2 describes the system architecture and the interaction between the AI, IoT, and mechanical subsystems. Section 3 presents the methodology, including dataset curation, model training, hardware assembly, and control logic. Section 4 evaluates system performance, confusion matrix and class evaluation interpretation, latency measurements, and live IoT validation. Section 5 concludes with recommendations, operational reflections, and directions for future scaling and deployment.

2. System Architecture

The system design consists of a three-layer system architecture that integrates an AI layer, an embedded IoT sensing and mechanical actuation layer, and a cloud-based monitoring layer. The design enables real-time waste classification, automated mechanical sorting, and continuous environmental monitoring. (see Table 1 for parts that make up the system).

2.1 Overview of Architecture

The system is composed of three tightly coupled layers:

- AI Layer (Edge Classification and Gateway): A Mini-PC (Intel NUC Core i3-3217U) runs the YOLOv5 and ResNet50 inference models for waste detection and classification. The ResNet50 classifier was fine-tuned on a custom dataset of 3,503 images distributed across six waste categories: Plastic (921), Metal (790), Paper (500), Cardboard (461), Glass (420), and Organics (411). The Mini-PC also serves as a gateway for transmitting telemetry data to the cloud.
- IoT Layer (Embedded Sensing and Actuation): An Arduino MEGA controls the mechanical sorting system and collects environmental sensor readings.
- Cloud Layer (Remote Monitoring and Data Persistence): The web dashboard hosted on Render.com displays live sensor readings, compartment fill levels, and geolocation data.

2.2 Functional Flow

The operational workflow sequence is as follows (refer to figure 1 for the system flow chart):

1. Image Acquisition: A camera module captures an image of the deposited waste.
2. Object Detection: YOLOv5 detects the waste object and isolates the region of interest.
3. Classification: The cropped image is passed to the fine-tuned ResNet50 CNNs architecture model, trained waste images are classified into one of six waste categories: Plastic, Paper, Metal, Glass, Cardboard, or Organics.
4. Command Dispatch: Classification results are sent via UART to the Arduino MEGA.

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5. Mechanical Sorting: The Arduino triggers a high-torque DC motor to rotate the sorting chamber to the correct compartment. A servo-actuated trapdoor releases the waste. A reed switch confirms alignment before the flap is opened.
6. Environmental Sensing: The ultrasonic sensor measures fill level, the DHT22 sensor records temperature and humidity, and the GPS module captures geolocation.
7. Data Transmission: Sensor readings are sent via UART to the Mini-PC, formatted into JSON, and transmitted via HTTP POST to the cloud.
8. Dashboard Visualisation: The web dashboard displays live bin status, environmental metrics, and GPS location.

2.3 Cost Analysis
A complete bill of materials was compiled, covering all electronics, sensors, mechanical components, and 3D printing materials (see table 2). The total fabrication cost was £1,231.17, which demonstrates the system's affordability for municipal-scale deployment considering it robustness.

Table 1. List of parts that make up the system architecture

Layer	Component	Function
AI	YOLOv5, ResNet50 on Mini-PC	Detection and classification
Gateway	Mini-PC (Wi-Fi)	HTTP communication to cloud
IoT	Arduino MEGA	Sensor control and motor actuation
Sensors	Ultrasonic, DHT22, GPS	Environmental sensing and tracking
Actuators	DC Motor, Servo Motor, Reed Switch	Mechanical sorting mechanism
Cloud	Render + MongoDB	Dashboard and data persistence

2.4 Design Rationale
This architecture was selected for the following reasons:
- Cost Affordability: Avoids over-reliance on high-end edge devices by leveraging an existing Mini-PC for dual use.
- Modularity: Each component can be debugged, replaced or upgraded independently.
- Scalability: More bins or sensors can be added with minimal code modification.
- Offline Capability: Waste classification and sorting operate locally in the mini pc, even without internet access.
- Cloud Extensibility: Enabling remote monitoring, analytics, and data persistence through MongoDB Atlas, which supports large-scale historical data storage and integration with other analytics tools.

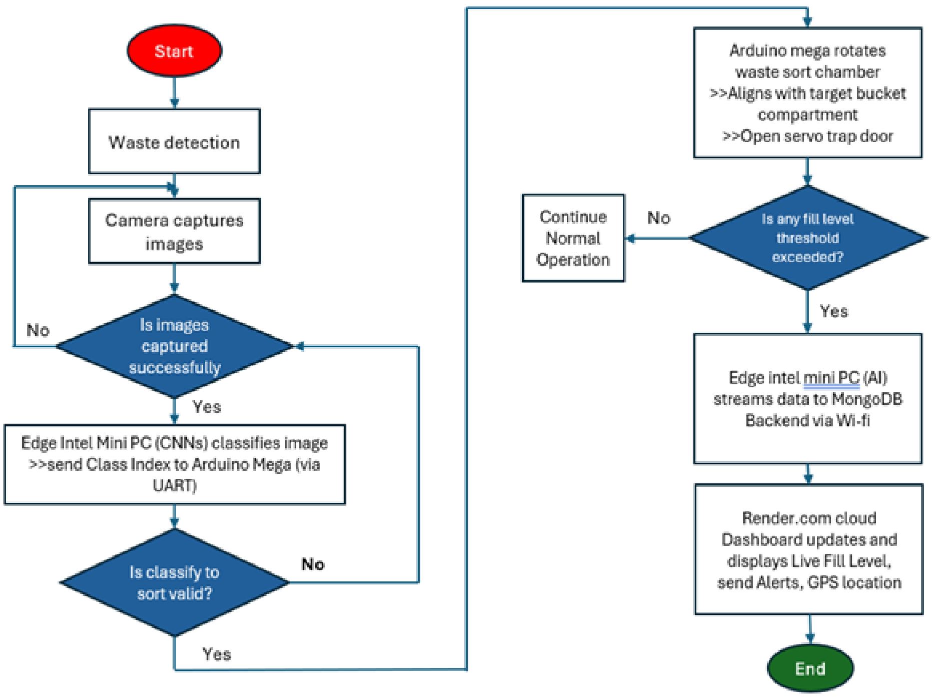

Figure 1. The system flow chart

Table 2. Cost analysis of the proposed system

Items	Quantity	Price (£)
Neodymium Bar Magnets (24-pack)	6	25.41
Samfox Turbo Worm Geared Motor	1	20.69
BRIMETI LED Driver 12V 150W	1	15.99
QitinDasen 12x Reed Switch	6	6.49
AITRIP GT-U7 GPS Module (2-pack)	1	18.99
Acolorl 5M COB LED Strip Light Kit	1 strip	20.99
HuLuWa Hook-Up Wire Kit (22 AWG)		15.69
Miuzei 15KG Digital Servo Motors (4-pack)	1	21.49
100A Dual Channel H-Bridge Motor Driver	1	76.46
Intel NUC Mini PC (Windows 10, Core i3-3217U),	1	120.99
3D Printed Smart Bin (Resin filament Full Assembly)	1	850
Camera	1	30
Ultra sonic sensor	1	3.99
TOTAL		£1231.17

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3. Methodology

This section outlines the integrated approach adopted in the design, training, and deployment of the AI-enabled waste classification system. The methodology follows a multi-phase pipeline comprising dataset preparation, deep learning model development, embedded system design, and real-time integration of the IoT and mechanical components.

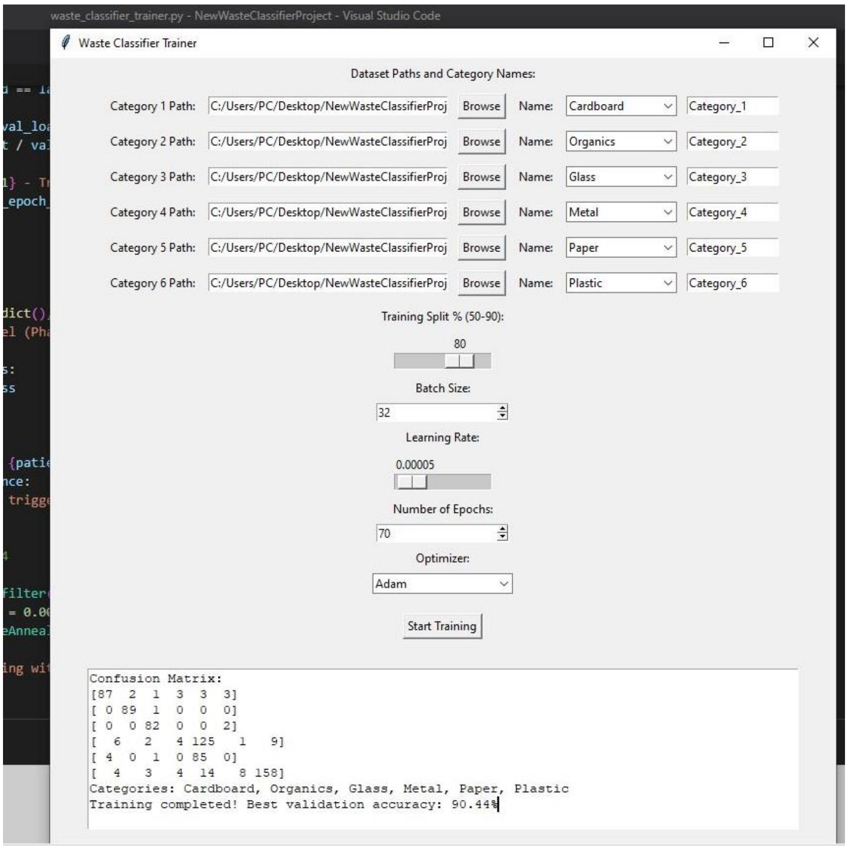


Figure 2. Validation accuracy of the model, and confusion matrix

3.1 Dataset composition and Class Distribution

A custom dataset was compiled from the publicly available in Kaggle's Real Waste Dataset [9], and reorganised into six core waste categories to reflect typical municipal solid waste types. The final waste image count per class as stated in section 2.1 amounts to a total of 3,503 images.

The images were then stored in individual class folders. Each image was resized to 224×224 pixels, normalised, and subjected to data augmentation, including random rotation, flipping, and colour jitter, to increase generalisation capacity and reduce overfitting.

3.2 AI Model and GUI Training System

The classification component was developed using a custom ResNet50-based convolutional neural networks (CNNs) [10] with label smoothing and a two-phase transfer learning pipeline. A Python GUI built with Tkinter as shown in figure 2, enables intuitive training configuration, including:

- Selection of dataset paths and class labels
- Setting epochs, batch size, learning rate, and optimiser.

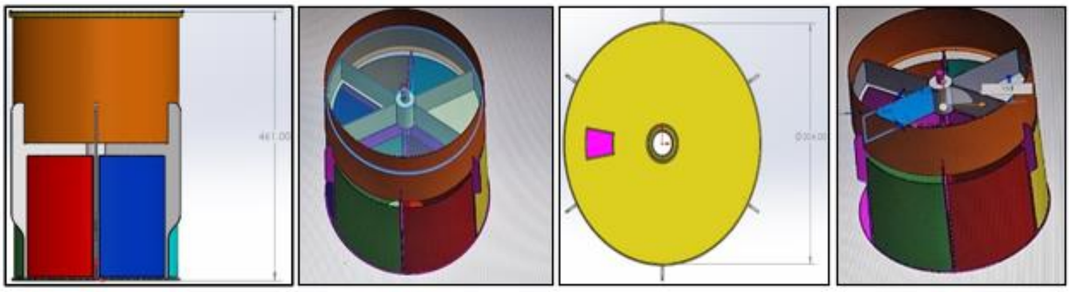


Figure 3. Left to right, 3D view of SolidWorks (CAD) Bin Design Structure

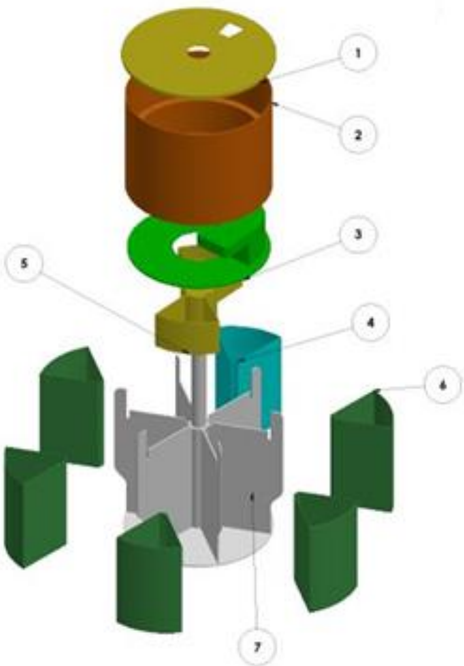
First, and before the classification stage, waste objects are detected using a lightweight YOLOv5 model, which isolates the region of interest (ROI) in real-time. This preprocessing step reduces background noise and increases classification accuracy by passing only the cropped waste segment to the ResNet50 classifier.

Visualisation of final validation accuracy of the model, and confusion matrix (as shown in figure 3) was achieved Phase 1 trains only the classifier head with the ResNet50 backbone frozen. Phase 2 unfreezes layer 3 and layer 4 for fine-tuning using CosineAnnealingLR.

The final model achieved 90.44% validation accuracy, with the GUI also generating a normalised confusion matrix and classification report. Macro-average precision: 0.91. Macro-average recall: 0.90. Macro-average F1-score: 0.90, Best per-class F1-score: 0.957 for Organics.

3.3 Embedded Control and Mechanical Sorting

The mechanical design concept of the smart bin (see figure 3) was created using SolidWorks, a professional CAD platform, with a height of 461mm (1.51ft) and a top view cover width of 304mm (1ft).



Item No.	Description	Qty.
1	Bin Cover	1
2	Upper Part of Bin	1
3	Housing for Motor	1
4	Waste Bucket	1
5	Waste Sorting Chamber	1
6	Waste Buckets	5
7	Base of Bin	1
8	Ball Bearings	2

Figure 4. Schematic structure for the designed smart bin and its components

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The bin is composed of six internal compartments. Figure 4-5 show a 3D schematic diagram of the bin's design structure, each compartment dedicated to a different waste category: cardboard, organics, glass, metal, paper, and plastic (see figure 4 for the assembly parts description). These compartments are arranged radially around a central sorting hub. The compartments are structurally separated using full-height resin walls to prevent waste contamination across boundaries. The compartmentalised floor is slightly sloped (see figure 5) which is the final 3D-printed physical bin from the SolidWorks 3D software design.

Table 3. Confusion matrix tabular representation

Class	Cardboard	Organics	Glass	Metal	Paper	Plastic
Cardboard	87	2	1	1	3	3
Organics	0	89	1	0	0	0
Glass	0	0	82	0	0	2
Metal	6	2	4	125	1	9
Paper	4	0	1	0	85	0
Plastic	4	3	4	14	8	158

Figure 5. Different images show the 3D-printed parts of the physical bin's design

4. Results and Evaluation

This section presents a consolidated evaluation of the AI-enabled smart bin system under live deployment, assessing model performance, responsiveness, and IoT-based telemetry in real time.

4.1 Confusion matrix and Class Wise Evaluation

A confusion matrix was generated (see figure 6 and table 3), providing a detailed breakdown of correct and incorrect classifications for every category followed by detailed per-class metrics evaluation(see table 4) such as recall, F1 score and precision. Organics recorded the highest

Table 4. Class-wise Evaluation

Class	TP	FP	FN	TN	Precision	Recall	F1-score
Cardboard	87	14	12	588	0.861	0.879	0.870
Organics	89	7	1	604	0.927	0.989	0.957
Glass	82	11	2	606	0.882	0.976	0.926
Metal	125	17	22	537	0.880	0.850	0.865
Paper	85	12	5	599	0.876	0.944	0.909
Plastic	158	14	33	496	0.919	0.827	0.870

overall metrics, Glass showed strong recall, Plastic had high precision but the lowest recall, and Metal, Cardboard, and Paper demonstrated balanced performance with F1-scores ranging from the mid-0.8s to low-0.9s.True Positive(TP), False Positive(FP), False Negative(FN), True Negative (TN) Precision, Recall, F1-Score.

4.2 Comparative Benchmarking with a selected few published classification models

Previous studies reported accuracies ranging from 72% to 97.49% (see table 5), with varying dataset types and class counts. Most offered real-time inference, except Aarif et al. (2022), [11], which used batch processing. This study's Yolov5 and fine-tuned ResNet50 achieved 90.4% accuracy across six waste categories with real-time capability which reflects a balance between complexity and reliability as its actuation and sensing telemetry loop which further enhances usability in smart infrastructure settings.

4.3 Real-Time Classification Snapshots

Real-time captures (see figure 7) demonstrate the effective detection and mapping of the six waste classes earlier mentioned in Table 2 classes using the integrated camera and inference pipeline.

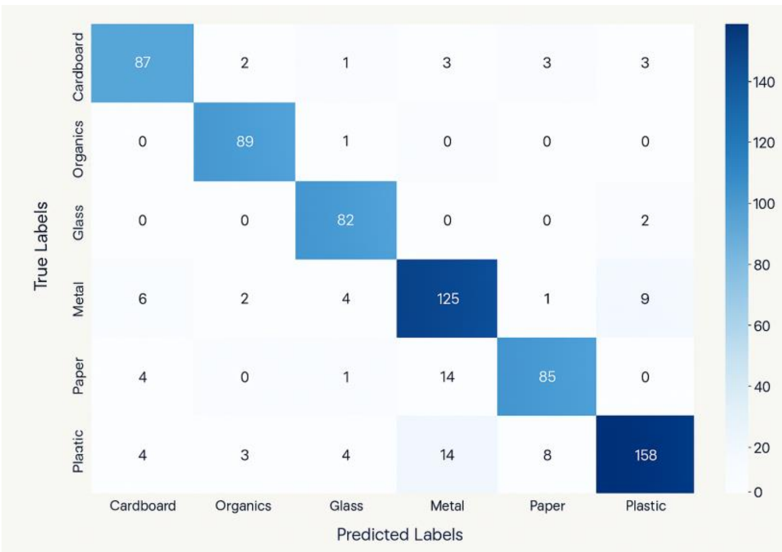

Figure 6. Confusion Matrix

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Figure 7. Different waste classification snapshots

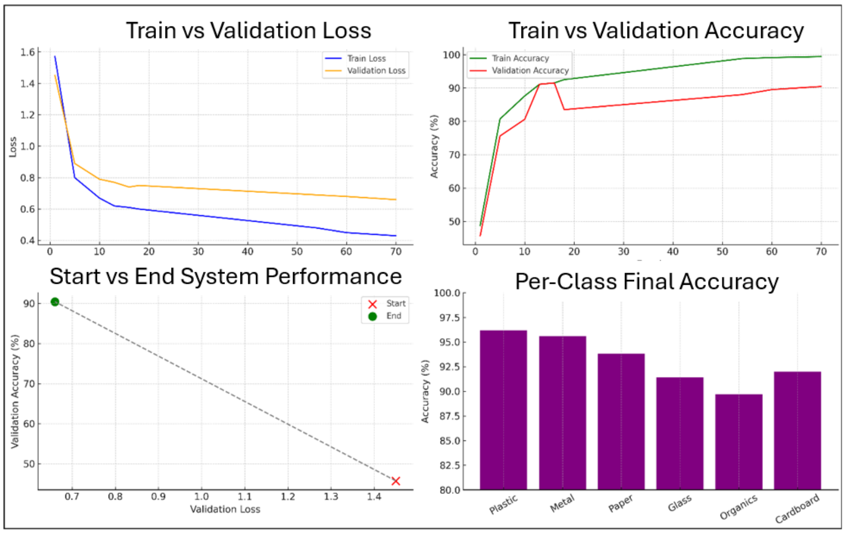

Figure 8. Combined system performance multi-panel plot, Accuracy and Loss Curves (Train vs Validation)

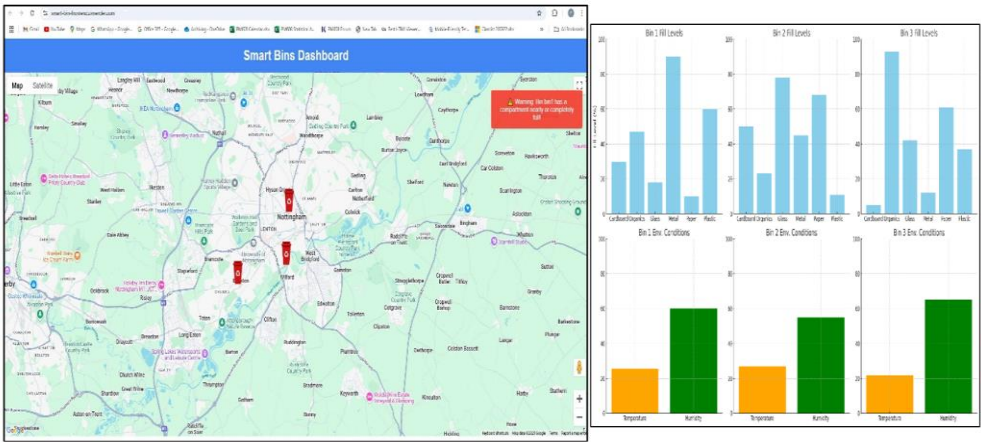

Figure 9. Live compartment fill levels, alerts (right), and bin location mapping (left).

This validates the YOLOv5–ResNet50 dual-stage approach in uncontrolled lighting and placement conditions.

4.4 Classification Accuracy

Figure 8 shows the training curves, which indicates consistent learning and minimal overfitting.

The ResNet50 model, trained via a custom GUI with two-phase fine-tuning, achieved 90.44% validation accuracy at the 60th Epoch of 70th epochs.

Table 5. Comparison with published works

Study / Author	Model Used	Dataset Type	Classes	Reported Accuracy	Real-Time Inference	IoT Integrated
Jabed & Shamsuzzaman (2022), [11]	YOLOv7	Non-decomposable mixed	4	95.9%	✅	❌
Sallang et al. (2021), [12]	SSD MobileNetV2	Paper,plastic, metal	5	~92%	✅	✅
Mohammed Aarif et al. (2022), [13]	Custom CNN	Biodegradable/non-bio	2	97.49%	❌ (batch)	✅
Voskergian & Ishaq (2023), [14]	YOLOv5s,YOLOv7/ YOLOv8s	E-waste object	10+	72% (mAP@50)	✅	✅

4.5 IoT monitoring and *Dashboard validation*

The system's cloud interface (Figure 9), powered by Render.com and MongoDB Atlas, displayed real-time bin fill status, live coordinates, temperature and humidity sensor readings and alert flags. The Integration demonstrates the viability of remote bin monitoring in urban or decentralised deployments.

5. Conclusion

The proposed smart bin system effectively unified AI-driven classification, mechanical sorting, and IoT-based sensing into a seamless, autonomous framework. Achieving a 90.44% validation accuracy, it demonstrated reliable real-time performance across hardware and cloud layers. Future enhancements will focus on edge retraining, solar autonomy, and smart routing for city-scale deployments. Future work includes optimizing AI models, expanding waste types, enabling off-grid operation, adding predictive scheduling, scaling networks, and strengthening cybersecurity.

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