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Development Of IoT-Enabled Waste Segregation System Using Carousel Disc Mechanism And AI-Driven Image Recognition

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Abstract

Rapid Urbanization and the escalating generation of Municipal Solid Waste present significant challenges Sustainable Waste Management, particularly in Developing Regions. Inefficient Source Segregation remains a major obstacle, leading to Contamination of Recyclables, Reduced Recycling Efficiency, and Increased Landfill dependency. This study proposes the Design and Development of an Intelligent Automated Waste Segregation System capable of Classifying Waste into four categories: Biodegradable (Wet), Dry, Electronic, and Unsorted (Residual). The proposed system integrates Sensor Modules, Computer Vision (CV), and Microcontroller-based Control, enhanced by AI-driven Image Recognition to achieve High Classification Accuracy. A Moisture Sensor identifies Biodegradable Waste, a Capacitive Sensor detects Dry Waste, and an Inductive Sensor recognizes Electronic or Metallic Waste, ensuring Precise Classification. A Modular Carousel-Disc Mechanism with Detachable Compartments enables Efficient Segregation and Simplified Disposal. Furthermore, Optional IoT Connectivity facilitates real-time Monitoring and Data Analytics, supporting integration with Smart City Infrastructure. Experimental Validation demonstrates Reliable Classification Accuracy and Scalability across Households, Institutions, and Public Facilities. By Automating Segregation at the Source, the System Minimizes Human Intervention, Improves Recycling Efficiency, and Contributes to Sustainable and Intelligent Urban Waste Management.

Keywords
AI-based Waste Classification, Intelligent Waste Segregation System, IoT-enabled Smart Bin, Sensor and Computer Vision Integration, Smart Waste Management

1. Introduction
Rapid urbanization, industrialization and population growth have significantly increased the generation of Municipal Solid Waste (MSW), creating a persistent challenge to sustainable urban development. Improper waste segregation at the source remains one of the most critical barriers to efficient recycling and resource recovery (Ahmed et al. 2024). In many developing regions, biodegradable, recyclable, electronic, and residual wastes are discarded together, leading to contamination, reduced recycling efficiency, and greater reliance on landfills. This results in elevated operational costs, greenhouse gas emissions, leachate formation, and the loss of recoverable resources (Thiagarajah et al. 2023).

Conventional manual segregation processes are labor-intensive, inconsistent, and expose workers to health hazards. Automated systems, though emerging, are often constrained by limited sensing accuracy, dependence on single-sensor modules, or the absence of data integration mechanisms (Ismail et al. 2023). Several studies have demonstrated IoT-based and sensor-driven approaches for real-time monitoring of waste fill levels (Afolalu et al. 2021); however, these systems rarely achieve accurate multi-category segregation. Likewise, image-based waste classification models using deep learning have shown promising results but remain restricted to controlled laboratory environments and are seldom integrated with segregation mechanism suitable for on-site deployment (Nafiz et al. 2023). More recently, integrated frameworks combining sensor and vision-based modules have been explored to enhance classification performance (Longo et al. 2021), yet the development of a cost-effective, scalable, and adaptive system capable of handling heterogeneous waste streams continues to pose a challenge.

This research bridges that gap by developing an intelligent waste segregation system that integrates sensor fusion, computer vision and a microcontroller-based control unit to autonomously classify waste into four categories: biodegradable (wet), dry, electronic, and residual. Building upon earlier sensor-based designs (Suvarnamma and Pradeepkiran 2021), the proposed model employs a multi-sensor array for preliminary material discrimination, coupled with a modular carousel-disc mechanism that distributes waste precisely into respective compartments.

By integrating multiple technologies into a single autonomous platform, this research aims to enhance classification accuracy, reduce human involvement, and optimize the overall waste-handling process. The outcome is a system that not only minimizes contamination and operational costs but also supports data-driven decision-making for municipal and industrial applications, an essential step toward realizing the vision of smart and sustainable cities.

1.1 Objectives

The primary aim of this research is to design and develop an intelligent automated waste segregation system capable of accurate, energy-efficient, and scalable classification of municipal solid waste at the point of disposal.
To achieve this aim, the study pursues the following specific objectives:

1. Develop a smart waste segregation unit capable of classifying waste into four categories—biodegradable (wet), dry, electronic, and residual using integrated sensing and AI/ML-based image recognition.
2. Enhance detection precision of and minimize misclassification of wastes by using sensor fusion modules.
3. Implement a machine learning–based computer vision system for visual waste identification and verification.
4. Employ a microcontroller-based control unit that coordinates sensor inputs, actuates the mechanical carousel-disc mechanism, and enables optional IoT connectivity for monitoring and data analytics.
5. Evaluate system performance in terms of classification accuracy, operational efficiency, and adaptability for domestic, institutional, and municipal applications.

The novelty of this work lies in its hybrid integration of sensor technology, artificial intelligence, and modular carousel disc mechanism within a unified and sustainable architecture. Unlike previous studies limited to either sensor-based or vision-based systems, this research introduces a comprehensive, adaptive, and cost-effective framework that advances intelligent waste management practices (Ahmed et al. 2024).

2. Literature Review

The rapid growth of urban populations and the increasing complexity of municipal solid waste (MSW) have created a strong demand for intelligent and automated segregation systems. Manual sorting is labor-intensive, error-prone, and unsafe, resulting in poor recycling efficiency and greater landfill dependency. To address these issues, researchers have focused on sensor-based detection, AI-driven classification, and IoT-enabled monitoring for real-time and scalable waste management (Ahmed et al. 2024; Thiagarajah et al. 2023; Hussain et al. 2023).

Early studies employed low-cost sensors to classify waste by electrical or physical properties. Inductive and capacitive sensors detected metals and plastics, while infrared and moisture sensors distinguished wet and dry waste (Suvarnamma and Pradeepkiran 2021; Afolalu et al. 2021). Ultrasonic and gas sensors supported fill-level detection and odor monitoring (Kumar et al. 2022; Singh et al. 2020). Microcontrollers such as Arduino and NodeMCU were combined with IoT modules like GSM, GPS, and RFID for communication (Vishnu et al. 2021; Cai et al. 2022). Although these systems improved efficiency, their accuracy declined in mixed-waste environments and lacked adaptability (Suvarnamma and Pradeepkiran 2021). Further, Mousavi et al. (2023) emphasized IoT-based optimization frameworks that enhance route planning and bin-level management through sensor data analytics, supporting the development of scalable and energy-efficient waste collection networks.

The integration of machine learning enabled image-based waste recognition using Convolutional Neural Networks (CNNs), achieving accuracies above 95% in various categories (Nafiz et al. 2023; Rahman et al. 2024). Some frameworks incorporated mechanical automation, such as conveyors or servo-actuated sorters, to support real-time classification (Holanda Filho et al. 2023; Ismail et al. 2023). However, their computational demand and energy requirements hindered adoption in low-cost applications (Debdas et al. 2022; Cai et al. 2022). Kaya et al. (2023) further demonstrated the potential of deep learning-based transfer learning models for waste classification, achieving high accuracy with reduced computational cost, validating the suitability of EfficientNet-based architectures for embedded deployment.

Recent research emphasizes hybrid architectures combining sensors, computer vision, and edge computing for improved reliability. Longo et al. (2021) introduced a 5G-enabled smart bin using photoelectric sensors and a ResNet-18 CNN, achieving 97.37% accuracy with Multi-Access Edge Computing (MEC). Their work briefly mentioned a rotating disc mechanism but did not detail its structure or operation. The present study extends this concept by designing a carousel disc mechanism for precise alignment and waste distribution. Other studies emphasized AI–IoT integration for scalable deployment and energy-efficient communication (Ahmed et al. 2024; Thiagarajah et al. 2023; Hussain et al. 2023).

Overall, research has progressed from single-sensor systems to AI- and IoT-driven hybrid frameworks. Earlier studies focused on sensing accuracy and connectivity (Afolalu et al. 2021; Suvarnamma and Pradeepkiran 2021), whereas recent works integrate deep learning and networked intelligence (Longo et al. 2021; Rahman et al. 2024; Ahmed et al. 2024). However, a gap persists in developing mechanically optimized, cost-effective, and scalable segregation systems. This study addresses that gap through a hybrid design integrating sensor fusion, AI-driven vision, and a carousel disc mechanism for accurate and sustainable waste management.

3. Methodology

This section presents the systematic approach adopted for designing and developing the intelligent waste segregation system. It outlines the overall system architecture, product design, control and decision-making framework, and system integration, describing how these modules collectively enable accurate, autonomous, and efficient waste segregation.

3.1 System Architecture

The proposed intelligent waste segregation system is designed as a multi-module unit integrated within a compact, detachable bin structure. The system architecture consists of four primary modules: sensing and detection, control and processing, segregation mechanism, and monitoring and feedback. Each module functions cohesively to enable efficient classification and disposal of waste. Detailed block diagram of this system architecture is shown in Figure 1.

This module employs a combination of sensors for material identification, volumetric measurement, and environmental monitoring. A moisture sensor detects biodegradable (wet) waste based on conductivity, while a capacitive sensor differentiates dry materials such as plastics or paper by their dielectric properties. An inductive sensor identifies metallic or electronic waste through electromagnetic field variation. A Time-of-Flight (ToF) sensor measures the distance between the inlet and deposited waste for precise detection, and a load cell monitors weight for volumetric analysis. Additionally, an ultrasonic sensor tracks fill levels to prevent overflow, while an MQ-series gas sensor monitors odor and emissions for hygiene assurance (Afolalu et al. 2021). These sensors collectively provide reliable, real-time data for classification, bin level estimation, and environmental safety.

This system employs a dual-carousel disc mechanism for mechanical segregation. The upper disc, featuring a cup-like extrusion, temporarily holds incoming waste, while the lower disc aligns with four outlet compartments - biodegradable, dry, electronic, and residual by rotating. Both discs are motor-driven and rotate synchronously to align their arc-shaped apertures with the appropriate compartment. Once aligned, waste drops by gravity into the correct section, ensuring minimal cross-contamination and precise segregation (Longo et al. 2021). The compact design allows reliable operation in limited spaces while maintaining high accuracy.

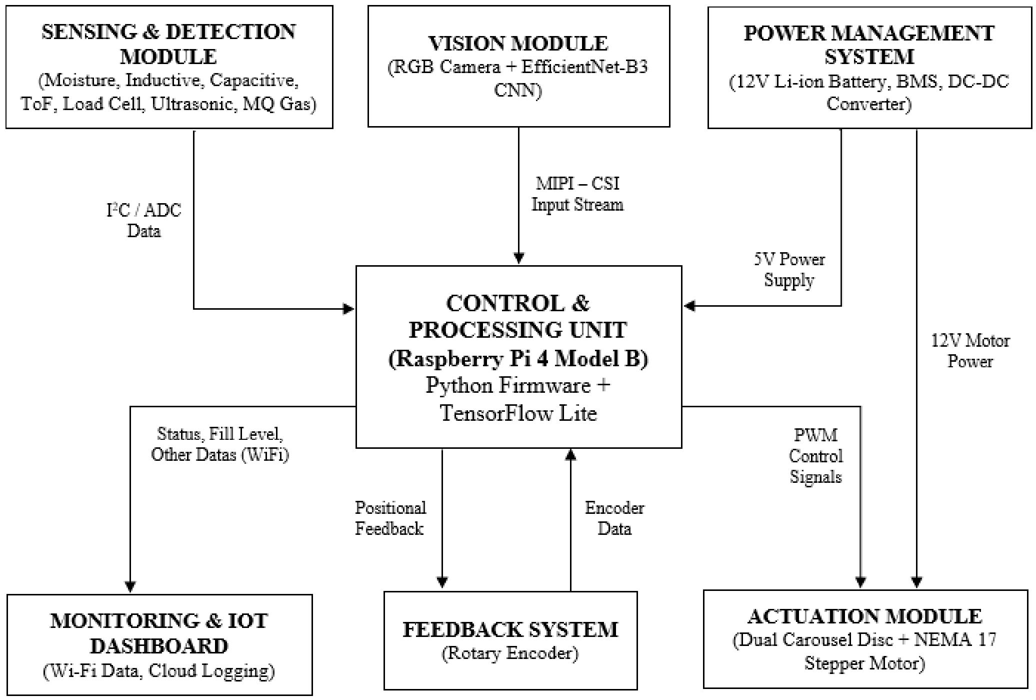

Figure 1. System Architecture of the proposed smart bin

The system employs Raspberry Pi as the central control unit for data processing, decision-making, and actuator operation. Its quad-core processor supports image classification through a camera module positioned near the waste inlet. Based on sensor and visual data, the controller triggers actuation commands to the dual-carousel disc segregation mechanism. The system transmits operational data such as fill level, gas concentration, and system status to an IoT dashboard via Wi-Fi for real-time monitoring and predictive maintenance (Ahmed et al. 2024). This unified control architecture ensures seamless coordination between sensing, computation, and actuation components.

3.2 Prototype Design and Integration

The prototype is developed as a compact, modular smart bin integrating mechanical, electronic, and sensing components. The system measures approximately 750 mm in height and 450 mm in width, optimizing stability and footprint. The structure is divided into a head unit, housing all electronics and sensors, and a body section containing four detachable compartments. The head portion includes the Raspberry Pi 4, moisture, capacitive, inductive, ToF, ultrasonic, and gas sensors, along with a camera for visual recognition. LED indicators display system status, while internal wiring channels ensure protection from external exposure.

The body section consists of four cylindrical compartments each 370 mm tall and 156 mm in diameter as shown in Figure 2, designated for biodegradable (green), dry (yellow), electronic (orange), and residual or unsorted (red) waste. These are independently detachable for easy cleaning and collection. Figure 3 shows the dual-carousel disc assembly, positioned above the compartments, comprises two 380 mm diameter discs (18 mm thick). The upper disc incorporates a cup-like downward extrusion as in Figure 3, for holding and guiding waste before it drops. The lower disc rotates in synchronization with the upper disc, ensuring precise alignment and minimal cross-contamination. This dual-rotation mechanism enhances segregation accuracy while maintaining compactness.

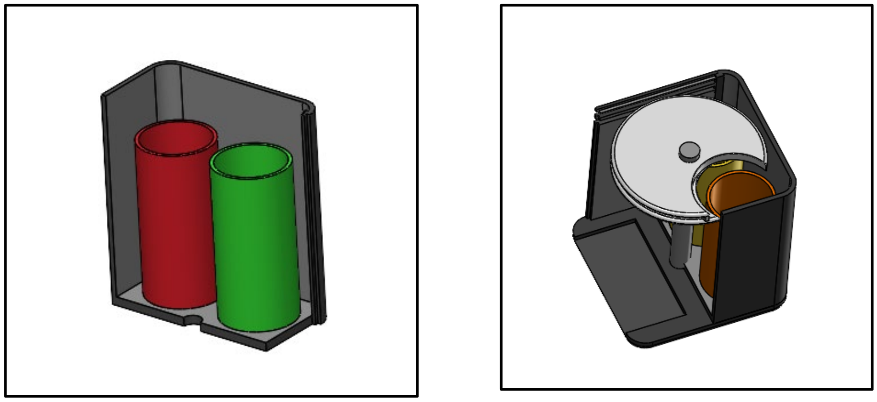

Figure 2. Waste Compartments

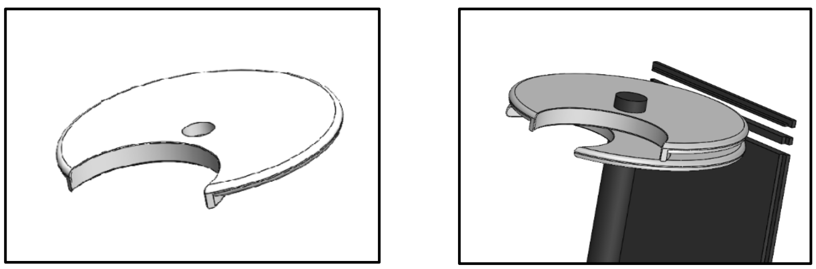

Figure 3. Carousel Disc and its Assembly with the Motor Driver

The overall assembly comprises head, body, compartments and dual carousel disc unit as shown in Figure 4, is modular and also enabling independent removal or servicing of each component. This structure enhances maintainability, scalability, and cost-effectiveness, forming a robust and adaptable waste segregation system that integrates sensor fusion, AI-assisted vision, and mechanical automation for sustainable waste management.

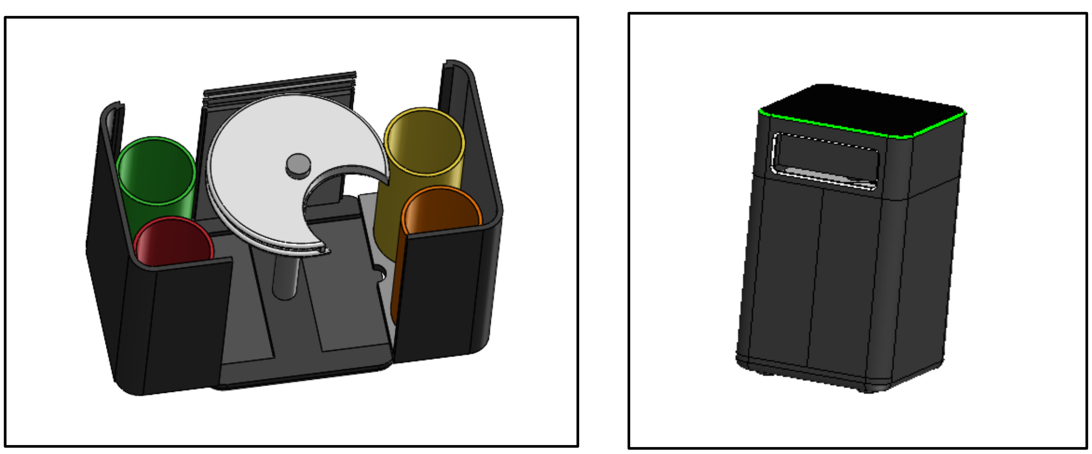

Figure 4. Overall Structure and Assembly

3.3 Control and Decision-Making Framework

The control framework integrates vision-based classification, multi-sensor data fusion, and automated actuation within a unified decision-making loop. This architecture ensures fast, accurate, and adaptive waste segregation suitable for real-time operation.

A pre-trained EfficientNet-B3 Convolutional Neural Network (CNN) is used for visual waste classification due to its superior accuracy-to-complexity ratio and efficiency on embedded computing platforms (Nafiz et al. 2023). An RGB camera placed near the waste inlet captures images, which undergo preprocessing operations such as resizing, contrast normalization, and background segmentation. The CNN extracts color, texture, and shape-based features to classify the object into four categories - biodegradable, dry, electronic, or residual. Each prediction generates a class label and confidence score, transmitted to the Raspberry Pi 4 controller for verification and control. This image-based inference provides rapid and reliable waste recognition within real-time constraints.

To strengthen classification reliability, the system integrates a sensor fusion module that corroborates visual predictions with physical sensor data. The moisture, capacitive, and inductive sensors provide supplementary inputs: moisture sensors detect wet or biodegradable waste through conductivity, capacitive sensors distinguish dry materials by dielectric variation, and inductive sensors detect metallic waste via electromagnetic field changes (Suvarnamma and Pradeepkiran 2021).

Each sensor's analog output is digitized and normalized before fusion. When the visual confidence score falls below a defined threshold, sensor readings are used to verify or correct the prediction. For example, if the CNN predicts electronic waste with moderate confidence but the inductive sensor detects a strong metallic response, the final classification is confirmed as electronic. This hybrid validation strategy minimizes misclassification due to lighting variations or partial occlusion, ensuring dependable performance under real-world conditions (Afolalu et al. 2021).

The Raspberry Pi 4 executes the integrated decision algorithm based on a hierarchical rule structure:

1. If the visual model confidence is high, the classification output is accepted directly.
2. For medium confidence, the sensor fusion data are used to validate and adjust the final class decision.
3. When low visual confidence occurs, the decision is driven primarily by sensor responses.

Once classification is finalized, the controller actuates the dual-carousel disc mechanism through precise servo or stepper motor control. The upper disc aligns its aperture with the appropriate compartment, enabling gravity-assisted segregation. Concurrently, the system logs classification data, sensor readings, and operational parameters to the IoT dashboard for real-time analysis.

3.4 System Integration

The entire system integrates sensing, computation, actuation, and mechanical subsystems interacts cohesively under a unified control architecture managed by the Raspberry Pi 4.

The Raspberry Pi 4 Model B coordinates all subsystems via GPIO, I²C, and CSI interfaces. The OV5640 5 MP camera connects through MIPI-CSI for high-speed image capture, while sensor modules communicate via I²C through an external ADC for synchronized data acquisition. The stepper motor driver receives PWM-based pulse and direction signals from dedicated GPIO pins, with a rotary encoder providing positional feedback for closed-loop control (Ahmed et al. 2024). Power is supplied by dual configuration source via a 12 V, 7 Ah Li-ion battery and a 12 V DC adapter, regulated through a DC–DC buck converter providing 5 V, 3 A for the controller and peripherals. An integrated Battery Management System (BMS) ensures overcharge and discharge protection, offering 6–8 hours of standalone operation or supports continuous use under mains power.

The dual-carousel disc assembly is fabricated from ABS for strength and low mass, with the NEMA 17 stepper motor driving the discs through a flexible coupling to reduce vibration. The upper disc performs 360° rotation for classification, while the lower disc aligns incrementally to the designated compartment. A rotary encoder feedback loop ensures accurate angular positioning. Support structures including sensor mounts and brackets are 3D-printed in PLA for modularity and ease of replacement, while the main frame and compartment housing use powder-coated mild steel and HDPE containers for corrosion resistance and easy maintenance.

The firmware developed in Python on the Raspberry Pi OS uses TensorFlow Lite for embedded CNN inference. Tasks such as sensing, image processing, classification, and actuation run in concurrent threads for minimal latency. A state-machine-based logic governs sequential transitions: initialization, detection, classification, actuation, standby. Encoder feedback continuously updates disc position for closed-loop correction. The system achieves an average control cycle of 3–4 seconds, ensuring efficient real-time segregation.

The overall operational sequence of the system is depicted as a cyclic workflow consisting of six major states:

1. Idle State: The system remains on standby, continuously monitoring the input slot via proximity sensing.
2. Object Detection: When an object is inserted, the proximity sensor activates the camera and sensor modules.
3. Data Acquisition: Simultaneous image capture and sensor data collection occur, providing multimodal input to the controller.
4. AI Classification and Sensor Fusion: CNN model performs visual classification and the fused sensor data verify or refine the result.
5. Actuation: Raspberry Pi 4 issues motor commands via PWM to rotate the carousel disc to the appropriate bin, then waste drops into the aligned compartment.
6. Reset and Feedback: The system returns the disc to its default position, logs the operation data, and resumes the idle state.

Error-handling routines are embedded to manage conditions such as mechanical jamming, sensor anomalies, or low-confidence classifications. For example, if a misclassification is detected through feedback analysis, the system initiates re-classification with updated sensor readings. Timing parameters (motor delay, image capture interval) are empirically tuned to optimize energy efficiency and operational reliability.

4. Data Collection

The dataset used for training the waste classification model was compiled from open-source repositories such as TrashNet, Kaggle and TACO (Trash Annotations in Context), covering four categories: biodegradable, dry, electronic, and residual wastes. These repositories offer image samples captured under varied lighting and environmental conditions, enhancing the model's ability to generalize across real-world scenarios (Nafiz et al. 2023). All images were resized to 224×224 pixels, normalized, and filtered to eliminate background noise and irrelevant features.

Data Augmentation techniques such as rotation, flipping and brightness adjustment expanded the dataset and prevented overfitting. The data were divided in an 80:20 ratio for training and testing (Ahmed et al. 2024). During evaluation, the EfficientNet-B3 model achieved an overall accuracy of 95.41% across all waste categories. Plastic waste showed the highest precision of 98.75% with the shortest inference time of 3sec, while electronic waste had the lowest accuracy of 92.5% and longest processing time of 7sec, as shown in Table 1. Similar performance trends have been observed in recent CNN-based waste classification studies (Ismail et al. 2023; Longo et al. 2021).This balanced and diverse dataset effectively supports the hybrid sensor–vision classification framework, ensuring accurate real time segregation under varying operational conditions.

Table 1. Dataset Partition and Classification Results

Categories	***Training***	***Validation***	***Test Images***	***Classified***	***Accuracy (%)***	***Time (Sec)***
Plastic	1500	300	80	79	98.75	3
Metal	1500	300	80	78	97.5	4
Glass	1500	300	80	76	95	6
Medical Waste	1500	300	80	76	95	4
Organic	1500	300	80	75	93.75	5
E-waste	1500	300	80	74	92.5	7

5. Results and Discussion

The system's performance was evaluated through experimental and analytical assessments, focusing on classification accuracy, detection response time, and overall operational efficiency. Quantitative and graphical analyses validated the reliability and effectiveness of the proposed intelligent segregation framework.

5.1 Numerical Results

Table 2 shows the performance of the sensor-based classification module, which achieved detection accuracies of 93% for paper, 94% for metal, and 92% for organic waste. Lower accuracies were observed for e-waste (70%) and glass (80%), indicating difficulty in distinguishing materials with overlapping electrical or reflective properties. Frequent misclassification of e-waste and glass as plastic further emphasized the need for complementary vision-based verification.

Table 2. Test Confusion Matrix for Sensor based Classification

		PREDICTED CLASS					
		Paper	**Plastic**	**Metal**	**Glass**	**E-waste**	**Organic**
TRUE CLASS	**Paper**	**465 (93%)**	15 (3%)	-	10 (2%)	-	10 (2%)
	Plastic	30 (4%)	**675 (90%)**	15 (2%)	15 (2%)	15 (2%)	-
	Metal	-	8 (2%)	**376 (94%)**	4 (1%)	12 (3%)	-
	Glass	20 (4%)	30 (6%)	20 (4%)	**400 (80%)**	30 (6%)	-
	E-waste	-	40 (13%)	30 (10%)	10 (3%)	**210 (70%)**	20 (7%)
	Organic	50 (5%)	-	-	-	30 (3%)	**920 (92%)**

The integrated EfficientNet-B3 CNN model significantly enhanced accuracy as shown in Table 3, achieving an overall accuracy of 98.3%, with paper (97%) and e-waste (89%) representing the highest and lowest category performances respectively. These results surpass previously reported CNN-based segregation systems which achieved up to 97.7% accuracy (Ismail et al. 2023; Longo et al. 2021). The confusion matrix revealed minimal off-diagonal errors, confirming the model's discriminative strength and validating its effectiveness for automated high precision waste segregation.

Table 3. Test Confusion Matrix for Proposed EfficientNet-B3 Model based Classification

		PREDICTED CLASS					
		Paper	**Plastic**	**Metal**	**Glass**	**E-waste**	**Organic**
TRUE CLASS	**Paper**	**485 (97%)**	5 (1%)	-	5 (1%)	-	5 (1%)
	Plastic	10 (1%)	**710 (95%)**	5 (1%)	15 (2%)	10 (1%)	-
	Metal	-	5 (2%)	**315 (95%)**	10 (3%)	-	-
	Glass	10 (2%)	15 (3%)	10 (2%)	**450 (90%)**	15 (3%)	-
	E-waste	-	12 (4%)	15 (5%)	5 (2%)	**278 (89%)**	-
	Organic	30 (3%)	20 (2%)	-	-	-	**950 (95%)**

5.2 Graphical Results

Figure 5(a) shows the accuracy curve over 100 epochs, where both training and validation accuracies exceed 95% after 15 epochs, indicating fast convergence and effective learning. Concurrently, Figure 5(b) displays the loss curve, with the validation loss reaching a minimum of 0.172 at epoch 8 and stabilizing thereafter. The close alignment between the curves confirms robust training behavior without significant overfitting. Overall, the results demonstrate that the hybrid sensor–vision framework ensures reliable real-time waste classification and mechanical segregation performance, effectively meeting the objectives of precision, adaptability, and operational efficiency.

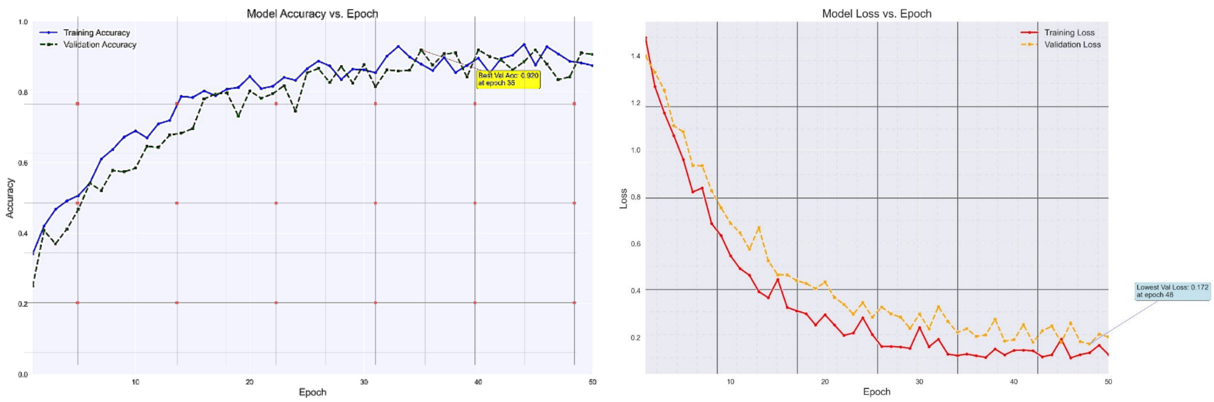

Figure 5. Model training performance: (a) Accuracy vs Epoch; (b) Loss vs Epoch

5.3 Proposed Improvements

While the system demonstrates high accuracy and stable operation, several refinements can further enhance performance and adaptability. Misclassification between e-waste and glass can be minimized by integrating a short-range Near-Infrared (NIR) or hyperspectral sensor to strengthen material differentiation (Afolalu et al., 2021). The carousel-disc mechanism can be upgraded with a closed-loop servo or stepper motor integrated with an encoder, ensuring smoother rotation and precise angular positioning within ±2° deviation of the target compartment. Modular quick-swap sensor mounts and detachable bin sections would simplify maintenance and allow scalable multi-unit deployment (Longo et al., 2021).

To improve autonomy, a compact solar charging unit may supplement the lithium-ion battery for off-grid operation. Computational efficiency can be increased through TensorFlow Lite quantization or TensorRT acceleration. An IoT-based dashboard displaying fill level, odor metrics, and bin location can enable optimized waste-collection routes and predictive maintenance (Ismail et al., 2023). Collectively, these improvements enhance precision, energy efficiency, and scalability for next-generation smart-city waste-management systems.

5.4 Validation

The system was validated experimentally under controlled and real-time conditions using 2,000 labeled waste samples across four categories such as biodegradable, dry, electronic, and residual. The EfficientNet-B3 CNN model was deployed on the Raspberry Pi 4 (4 GB) via TensorFlow Lite, achieved an overall accuracy of upto 97.7% with an average inference time of 1.92 s per image, confirming suitability for embedded real-time operation. Table 2 presents the sensor-based detection accuracy, while Table 3 summarizes CNN-based classification results.

Figure 6 compares various CNN architectures in terms of classification accuracy and mean inference time. EfficientNet-B3 achieved the optimal trade-off, recording 93.8% accuracy with 65 ms inference time. Deeper models such as ResNet-50 and NASNet-A-Mobile produced marginal accuracy gains but at higher latency (>100 ms), while lighter models like MobileNetV2-small and SqueezeNet-1.0 offered faster execution with reduced precision (Ismail et al. 2023; Longo et al. 2021). Thus, EfficientNet-B3 was validated as the optimal CNN for real-time waste segregation, balancing accuracy and computational efficiency.

For mechanical validation, the NEMA 17 stepper motor driven by a DRV8825 controller maintained precise carousel disc alignment with an angular deviation below 1.8° across 100 continuous cycles, achieving an average cycle time of 3.2 s. IoT validation confirmed stable communication between the Raspberry Pi and the cloud dashboard, maintaining latency 300 ms and system uptime above 98%, demonstrating dependable real-time monitoring and control for municipal waste management operations.

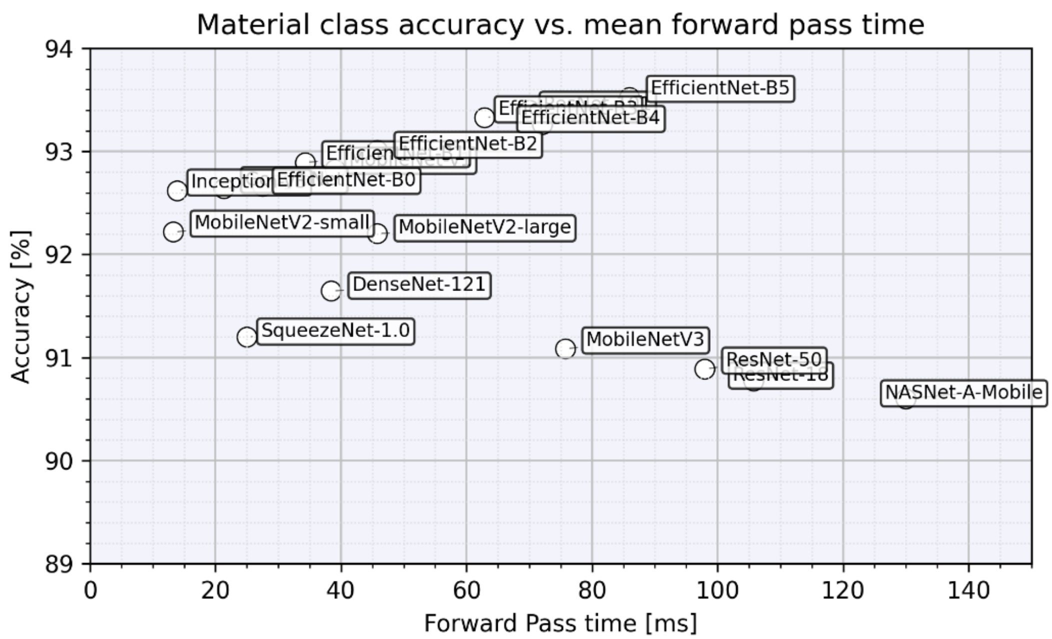

Figure 6. Accuracy vs. Mean Forward Pass Time for Various CNN Architectures

6. Conclusion

The increasing challenges of urbanization and the inefficiencies of manual waste segregation highlight the urgent need for automated and intelligent waste management systems. This research successfully developed and validated an intelligent waste segregation unit integrating a dual-carousel mechanism with hybrid sensor fusion and computer vision based classification. The proposed system achieved up to 97.7% classification accuracy, efficiently segregating multiple waste categories without human intervention.

The key contribution of this work lies in the integration of scalar sensor data with deep visual feature extraction using the EfficientNet-B3 model, enabling precise classification even for visually similar materials such as certain plastics and e-waste. Experimental validation confirmed that the system meets its objectives of accuracy, reliability, and real time functionality. Future developments will focus on improving robustness for diverse waste types, optimizing the carousel mechanism for higher throughput and implementing large-scale field trials to evaluate long-term performance. Overall, the proposed system establishes a scalable, cost-effective, and sustainable framework for modernizing waste management practices in both domestic and municipal environments.

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Biographies

Prof. V. Velmurugan completed his Bachelor's Degree from Bharathiyar University, Coimbatore, then Completed his Post Graduate Degree from Madras Institute of Technology, Anna University, Chennai and Ph.D. from College of Engineering, Anna University, Chennai. He is currently Working as Associate Professor in the Department of Mechanical and Automation Engineering at Sri Sairam Engineering College, Chennai with 20 years of experience in Teaching and Research. His areas of specialization include Smart and Composite Materials, Manufacturing, Finite Element Analysis, Engineering Mechanics, Engineering Graphics, Process Planning, and Cost Estimation. He has published several Journal Papers and Research Papers in National and International Conferences and Contributed to 2 Book Chapters. He has also Published 2 Patents. To date, He has attended 35 Workshops and 22 Faculty Development Programs (FDPs). He had received recognition from the former President of India, Dr. A. P. J. Abdul Kalam, for a L-Ramp awarded project at IIT Madras in 2007. He has also completed 8 Modules at NITTTR, Chennai. His professional memberships include ISTE, IEEE, IAENG, UAMAE, and IFERP. With a strong record of Academic and Research Contributions, he continues to Mentor Students in Innovative and Sustainable Engineering Solutions.

Bhuvaneshwaran M is an Undergraduate Student in the Department of Mechanical and Automation Engineering at Sri Sairam Engineering College, Chennai. He possesses a solid foundation in core mechanical engineering principles and has developed growing expertise in mechanical design, finite element analysis, and simulation. His technical proficiency extends across various software platforms including SolidWorks, Fusion 360, HyperMesh, and MATLAB. As an active member of a recognized Electric All-Terrain Vehicle (ATV) fabrication team, he has participated in national-level competitions such as SAE Baja and ATVC, gaining hands-on exposure to design validation, manufacturing processes, cost analysis, DFMEA, GD&T, troubleshooting, and vehicle testing. This experience has strengthened his ability to apply theoretical knowledge to practical challenges. His research and academic interests focus on robotics, machine learning, and aerospace systems, where he aims to leverage computational and design techniques to develop innovative and sustainable engineering solutions.

Jagan Babu R is an Undergraduate Student in the Department of Mechanical and Automation Engineering at Sri Sairam Engineering College, Chennai. His academic focus lies in robotics, artificial intelligence, and automation, with a keen interest in integrating intelligent systems to enhance industrial and engineering applications. He has acquired technical competence in the Robot Operating System (ROS), blockchain-based decentralized applications (DApps), and advanced deep learning architectures such as convolutional neural networks (CNNs). Through his academic and personal projects, he has worked on AI-driven detection systems and machine vision technologies, demonstrating his ability to connect theoretical frameworks with real-world implementations. He continues to explore interdisciplinary research avenues that merge robotics, AI, and network theory, aspiring to contribute to the advancement of smart and autonomous systems for industrial and societal benefit.

Pravin M is an Undergraduate Student in the Department of Mechanical and Automation Engineering at Sri Sairam Engineering College, Chennai. He is having a foundational knowledge in core mechanical principles and aims to excel as a future designer with his experience in NX Cad and Fusion 360. His interests are focused on the field of thermal engineering and robotics. He consistently applies his creative problem-solving skills and technical knowledge to his work in project teams and technical activities.

Janardhanan R is an Undergraduate Student in the Department of Mechanical and Automation Engineering at Sri Sairam Engineering College, Chennai. He is a versatile and forward-thinking engineering professional with a multidisciplinary skill set encompassing software development, mechanical design, and electronic systems. His technical expertise includes programming in Python, Java, and C, and mobile application development using Flutter for cross-platform Android and Windows environments. Alongside his software proficiency, he has a fundamental understanding of PTC Creo and exhibits a strong interest in design modeling, product development, and system integration. His interdisciplinary approach enables him to bridge mechanical and electronic domains effectively, fostering holistic solutions to engineering challenges. Recognized for his leadership, teamwork, and communication abilities, he actively contributes to collaborative projects and encourages innovation within his peers.He aspires to develop intelligent, sustainable, and interconnected systems that integrate digital intelligence with advanced mechanical design for future-ready engineering solutions.

Deepan A is an Undergraduate Student in the Department of Mechanical and Automation Engineering at Sri Sairam Engineering College, Chennai. He is cultivating foundational skills in design software like AutoCAD and Fusion 360. He has a growing interest in the Automobile industry. As a proactive and diligent learner, he successfully balances a strong academic focus with active participation in technical clubs and project-based learning, demonstrating a clear drive to connect theoretical knowledge with practical, industry-relevant applications.