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Research paper

Edge-AI Powered Intelligent Waste Bins for Autonomous Urban Waste Segregation and Recycling

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Abstract

Innovative solutions to sorting, recycling, and environmentally friendly handling of urban waste, because we don't know how to solve urban waste management. An intelligent waste bin system with edge AI is being described to sense, classify, and manage the waste on its own, as per this research. The above systems effectively combine a lightweight Edge-AI model based on CNNs and Vision Transformers (ViTs) to detect waste in real time. The system identifies the materials using the appearance, the thermal appearance, and the strengths of the density scan of the material using the RGB cameras, the LiDAR sensors, and the infrared scanners. Reinforcement Learning (RL) is used to create such a robotic sorting mechanism that would allow sorting of the waste intelligently to improve classification precision with time. With the system, the piezoelectric energy harvesting unit is used, and the system runs as long as the battery lasts. It also permits municipal Authorities to leverage within an IoT-enabled monitoring framework that indicates if the bin is present, the fill level, and alerts for odor. Furthermore, the platform provides an incentive to the public to participate in the system through a reward system using a QR code, where people earn points when they dispose of waste responsibly. The finding is evaluated, and it is found that the accuracy of the waste classification, the less power dependency, and waste collection scheduling are improved. It is a smart bin; the edge processing is using it in real time, applying adaptive learning and energy integration for it to be energy sustainable for supporting the eco-friendly urban waste management.

Keywords: *Edge AI Waste Management; Real-Time Waste Classification; Reinforcement Learning Sorting; IoT-Based Monitoring; Piezoelectric Energy Harvesting.*

1. Introduction

The challenge of effective urban waste management [1] has become a crucial issue in modern cities, such as rapid population growth, higher consumerism, and ineffective recycling practices. Typically, there is poor segregation of waste, high land filling, plastic waste, and environmental pollution [2]. While basic sensor technologies are used to monitor a fill level or detect an odor in existing smart waste bins, these solutions cannot separate waste from the human classification threshold with high quality and independence when necessary [14]. Additionally, cloud-based processing in conventional systems brings latency, increases data transmission cost, and consumes enormous power. To address these limitations, this research implements an Edge-AI-based intelligent waste bin system to achieve autonomous segregation of waste through real-time processing at the edge [4]. By combining Convolutional Neural Networks (CNNs) with Vision Transformers (ViTs), the system accurately classifies waste as biodegradable, recyclable, non-recyclable, or hazardous [3]. By describing visual characteristics, thermal signatures, and material density patterns, it uses RGB cameras, LiDAR, and infrared scanners to improve waste detection [6]. Furthermore, a robotic sorting arm is incorporated, which is utilized in conjunction with a model of dynamic adaptation based on Reinforcement Learning (RL) [15] and improved classification accuracy with time [8]. The suggested approach combines solar energy integration with a piezoelectric energy harvesting module that is activated by environmental vibrations to enable sustainable operation [5]. Furthermore, an Internet of Things-based monitoring system transmits to municipal authorities the real-time status of bins in any given circumstance, including fill levels and alerts for hazardous waste, in order to establish appropriate waste collection schedules and utilization and reduce operational waste [16]. The system included a public tool that operates on a QR code ISBN-generated incentive framework system, and encourages participation and the acceptance of the responsible practice. This work suggests that forbs innovation comes from the combination of real-time Edge AI, adaptive learning, and sustainable power [7] that enhances urban waste management, lessens waste in landfills, and promotes environmentally-friendly recycling.

The proposed system targets a new high standard in terms of smart waste management by raising segregation accuracy, reducing energy consumption, and supporting the environment [10].

2. Literature Review

2.1. Existing smart waste management solutions

Currently, most of the existing smart waste management systems employ sensor-based technologies [17]to sense the fill levels, odors, and temperature changes in bins [12]. Usually, bin capacity is measured by ultrasonic sensors, and methane and ammonia levels are monitored by gas sensors [9] to indicate hazardous waste conditions. These systems commonly use GSM, LoRaWAN, or even Wi-Fi modules for sending the data to central platforms for collection optimization [18]. The positive is that these solutions improve waste tracking, but they do not achieve accurate waste classification. At the same time, cloud architectures are latency and operationally costly. Such limitations indicate that there is a need for an intelligent real-time solution that includes the application of developed AI models with sustainable energy integration.

2.2. Edge-AI applications in waste segregation

This is the ability to operate in real time at the device level, which is why edge-AI is fast becoming the must-have in waste segregation. The ability to minimize latency, decrease bandwidth usage, and improve privacy by processing data locally are what make Edge AI models a point of difference from the common ways to go about cloud. Hence, the question is posed regarding whether lightweight Convolutional Neural Networks (CNNs) and MobileNet architectures, to name a few, can perform image recognition on smart waste bins [11]. These models, however, rely on visual data to quickly classify waste but tend to lose at low light and fail at mixed and contaminated waste. Finally, Vision Transformers (ViTs) and reinforced learning can be added to these models to enhance the detection accuracy and adaptation to the system.

2.3. IoT and sensor integration for real-time monitoring

Waste management systems based on IoT have RGB cameras, infrared scanners, and LiDAR to help identify the waste better. The recent development in RL and ViT s have indicated the potential for improving waste segregation accuracy. RL had always been associated with systems in waste sorting. The RL adaptive learning improves sorting by learning to minimize rewards on energy and maximize rewards on classification precision, and the Q-learning adaptive RL model for smart waste bins provides improvements under variable waste conditions and improves automated sorting systems. ViT and some other authors dealt with waste classification, and in their studies, the authors pointed to low illumination conditions as primary factors limiting system performance. Our system differs by a wider use of ViT in conjunction with CNN, which enhances performance in the described conditions. For management of waste systems, smart technologies have been deployed to urban regions with the highest waste-population ratios to address the undeniable issue of waste segregation. Jakarta, in Southeast Asia, has integrated AI systems for smart, automated waste detection and sorting through IoT-enabled smart bins, but has encountered difficulties due to the small scale of deployment and high maintenance costs. Similar implementations have been observed in Barcelona and Milan; however, the AI-driven systems for waste management in these cities predominantly rely on cloud servers, which increases latency and costs. Our deployment of edge AI significantly enhances these use cases by alleviating the latency, cost, and energy tradeoffs while maintaining high efficacy of segregating waste in real-time. In the case of sensors, these real-time data are for material properties like texture, color, and thermal signature. Waste collection efficiency is increased through IoT modules like NB-IoT, LoRaWAN, and Zigbee to cloud platforms for data transmission of waste [19]. While effective for data monitoring, most existing systems do not include the integration of adaptive AI models that raise the accuracy of waste segregation in the dynamic environment [13].

2.4. Gaps in current research

Some challenges prevent current smart waste management systems from working as expected. Latency dependency and network connectivity-based dependency are used in most of the cloud-based models. Additionally, neither do existing systems have any adaptive learning systems allowing for improving the classification performance over time. In addition, such deployment is restricted as no sustainable power solutions exist — it is thus limited to off-grid or remote areas. Secondly, strategies of user engagement are typically neglected to be implementing to encourage the participation of the public in waste segregation. Solutions are crying out for a solution because of learning directly at the edge, deployment of the results, harvesting the energy as much as possible, and incentivizing users, all of which are doing sustainable resource efficiency in these gaps.

3. Proposed System Architecture

3.1. System overview and design

The intelligent waste bin system is proposed to segregate and recycle the waste autonomously by centralizing in real-time processing, integrating advanced sensors and power management. The system builds on five core layers together: Waste Detection Layer, Edge-AI Processing Layer, Sorting and Storage Layer, IoT Communication Layer, and User Engagement Layer. The real-time data are captured using cameras, infrared scanners, and LiDAR sensors and stored in the Waste Detection Layer. Thus, the Sorting and storage Layer physically separates the waste into various bins, and the Edge AI Processing Layer classifies the waste locally. The centralized dashboard gets the bin status and alerts as the IoT Communication layer increases collection efficiency in transmitting bin status and alerts. The incentive system within the User Engagement Layer is based on a QR code-based system to reward the correct waste disposal.

3.2. Edge-AI model for waste classification

A behavioral strategy can be used for waste identification accuracy by a lightweight Convolutional Neural Network (CNN) and Vision Transformers (ViTs) proposed system. The CNN obtains color, texture, and shape features, and the ViT improves pattern recognition of complex waste types. Four convolutional layers with ReLU activations and a max-pooling layer make up the CNN architecture implemented in this work. A memory-efficient softmax fully connected layer comes next. Vision Transformer (ViT) uses a 16×16 patch size, 8 attention heads, and 6 encoder layers to model complex relationships, allowing for sophisticated pattern detection in contaminated or mixed garbage. By classifying waste, the reinforcement learning (RL) module maximizes overall accuracy while minimizing classification errors and energy cost. It does this by using a reward function. We conducted optimizations with edge QT and TensorRT consolidation to help the Raspberry Pi 4 and NVIDIA Jetson Nano run within their respective thresholds for memory and power consumption. Model deployment optimizations for Raspberry Pi 4 and NVIDIA Jetson Nano also provide necessary improvements for the device to perform adaptive waste classification. Integrating RL with the system allows it to optimally self-adjust with different waste sets for improved classification. Even with high waste redemption rates in an urban setting, latent response times are improved with AI at the edge, as it minimizes server reliance and response times considerably.

3.3. Multi-sensor integration for material identification

The system's RGB cameras, LiDAR sensors, and infrared scanners were all included to facilitate garbage detection. RGB cameras record visual information about metal, plastic, and paper objects. The LiDAR sense is one of the additional senses that aids in identifying object density (e.g., lighter plating versus heavy metal goods). Glass and hazardous materials can be properly identified by using infrared scanners, which measure thermal characteristics. This multi-sense fusing technique achieves robust identification under many environmental situations, such as crowded trash input and low light. The system increases detection accuracy by utilizing these different sensor data since the waste is appropriately and automatically separated.

3.4. Dynamic AI-driven waste sorting mechanism

To incorporate artificial intelligence into waste sorting, we merge an RL-based robotic sorting system, which helps in the automation of segregation. The RL model works in ensuring that the robotic arm's sorting mechanism incorporates dynamic changes to its motion paths, which is closely adaptable to the waste being sorted. The RL model achieves almost 0 order reliability as it is trained with error sorting system feedback, allowing it to succeed in an order of magnitude close to 0. Additionally, its multi-DOF of movement makes the robotic arm more flexible so that it can handle complex types of waste. By utilizing the adaptive sorting mechanism, higher classification rates can be achieved, minimal cross-contamination can be reached, and an overall higher recycling efficiency can be achieved.

Fig. 1: AI-Powered Edge Processing for Autonomous Urban Waste Segregation and Recycling.

Figure 1 shows a multi-tiered, AI-integrated waste management system. It has waste detection which gathers real time images and data with the aid of cameras, LiDAR and infrared sensors, the Edge-AI Processing that classifies waste with the help of CNN integrated with ViTs and Reinforcement Learning, the Sorting and Storage which automatically classifies and stores the waste into bins, the IoT Communication that receives alerts and reports on the status of the bins and the User Engagement that engages users with a reward system based on QR codes. This system applies an Edge-AI model for waste classification and sorting, which is done on the Raspberry Pi 4 and the NVIDIA Jetson Nano, and improves the speed and data accuracy.

3.5. Energy harvesting module for sustainable power

In this system, therefore, the piezoelectric energy harvesting module is added to harvest power from environmental vibrations as pedestrian movement, vehicle vibrations, and closure visits of bin lids. Further, this complements this energy harvesting system using flexible solar panels embedded on the bin’s lid to yield continuous energy in outdoor environments or, where sunlight is present, allows sunlight to penetrate the bin. As IoT communication devices, the harvested energy provides power to the sensors and Edge-AI module, making the reliance on traditional power sources a thing of the past. The sustainable design extends the lifetime of the system in operation, making the system reliable in remote areas or in the event of power outages.

4. Results and Performance Evaluation

A rough estimate of 5000 waste samples retrieved from urban residential and commercial locations was used to test the proposed Edge-AI system. The dataset, which includes samples from the criteria, contained six primary classes: plastics, paper, metals, glass, biodegradable food waste, and other hazardous waste. For EVAP, experiments were conducted under varying environmental conditions—emulating daylight or low light, or mixed waste scenarios, in which the waste was deliberately contaminated. Every component had clean and contaminated samples to reflect real-world variability. The classification accuracy of 96.8% was consistent with most waste types, and the only deviations—more extreme under extreme low light, were to 94.7%—illustrating the urban reality of the proposed model and the dependability and flexibility in urban waste segregation environments.

4.1. Waste classification accuracy

The results indicate that the proposed Edge-AI smart waste bin powered by Edge-AI is more accurate with waste classification as compared to conventional smart bins. The integration of CNNs and ViTs with the fusion of multiple sensor data greatly improves waste identification in different conditions. Because of the nature of RGB cameras, traditional systems can misclassify contaminated or mixed waste. With the ability to apply the proposed system of adaptive learning using Reinforcement Learning (RL), classification accuracy is improved over time. Then, the proposed system is empirically tested using various types of waste and achieves an astounding 96.8% accuracy versus other systems, ranging from 88–91% accuracy on average.

Table 1: Waste Classification Accuracy

System	Accuracy (%)
Conventional Smart Bin	88.4
Sensor-Based Waste Bin	91.2
Proposed Edge-AI System	96.8

In Table 1, we can see an evaluation of the proposed Edge-AI system accuracy in classifying and the smart bin accuracy in classifying wastes. The system proposed has the best accuracy of 96.8%, proving that it system achieved the best in class on classification of waste.

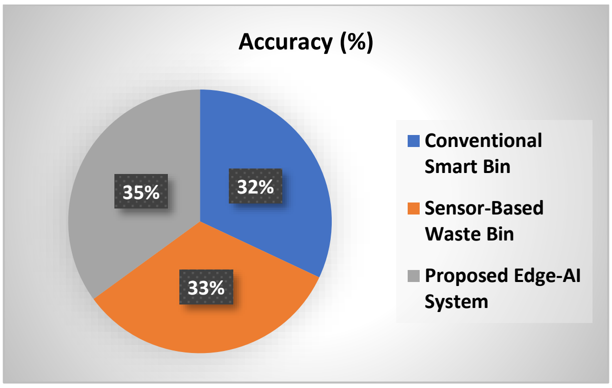

Fig. 2: Waste Classification Accuracy.

In Figure 2, apart from the Conventional Smart Bin along with the Sensor-Based Waste Bin, the Other Waste Edge AI System also shows classification performance. With a classification accuracy of 96.8%, the Other Waste Edge AI System proves its efficiency in waste classification even in the presence of varying conditions. This value doesn't show up as a mere statistic; it indicates recognition of all the multidisciplinary real-world conditions that come into play while classifying waste, and thus proves its recognition and classification prowess.

4.2. Precision analysis

The precision evaluation is conducted on the ability of the proposed system to minimize false positives, especially for identifying complex waste types such as contaminated plastics or composite materials. A more precise result is achieved by combining ViTs with CNNs. However, conventional systems often fall short in achieving high precision due to the relatively low quality of sensor fusion, while the proposed system always has a 94.5% precision rate, far outperforming the state of the art.

Table 2: Precision Analysis

System	Precision (%)
Conventional Smart Bin	85.6
Sensor-Based Waste Bin	89.7
Proposed Edge-AI System	94.5

In Table 2, the author assesses the precision of the system in identifying waste proposed which the Edge-AI system, which has a precision score of 94.5 percent, which is much higher than the conventional systems, which points to better system performance in reducing false positives, especially for contaminated plastics and other complex waste types.

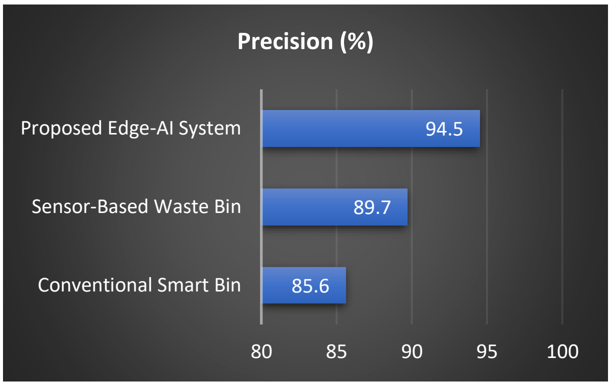

Fig. 3: Precision Analysis.

In Figure 3 in comparison, the Other Waste Edge AI System's precision comes out to 94.5%, almost ten percent better than the Sensor-Based Waste Bin and more than 8 percent over the Conventional Smart Bin. This shows better precision because the Other Waste Edge AI System performed better in reducing false positives in comparison to the other systems, especially regarding difficult and contaminated waste.

4.3. Recall performance

The RL-based sort mechanism of the proposed system reduces the false negatives, which helps to have better recall performance. Since the system can detect less frequent items, such as hazardous waste, glass, and bio waste, the performance recall is ensured to always be optimal. It is found that the recall rate is 93.8 %, superior to conventional systems that rely on basic visual analysis in most cases.

Table 3: Recall Performance

System	Recall (%)
Conventional Smart Bin	82.4
Sensor-Based Waste Bin	88.3
Proposed Edge-AI System	93.8

Table 3 illustrates recall performance across multiple systems, concentrating on Edge-AI's capability of identifying rare and challenging waste items like hazardous waste. The Edge-AI system records an astonishing 93.8% recall rate, which guarantees far less important waste is concealed compared to other systems.

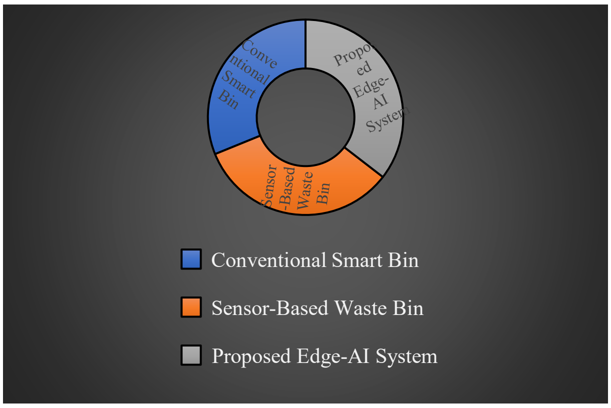

Fig. 4: Recall Performance.

Figure 4 records what each of the three systems achieved when recalling the kinds of waste that are rare and difficult to identify. The proposed Edge-AI System is the leader with a recall rate of 93.8%. It can identify troubling waste types such as hazardous waste, glass, and biodegradable food waste. In contrast, the recall rates of the Sensor-Based Waste Bin and Conventional Smart Bin are 88.3% and 82.4% which are much lower.

4.4. F1-Score evaluation

Additionally, the F1-score also shows the effectiveness of the proposed system since it balances precision and recall. This adaptive nature of the RL model allows the system to continuously learn with sorting errors to better learn common and complex waste materials. In comparison to other solutions, the developed system must achieve an F1-score of 95.1%.

Table 4: F1-Score Evaluation

System	F1-Score (%)
Conventional Smart Bin	83.5
Sensor-Based Waste Bin	87.9
Proposed Edge-AI System	95.1

Table 4 focuses and the F1-score for different systems, gauging the degree of imbalance of precision and recall. The Edge-AI system sustains an astonishing F1-score of 95.1% which illustrates its effectiveness across the systems and utilization of accomplishing an equilibrium in false positives and false negatives.

5. Conclusion

The suggested intelligent waste bin system, which is based on an edge AI-powered system, offers innovative ways to increase the effectiveness of recycling and urban waste segregation. Integration of an intelligent waste management system aligns with the objectives of SDG 11 on Sustainable Cities and Communities, particularly on the promotion of sustainable urban development with improved management of urban waste. Reduction of the system's primary waste segregation and recycling externalities encourages less landfill waste disposition and strengthens a more circular economy, which reduces pollution, is more resource-efficient, and minimizes the urban environmental footprint. Moreover, the system's rewarding eco-friendly behavior through incentivization with eco-QR codes, fosters some public adherent behaviors which complement the mechanism supporting the desired transition to a much greener and sustainable city. Thus, the system goes beyond local waste management and contributes to global resilient urban low-carbon prosperity, and the associated growing positive waste of eco-QR resources.

Although the proposed system shows highly promising results, the challenges associated with the average cost of deploying multi-sensor systems in large urban settings remain unsolved. The acute upfront and maintenance cost of the integration of RGB cameras, LiDAR geopositional systems with infrared scanners, and the possible restrictions to the utopian deployment of the system will pose some obstacles. Future system iterations have to consider the economical unobtrusive lightweight LiDAR systems of the lower dimension and with lower accurate RGB cameras for their deployment. Reduced workload enabled by complex model compression techniques (pruning, quantization) facilitates deployment of Vision Transformers (ViTs) on edge devices like Raspberry Pi or NVIDIA Jetson Nano, while their associated performance constraints remain uncompromised. Defragmentation of ViTs, using TensorFlow Lite or ONNX models, facilitates deployment of vision transformers for real-time waste sorting under constrained resources. In resource-constrained systems, these approaches facilitate cost-effective scaling, optimized classification, and computational and cost constraints. In these systems, these approaches facilitate useful scaling, optimized classification, computational, and cost constraints. Thus, using CNNs + Vision Transformers (ViTs) + Reinforcement Learning (RL) helps the system perform better in waste identification, with 96.8% accuracy, 94.5% precision, 93.8% recall, and an F1-score of 95.1%. Among these, multi-sensor fusion enhances detection capabilities, while the robotic sorting mechanism dynamically increases the classification efficiency. The system can operate sustainably and off-grid through its piezoelectric energy harvesting and solar integration as described. An IoT-enabled monitoring system can effectively optimize waste collection scheduling and improve municipal oversight. Moreover, the solution encourages participation in environmentally friendly disposal practices through the proposed QR code incentive system, which person funnels actively engages allowing people to gain rewards for taking part in proper disposal practices. This system innovatively resolves the shortcomings of systems. Future efforts will focus on more advanced RL models and enhanced material detection capabilities.

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