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Original Research Article

EcoBinX: Smart AI dustbin that sorts, compresses and recycles waste automatically using machine learning and IoT

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ABSTRACT

Waste management has become one of the most pressing environmental challenges faced by modern society. Rapid urbanization and population growth have led to an increase in the volume of solid waste generated worldwide. Improper waste disposal and lack of segregation contribute to environmental pollution, inefficient recycling, and health hazards. Traditional waste collection systems rely heavily on manual segregation and monitoring, which often results in inefficient waste management practices. This paper presents EcoBinX, a smart waste management system that integrates machine learning, computer vision, embedded systems, and Internet of Things (IoT) technologies to automate waste classification, sorting, compression, and monitoring. The proposed system uses a camera to capture images of waste items, which are processed using a machine learning model trained with Python, OpenCV, and Tensor Flow. The model identifies different waste categories such as plastic, metal, paper, and organic waste using deep learning techniques. Once the waste type is detected, a microcontroller activates a servo-based sorting mechanism that directs the waste into the appropriate compartment. Additionally, the system incorporates a compression module that reduces the volume of recyclable materials to improve bin capacity. The bin is also equipped with IoT connectivity that sends real-time data about bin levels and system performance to a cloud-based monitoring dashboard. Experimental evaluation demonstrates that the proposed system achieves high accuracy in waste classification and significantly improves waste segregation efficiency. EcoBinX provides a scalable and cost-effective solution that can support smart city initiatives and sustainable waste management practices.

1. Introduction

Waste management has become an important global concern due to the rapid growth of urban populations and industrial activities [1, 2]. According to environmental studies, millions of tons of municipal solid waste are generated every year across the world [3]. Improper waste disposal not only causes environmental pollution but also affects public health and ecological balance [4, 5].

One of the primary issues in waste management is the lack of proper waste segregation at the source [6, 7]. In many urban areas, different types of waste such as plastic, metal, organic matter, and paper are disposed of in the same container. When these materials are mixed, recycling becomes difficult and inefficient [8]. As a result, a large amount of potentially recyclable waste ends up in landfills [2]. Traditional waste bins do not provide any mechanism to identify or separate waste automatically. Manual waste segregation is labor-intensive and often ignored in public spaces [3, 7]. With the advancement of Artificial Intelligence (AI) and Internet of Things (IoT) technologies, intelligent waste management systems can now be developed to automate the process of waste classification and monitoring [9, 10].

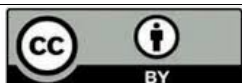
The goal of this research is to design and implement a smart dustbin system called EcoBinX that can automatically detect, sort, compress, and monitor waste using modern technologies. The system combines machine learning for image-based waste classification [11], servo-controlled sorting mechanisms [7], and IoT connectivity for real-time monitoring.

2. Literature review

Several researchers have explored the use of intelligent technologies for improving waste management systems [1]. Smart waste management solutions often combine sensors, wireless communication, and machine learning techniques to enhance waste monitoring and classification [9, 10].

Early research focused on IoT-based waste monitoring systems. These systems use ultrasonic sensors to detect the fill level of garbage bins and send notifications to waste collection authorities when the bins are full [6, 12]. While these systems improve collection efficiency, they do not address the issue of waste segregation.

Another approach involves the use of machine learning algorithms for waste classification. Researchers have



developed models that use image processing techniques to identify different types of waste materials [13, 14]. Convolutional Neural Networks (CNNs) have been widely used for image recognition tasks and have demonstrated promising results in waste classification [2].

Some studies have proposed automatic waste segregation systems using mechanical sorting mechanisms. However, many of these systems rely on predefined sensors such as metal detectors or infrared sensors, which limit their ability to classify multiple waste types [7, 15].

In recent years, AI-powered recycling stations have been introduced in several countries. These systems use computer vision and machine learning to guide users in disposing of waste correctly [16]. Although effective, these systems are often expensive and not suitable for small-scale deployment.

The EcoBinX system addresses these limitations by integrating machine learning-based classification, automated sorting mechanisms, waste compression, and IoT monitoring in a single compact system [10]. This integration makes the system suitable for educational institutions, offices, and smart city applications [17].

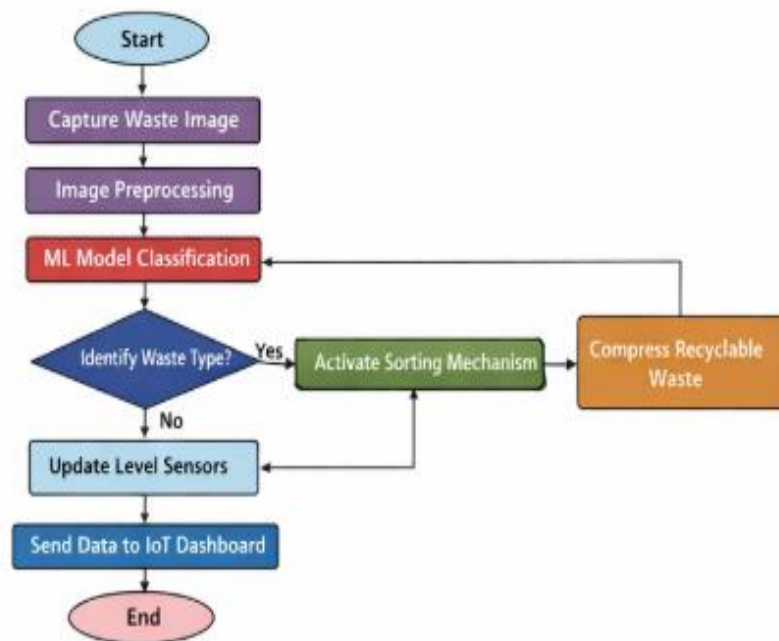
3. Proposed system

The EcoBinX system is designed to automate the process of waste segregation and monitoring. The system consists of three major functional modules:

1. Waste Detection Module
2. Sorting and Compression Module
3. IoT Monitoring Module

When a user disposes of waste into the bin, a camera positioned above the waste inlet captures an image of the object. The captured image is processed using a machine learning model that has been trained to recognize different waste categories. Once the waste type is identified, the classification result is transmitted to the microcontroller. The microcontroller then activates a servo motor that moves the sorting mechanism to direct the waste into the correct compartment.

Recyclable waste materials such as plastic bottles and paper are passed through a compression mechanism that reduces their volume. This allows the bin to store more waste before requiring disposal. The system also includes ultrasonic sensors that monitor the fill level of each compartment. This data is transmitted to a cloud server using an IoT communication module, enabling real-time monitoring through a dashboard.



4. Dataset preparation

The performance of a machine learning model largely depends on the quality and diversity of the dataset used for training [13]. For the EcoBinX system, a dataset containing images of different types of waste materials was prepared to train the waste classification model. The dataset includes common categories of municipal waste such as plastic, paper, metal, and organic waste [18]. These categories were selected because they represent the most frequently generated waste types in residential and public environments [2].

To build the dataset, images were collected from publicly available waste image repositories, environmental research datasets, and open-source platforms such as Kaggle [19]. Additional images were captured manually using a camera to

simulate real-world waste disposal conditions. This approach ensured that the dataset contained a variety of lighting conditions, object orientations, and background variations, making the model more robust for practical deployment [13].

Each image in the dataset was manually labelled according to its waste category. Proper labelling is essential because supervised machine learning algorithms rely on labelled data to learn patterns and relationships between input images and output classes [11]. The labelled dataset was organized into separate directories corresponding to each waste category.

Before training the model, several pre-processing steps were applied to the dataset to improve model performance. All images were resized to a standard resolution of 224×224 pixels, which matches the input requirements of most

convolutional neural network models [14]. The pixel values of the images were normalized to a range between 0 and 1 to ensure consistent input values for the model. Noise reduction techniques and basic image filtering were also applied to remove irrelevant background artifacts [20].

To increase the diversity of the dataset and prevent overfitting, data augmentation techniques were used. These techniques include image rotation, horizontal flipping, zooming, and brightness adjustments [21]. Data augmentation artificially expands the dataset and helps the model generalize better to unseen data. The prepared dataset was then divided into three subsets:

- Training dataset (70%) used for training the machine learning model
- Validation dataset (15%) used for tuning model parameters during training
- Testing dataset (15%) used to evaluate the final performance of the model

This structured dataset preparation process ensures that the machine learning model used in the EcoBinX system can accurately classify different types of waste materials under varying conditions [13].

5. Machine learning model

The EcoBinX system uses a machine learning-based image classification model to identify different types of waste materials automatically [11]. The objective of the machine learning model is to analyse images captured by the camera module and classify them into predefined waste categories such as plastic, paper, metal, and organic waste.

For this purpose, a Convolutional Neural Network (CNN) architecture was used. CNN models are widely used in computer vision applications because they are capable of extracting meaningful spatial features from images [14]. The CNN model learns to recognize patterns such as texture, shape, and colour that help distinguish different types of waste materials.

The machine learning model consists of several layers that work together to perform classification. The first layers of the network are convolutional layers, which apply multiple filters to the input image to extract important features. These filters detect edges, shapes, and patterns that are useful for identifying waste objects [13].

After the convolutional layers, pooling layers are applied to reduce the spatial dimensions of the feature maps. Pooling helps decrease computational complexity and prevents overfitting by retaining only the most important features [21]. In the EcoBinX system, max-pooling operations were used to down-sample the feature maps while preserving essential information.

The extracted features are then passed to fully connected layers, which perform the final classification task. These layers combine the features learned from previous layers and map them to the output classes representing the different waste categories [11].

The output layer of the network uses a SoftMax activation function, which generates probability values for each waste class. The class with the highest probability is selected as the predicted category for the waste item [13].

The model was trained using a labelled dataset of waste images. During training, the model learns by minimizing a categorical cross-entropy loss function, which measures the difference between predicted outputs and actual labels [14]. An

optimization algorithm such as Adam optimizer was used to update the model parameters and improve classification accuracy.

After training, the model was tested on unseen data to evaluate its performance. The trained model demonstrated high accuracy in identifying different waste categories and was integrated into the EcoBinX system for real-time waste classification [11].

By using machine learning techniques, the EcoBinX system can automatically identify waste materials without relying on manual input, making the waste segregation process more efficient and intelligent [9].

6. System architecture

Hardware Components

The EcoBinX system uses the following hardware components:

- Camera module for image capture
- Raspberry Pi or Arduino microcontroller
- Servo motors for automated sorting
- Ultrasonic sensors for bin level detection
- Compression motor mechanism
- ESP8266/ESP32 Wi-Fi module
- Power supply unit

Software Components

The software architecture includes:

- Python programming language
- OpenCV library for image processing
- TensorFlow/Keras for machine learning classification
- Arduino IDE for microcontroller programming
- Cloud platforms such as Firebase or Things Board for IoT monitoring.

7. Algorithm for waste classification

The EcoBinX system uses a machine learning-based classification algorithm to identify the category of waste items placed inside the smart bin [11]. The main objective of the algorithm is to analyse images captured by the camera and classify them into predefined categories such as plastic, paper, metal, and organic waste. The classification process involves several steps including image acquisition, pre-processing, feature extraction, and prediction using a trained machine learning model [13].

When a user disposes of waste into the bin, the camera captures an image of the object. The captured image is then processed using image pre-processing techniques to improve the quality of the input data. These pre-processing steps include resizing the image, normalizing pixel values, and removing noise [14]. After pre-processing, the image is passed to the trained machine learning model.

The model analyses the visual features of the image such as shape, texture, and colour patterns to determine the type of waste [21]. The classification result is then transmitted to the microcontroller, which activates the appropriate sorting mechanism [7]. Based on the predicted category, the sorting system directs the waste into the correct compartment [15].

The algorithm ensures that waste classification is performed automatically and efficiently, enabling real-time waste segregation in the EcoBinX system.

Pseudocode for Waste Classification Algorithm

Input: Image captured from camera

Output: Waste category (Plastic, Paper, Metal, Organic)

Step 1: Start

Step 2: Capture image from camera module

Step 3: Pre-process image

a. Resize image to required input size

b. Normalize pixel values

c. Remove noise using filtering

Step 4: Load trained machine learning model

Step 5: Extract image features using CNN layers

Step 6: Perform classification using softmax output layer

Step 7: Identify waste category with highest probability

Step 8: Send classification result to microcontroller

Step 9: Activate corresponding sorting mechanism

Step 10: End

Explanation of the Algorithm

The algorithm begins by capturing an image of the waste item using the camera module installed in the smart bin. The captured image is then pre-processed to ensure that it meets the input requirements of the machine learning model. Pre-processing improves the quality of the image and helps the model extract meaningful features.

Next, the pre-processed image is fed into the trained convolutional neural network model. The CNN layers analyse the image and extract features that represent important characteristics of the waste object. The fully connected layers then perform classification and determine the most likely waste category.

Finally, the classification result is sent to the microcontroller, which activates the sorting mechanism. The waste item is then directed into the appropriate compartment, enabling automatic waste segregation.

This algorithm forms the core of the EcoBinX system and enables intelligent waste classification using machine learning techniques.

8. Methodology

The methodology of the EcoBinX system describes the step-by-step process through which the smart dustbin performs automatic waste detection, classification, sorting, compression, and monitoring. The system combines machine learning, image processing, embedded hardware, and IoT technologies to create an intelligent waste management solution.

The working process of the EcoBinX system is divided into several stages, which together enable efficient waste segregation and monitoring.

1. Waste Input Detection

The process begins when a user places a waste item into the inlet of the smart bin. An ultrasonic or proximity sensor detects the presence of an object and activates the camera module. This ensures that the system captures an image only when waste is present, reducing unnecessary processing.

2. Image Capture

Once waste is detected, the camera module captures an image of the waste item. The image is then sent to the processing unit, such as a Raspberry Pi or computer running the machine learning model.

3. Image Pre-processing

The captured image is pre-processed before being analysed by the machine learning model. Image pre-processing

improves the quality and consistency of the input data. The pre-processing steps include:

- Resizing the image to the required input size (e.g., 224×224 pixels)
- Normalizing pixel values
- Removing noise or unwanted background elements
- Adjusting brightness or contrast if necessary

These steps help the model extract more accurate features from the image.

4. Waste Classification Using Machine Learning

After pre-processing, the image is passed to the trained Convolutional Neural Network (CNN) model. The model analyses the visual features of the waste item, including its shape, texture, and colour patterns.

The CNN model then predicts the category of the waste item, such as:

- Plastic
- Paper
- Metal
- Organic waste

The classification result is sent to the microcontroller for further action.

5. Automated Sorting Mechanism

Based on the classification result, the microcontroller activates the servo motor-based sorting mechanism. The servo motor rotates to align the waste item with the correct compartment inside the bin.

For example:

- Plastic waste → Plastic bin compartment
- Paper waste → Paper bin compartment
- Metal waste → Metal bin compartment
- Organic waste → Organic waste compartment

This automated sorting process ensures that waste is properly segregated without manual intervention.

6. Waste Compression

For recyclable materials such as plastic bottles and paper, the system includes a compression mechanism that reduces the volume of waste. A motor-driven press compresses the waste after sorting, allowing the bin to store more waste before it needs to be emptied.

This feature improves storage efficiency and reduces the frequency of waste collection.

7. Bin Level Monitoring

The system uses ultrasonic sensors to monitor the fill level of each waste compartment. These sensors continuously measure the distance between the waste surface and the top of the bin.

When the bin reaches a predefined threshold level, the system records the bin status and prepares it for transmission to the monitoring platform.

8. IoT-Based Monitoring

The EcoBinX system includes an IoT communication module such as ESP8266 or ESP32. This module transmits bin status data to a cloud-based monitoring platform.

The dashboard provides information such as:

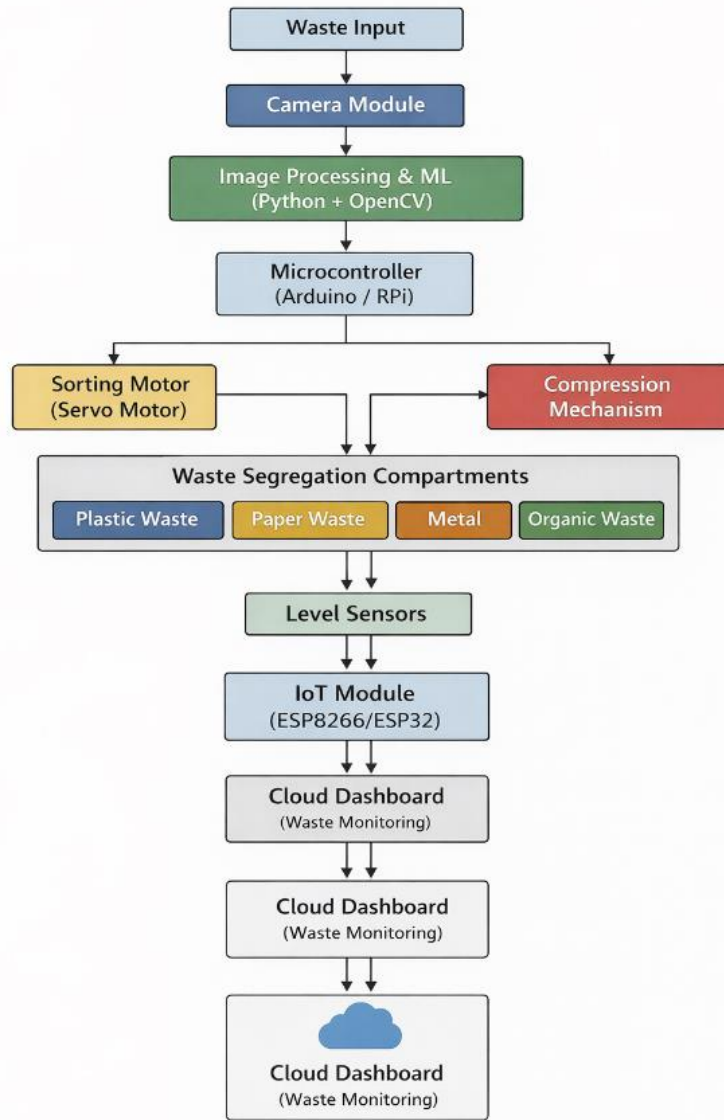
- Bin fill level
- Waste category distribution
- System alerts

This allows administrators or waste management authorities to monitor the bin remotely and schedule waste collection efficiently.

9. System Feedback and Reset

After the waste sorting and monitoring process is completed, the system resets the sorting mechanism to its default position. The system then waits for the next waste input and repeats the entire process.

The system sends real-time data to the IoT dashboard for monitoring.



Waste Sorting and Monitoring Flowchart

9. Implementation

The implementation of EcoBinX involves both hardware and software integration. The machine learning model was developed using Python and TensorFlow. A dataset containing images of different waste categories was used to train the model. The model was trained to classify waste into categories such as plastic, metal, paper, and organic materials. The image classification process was implemented using the OpenCV library, which allows for real-time image capture and pre-processing.

The sorting mechanism was controlled using an Arduino microcontroller and servo motors. Based on the classification result, the servo motor rotates to direct the waste into the corresponding compartment. The IoT module was implemented using an ESP8266 Wi-Fi module, which sends bin status data to a cloud platform. The dashboard displays

information such as bin fill level, waste type distribution, and system alerts.

10. Environmental impact

The EcoBinX system contributes to improved environmental sustainability by promoting efficient waste segregation and responsible disposal practices [2]. One of the major challenges in waste management is the mixing of recyclable and non-recyclable materials, which reduces the efficiency of recycling processes and increases the volume of waste sent to landfills [4]. By automatically classifying and separating waste materials, the EcoBinX system helps ensure that recyclable materials such as plastic, paper, and metal are properly sorted at the source [11].

Proper segregation of waste significantly reduces environmental pollution. When recyclable materials are separated early in the waste management process, they can be

reused in manufacturing industries instead of being disposed of in landfills [8]. This helps conserve natural resources and reduces the need for raw material extraction [3]. For example, recycling paper reduces the demand for wood pulp, while recycling metals decreases the need for mining activities that can damage ecosystems.

The compression mechanism integrated into the EcoBinX system further enhances environmental benefits by reducing the volume of recyclable waste [6]. By compressing materials such as plastic bottles and paper, the system increases the storage capacity of waste bins. This reduces the frequency of waste collection and transportation, which in turn helps lower fuel consumption and greenhouse gas emissions produced by waste collection vehicles [5].

In addition, the IoT-based monitoring feature of the EcoBinX system enables efficient waste management planning [12]. Real-time monitoring of bin fill levels allows authorities to schedule waste collection more effectively, preventing overflow and reducing unnecessary collection trips [10]. This contributes to more efficient use of resources and helps maintain cleaner public environments.

Overall, the implementation of smart waste management systems like EcoBinX can play an important role in supporting sustainable urban development [2]. By combining automation, artificial intelligence, and IoT technologies, the system encourages responsible waste disposal, improves recycling efficiency, and helps reduce the environmental impact of waste generation [9].

11. Performance comparison with existing systems

Several smart waste management systems have been proposed in recent years using technologies such as IoT sensors, machine learning models, and automated sorting mechanisms. These systems aim to improve waste collection efficiency and promote recycling. However, many existing systems focus only on monitoring bin levels rather than providing complete waste segregation and management capabilities.

Traditional smart bins typically use ultrasonic sensors to detect the fill level of waste containers and send alerts when the bin is full. While this approach helps optimize waste collection routes and reduce operational costs, it does not address the problem of waste segregation at the source.

Some research systems integrate machine learning models for waste classification, which improve recycling efficiency by automatically identifying waste types. AI-based classification systems have demonstrated significant improvements in sorting accuracy compared to manual waste segregation.

Despite these advancements, many existing systems still face limitations such as high implementation costs, limited functionality, and lack of integrated monitoring features.

The proposed EcoBinX system improves upon these approaches by combining multiple functionalities within a single system. It integrates machine learning-based waste classification, automated sorting mechanisms, waste compression, and IoT-based monitoring, making it a comprehensive solution for smart waste management.

12. Limitations of the system

Although the EcoBinX system demonstrates promising results, there are some limitations that must be considered. The accuracy of the machine learning model may be affected by variations in lighting conditions, image quality, and the

appearance of waste objects. Additionally, complex waste materials that contain multiple components may be difficult to classify accurately. Mechanical limitations of the sorting mechanism may also affect the system's performance if waste objects are irregularly shaped or too large. Future research can focus on improving the robustness of the classification model and enhancing the mechanical design of the sorting system.

13. Results and discussion

The performance of the EcoBinX system was evaluated through several experiments. The machine learning model was trained using a dataset of waste images collected from publicly available sources. The model achieved an average classification accuracy of approximately 90% under controlled conditions. The automated sorting mechanism successfully directed waste into the appropriate compartments based on classification results. The compression module reduced the volume of recyclable waste by approximately 50%, allowing the bin to store more waste before requiring disposal. The IoT monitoring system provided real-time updates about bin status, enabling efficient waste management, and reducing the risk of overflowing bins.

14. Advantages

The EcoBinX system provides several benefits:

- Automatic waste segregation
- Improved recycling efficiency
- Reduced environmental pollution
- Real-time monitoring of waste bins
- Increased storage capacity through compression
- Reduced human effort in waste management

15. Applications

The proposed system can be deployed in various environments such as:

- Educational institutions
- Corporate offices
- Public parks and transportation hubs
- Shopping malls
- Smart homes
- Smart city waste management systems

16. Future scope

The EcoBinX system demonstrates the potential of integrating machine learning, automation, and IoT technologies for intelligent waste management. Although the current system provides automated waste classification, sorting, compression, and monitoring, several improvements and enhancements can be implemented in the future to further increase its efficiency and usability.

One important future enhancement is the integration of advanced deep learning models to improve the accuracy of waste classification. More complex neural network architectures and larger datasets can help the system recognize a wider variety of waste materials, including mixed or partially damaged objects. This will enable the system to perform more reliable classification in real-world conditions.

Another possible improvement is the integration of a mobile application for remote monitoring and management of the smart bin. A mobile interface could allow administrators to receive notifications when bins reach their capacity, monitor

waste generation statistics, and schedule waste collection more efficiently.

The EcoBinX system can also be enhanced by incorporating solar-powered energy systems. Using renewable energy sources would reduce the system's dependence on external power supplies and make it more suitable for outdoor environments such as parks, streets, and public spaces.

Future versions of the system may include robotic arms or advanced mechanical mechanisms for handling complex waste items that may not easily pass through the current sorting mechanism. This would further automate the waste segregation process and increase the system's capability to handle a broader range of waste materials.

Additionally, integrating data analytics and predictive algorithms can help analyze waste generation patterns over time. This information could be used by municipal authorities to optimize waste collection schedules and improve overall waste management strategies.

17. Conclusions

This research presented EcoBinX, a smart waste management system that integrates machine learning, IoT, and embedded technologies to automate waste classification, sorting, compression, and monitoring. The system demonstrates how modern technologies can be applied to address environmental challenges related to waste management.

The results show that EcoBinX can significantly improve waste segregation efficiency and reduce environmental pollution. With further development and deployment, systems like EcoBinX can contribute to the development of cleaner and more sustainable cities.

Authors' contributions

All authors contributed equally to the conception, design, data analysis, interpretation of results, and preparation of the manuscript. All authors reviewed and approved the final version of the manuscript for publication.

Conflicts of interest

The author declares no conflict of interest.

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Data availability

No new data were created.

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