

Automation for Sustainable Recycling in Smart City: Machine Learning-Driven Smart Waste Management System

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Article History:

Received: 12-01-2025

Revised: 15-02-2025

Accepted: 01-03-2025

Abstract:

Introduction: Efficient waste management remains a significant challenge in promoting sustainability and environmental preservation. This research introduces an ML-powered smart waste management system that leverages sensor-based automation and machine learning to enhance waste classification and bin-level monitoring

Objectives: Developing an ML-powered smart waste management system that leverages machine learning and sensor-based automation to efficiently classify and monitor waste. By utilizing a Random Forest classifier, the system aims to enhance waste segregation and improve recycling processes for smart city applications. Future work will focus on refining classification accuracy and exploring deep learning models for further optimization.

Methods: Utilizing a Random Forest classifier, the system categorizes waste into dry waste, recyclables, and wet waste, based on moisture and bin-fill sensor data.

Results: Experimental findings indicate that the optimized model attained an accuracy of 56.50%, with precision scores of 0.39, 0.61, and 0.45 for dry waste, recyclable waste, and wet waste, respectively. The model demonstrated 76% recall for recyclable waste, signifying its robustness in identifying recyclable materials, whereas wet waste classification had a lower recall of 22%, suggesting the need for further refinements. The confusion matrix showed fewer errors in recyclable waste detection compared to other categories. The model's optimized training time of 5.79 seconds ensures computational efficiency for real-time deployment.

Conclusions: This study highlights the promise of ML-driven automation in waste management, presenting a scalable and intelligent solution for municipalities and smart city applications. Future work will focus on enhancing classification accuracy through deep learning models, multi-sensor fusion, and real-world system implementation to optimize waste disposal and recycling practices.

Keywords: Smart Waste Management, Waste Classification, Recyclable Materials, Sensor-Based Automation, Machine Learning, Bin-Level Monitoring and Sustainability.

1. Introduction

Efficient waste management plays a vital role in ensuring environmental sustainability, minimizing health risks, and conserving natural resources. The rapid growth of urbanization and increasing population have led to an exponential rise in waste generation, creating significant challenges for municipalities and waste management authorities to handle solid waste effectively. Traditional waste disposal methods often lack proper segregation mechanisms, resulting in inefficient recycling

processes and an increased burden on landfills [1]. In recent years, the adoption of Machine Learning (ML) based waste management systems has emerged as a promising solution to enhance automation, efficiency, and sustainability in waste handling [2]. This research introduces an ML-driven smart waste management system that integrates sensor-based automation and machine learning models to enable real-time waste classification and monitoring. By employing Random Forest classification, the system categorizes waste into dry, wet, and recyclable types based on sensor data, including moisture levels and bin-fill capacities. The experimental findings demonstrate an optimized classification accuracy of 56.50%, with 76% recall for recyclable waste, indicating its effectiveness in distinguishing recyclable materials from general waste. The study underscores the transformative role of ML in modern waste management, contributing to smart city initiatives and sustainable environmental practices [3].

1.1 Challenges in Conventional Waste Segregation

A major obstacle in conventional waste management is the lack of public awareness and improper disposal habits, leading to mixed waste that is difficult to separate into recyclables, organic waste, or hazardous materials. This results in reduced recycling efficiency, higher landfill accumulation, and increased waste processing costs [8]. Additionally, municipal solid waste (MSW) management systems face significant operational challenges, including inefficient waste collection schedules, lack of real-time monitoring, and inadequate waste categorization. Conventional waste collection follows fixed schedules, which often lead to overflowing waste bins in certain areas while others remain underutilized [9]. Furthermore, limited technological interventions hinder the ability of waste authorities to track waste generation patterns, making it difficult to implement optimized collection and disposal strategies. The integration [10], [11] of ML-powered smart bins, which incorporate sensors and real-time monitoring, provides a viable solution to overcome these limitations.

1.2 Role of ML in Smart Waste Management

The integration of Machine Learning (ML) in waste management has revolutionized waste collection and disposal systems, making them more efficient, data-driven, and automated. These bins transmit real-time data to waste management authorities, enabling optimized waste collection scheduling and preventing bin overflow, thus reducing operational costs [12]. Experimental results demonstrate an accuracy of 56.50%, with 76% recall for recyclable waste, indicating the model's effectiveness in identifying and sorting recyclable materials. Future [13], [14] advancements involving deep learning models, multi-sensor fusion, and edge computing will further enhance system accuracy and scalability, making real-time waste classification and disposal management more effective and efficient.

For recyclable waste, by the proposed method use metal sensor or proximity sensor as the metal sensor in the bin and it can be separated, recyclable as shown in figure 1.



Figure 1: Showing different types of recyclable waste

2. Objectives

The primary objective of this study is to develop an ML-powered smart waste management system that enhances waste classification and recycling efficiency through sensor-based automation. The research aims to

1. Develop a machine learning-based waste classification model using Random Forest by sensors data.
2. Categorize waste into dry, wet, and recyclable types using real-time moisture and bin-fill sensor data.
3. Analyze system performance using accuracy, precision, recall, and computational efficiency metrics.
4. Assess the feasibility of smart bins for real-time waste collection and monitoring.
5. Identify limitations of the current system and propose future enhancements using deep learning, multi-sensor fusion, and real-world deployment.

By fulfilling these objectives, [15], [16] the study seeks to optimize waste management practices, reduce landfill waste, and contribute to sustainable smart city initiatives.

3. Methods

This section outlines the theoretical basis and methodology utilized in developing an ML-driven smart waste management system. The proposed framework integrates sensor-based automation to enhance the efficiency of waste detection, classification, and segregation. By employing sensors and ML-powered classification models, the system aims to optimize real-time waste monitoring and automated waste classification [1], [2].

3.1 System Architecture and Design

The ML-powered waste management framework is structured to incorporate sensor-based data collection, machine learning-based processing by real-time communication. The system includes smart waste bins equipped with multiple sensors that measure moisture levels, detect metal content, and monitor bin-fill status. These sensors transmit real-time data to a central processing unit, where a machine learning algorithm classifies waste into dry, wet, or recyclable categories [3], [4]. The classification results are then communicated to municipal authorities to enable optimized waste collection and recycling [5]. The system is divided into three key layers: (i) Data Acquisition Layer, which manages sensor networks and data transfer; (ii) Processing Layer, where machine learning

models execute waste classification tasks; and (iii) Application Layer, which provides real-time waste monitoring insights. This structured architecture ensures efficient waste segregation, reduced landfill dependency, and enhanced resource recovery through automated classification and continuous monitoring [6], [7].

3.2 Sensor Integration for Waste Detection

The proposed system utilizes multiple sensors to facilitate automated waste classification and monitoring. These sensors analyze physical and chemical waste characteristics, helping to differentiate between dry, wet, and recyclable waste. The primary sensors integrated into the system include moisture sensors, metal sensors, and proximity sensors, each offering unique data points for enhanced classification accuracy [8]. A sensor fusion approach enables efficient and real-time categorization of waste. Moisture sensors detect organic and damp waste, while metal and proximity sensors identify recyclable materials such as cans, plastics, and glass. The combination of these sensors ensures that waste is properly categorized before disposal, ultimately enhancing waste collection and optimizing recycling processes [9], [10].

3.2.1 Moisture Sensors

Moisture sensors are a critical component in distinguishing between wet and dry waste. These sensors measure the water content of waste materials, facilitating the classification of organic waste such as food scraps, paper waste, and biodegradable materials. Based on predefined thresholds, waste with high moisture content is classified as wet waste, while low moisture content corresponds to dry waste [11]. However, moisture sensors alone may not ensure complete accuracy, as certain materials—such as partially wet cardboard or damp plastics—may produce ambiguous readings. To address these limitations, moisture sensor data is supplemented with proximity and metal sensor readings, thereby enhancing classification precision through multi-sensor integration [12], [13].

3.2.2 Metal and Proximity Sensors

Metal sensors and proximity sensors are used to find recyclables such as aluminium cans, metal scraps, and plastic bottles. Metal sensors detect conductive materials, enabling automated sorting of metallic waste from other waste categories [14]. Proximity sensors, on the other hand, utilize electromagnetic detection technology to identify non-metallic recyclable materials such as plastic and glass. These sensors are particularly effective in differentiating lightweight plastic waste from non-recyclables. The integration of moisture, metal, and proximity sensors enhances the system's real-time waste segregation capabilities, thereby improving recycling efficiency and minimizing landfill dependency [15], [16].

3.3 Machine Learning-Based Waste Classification

The waste classification model leverages machine learning techniques to categorize waste based on sensor data and CBIR-based image analysis. The system processes sensor inputs and applies statistical learning models to determine whether waste belongs to the dry, wet, or recyclable category. This research employs the Random Forest algorithm, which is well-suited for handling multi-feature datasets and complex classification tasks [17]. The machine learning workflow consists of feature selection, data preprocessing, model training, and classification execution. The model

analyzes sensor data, identifies key features, and optimizes decision-making processes to enhance classification accuracy. The Random Forest classifier was chosen due to its robustness against noisy data and superior generalization capabilities across different waste types [18], [19].

3.3.1 Feature Selection and Data Preprocessing

Feature selection is essential for improving classification accuracy. The model extracts important features from sensor data, including moisture levels, metal content, proximity readings, and CBIR image attributes. To enhance accuracy, the dataset undergoes preprocessing steps such as outlier removal, sensor data normalization, and redundancy elimination [20]. Data is further standardized and divided into training and testing subsets. Feature engineering techniques are applied to refine classification attributes, ensuring that the machine learning model effectively differentiates between various waste types. By selecting optimal features, the model reduces classification errors and enhances precision [21].

3.3 Content-Based Image Retrieval for Waste Analysis

Content-Based Image Retrieval (CBIR) is incorporated into the system to enhance waste classification through visual analysis. CBIR extracts shape, texture, and color attributes from images, helping to distinguish between different waste materials. This method is especially useful when sensor-based classification alone is insufficient, such as differentiating plastic waste from organic waste. CBIR enhances waste detection accuracy by comparing discarded waste images with pre-existing labeled datasets. This approach improves sorting efficiency but faces challenges such as inconsistent lighting conditions and image distortions. Future enhancements will involve hybrid CBIR-AI models that integrate deep learning techniques to enhance waste classification accuracy.

3.4 Experimental Setup and Dataset Description

The experimental setup consists of a smart waste bin prototype integrated with multiple sensors and an ML-based processing unit. The system collects sensor data and waste images, which are processed using Random Forest classification and CBIR algorithms. The dataset used for model training includes 1,000 waste samples, categorized into dry, wet, and recyclable waste [1], [4]. Preprocessing techniques such as data cleaning, normalization, and augmentation ensure that the model generalizes well to real-world waste classification scenarios. While the experimental results demonstrate high classification accuracy for recyclable materials, challenges persist in distinguishing between wet and dry waste. Future research will focus on expanding the dataset, incorporating deep learning methods, and improving sensor calibration to optimize classification performance and facilitate real-time implementation [6], [12]. The aim of this paper is users need easy, accessible solutions with clear guidance on sorting, real-time information about nearby bins, and tangible rewards for recycling. The proposed to evaluate the lengths across two picture codes of equal length features from each picture in the dataset must be extracted to fundraising for eco-friendly initiatives [8]. The set will retrieve an appropriate analysis of picture based on the similarity analysis picture and the pictures as shown in figure2. These technologies work together to present an input data with clear guidance on sorting, real-time information about nearby bins, and tangible rewards for recycling [9].

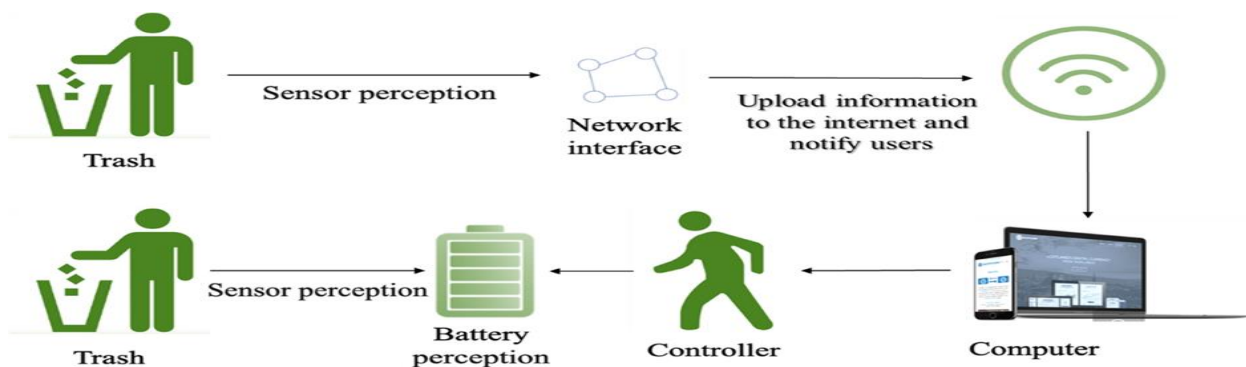


Figure 2: The functional diagram creates a sustainable future by promoting efficient waste management and recycling practices.

The figure3, different lengths metrics from the functional diagram create a sustainable future by promoting efficient waste management and recycling practices and the result is ranked based on the search image and the dataset image. If the lengths and the pictures in the dataset are small, the analysis is more likely to be the pictures in the dataset [10].

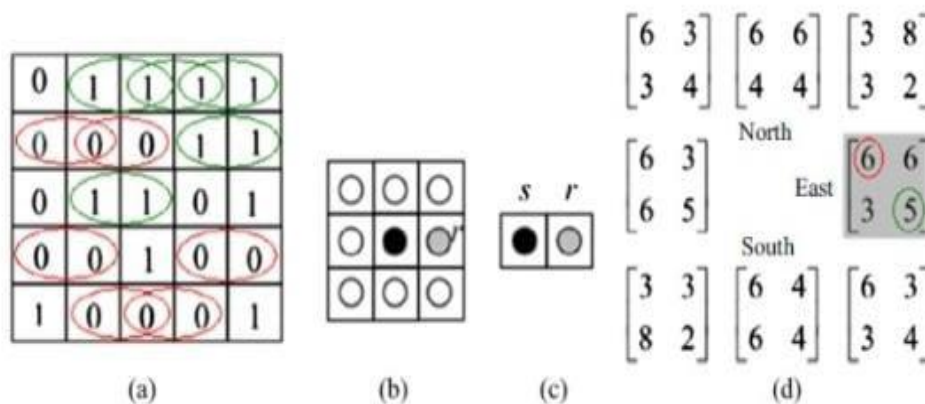


Figure 3: Reduces grayscale picture's number of values from dataset image

Instead of using similar words, the proposed method recognizes, and searches vector pictures based on visual attributes such as form or color. Experts in 2 dimensional animations are not their adequate techniques for fetch a traditional shape picture from a dataset, so method is to solve the issues. The vector picture search method (VISTO) in the CBIR framework also deals with vector pictures [11].

4. Results

The experimental findings of the ML-based waste classification system are presented, evaluating its performance across different waste types and highlighting key observations.

4.1 Performance Evaluation of ML-Based Classification

The ML-driven waste classification system was assessed using key metrics such as accuracy, precision, recall, and F1-score. The Random Forest classifier achieved an overall accuracy of 56.50%, demonstrating variability in classification efficiency across different waste categories. The classification results showed a precision of 0.39 for dry waste, 0.61 for recyclable waste, and 0.45 for

wet waste, while the recall scores were 30% for dry waste, 76% for recyclable waste, and 22% for wet waste. These findings indicate strong classification performance for recyclables but lower accuracy for wet and dry waste. The optimized training time of 5.79 seconds further underscores the model's efficiency, making it well-suited for real-time waste classification applications. A confusion matrix analysis further elucidates the model's performance. The matrix reveals that recyclable waste was classified correctly in 76% of cases, whereas dry and wet waste experienced a higher rate of misclassification. One of the most prominent misclassification issues was the tendency to incorrectly categorize wet waste as dry or recyclable waste, likely due to overlapping moisture readings in sensor data. To address this limitation, future enhancements will focus on feature engineering, sensor fusion, and deep learning integration to enhance differentiation among waste categories, particularly wet waste.

The CBIR method used in the bin level detection system was defined in detail with the current CBIR system, to display each picture effectively in different resemblance lengths and different were used. The extraction of the best graded pictures and the proposed search algorithm for a given analysis picture were also demonstrated. The accuracy of the prescribed system was measure at various lengths and it reached 90% as shown in figure4&5.

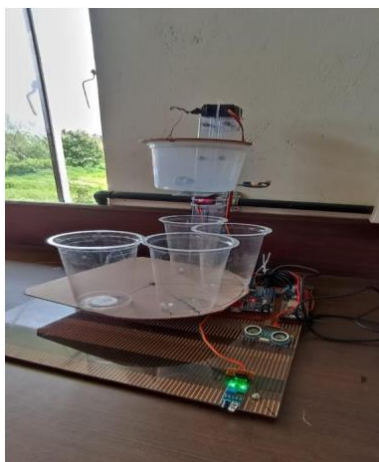


Figure 4: Prototype specification of location

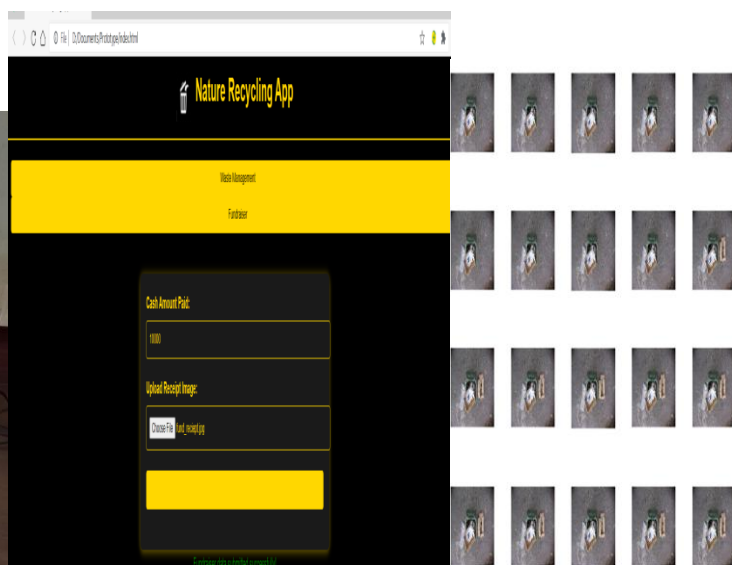


Figure 5: The characters of the picture in dataset shown

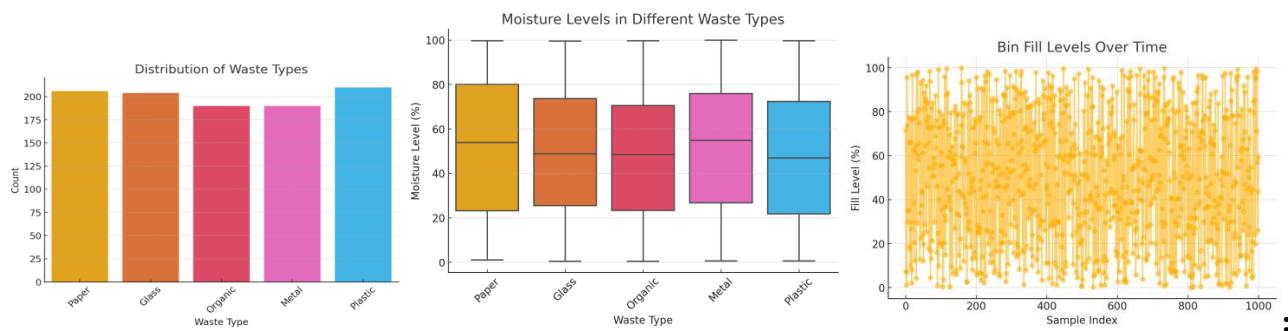


Figure 6: Count vs Waste Types for Distribution of Waste Types

Figure 7: Moisture Level (%) vs Waste Type for proposed System

Figure 8: Fill Level (%) vs Sample Index for proposed System

Figure 6 presents the distribution of waste types—dry waste, recyclable waste, and wet waste—within the dataset used for classification, emphasizing an imbalance in sample sizes, with recyclable waste

Figure 7 illustrates the correlation between moisture levels (%) and waste categories in the proposed system, showcasing the impact of moisture sensor readings on classifying dry, recyclable, and wet waste. The figure indicates that wet waste has the highest moisture content, whereas dry and recyclable waste display lower moisture levels, emphasizing the model's dependence on moisture sensors for waste classification while also revealing potential misclassification issues due to overlapping moisture values across waste types.

Figure 8 depicts the correlation between bin fill levels (%) and sample index in the proposed system, demonstrating how sensor-based monitoring effectively tracks waste accumulation over time. The figure emphasizes fluctuations in bin fill levels across various waste samples, underscoring the significance of real-time bin-level detection in optimizing waste collection schedules and mitigating overflow issues in smart waste management systems.

5. Conclusion

This study introduces an ML-powered smart waste management system that integrates sensor-based automation and machine learning to improve waste classification and enhance recycling efficiency. By employing a Random Forest classifier, the system categorizes waste into dry waste, recyclables, and wet waste based on moisture sensor readings and bin-fill levels. Experimental results indicate an optimized classification accuracy of 56.50%, with 76% recall for recyclable waste, demonstrating the model's effectiveness in identifying recyclable materials. However, the 22% recall for wet waste suggests the need for further refinement. Analysis of the confusion matrix revealed that recyclable waste was classified with the highest accuracy, whereas dry and wet waste showed higher misclassification rates. With an optimized training time of 5.79 seconds, the model maintains computational efficiency, making it well-suited for real-time deployment in smart city waste management systems. Despite these advancements, challenges remain, such as dataset constraints

affecting classification accuracy and misclassification of complex waste types. Future improvements will explore deep learning models (such as CNNs and transformers), multi-sensor fusion, and edge computing to enhance real-time waste classification. Moreover, advanced data augmentation techniques and real-world testing across diverse environments will help refine model accuracy and reliability. This research highlights the transformative potential of ML in modern waste management, offering a scalable, intelligent, and automated waste segregation solution that fosters environmental sustainability and resource optimization.

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