



IoT-Enabled Smart Waste Management System Using Computer Vision for Automated Waste Segregation

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Abstract

Efficient waste management is a critical requirement for sustainable urban development. This paper presents an IoT-enabled smart waste management framework that integrates computer vision techniques for automated waste segregation. Waste images are classified into biodegradable, recyclable, and hazardous categories using a Convolutional Neural Network (CNN). The working dataset contained approximately 30,000 labeled images organized into the three target classes; TrashNet was a confirmed public source, supplemented by publicly accessible waste images. Image preprocessing includes resizing, normalization, and augmentation, with augmentation applied to the training data. The dataset is divided into 75% training, 15% validation, and 10% testing sets. The CNN correctly classified 2,890 of 3,000 test images, giving an overall accuracy of 96.33%. Macro precision, recall, and F1-score are approximately 96.33%. The IoT component is presented as a proposed integration architecture for linking classification with bin fill-level monitoring and collection alerts. An illustrative threshold-based scheduling scenario reduces weekly trips from 20 to 13 (35%); this is a simulated/illustrative result rather than a field-trial measurement.

Keywords: IoT, Smart Waste Management, Computer Vision, CNN, Waste Segregation, Smart Cities, Deep Learning



1. Introduction

The rapid growth of urban populations and industrial activities has resulted in a substantial increase in the amount of solid waste generated every day. Managing this waste has become one of the major challenges faced by municipalities and environmental agencies. Traditional waste management practices mainly rely on manual sorting and routine collection schedules, which are often inefficient, expensive, and prone to human error. In many cases, recyclable and biodegradable materials are mixed together, reducing recycling efficiency and increasing the amount of waste sent to landfills. These issues highlight the need for a more intelligent and automated approach to waste management.

Recent advancements in Artificial Intelligence (AI), Computer Vision, and the Internet of Things (IoT) have created new opportunities for developing smart waste management systems. These technologies enable automatic identification of waste materials, continuous monitoring of waste bins, and real-time communication between devices, leading to improved efficiency and better utilization of available resources. By integrating these technologies, waste management can become faster, more accurate, and environmentally sustainable.

Computer Vision is an important branch of Artificial Intelligence that enables computers to interpret and analyze digital images. When combined with deep learning algorithms such as Convolutional Neural Networks (CNNs), Computer Vision can accurately recognize different types of waste from captured images. Instead of relying on manual sorting, the system can automatically classify waste into categories such as biodegradable, recyclable, and hazardous materials. This automated classification improves segregation accuracy, supports recycling activities, and minimizes human involvement in handling waste.

The Internet of Things complements this process by connecting physical devices, sensors, and communication modules to the internet. Smart sensors installed inside waste bins continuously measure the fill level of the bins and transmit this information to a cloud platform or monitoring system. Real-time monitoring helps waste collection authorities identify bins that require immediate attention rather than following fixed collection schedules. As a result, unnecessary vehicle movements can be reduced, fuel consumption can be minimized, and overall collection efficiency can be improved.



The proposed IoT-enabled Smart Waste Management System combines image-based waste classification with IoT-based monitoring to create an automated waste segregation framework. A camera captures images of waste items, and a trained CNN model processes these images to determine the appropriate waste category. According to the classification result, the waste is directed to the corresponding compartment. At the same time, ultrasonic sensors continuously monitor the fill level of each compartment and send status updates through an IoT communication module to a centralized monitoring platform. Whenever the waste level exceeds a predefined limit, notifications can be generated to assist waste collection personnel in planning timely collection.

The integration of AI and IoT offers several practical benefits compared with conventional waste management methods. Automated waste segregation reduces manual effort, improves the accuracy of classification, and encourages effective recycling. Continuous monitoring prevents overflow of waste bins, supports optimized collection routes, and lowers transportation costs. In addition, the system contributes to cleaner public spaces, reduced environmental pollution, and more efficient use of municipal resources.

As cities continue to expand, adopting intelligent waste management solutions becomes increasingly important for achieving sustainable urban development. The proposed system demonstrates how Computer Vision and IoT technologies can work together to improve waste segregation, monitoring, and collection. By reducing human intervention and enabling real-time decision-making, the system provides an efficient, reliable, and scalable solution for modern waste management applications while supporting the development of cleaner and smarter cities.

Objectives

1. Develop and evaluate an automated waste classification model using CNN.
2. Propose the integration of IoT sensors for real-time bin fill-level monitoring.
3. Design a cloud-based waste monitoring and analytics framework.
4. Demonstrate demand-based waste collection scheduling using fill-level information.
5. Evaluate classification performance and discuss the potential for improving operational efficiency and environmental sustainability.

Literature Review



The rapid increase in municipal solid waste has encouraged researchers to develop intelligent waste management systems that improve waste segregation, monitoring, and collection. Recent advances in Artificial Intelligence (AI), Computer Vision, Machine Learning, and the Internet of Things (IoT) have enabled the development of smart waste management solutions that reduce manual intervention while improving recycling efficiency and environmental sustainability.

One of the earliest areas of research focused on IoT-based smart waste monitoring systems. These systems use ultrasonic sensors, infrared sensors, GSM, Wi-Fi, or LoRa communication modules to monitor the fill level of waste bins and transmit the collected information to a cloud platform. Municipal authorities can remotely monitor the status of bins and optimize collection schedules based on real-time data instead of following fixed routes. Such systems reduce unnecessary fuel consumption, lower operational costs, and prevent overflowing bins. However, these solutions mainly concentrate on monitoring waste levels and do not identify the type of waste being disposed of. Similar IoT-enabled monitoring approaches have been reported in the literature [4], [5], [10].

Several researchers have also explored Computer Vision-based waste classification using deep learning techniques. Convolutional Neural Networks (CNNs) have become the most widely adopted approach because they automatically learn visual features from waste images without requiring manual feature extraction. Most studies train CNN models using publicly available datasets such as TrashNet to classify waste into categories including paper, plastic, metal, glass, cardboard, and organic waste. These methods have demonstrated high classification accuracy and significantly improve recycling by reducing human errors during waste segregation. Nevertheless, many image classification systems operate independently and do not include real-time monitoring or smart waste collection mechanisms. CNN-based waste classification has also been investigated in prior studies [11], [13], [14].

Recent studies have demonstrated that deep learning can support automated waste classification, while IoT-enabled systems can provide sensing and monitoring functions [4], [11], [13]. However, classification performance and system-level deployment performance should be evaluated separately.

Lam et al. developed an intelligent smart trash bin by integrating Computer Vision with IoT technologies. In their system, a camera captures images of waste materials, while a CNN model classifies the waste and automatically directs it to the appropriate compartment. IoT connectivity allows the bin status to be



monitored through a mobile application. Although the system achieved approximately 90% classification accuracy, its implementation was limited to a controlled prototype environment and requires further validation for large-scale deployment in public waste management systems. [6]

Recent studies have investigated the integration of **Artificial Intelligence and IoT** for developing smart city waste management solutions. These systems combine image processing, smart sensors, cloud computing, and communication technologies to automate waste collection and improve operational efficiency. IoT sensors continuously monitor waste levels, while AI algorithms assist in route optimization, predictive analytics, and waste segregation. Such integrated approaches reduce transportation costs, minimize fuel consumption, and improve resource utilization. However, many existing systems primarily emphasize smart monitoring and route optimization rather than accurate automated waste classification.

Several review papers have highlighted the growing importance of AI-driven waste management. These studies conclude that Computer Vision significantly improves waste classification accuracy, while IoT technologies enable continuous monitoring of waste bins and intelligent decision-making. They also identify several challenges, including variations in lighting conditions, limited training datasets, object overlap, sensor reliability, and computational requirements for deploying deep learning models on embedded devices. These limitations indicate the need for more robust and integrated waste management frameworks capable of performing both intelligent classification and real-time monitoring. Recent reviews also identify deployment challenges involving dataset diversity, sensor reliability, and embedded computational requirements [3], [15].

Another important direction in current research involves cloud-enabled waste management platforms. These platforms collect sensor data from multiple smart bins and present the information through web dashboards or mobile applications. Authorities can visualize waste levels, receive notifications when bins become full, and schedule waste collection accordingly. Although these systems improve monitoring efficiency, most assume that waste has already been segregated and therefore provide limited support for automated recycling processes.



Research Gap

The literature shows progress in both IoT-based monitoring and Computer Vision-based waste classification, but these capabilities are often evaluated separately. This study evaluates a three-class CNN classifier and proposes an integration workflow linking classification with fill-level sensing, cloud monitoring, and threshold-based collection alerts. The CNN results are experimentally reported; the complete IoT/cloud deployment remains proposed.

To overcome these limitations, the proposed **IoT-Enabled Smart Waste Management System Using Computer Vision for Automated Waste Segregation** combines a CNN-based waste classification model with IoT-enabled smart monitoring. The proposed system automatically classifies waste into biodegradable, recyclable, and hazardous categories while simultaneously monitoring the fill level of each waste compartment using ultrasonic sensors. Real-time notifications and cloud-based monitoring enable efficient waste collection, reduce manual effort, improve recycling efficiency, and support sustainable waste management practices in smart cities.

Proposed Methodology

Overview

The proposed IoT-Enabled Smart Waste Management System combines Computer Vision, Deep Learning, and the Internet of Things (IoT) to automate waste segregation and monitor waste bins in real time. The system is designed to classify waste into three categories—biodegradable, recyclable, and hazardous—and automatically direct the waste to the appropriate compartment.

Simultaneously, IoT sensors continuously measure the fill level of each compartment and transmit the information to a cloud-based monitoring platform.

The methodology consists of five major stages: data collection, image preprocessing, waste classification, automated segregation, and IoT-based monitoring. The overall workflow is illustrated in Figure 3.1.

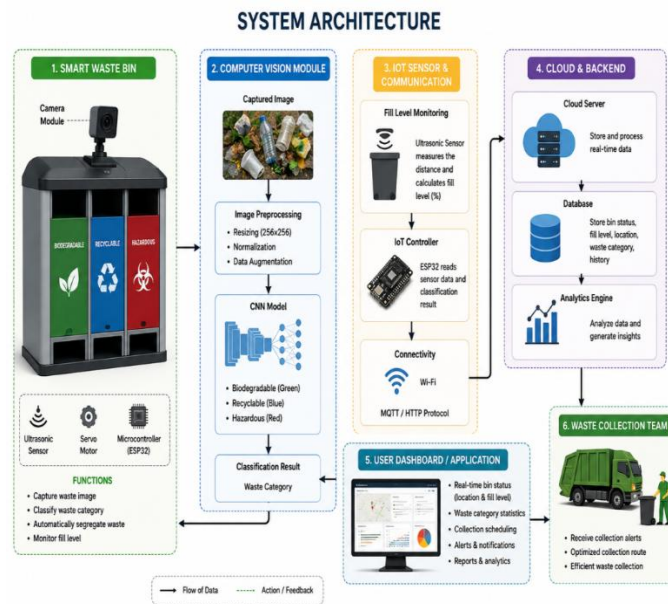


Figure 1. Detailed System Architecture of the Proposed IoT-Enabled Smart Waste Management System

Smart Waste Bin (Edge Layer)

The smart waste bin serves as the primary data acquisition unit. A camera module mounted on the bin captures images of waste items deposited by users. Ultrasonic sensors continuously monitor the fill levels of individual waste compartments, while optional temperature and gas sensors detect hazardous environmental conditions. Servo motors control the opening and closing mechanisms of dedicated compartments for biodegradable, recyclable, and hazardous waste. The collected sensor data and images are forwarded to the edge processing unit for analysis.

Edge Processing Unit

The proposed edge processing unit is based on an ESP32-class controller/edge device for interfacing with the camera, sensors, and actuators. Captured images undergo preprocessing operations such as resizing to 256×256 pixels and normalization before CNN classification into biodegradable, recyclable, and hazardous categories. Based on the classification result, a control signal can be sent to the corresponding



servo mechanism. Edge-device inference latency and resource usage were not measured in the present experiment and are identified for future prototype validation.

The CNN architecture consists of multiple convolutional and pooling layers followed by fully connected layers and a Softmax output layer. This local processing minimizes latency and enables real-time waste segregation.

Connectivity Layer

The proposed connectivity layer uses Wi-Fi for communication between the edge device and cloud infrastructure. MQTT is specified as the preferred lightweight protocol for transmitting classification results, sensor readings, and bin-status information. Secure transport can be incorporated in a future deployed prototype.

Cloud and Backend Layer

The cloud layer is a proposed component for centralized storage, processing, and management of waste-related information. A database can store classification results, sensor readings, and collection records, while MQTT-based messaging and REST services can support communication with user applications. These cloud functions were not independently field-validated in the present classification experiment.

Data Processing and Analytics Layer

This layer performs real-time data processing and advanced analytics. Incoming data streams are analyzed to generate insights related to waste generation patterns, bin utilization, and collection schedules. Machine learning models identify trends, predict bin overflow conditions, and optimize collection routes. The analytics engine also supports anomaly detection and predictive maintenance of smart bins.

User Interface Layer

The user interface layer provides access to system information through web dashboards, mobile applications, and administrative portals. Municipal authorities can monitor real-time bin status, fill levels, waste category distribution, and collection schedules. The system generates alerts and notifications through SMS, email, or mobile applications whenever bins reach predefined thresholds or require maintenance.



Operational Workflow

1. A waste item is deposited into the smart bin.
2. The camera captures the image of the waste.
3. The edge processing unit preprocesses the image.
4. The CNN model classifies the waste category.
5. Servo motors automatically direct the waste into the appropriate compartment.
6. Ultrasonic sensors measure the fill level of each compartment.
7. Sensor data and classification results are transmitted to the cloud through Wi-Fi.
8. The cloud platform stores, analyzes, and visualizes the collected information.
9. Real-time alerts and collection schedules are generated for waste management authorities.
10. Collection teams receive optimized routes and notifications for efficient waste collection.

This architecture enables automated waste segregation, real-time monitoring, reduced operational costs, improved recycling efficiency, and enhanced sustainability for smart city environments.

Dataset Description

A working dataset of approximately 30,000 labeled images was organized into biodegradable, recyclable, and hazardous classes. TrashNet was a confirmed public source, supplemented by publicly accessible waste images. An exact source-wise manifest for the supplementary images was not retained; unsupported source-wise counts are therefore not reported and this is acknowledged as a limitation.

- **Biodegradable Waste:** Food waste, leaves, fruits, vegetables, paper tissues.
- **Recyclable Waste:** Plastic bottles, paper, cardboard, metal cans, glass bottles.
- **Hazardous Waste:** Batteries, electronic waste, chemical containers, fluorescent lamps.

The collected dataset is divided into training, validation, and testing subsets for model development.

Table 1: Dataset Statistics

Category	Images
Biodegradable	10,000
Recyclable	10,000



Category	Images
Hazardous	10,000
Total	30,000

Data Preprocessing

Data preprocessing is an essential stage because image quality directly affects classification performance. The working dataset contained images from TrashNet and supplementary publicly accessible waste images with variations in lighting, background, angle, and resolution. Preprocessing was performed to make the images more uniform and suitable for CNN training.

Image Resizing

All input images were resized to **256 × 256 pixels**. This ensures that every image has the same dimension before being passed into the CNN model. Uniform image size also reduces computational complexity and improves training stability.

Image Normalization

The pixel values of each image were normalized from the range **0–255** to **0–1**. Normalization helps the model learn faster and prevents large pixel values from dominating the training process.

Noise Removal

Some images contained unwanted background noise, shadows, or unclear regions. Basic filtering techniques were applied to reduce noise and improve image clarity. This helps the model focus more on the waste object rather than the background.

Data Augmentation

Data augmentation was applied only within the training workflow to increase diversity and reduce overfitting. Validation and test images were not augmented for performance reporting. The following augmentation techniques were used:

- Horizontal flipping



- Rotation
- Brightness adjustment
- Contrast adjustment
- Zooming
- Slight shifting

These techniques help the model recognize waste objects under different real-world conditions.

Dataset Splitting

The final working dataset contained approximately 30,000 labeled images across three classes: biodegradable, recyclable, and hazardous. The data were divided into 75% training, 15% validation, and 10% testing subsets. The split was performed before augmentation so that augmented versions of training images were not introduced into the validation or test subsets. A documented perceptual-hash audit for duplicate/near-duplicate images was not retained and is acknowledged as a reproducibility limitation.

Table 2: Dataset Splitting

Dataset Portion	Percentage	Approximate Images
Training Set	75%	22,500
Validation Set	15%	4,500
Testing Set	10%	3,000

Class Label Encoding

The waste categories were encoded into numerical labels for model training:



Table 3: Class Label Encoding

Class	Label
Biodegradable	0
Recyclable	1
Hazardous	2

After preprocessing, the images were passed to the CNN model for automated classification.

Hyperparameter Configuration

The hyperparameters used for CNN training are presented in Table 4. The available record does not preserve the framework version, random seed, exact training hardware, model size, or edge-device latency; these are acknowledged as reproducibility limitations.

Table 4: Hyperparameter Configuration

Hyperparameter	Value
Input Image Size	$256 \times 256 \times 3$
Number of Classes	3
Convolution Filters	32, 64
Kernel Size	3×3
Pooling Type	Max Pooling
Dense Layer Neurons	128
Dropout Rate	0.5
Activation Function	ReLU
Output Activation	Softmax
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	50
Loss Function	Categorical Cross-Entropy



Validation Split	15%
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The Adam optimizer was employed because of its adaptive learning capability and efficient convergence. ReLU activation was used in hidden layers to improve computational efficiency, while Softmax activation was applied in the output layer to classify waste into biodegradable, recyclable, and hazardous categories. A dropout rate of 0.5 was introduced to reduce overfitting and improve model generalization.

IoT Integration and Cloud Monitoring

The proposed smart waste management architecture integrates Internet of Things (IoT) technologies with cloud computing to support real-time monitoring, automated waste segregation, and demand-based waste collection. In the present study, the CNN classification component was experimentally evaluated; the IoT/cloud subsystem described in this section represents the proposed deployment architecture and requires prototype and field validation.

IoT Hardware Components

The proposed smart waste bin includes the following hardware components for future prototype implementation:

- **ESP32 Microcontroller:** Acts as the central processing and communication unit.
- **Camera Module:** Captures images of waste materials for classification.
- **Ultrasonic Sensor:** Measures the fill level of waste compartments.
- **Servo Motors:** Automatically direct waste into appropriate bins based on classification results.
- **Wi-Fi Module:** Enables wireless communication with cloud servers.

In the proposed workflow, the camera captures an image when waste is deposited, while an ultrasonic sensor measures the fill level of the corresponding compartment.

Real-Time Data Transmission

In the proposed deployment, the edge controller can transmit the following information to the cloud platform:



- Waste category (Biodegradable, Recyclable, or Hazardous)
- Bin fill level percentage
- Timestamp of waste disposal
- Bin identification number
- System status information

The proposed communication workflow uses Wi-Fi with MQTT for lightweight IoT messaging. Security mechanisms should be configured and validated during future physical deployment.

Cloud-Based Monitoring Platform

The proposed cloud platform serves as a centralized system for storing, processing, and analyzing waste-management data. Its intended functions include:

- Storage of sensor readings and classification results
- Real-time monitoring of bin status
- Historical data management
- Generation of waste analytics reports
- Collection route optimization
- Alert generation for overflow prevention

In a future implementation, incoming data can be stored in an appropriate cloud database for analysis and visualization. The database platform was not experimentally benchmarked in the present study.

Waste Collection Optimization

One intended advantage of the proposed system is demand-based waste collection. Traditional systems may follow fixed schedules regardless of actual bin status, whereas the proposed framework can schedule collection according to measured fill levels. This collection logic is evaluated here only through an illustrative scenario rather than a municipal field trial.



When the fill level exceeds an illustrative threshold of 80%, the proposed system can generate a collection request. Potential reductions in unnecessary trips, fuel consumption, and operating cost require field measurements before they can be claimed as experimentally demonstrated benefits.

User Dashboard and Alerts

A web-based dashboard is proposed to provide access to waste-management information. Intended monitoring functions include:

- Current fill levels of all bins
- Waste category statistics
- Collection schedules
- Historical waste generation trends
- System health status

The proposed dashboard can generate alerts when a bin reaches a predefined capacity or requires maintenance; these notification functions require validation in a deployed prototype.

Benefits of IoT and Cloud Integration

The integration of IoT devices and cloud computing offers several advantages:

- Automated waste monitoring
- Reduced operational costs
- Improved collection efficiency
- Real-time decision making
- Enhanced recycling management
- Scalable smart city deployment

The proposed IoT-enabled cloud framework is intended to support continuous monitoring, analytics, and demand-based collection. The present study does not claim field-validated reductions in cost or fuel consumption; these system-level benefits require future deployment studies.

Experimental Results

The proposed CNN-based waste classification model was evaluated using accuracy, precision, recall, and F1-score on a test set of 3,000 images. The confusion matrix contains 2,890 correct predictions, giving an overall accuracy of 96.33%. Metrics were recomputed from the same test predictions. Macro-averaged precision, recall, and F1-score are approximately 96.33%, 96.33%, and 96.33%, respectively.

Table 5. Classification Performance

Metric	Value
Accuracy	96.33%
Precision (Macro)	96.33%
Recall (Macro)	96.33%
F1-Score (Macro)	96.33%

The graphical representation of the model performance is shown in Figure 2.

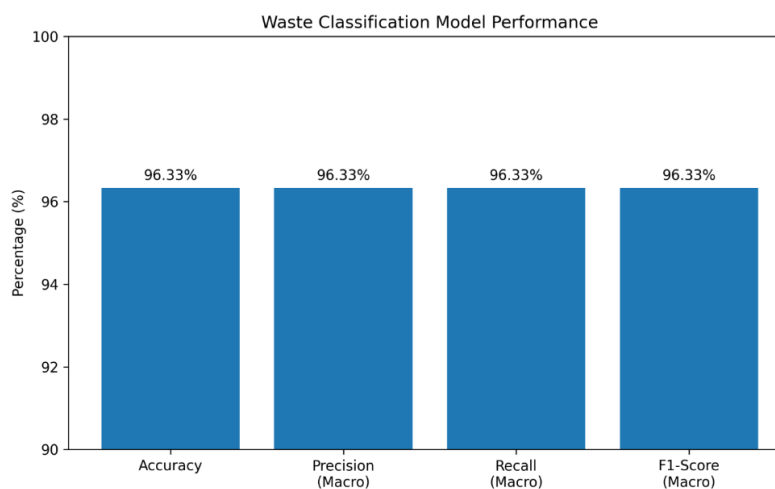


Figure 2. Classification performance of the proposed CNN model

Confusion Matrix

The confusion matrix shows that most test images were correctly classified. Hazardous waste achieved the highest recall, while a small number of biodegradable and recyclable samples were misclassified. Class-wise precision, recall, and F1-score are reported in Table 6 together with the correct-prediction counts.

Among the three classes, 960 of 1,000 biodegradable images, 955 of 1,000 recyclable images, and 975 of 1,000 hazardous images were correctly classified. Using the complete confusion matrix, the corresponding class-wise precision/recall/F1 values are approximately 96.00/96.00/96.00%, 95.98/95.50/95.74%, and 97.01/97.50/97.26%, respectively.

Table 6. Confusion Matrix

Waste Category	Correct Predictions	Total Samples	Accuracy (%)
Biodegradable	960	1000	96.0
Recyclable	955	1000	95.5
Hazardous	975	1000	97.5

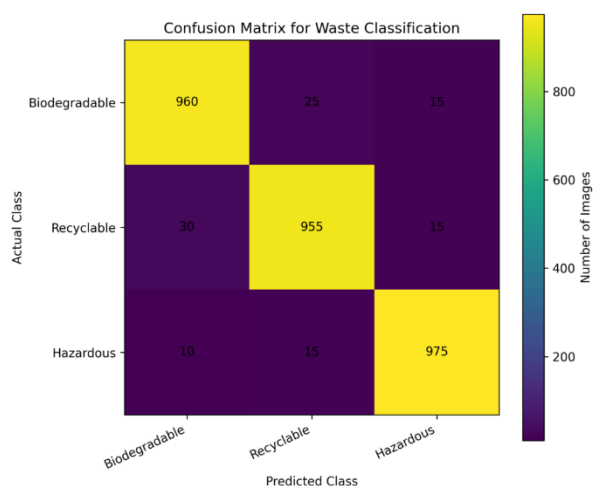


Figure 3. Confusion Matrix Showing Classification Results for Biodegradable, Recyclable, and Hazardous Waste Categories

The diagonal elements of the confusion matrix represent correct classifications, while the off-diagonal elements indicate errors. The concentration of predictions along the diagonal demonstrates strong classification performance across the three classes. The aggregate and class-wise metrics reported above are derived from this same set of 3,000 test predictions.

5.1 Collection Efficiency Analysis

The collection-efficiency analysis is presented as an illustrative threshold-based scheduling scenario, not as a field-trial result. A conventional fixed schedule of 20 trips per week is compared with an illustrative demand-based schedule of 13 trips per week when collection is triggered by an 80% fill-level threshold.

Table 7. Collection Efficiency Analysis

Parameter	Fixed-Schedule Baseline	Illustrative Threshold-Based Scenario
Collection Trips/Week	20	13
Operational Cost	Not measured	Not measured
Fuel Consumption	Not measured	Not measured
Trip Reduction	Baseline	35% (illustrative)

The illustrative reduction is $(20 - 13) / 20 \times 100 = 35\%$. Because the present study did not record a field-trial duration, deployed bin locations, measured route distance, fuel consumption, or collection cost, the 35% value should be interpreted only as a simulated/illustrative scheduling outcome rather than an experimentally demonstrated operational saving.

Conclusion

The IoT-Enabled Smart Waste Management System Using Computer Vision for Automated Waste Segregation presents an approach that combines experimentally evaluated CNN-based waste classification with a proposed IoT monitoring architecture. On the 3,000-image test set, the CNN correctly classified 2,890 images, corresponding to an accuracy of 96.33%, with macro precision, recall, and F1-score of approximately 96.33%. The IoT sensing, cloud monitoring, threshold alerts, and collection-scheduling components are presented as proposed deployment features that require future prototype and field validation. The previously reported 35% reduction in collection trips is therefore interpreted as an illustrative threshold-based scenario rather than a field-trial measurement. Future work should preserve a complete dataset source manifest, perform duplicate-safe splitting, compare established baseline/transfer-learning models, document software and hardware configurations, measure edge-device latency and resource usage, and conduct controlled multi-bin field trials.

Future Work

Future enhancements include:

1. Edge AI deployment for real-time inference.
2. Transformer-based vision models.
3. Additional waste categories.
4. Autonomous waste collection vehicles.
5. Predictive waste generation forecasting.

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