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AI-Powered Smart Waste Segregation System for Sustainable Smart Cities Using Machine Learning

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ABSTRACT: Rapid urbanization and population growth have intensified waste management challenges across modern cities. Traditional manual waste segregation is inefficient, inconsistent, and poses health risks to workers. This paper proposes an AI-Powered Smart Waste Segregation System (AISWSS) that leverages machine learning algorithms — specifically Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and Random Forest classifiers — to automate real-time classification of municipal solid waste into six categories: organic, plastic, metal, glass, paper, and e-waste. The system integrates a compact embedded camera module, a Raspberry Pi 4 processing unit, and a servo-driven mechanical segregation actuator. Trained on a dataset of 28,000 labeled waste images across diverse lighting and orientation conditions, the proposed CNN model achieves a classification accuracy of 97.4%, outperforming conventional ML baselines. The system reduces manual sorting labor by an estimated 85% and increases material recovery rates by 40%. Experimental results demonstrate robust real-time performance at 12 frames per second. This research contributes a scalable, cost-effective, and energy-efficient solution aligned with UN Sustainable Development Goal 11 (Sustainable Cities and Communities).

KEYWORDS: waste segregation; machine learning; convolutional neural network; smart city; image classification; sustainability; random forest; SVM

I. INTRODUCTION

The global generation of municipal solid waste (MSW) has reached alarming proportions, exceeding 2.01 billion tonnes per year according to the World Bank, with projections indicating a rise to 3.40 billion tonnes by 2050 [1]. In developing nations, less than 30% of generated waste undergoes proper segregation and recycling, leading to environmental contamination, groundwater pollution, and significant greenhouse gas emissions from unsegregated

landfills. Smart cities worldwide are actively seeking intelligent, automated solutions to address this crisis. Traditional waste management relies heavily on manual segregation at collection points, which is labor-intensive, error-prone, and exposes workers to hazardous materials including chemical residues, sharp objects, and pathogenic microorganisms. Conventional sensor-based sorting systems, such as near-infrared (NIR) spectroscopy and metal detectors, are cost-prohibitive for widespread deployment in low-to-middle-income urban environments, and their fixed-rule processing lacks adaptability.

Recent advances in machine learning, particularly deep learning-based image classification, offer a transformative approach to waste segregation. CNNs have demonstrated exceptional capability in recognizing visual patterns under varied conditions, making them ideal for the heterogeneous visual characteristics of real-world waste objects. However, prior studies have predominantly focused on binary classification (recyclable vs. non-recyclable) or laboratory-controlled datasets that do not reflect real deployment environments.



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This paper presents a novel AI-Powered Smart Waste Segregation System (AISWSS) that addresses these gaps. The primary contributions of this work are: (1) a six-category real-time waste classifier trained on a large, diversified image dataset with data augmentation; (2) a comparative study of CNN, SVM, and Random Forest performance on the same dataset; (3) an end-to-end hardware-software integration design deployable on edge computing platforms; and (4) an energy consumption and cost analysis validating suitability for smart city infrastructure.

The remainder of this paper is organized as follows: Section II reviews related work. Section III describes the proposed system architecture. Section IV details the dataset and methodology. Section V presents experimental results and comparative analysis. Section VI discusses real-world deployment considerations. Section VII concludes the paper.

II. RELATED WORK

Research on automated waste classification has evolved substantially over the past decade. Awe et al. [2] first demonstrated the use of CNNs for waste image classification achieving 78% accuracy on a two-class dataset. Subsequent work by Yang et al. [3] introduced the TrashNet benchmark dataset containing 2,527 images across six categories, and applied a deep residual network achieving 85.3% accuracy. However, their work did not address real-time inference on embedded hardware.

Vo et al. [4] explored transfer learning using VGG-16 pre-trained on ImageNet for waste classification, achieving 89.2% accuracy on the TrashNet dataset. While transfer learning improved convergence speed, the large model footprint (500+ MB) renders direct deployment on microcontrollers infeasible. Mittal et al. [5] proposed a lightweight MobileNetV2-based classifier with 93.1% accuracy and 17ms inference time on a standard GPU, but their evaluation did not include real-world heterogeneous waste samples.

SVM-based approaches were investigated by Chu et al. [6], combining handcrafted features — histogram of oriented gradients (HOG), local binary patterns (LBP), and color histograms — with SVM classifiers. Their system achieved 81.6% accuracy at higher inference speed, making it suitable

for resource-constrained environments. Random Forest classifiers applied to spectral features of waste materials achieved 88% accuracy in [7] but required specialized hyperspectral imaging hardware unavailable in consumer-grade cameras.

IoT-integrated waste management systems have been explored by Pardini et al. [8], who combined fill-level ultrasonic sensors with route optimization algorithms. Their system, however, lacked waste type classification capability. Misra et al. [9] proposed a smart bin with RFID-based waste tracking for corporate environments but did not address heterogeneous municipal waste categories. Recent work by Adedeji and Wang [10] proposed a deep neural network achieving 96.0% on an augmented TrashNet dataset but evaluated only offline batch processing.

The gap in the literature is the absence of a system that simultaneously achieves high classification accuracy (>95%), real-time inference on edge hardware, multi-class segregation across six waste categories, and robust performance under real-world illumination and orientation variability. The proposed AISWSS directly addresses these limitations.

III. PROPOSED SYSTEM ARCHITECTURE

A. Overview

The AISWSS comprises three tightly integrated subsystems:

(1) the Image Acquisition Module (IAM), (2) the Machine Learning Inference Engine (MLIE), and (3) the Mechanical Segregation Unit (MSU). The overall pipeline follows a real-time closed-loop design where waste objects placed on a motorized conveyor belt are captured, classified, and physically diverted to labeled collection bins. Figure 1 illustrates the system block diagram.

B. Image Acquisition Module (IAM)

The IAM consists of a Raspberry Pi Camera Module v2 (8 MP, Sony IMX219 sensor) mounted 25 cm above the conveyor belt in a custom-fabricated housing equipped with diffused LED ring illumination. The ring-light arrangement minimizes specular reflections from metallic and glass waste surfaces. A mechanical shutter, synchronized with the conveyor's photoelectric sensor, triggers image capture when a waste item enters the sensing zone, ensuring motion-free frames at a



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conveyor speed of up to 0.15 m/s. Images are captured at 640x480 resolution and passed to the MLIE in under 12 milliseconds.

C. Machine Learning Inference Engine (MLIE)

The MLIE runs on a Raspberry Pi 4 Model B (4 GB RAM, quad-core ARM Cortex-A72, 1.5 GHz). The trained CNN model is converted to TensorFlow Lite (TFLite) format and quantized to 8-bit integer precision, reducing the model footprint from 48 MB to 11.3 MB and decreasing per-frame inference time from 89 ms (FP32) to 37 ms (INT8), enabling 12+ FPS throughput. The MLIE outputs one of six class labels with an associated confidence score.

D. Mechanical Segregation Unit (MSU)

The MSU employs three high-torque SG90 servo motors configured as diverter gates at bifurcation points along the conveyor path. Based on the MLIE classification output, the appropriate gate opens within 15 ms of the inference result, directing waste to one of six labeled collection bins. A single-board microcontroller (Arduino Mega 2560) handles servo timing and interlock logic, communicating with the Raspberry Pi via UART at 115,200 baud. A watchdog timer resets the system if a classification result is not received within 500 ms.

E. Data Communication and Monitoring

The system transmits classification statistics — category, confidence, timestamp, and cumulative bin fill level — to a cloud dashboard via MQTT protocol over Wi-Fi (IEEE 802.11n). The dashboard provides real-time visualization, daily waste composition reports, and fill-level alerts for collection teams. The entire system operates on a 12 V DC supply (peak power: 18 W), suitable for solar-panel powered deployment in remote smart city nodes.

IV. DATASET AND METHODOLOGY

A. Dataset Preparation

A proprietary dataset — WasteNet-28K — was compiled for this study, containing 28,000 RGB images of waste items across six categories: Organic (4,800 images), Plastic (5,200 images), Metal (4,500 images), Glass (4,200 images), Paper (4,800 images), and E-Waste (4,500 images). Images were collected from three sources: (i) the publicly available TrashNet dataset [3] (2,527 images), (ii) original photographs captured at three municipal waste collection centers in Bengaluru, India (18,000 images), and (iii) web-scraped and licensed images from stock repositories (7,473 images). All images were taken under diverse lighting (fluorescent, incandescent, daylight, flash), orientations (0°, 45°, 90°, 135°), and backgrounds (conveyor belt, soil, floor tiles).

B. Data Preprocessing and Augmentation

Images were resized to 224x224 pixels and normalized using per-channel mean subtraction (ImageNet statistics). To address class imbalance and improve model generalization, offline data augmentation was applied generating five augmented copies per original image, including: horizontal and vertical flipping, rotation ($\pm 30^\circ$), Gaussian noise injection ($\sigma = 0.01$), brightness jitter ($\pm 20\%$), and random cropping. The final augmented dataset contains 140,000 images split into 70% training (98,000), 15% validation (21,000), and 15% testing (21,000) subsets with stratified sampling to preserve class distribution.

C. CNN Architecture

The proposed CNN architecture — WasteNet-CNN — is a custom design inspired by VGG-16 and MobileNetV2, optimized for edge deployment. The network consists of five convolutional blocks. Blocks 1–2 each contain two Conv2D layers (3x3 kernel, ReLU activation) followed by Batch Normalization and MaxPooling (2x2). Blocks 3–5 employ three Conv2D layers with increasing filter depth (64→128→256→512→512). Global Average Pooling replaces fully connected layers to reduce parameters, followed by two dense layers (512 and 128 neurons) with Dropout ($p=0.5$) and a final Softmax output layer. The total trainable parameters are 8.4 million, significantly smaller than VGG-16 (138M) while maintaining high accuracy.

D. SVM and Random Forest Baselines

For comparative evaluation, SVM and Random Forest classifiers were trained on hand-crafted feature vectors extracted from the same image set. Each image was represented by a 512-dimensional feature vector concatenating: (i) a 64-bin color histogram in HSV space, (ii) a 256-bin HOG descriptor, (iii) 128-bin LBP histogram, (iv) 64 DFT magnitude coefficients. The SVM used a radial



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basis function (RBF) kernel with $C=10$ and $\gamma=0.001$, optimized by 5-fold cross-validation. The Random Forest comprised 500 decision trees with maximum depth of 20 and the Gini impurity criterion.

Metric	CNN (TFLite)	SVM	Random Forest
Inference Time	37 ms	8 ms	21 ms
Model Size	11.3 MB	6.2 MB	18.7 MB
RAM Usage	189 MB	MB	143 MB
CPU Usage	68%	1%	74%
Accuracy	97.4%	82.3%	88.6%

TABLE II. RUNTIME PERFORMANCE ON RASPBERRY PI 4

A. Training Protocol

The CNN was trained for 60 epochs with early stopping (patience=10) using the Adam optimizer (initial learning rate=0.001, $\beta_1=0.9$, $\beta_2=0.999$) and categorical cross-entropy loss. A cosine annealing learning rate schedule was applied. Training was performed on an NVIDIA Tesla T4 GPU (Google Colab Pro+). The trained model was exported to TensorFlow Lite with full-integer quantization calibrated on a 500-sample representative dataset.

E. EXPERIMENTAL RESULTS AND ANALYSIS

a. Classification Accuracy

Table I presents the per-class precision, recall, and F1-score for the three evaluated models on the 21,000-image test set. The proposed WasteNet-CNN achieves a macro-average accuracy of 97.4%, surpassing SVM (82.3%) and Random Forest (88.6%). Per-class analysis reveals that the CNN achieves the highest gains over baselines for the E-Waste category (99.1% vs. 77.4% SVM), which contains visually complex objects such as circuit boards, cables, and batteries that require texture-level feature abstraction beyond handcrafted descriptors.

Category	CNN P (%)	CNN R (%)	CNN F1 (%)	SVM F1 (%)	RF F1 (%)	Samples
Organic	97.1	96.8	96.9	83.2	89.4	3,600
Plastic	97.8	97.5	97.6	81.7	88.1	3,900
Metal	98.2	97.9	98.0	84.6	90.2	3,375
Glass	96.4	96.9	96.6	80.3	86.5	3,150
Paper	97.3	97.0	97.1	82.9	89.0	3,600
E-Waste	99.2	99.0	99.1	77.4	87.4	3,375
Macro Avg	97.7	97.5	97.4	82.3	88.6	21,000

TABLE I. CLASSIFICATION PERFORMANCE

COMPARISON (P=Precision, R=Recall, RF=Random Forest)



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b. Inference Speed and Resource Utilization

Table II summarizes the runtime performance of each model on the Raspberry Pi 4. The quantized TFLite CNN achieves 37 ms per frame (27 FPS burst, 12 FPS sustained with I/O), exceeding the 10 FPS minimum required for the conveyor speed of 0.15 m/s. The SVM achieves faster inference (8 ms) due to its linear decision function, but its lower accuracy limits practical utility. RAM consumption for the quantized CNN (189 MB including OS overhead) fits within the 4 GB platform capacity.

c. Comparison with State-of-the-Art

Table III compares the proposed WasteNet-CNN with state-of-the-art systems from the literature. The proposed system achieves the highest accuracy (97.4%) while maintaining real-time edge inference capability. Notably, Adedeji and Wang [10] achieve 96.0% but only in offline batch mode. Our system's simultaneous optimization of accuracy, inference speed, and hardware footprint represents a unique advancement.

Study	Accuracy	Classes	Real- Time	Edge Deploy
Yang et al. [3]	85.3%	6	No	No
Vo et al. [4]	89.2%	6	No	No
Mittal et al. [5]	93.1%	6	Yes (GPU)	No
Adedeji & Wang [10]	96.0%	6	No	No
Proposed AISWSS	97.4%	6	Yes (Edge)	Yes (RPi4)

TABLE III. COMPARISON WITH STATE-OF-THE-ART WASTE CLASSIFICATION SYSTEMS

F. DEPLOYMENT AND IMPACT ANALYSIS

A. Real-World Pilot Deployment

A pilot deployment of five AISWSS units was conducted over 90 days at the BBMP Ward 68 Waste Collection Center, Bengaluru. During this period, the system processed 12,840 kg of mixed municipal waste. The manual sorting baseline (three human workers per shift) was replaced with the automated system. The pilot achieved 94.8% real-world accuracy (vs. 97.4% in lab testing), with the 2.6% gap attributed to heavily soiled or partially occluded items. No system failures due to mechanical faults were recorded; two software restarts occurred due to MQTT broker connectivity loss.

B. Environmental and Economic Impact

The AISWSS demonstrated a 40.2% improvement in material recovery rate compared to the manual baseline (68.7% recovery vs. 49.0%), primarily driven by accurate segregation of mixed plastics and e-waste that were frequently misclassified by human sorters under fatigue. Carbon footprint calculations indicate that correct diversion of 2,847 kg of organic waste to composting facilities prevented an estimated 1.14 tonnes of CO₂-equivalent methane emissions over the pilot period. The capital cost per unit (approx. INR 18,500 / USD 222) is 76% lower than commercial NIR-based sorters, and the payback period in labor savings is estimated at 14 months at Indian municipal wage rates.

C. Limitations and Future Work

The current system has the following limitations: (1) performance degrades for heavily soiled or multi-material composite items (e.g., laminated packaging); (2) the six-category schema does not cover all waste types encountered in practice (e.g., textiles, hazardous medical waste); and (3) the conveyor design requires items to be placed individually, limiting throughput for bulk waste streams. Future work will incorporate multi-label classification for composite materials, extend the category schema to twelve classes, and investigate the use of depth cameras and weight sensors as additional input modalities to improve classification of non-visually-distinct items. Integration with smart city traffic and routing systems for optimized collection scheduling is also planned.



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V. CONCLUSION

This paper presented AISWSS, an AI-powered smart waste segregation system that integrates a custom-trained CNN, a Raspberry Pi 4 edge computing platform, and a servo-driven mechanical diverter to achieve real-time, six-category waste classification. The proposed WasteNet-CNN model achieved 97.4% macro-average accuracy on the 21,000-image WasteNet-28K test set, outperforming SVM (82.3%) and Random Forest (88.6%) baselines, and surpassing all comparable published systems while enabling edge deployment. A 90-day real-world pilot in Bengaluru validated system robustness with 94.8% operational accuracy, a 40% improvement in material recovery, and an 85% reduction in manual sorting labor. At a unit cost of approximately USD 222, the AISWSS offers a scalable, economically viable pathway for sustainable waste management in smart cities, directly supporting SDG 11. The open-source release of the WasteNet-28K dataset and model weights is planned to facilitate future research in this domain.

VI. ACKNOWLEDGMENT

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