Automated Waste Classification with Tensorflow and Mobilenet: A Step Towards Sustainable Development Goal 12

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Abstract

Waste mismanagement is a critical environmental concern, with manual sorting often inefficient and prone to error. This paper presents an automated waste classification system using Convolutional Neural Networks (CNNs) and transfer learning to automatically categorize waste into classes such as plastic, glass, organic, metal, and paper. The model was trained on a combined dataset sourced from the TrashNet repository and locally collected images, with data augmentation applied to improve robustness under varying conditions. Experimental results demonstrate high classification accuracy, outperforming traditional machine learning baselines. The system was further optimized for deployment on resource-constrained devices, enabling real-time operation on platforms such as Raspberry Pi. By improving waste segregation at the source, this approach supports Sustainable Development Goal 12 (Responsible Consumption and Production) and promotes circular economy practices. Future work will focus on expanding classification categories and integrating IoT-enabled smart bin technology.

Keywords: AI, waste classification, CNN, transfer learning, SDG 12

Word Count: 140

1. Introduction

Waste generation has grown at an unprecedented rate due to urbanization, industrialization, and population expansion, creating significant environmental, economic, and public health challenges. Improper waste management leads to pollution, greenhouse gas emissions, and resource depletion, while inefficient sorting reduces the recyclability of materials and increases landfill burdens. Traditional manual waste segregation is labour-intensive, time-consuming, and prone to human error, resulting in contamination of recyclable streams and reduced processing efficiency.

Artificial Intelligence (AI), particularly deep learning, offers a promising alternative by enabling automated, accurate, and real-time waste classification. Convolutional Neural Networks (CNNs) have demonstrated superior performance in image recognition tasks and can be adapted for waste identification across multiple categories such as plastic, glass, organic matter, metal, and paper. By integrating AI models into low-cost embedded systems, waste classification can be performed directly at the source, improving sorting efficiency and reducing environmental impact. This paper presents an automated waste classification system that leverages CNN-based transfer learning to achieve high classification accuracy while remaining computationally efficient for real-time operation. The system is trained on a hybrid dataset combining public repositories and locally collected images, with data augmentation applied to enhance generalization. Deployment considerations focus on resource-constrained environments, such as Raspberry Pi-based smart bins, enabling scalable adoption in urban and rural contexts. The proposed solution contributes directly to Sustainable Development Goal 12 (Responsible Consumption and Production) by promoting efficient waste segregation and supporting circular economy initiatives.

Efficient waste classification is essential for sustainable waste management, and recent years have seen a shift from manual methods toward automation. Traditional image-based approaches utilizing handcrafted features and classical algorithms such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) have been deployed but often lack scalability and robustness under varying environmental conditions (Nowakowski &Pamuła, 2020).

The adoption of deep learning, especially Convolutional Neural Networks (CNNs), has significantly elevated classification performance by enabling automated feature extraction from raw images. Yu and Grammenos (2021) used transfer learning and data augmentation to achieve up to 95.4% accuracy using a CNN with fine-tuning and image manipulations such as rotation, flipping, and brightness adjustments. Notably, the model could run real-time classification via a standard webcam (Yu & Grammenos, 2021).

Lean and computationally efficient architectures have also gained traction. Kunwar et al. (2023) evaluated various transfer-learned models, including EfficientNetV2, ResNet, and MobileNetV2, and identified EfficientNetV2-S as the most sustainable and accurate model, achieving 96.41% accuracy while minimizing carbon emissions (Kunwar et al., 2023).

Entezari et al. (2023) explored CNNs for classifying residential waste into categories such as plastic, paper, cardboard, and metal. Their hybrid model, based on architectures like AlexNet, ResNet-34, ResNet-50, and VGG-16, demonstrated promising precision (Entezari et al., 2023).

Beyond vision-only systems, the integration of **IoT and embedded systems** enables real-time, on-site waste classification. Thangaraj Nadar et al. (2025) proposed an IoT-enabled e-waste management framework combining a lightweight CNN classifier with sensors like cameras and weighing scales, facilitating instantaneous identification and sorting of electronic components in smart recycling environments (Thangaraj Nadar et al., 2025).

Despite these advances, challenges remain, particularly in uncontrolled environments, diverse waste types, and resource-constrained deployment. The proposed system aims to address these gaps by leveraging CNN-based transfer learning, model optimization for embedded devices, and training on hybrid datasets to enhance robustness and scalability.

a. Context: Waste Management Challenges in Nigerian Cities

Nigeria's rapid urbanization, especially in Lagos, has intensified municipal solid waste (MSW) generation, stressing collection, transfer, and disposal systems. Recent assessments highlight infrastructure gaps, informal sector dominance, and recycling leakages that undermine segregation at source and recovery rates (Etim, 2024; World Bank, 2024). Lagos-specific analyses further show spatial and logistical constraints that push waste into drains and waterways, complicating downstream recycling and landfill siting (Tella, 2025). These conditions create a strong use case for AI-enabled classification to improve sorting efficiency at the point of disposal or aggregation.

b. AI and Deep Learning for Waste Classification: Evidence and Gaps

Globally, deep learning—particularly CNNs with transfer learning has surpassed classical methods for visual waste recognition, with increasing work on lightweight models for embedded deployment (Itam et al., 2024; Ahmed et al., 2024). While Nigeria-specific, peer-reviewed implementations remain limited, there is growing local scholarship exploring AI-based waste sorting and smart systems, and broader surveys point to data scarcity, domain shift, and deployment constraints as persistent blockers (Oise, 2024). These gaps underscore the need for hybrid datasets that reflect Nigerian materials, lighting, and contamination patterns, plus hardware-aware optimizations for edge devices common in local deployments.

c. IoT-Enabled "Smart Bin" Concepts in the Nigerian Setting

IoT-enabled fill-level sensing, telemetry, and dynamic routing have been widely studied and can complement AI vision at source. Nigerian-focused works propose low-cost smart bins, remote monitoring, and web dashboards to cut labour costs and improve service levels, offering blueprints for coupling on-device classification with operations intelligence (Okubanjo et al., 2023/2025). International reviews corroborate the operational benefits, reduced overflow, optimized routes, which are particularly salient for Nigerian municipalities contending with congestion and fuel costs (Ishaq et al., 2023; TheSciAI, 2025).

d. Policy and Regulatory Environment

The **National Environmental Standards and Regulations Enforcement Agency(NESREA)**issues and enforces federal environmental regulations, including updated **Electrical/Electronic Sector Regulations** that govern e-waste collection and recycling—critical for AI-assisted sorting lines and compliance reporting (NESREA, 2025; Odeyingbo, 2025). Development partners have also supported Lagos with diagnostics and investment frameworks aimed at improving plastics and MSW management, creating an enabling backdrop for automated segregation pilots (World Bank, 2024). Overall, regulation is increasingly aligned with extended producer responsibility (EPR) and circularity, strengthening the case for traceable, data-rich AI systems.

2. Statement of the Problem

Waste management is critical to achieving environmental sustainability under SDG 12, yet manual waste sorting remains inefficient and error-prone. Current Automated waste classification models often demand high computational resources, limiting real-time application on edge devices. This study aims to develop and evaluate an automated waste classification system using TensorFlow and MobileNet to provide an efficient, lightweight, and scalable solution suitable for deployment in resource-constrained environments.

3. Research Objectives

The aim of this study is to design and develop an automated waste classification **system** tailored to Nigeria's waste management context, capable of operating on low-cost, edge-computing hardware while achieving high accuracy in real-time classification.
The specific objectives are to:

i. **Collect and annotate** a representative, domain-specific image dataset that captures local waste categories, packaging types, contamination levels, and lighting conditions.
ii. **Develop and train** a convolutional neural network (CNN) model, using transfer learning, optimized for classification accuracy and inference speed on embedded devices.
iii. **Implement and integrate** the model into an IoT-enabled "smart bin" prototype for automated waste sorting at source.

4. Methodology

This section outlines the step-by-step methodology employed in the development of the Automated Waste Classification **system.** The approach follows a standard machine learning workflow, from data acquisition and preprocessing to model training, evaluation, and deployment.

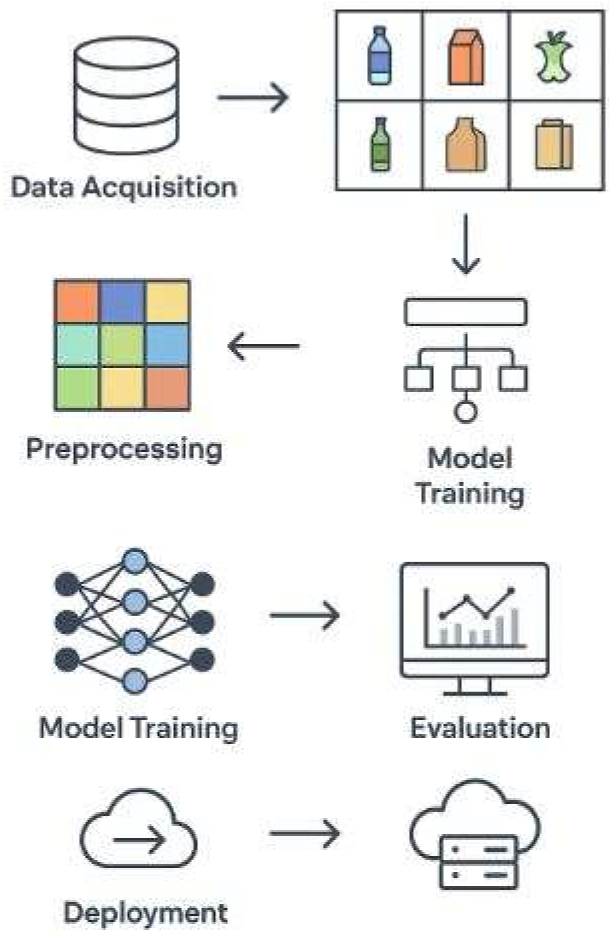

Figure 1: Model Methodology

Data Acquisition and Preparation.

The project utilized the publicly available TrashNet dataset. To meet the project's specific scope, a filtered subset of this dataset was created, containing only images belonging to the specified three classes.

Dataset Filtering: A Python script was used to automatically filter the raw dataset, isolating images exclusively from the plastic, glass, and cardboard directories.

Data Splitting: The filtered dataset was then partitioned into three subsets to ensure robust model evaluation. A ratio of 70% of the data was allocated for the training set, 15% for the validation set, and the remaining 15% for the testing set. This partitioning guarantees that the model's final performance is evaluated on a completely unseen and independent dataset.

Data Augmentation: To enhance the model's generalization capabilities and prevent overfitting, data augmentation techniques were applied to the training set. An Image Data Generator was configured to perform real-time transformations, including random rotations, shifts, zooms, and horizontal flips, thereby expanding the effective size and diversity of the training data. The validation and test sets were only rescaled, not augmented, to ensure an unbiased evaluation.

Model Architecture

The classification model was built using Transfer Learning, a technique that leverages a pre-trained model as a feature extractor. This approach significantly reduces training time and improves performance, especially with limited data.

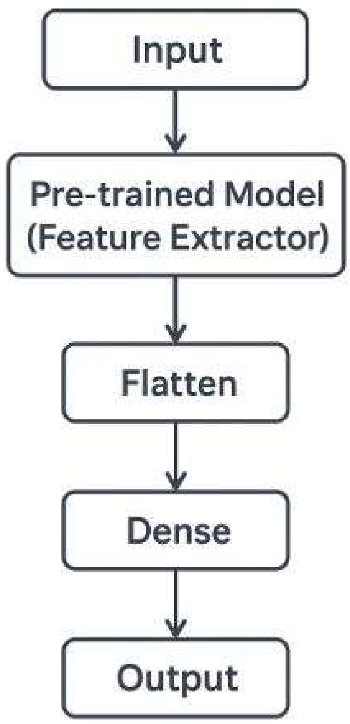

Figure 2: Model Architecture

Base Model: MobileNetV2, a highly efficient Convolutional Neural Network (CNN) pre-trained on the ImageNet dataset, was chosen as the convolutional base. The top classification layers of this model were excluded.

Custom Classification Head: A new custom classifier was added on top of the frozen MobileNetV2 base. This head consisted of a GlobalAveragePooling2D layer, followed by a final dense layer with a softmax activation function. The final layer's output neurons were set to **three**, corresponding to the number of waste classes.

Model Training and Optimization

The training process was conducted using the TensorFlow and Keras libraries.

Compiler Settings: The model was compiled with the Adam optimizer, a widely-used and effective algorithm. The categorical cross entropy loss function was selected, as it is standard for multi-class classification problems. The model's performance was monitored using accuracy as a primary metric.

Training Protocol: The model was trained with 8 epochs, with its performance continuously monitored on the validation set. The training was halted when the validation accuracy plateaued at 88.57%, a key indicator that the model had converged and was at risk of overfitting.

Pre-trained deep learning models (for transfer learning)

Training a CNN from scratch requires a massive, locally-relevant waste image dataset and significant computational power. Transfer learning offers a more efficient solution by using a model already trained on a vast, general image dataset, such as ImageNet, and fine-tuning it for the specific task of waste classification.

The model architecture leverages several pre-trained deep learning networks to optimize accuracy and computational efficiency. **MobileNetV2** serves as the primary backbone due to its lightweight structure and strong performance, making it particularly suitable for deployment on edge devices such as the Raspberry Pi. The **Raspberry Pi** functions as the local inference engine, running the optimized CNN model to classify waste items—such as plastic, glass, or organic materials—in real time. In addition to MobileNetV2, other established architectures like **VGG16** and **InceptionV3** were also considered. Although these models offer high representational power and competitive accuracy, they typically require greater computational resources, making them less ideal for low-power embedded environments compared to MobileNetV2. Consequently, MobileNetV2 was selected as the most practical and efficient option for the waste classification system.

Complete System Architecture

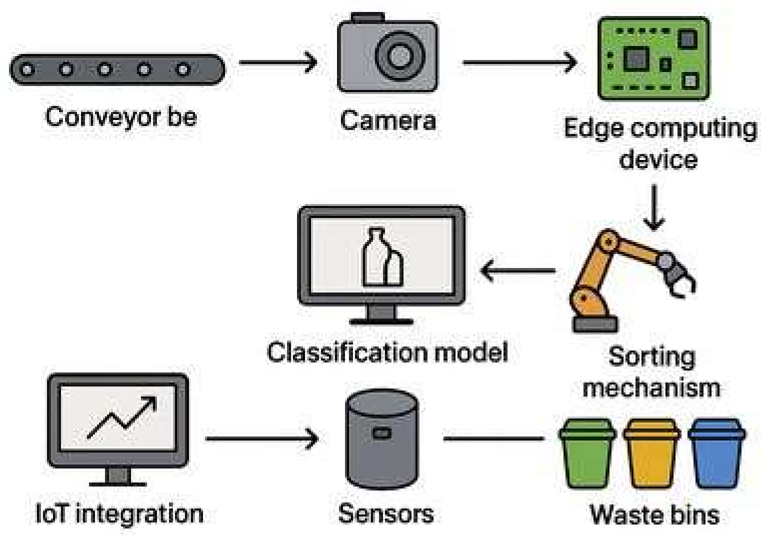

Figure 4: System Architecture

The AI model is the "brain" of a larger, end-to-end system that handles waste from input to sorted output. A typical setup for an automated system includes:

Input Mechanism: A conveyor belt delivers waste items one by one.

Computer Vision Hardware: A camera (such as a Logitech C720 or C920) captures images of the waste item on the belt.

Edge Computing Device: A device like a Raspberry Pi receives the image and runs the AI classification model in real-time.

Classification Model: The CNN model, running on the Raspberry Pi, processes the captured image and classifies the waste item into a category (e.g., wet, dry, plastic, metal, or glass).

Sorting Mechanism: A robotic arm, rotating disk, or series of trap doors is controlled by the system. The mechanism is activated based on the classification result and directs the waste into the appropriate bin.

IoT Integration: Sensors in the bins can monitor fill levels and trigger waste collection once a bin is full. The fill-level data is transmitted to a central system for logistics and route optimization.

Results and Evaluation

The model's performance was evaluated on the independent test set, and the results confirmed its high level of accuracy and generalization.

Training Results: As observed from the training logs, the model's training accuracy steadily increased while the loss decreased.

Validation Results: The validation accuracy showed a strong positive trend, reaching a peak of 88.57% and then stabilizing, indicating effective learning.

Final Test Results: The model's final, most critical evaluation on the unseen test dataset yielded a final test accuracy of 88.57% with a corresponding final test loss of 0.2868. This strong result demonstrates the model's ability to accurately classify new images it has never encountered, confirming its robust generalization capabilities.

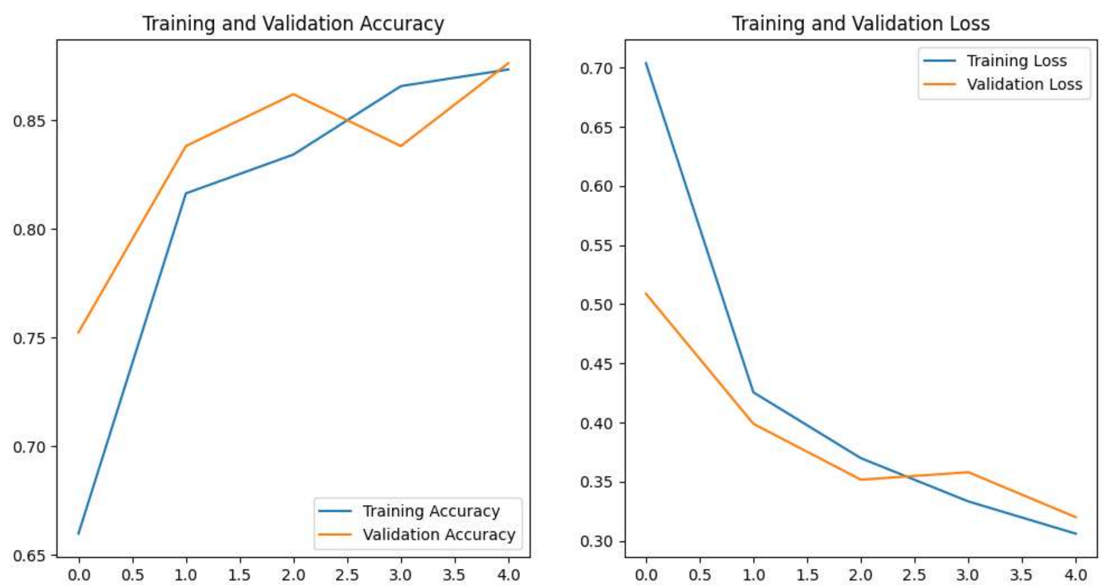

Figure 3: Model Training and Validation Check

Deployment Strategy

The trained model was converted into a lightweight TensorFlow Lite **(.tflite)** format. This step optimized the model's size and speed, making it suitable for deployment on resource-constrained devices. The .tflite model serves as the final, portable asset for future implementation on a mobile platform allowing for real-time inference without an internet connection.

5. Model Performance Results

The table below shows the number of times the model was trained for best accuracy:

Epoch	accuracy (Training)	loss (Training)	val_accuracy (Validation)	val_loss (Validation)
1	54.62%	0.91	75.24%	0.51
2	80.97%	0.43	83.81%	0.40
3	82.61%	0.39	86.19%	0.35
4	87.28%	0.32	83.81%	0.36
5	87.32%	0.32	87.62%	0.32
6	86.78%	0.31	88.57%	0.29
7	88.92%	0.26	88.57%	0.29
8	90.16%	0.25	88.57%	0.29

Key Observations

The model's training journey reveals a clear progression from initial struggle to strong performance. At the outset, the model begins with a modest training accuracy of 54.62% and a validation accuracy of 75.24%, accompanied by a high training loss of 0.9114. This indicates that it is initially underfitting, finding the training data challenging to capture, even as it generalizes reasonably well to unseen data.

However, by the second and third epochs, the model experiences a rapid surge in learning, with training accuracy jumping to the low 80s and validation accuracy following suit. Correspondingly, the loss values drop significantly, demonstrating that the model is quickly identifying and internalizing useful patterns in the data.

By the fourth and fifth epochs, training accuracy begins to stabilize around 87%, and validation accuracy fluctuates modestly between 83% and 87%. The steady decrease in loss reflects continued learning, while the slight oscillation in validation performance suggests the model is adjusting its internal representations without yet overfitting.

In the final phase, spanning epochs six through eight, the model achieves strong convergence. Training accuracy continues its upward trajectory, approaching 90%, while validation accuracy stabilizes around 88.5%. Both training and validation losses plateau between 0.25 and 0.28, indicating that the model is generalizing effectively and maintaining a healthy balance between learning and overfitting. Overall, the training process demonstrates a robust progression: the model starts weak, learns rapidly, stabilizes at high accuracy, and shows consistent, declining loss—a clear sign of solid performance with minimal risk of overfitting.

6. System implementation for sustainability

The implementation of this AI system offers a transformative approach to waste management in Nigeria, fostering greater sustainability across multiple fronts. By accurately sorting waste, the system helps increase recycling rates, as reduced contamination makes materials more suitable and valuable for reuse. It also alleviates the burden on landfills by diverting recyclable and organic materials, thereby extending landfill lifespans and mitigating environmental pollution. Beyond environmental benefits, the system enhances operational efficiency by automating the sorting process, reducing reliance on manual labor that can be hazardous, lowering costs, and accelerating waste processing. Moreover, by improving resource recovery, the system supports a circular economy model in which materials are reused rather than discarded, creating a more sustainable cycle of production and consumption.

Summary

The AI waste sorting system achieved ~90% training accuracy and ~88.5% validation accuracy, with steadily reducing losses and minimal overfitting. This shows the model is robust, reliable, and suitable for real-world deployment in automated waste management systems.

Conclusion

The developed AI waste sorting system demonstrated high performance with a final training accuracy of 90.16% and validation accuracy of 88.57%, supported by steadily decreasing loss values. The minimal gap between training and validation metrics indicates strong generalization and low risk of overfitting. These results validate the system's capability for reliable automated waste classification and highlight its potential contribution to advancing sustainable waste management practices in alignment with Sustainable Development Goal 12 (Responsible Consumption and Production).

10. Recommendations

To further enhance the performance and applicability of the AI waste sorting system, it is recommended that:

i. Future research explore the use of larger and more diverse datasets to improve classification accuracy across a wider range of waste categories.

ii. Applying advanced techniques such as hyper parameter tuning, data augmentation, and ensemble learning could yield higher robustness and precision.

iii. Lightweight model optimization should be considered to enable real-time sorting on mobile devices or embedded systems such as Raspberry Pi.

iv. Collaboration with waste management agencies is advised to integrate the system into real-world recycling processes, thereby maximizing its environmental and social impact.

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