Journal of Science Engineering Technology and Management Science
Volume 02, Issue 04, April 2025 *ISSN: 3049-0952*
www.jsetms.com *DOI:10.63590/jsetms.2025.v02.i04.64-71*

SMART WASTE MANAGEMENT: AI-BASED TRASH CLASSIFICATION SYSTEM

U. Satya Narayana, B. Poojitha, Sk. Asiff, Dr. P. Nagendra Kumar
Department of Computer Science and Engineering (AI&ML), Geethanjali Institute of Science and Technology, Nellore, Andhra Pradesh, India.

To Cite this Article
U. Satya Narayana, B. Poojitha, Sk. Asiff, Dr. P. Nagendra Kumar," Smart Waste Management: Ai-Based Trash Classification System", Journal of Science Engineering Technology and Management Science, Vol. 02, Issue 04, April 2025,pp: 64-71, DOI: http://doi.org/10.63590/jsetms.2025.v02.i04.pp64-71
Submitted: 09-03-2025 *Accepted: 18-04-2025* *Published: 26-04-2025*

ABSTRACT
Effective waste management is essential in India to ensure environmental sustainability and safeguard public health. With rapid urbanization and a growing population, the volume of waste generated has increased significantly, placing immense pressure on traditional disposal systems. This has led to environmental pollution, ecosystem damage, and various health risks. Conventional waste management methods—such as manual sorting, rule-based categorization, and exporting waste—are increasingly proving to be inadequate. Manual sorting is time-consuming, labor-intensive, and prone to human error, while rule-based systems lack the flexibility to adapt to varied and changing waste types. Exporting waste, on the other hand, raises serious environmental and ethical concerns due to potential mishandling. To address these issues, this research leverages a large-scale image dataset containing millions of waste item images to build and assess robust waste classification models. It utilizes MobileNetV2 and a lightweight convolutional neural network (CNN) to develop an AI-driven system capable of accurately classifying different types of waste. This intelligent classification system can be integrated into smart bins and recycling infrastructures to automate the sorting process, ultimately improving recycling efficiency and minimizing environmental impact.

Keywords: Smart waste management, Trash classification, Artificial Intelligence, MobileNetV2, CNN.

1. INTRODUCTION

In India, waste generation presents a significant challenge, particularly in urban areas where rapid urbanization and population growth have led to a substantial increase in municipal solid waste. As of 2022, urban regions generate approximately 150,000 metric tons of solid waste daily, with Maharashtra being one of the leading contributors. This surge in waste generation is not confined to cities alone; rural areas also experience a rise in waste production due to increased population and consumerism, generating an estimated 0.3 to 0.4 million metric tons of solid waste each day.

Improper waste management in both urban and rural settings poses severe health risks to local communities. Exposure to hazardous and biomedical waste can lead to respiratory illnesses, infections, and long-term health conditions such as cancer. Additionally, open dumping and burning of waste release harmful pollutants into the air and soil, contributing to respiratory and other health issues.

To address these challenges, India has established numerous waste processing units and e-waste collection centers. As of 2023, there are several solid waste treatment plants operational and under construction across the country, employing various methods such as composting, vermicomposting, and waste-to-energy technologies. These facilities aim to reduce the environmental impact of waste and promote resource recovery. However, the effectiveness of these units depends on efficient waste segregation at the source, highlighting the need for automated trash classification systems to enhance waste sorting and processing efficiency.

Automated trash classification employs advanced technologies like artificial intelligence and machine learning to accurately identify and segregate different types of waste. Implementing such systems can significantly improve the efficiency of waste processing units, reduce human exposure to hazardous materials, and minimize environmental pollution. By integrating automated waste sorting solutions, India can enhance its waste management infrastructure, protect public health, and move towards a more sustainable future.

2. LITERATURE SURVEY

Aberger, Julian et al. [1] discussed the transformative potential of Machine Learning and Artificial Intelligence in waste management, emphasizing the increasing importance of digitalization and improved recyclate quality. Despite these advancements, they noted that manual sorting remained largely a digital black box. Their research outlined the design of a novel, human-centric AI-powered assistance system aimed at supporting sorting workers by enhancing decision-making and providing real-time assistance during the sorting process, thereby advancing the digitalization of manual sorting. They explored potential use cases, system requirements, and essential components, highlighting the necessity of high-quality, use-case-specific data for model training. Upon evaluating publicly available datasets and finding them inadequate, they conducted near-industry-scale experiments to acquire the necessary data. This data facilitated the training and development of key system components, including object recognition, classification, and action recognition models. The results indicated that transfer learning with a balanced dataset was effective for waste-sorting applications, with the classification model achieving 81% accuracy on an experimentally acquired balanced dataset, surpassing the accuracy of the pre-trained model on its original dataset.

Samal, Choudhury Gyanaranjan et al. [2] provided an overview of the application of machine learning techniques—including support vector machines (SVM), artificial neural networks (ANNs), random forests (RF), K-nearest neighbors (KNN), and deep convolutional neural networks (DCNNs)—in the estimation, classification, and prediction of construction and demolition waste. Their study highlighted that DCNNs achieved an impressive accuracy of 94% in estimating and classifying construction waste. The authors concluded that machine learning models are well-suited for predicting and classifying construction waste, offering promising solutions for sustainable waste management in the future. This paper provided valuable insights into how machine learning can revolutionize waste management practices and guide future research.

Li, Lingbo et al. [3] proposed a new garbage image classification model using the ResNet-50 network as its core architecture. They introduced a redundancy-weighted feature fusion module, enabling the model to fully utilize valuable feature information while filtering out redundant data from multi-scale features. This approach reduced the number of model parameters and improved oveSrall performance. Additionally, they replaced the standard 3×3 convolutions in ResNet-50 with depth-separable convolutions, significantly enhancing computational efficiency while maintaining the original convolutional structure's feature extraction capability. To address class imbalance, they incorporated a weighting factor into the Focal Loss function, mitigating its negative impact on model performance and improving robustness. Experimental results on the TrashNet dataset demonstrated that the proposed model effectively reduced parameters, increased detection speed, and achieved an accuracy of 94.13%, surpassing most existing deep learning-based waste classification models, highlighting its strong practical value.

Ramos, Edgar et al. [4] conducted a comprehensive study to evaluate the efficiency and effectiveness of machine learning (ML) methods in detecting and classifying plastic waste (PW). Recognizing the growing environmental concerns and the potential of information processing, the researchers hypothesized that ML models could enhance sustainable PW management practices. They examined two scientific article repositories spanning from 2000 to 2023, identifying 188 articles. After a systematic screening process, 28 articles were selected, with an additional 28 included through snowballing. The study observed that accuracy in detection or classification tasks often surpassed the 80% benchmark, with further improvements noted when model combinations were employed. Convolutional Neural Networks (CNNs) emerged as the most commonly used models in these applications.

Ahmed Khan et al. [5] proposed a study investigating the critical role of efficient trash classification in achieving sustainable solid waste management within smart city environments. They conducted a comparative analysis of various trash classification methods utilizing deep learning models built on convolutional neural networks (CNNs). Leveraging the PyTorch open-source framework and the TrashBox dataset, they performed experiments involving ten unique deep neural network models, aiming to maximize training accuracy. Through extensive experimentation, they observed the consistent superiority of the ResNeXt-101 model compared to others, achieving exceptional training, validation, and test accuracies. These findings illuminate the potential of CNN-based techniques in significantly advancing trash classification for optimized solid waste management within smart city initiatives. Lastly, they proposed a distributed framework based on federated learning that can be used to optimize the performance of a combination of CNN models for trash detection.

Ahmed, Abduselam et al. [6] proposed a comparative study of several deep learning models to categorize waste into six classes: cardboard, plastic, glass, metal, paper, and general trash. They retrained and implemented various deep learning architectures—including MobileNet, ResNet, EfficientNet, and DenseNet—on a Raspberry Pi platform. The performance of these models was evaluated using the TrashNet dataset, focusing on classification accuracy, inference time, and maximum frames per second (FPS). The results demonstrated that EfficientNet B3 achieved the best performance across the compared parameters, with a testing accuracy of approximately 86%, while DenseNet exhibited the lowest performance, with an accuracy of 79%. Additionally, the models were assessed for their suitability on embedded devices; MobileNetV2 was the fastest in classification tasks, whereas EfficientNet B7 was the slowest. Considering both accuracy and speed, EfficientNet B3 emerged as the most suitable model for real-time applications.

Sayem, Faizul Rakib et al. [7] proposed robust waste image classification and object detection studies using deep learning models, utilizing 28 distinct recyclable categories of waste images comprising a total of 10,406 images. For the waste classification task, they introduced a novel dual-stream network that outperformed several state-of-the-art models, achieving an overall classification accuracy of 83.11%. Additionally, they introduced the GELAN-E (generalized efficient layer aggregation network) model for waste object detection tasks, obtaining a mean average precision (mAP50) of 63%, surpassing other state-of-the-art detection models. These advancements demonstrate significant progress in the field of intelligent waste management, paving the way for more efficient and effective solutions.

Adharsh, C. S. et al. [8] proposed an automated technology designed to accurately detect and sort waste, recognizing the pivotal role of waste sorting in cost-effective recycling. Their research focused on identifying and categorizing individual waste items depicted in photographs by employing deep learning techniques, specifically convolutional neural networks (CNNs) such as ResNet, MobileNetV2, and DenseNet. The primary objective was to optimize waste management processes through precise classification, thereby enhancing the efficiency of recycling operations. By implementing and retraining these models on platforms like the Raspberry Pi, they evaluated performance metrics including classification accuracy, inference time, and maximum frames per second (FPS) using datasets such as TrashNet. Their findings indicated that models like EfficientNet B3 achieved superior performance, balancing both accuracy and speed, making them suitable for real-time applications in automated waste sorting systems.

Jayaraman, Vaishnavi et al. [9] proposed the MSW-Net model, a hierarchical stacking approach designed for the automated classification of municipal solid waste (MSW). This model integrates a customized Convolutional Neural Network (CNN) and a Bayesian-Optimized MobileNet as base models, with Gradient Boosting serving as the meta-classifier. The MSW-Net model demonstrated exceptional performance, achieving accuracy rates of 99% during training, 95% in validation, and 96.43% in testing phases. Furthermore, during testing, the model attained precision, recall, and F1 scores of 96.42%, 96.43%, and 96.42%, respectively. These results indicate that the MSW-Net model surpasses existing models in waste sorting accuracy, offering a viable solution for municipal authorities to classify waste with minimal human intervention.

Smith, Rory Cornelius et al. [10] investigated the performance of logistic regression for image classification using three different subsets of labeled images. These included the original dataset, a balanced but under-sampled dataset with an equal number of blocked and unblocked images, and an augmented dataset where Gaussian noise was used to increase the number of unblocked images. The study found that the data augmentation method improved model accuracy by 8%, achieving an overall classification accuracy of 88%. By reducing dataset bias, the study also demonstrated potential solutions for applying this methodology across a network of cameras. These findings enable authorities in both data-rich and data-scarce regions to leverage machine learning for advancing distributed, data-driven flood warning systems, ultimately helping to protect people, infrastructure, and the environment.

3. PROPOSED METHODOLOGY

In the proposed system, transfer learning plays a pivotal role in enhancing the performance of garbage image classification. Transfer learning is a machine learning technique where a model developed for a particular task is reused as the starting point for a model on a second task.

3.1 MobileNet-V2 Feature Extraction

Figure 1. illustrates the MobileNetV2-based feature extraction process used in an automated trash classification system for efficient waste sorting. The process begins with an input image of size 128×128×3, representing a colored trash image with three RGB channels. The image first undergoes preprocessing, where it is resized to a standard dimension for uniformity, enhancing the model's ability to process different waste images effectively.

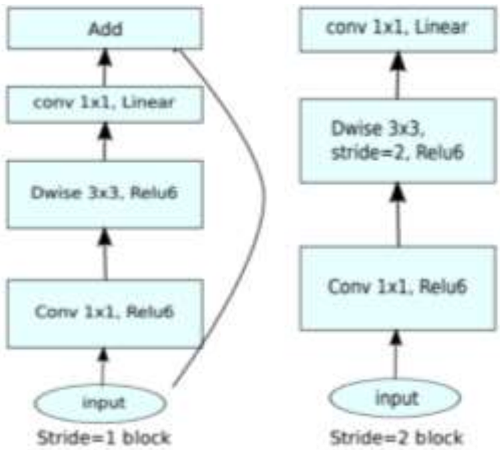

Fig. 1: MobileNetV2 Block Diagram.

After preprocessing, the image is passed through the MobileNetV2 convolutional layers, which extract important features. Initially, a 3×3 convolution layer with ReLU activation is applied to detect low-level patterns like edges and textures. As the image moves through multiple layers, it undergoes downsampling using max pooling (2×2) to reduce dimensions while preserving crucial information. The architecture contains depthwise separable convolutions, which help maintain computational efficiency and make the model lightweight, allowing it to be deployed in real-world applications.

Further down the network, the feature maps shrink in spatial size while increasing in depth. At the final stage of MobileNetV2, the output is a 4×4×1280 feature map, which is then flattened into a one-dimensional vector. This 1280-dimensional feature vector represents the most important characteristics of the trash image, making it easier for the classifier to distinguish between different waste categories.

The final stage consists of a fully connected classifier that uses the extracted features to predict the waste category. A softmax activation function is applied to generate probability scores for different classes (C1, C2, ..., Cn), identifying the type of trash. This MobileNetV2-based approach ensures efficient and accurate waste classification while maintaining a lightweight model suitable for real-world deployment in waste management systems.

4. RESULTS AND DISCUSSION

Figure 2. Describes the dataset is uploaded to the system for processing. The dataset contains different waste categories, including 'battery', 'biological', 'brown-glass', 'cardboard', 'clothes', 'green-glass', 'metal', 'plastic', and 'shoes'. This step ensures that the system has the necessary data for training and testing

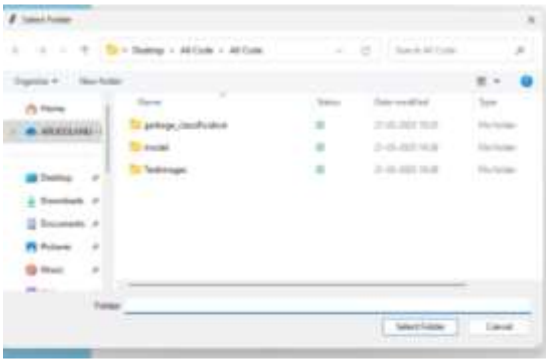

Fig. 2: Dataset Uploading.

Fig. 3: MobileNetV2 Feature Extraction

Illustrates about the system preprocesses the images to standardize their format. MobileNetV2 extracts features from the images, creating a feature representation with dimensions (4584, 10, 10, 1280). This means that 4,584 images are processed, each represented with a 10x10 spatial feature map and 1,280 feature channels. These features help in classifying waste categories.

Figure 4. Shows the dataset is split into training and testing sets. The training set contains 3,667 samples, while the testing set has 917 samples. The output labels are also divided accordingly. This step ensures that the model learns from the training data and is tested on unseen data for fair performance evaluation

Fig. 4: Train Test Splitting.

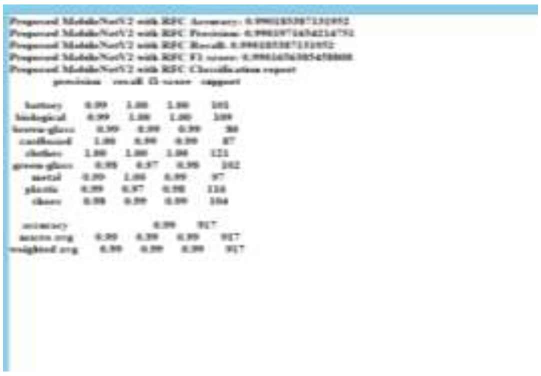

Fig. 5: Proposed Methodology Performance.

Figure 5. Illustrates the proposed model, which combines MobileNetV2 feature extraction with a RFC, achieves the highest accuracy of 99.02%. The precision, recall, and F1-score are all around 0.990. The classification report shows near-perfect predictions for all categories, making this model highly effective for automated waste classification.

Table 1 describes the Proposed Model using MobileNetV2 for Feature Extraction and a Random Forest Classifier (RFC) outperformed both LRC and NBC, achieving an impressive accuracy of 99.01%, with precision, recall, and F1-score all around 99%. This model demonstrated near-perfect classification across all waste categories, with battery, biological, and clothes achieving a perfect F1-score of 1.00.

Table 1. Proposed MobileNetV2 with RFC Classification Report

Class	Precision	Recall	F1-score	Support
Battery	0.99	1.00	1.00	101
Biological	0.99	1.00	1.00	109
Brown-glass	0.99	0.99	0.99	80
Cardboard	1.00	0.99	0.99	87
Clothes	1.00	1.00	1.00	121
Green-glass	0.98	0.97	0.98	102
Metal	0.99	1.00	0.99	97
Plastic	0.99	0.97	0.98	116
Shoes	0.98	0.99	0.99	104

Even previously challenging categories such as brown-glass and green-glass were classified with high precision (0.99) and recall (0.99 for brown-glass, 0.97 for green-glass). This massive improvement highlights the effectiveness of using deep learning-based feature extraction with MobileNetV2, which captures fine details in images, and Random Forest Classifier, which makes robust predictions based on extracted features. The results confirm that this methodology is highly reliable and suitable for automated waste classification, potentially leading to more efficient waste sorting and recycling processes in practical applications.

5. CONCLUSION

The integration of MobileNetV2 as a feature extractor coupled with the Random Forest Classifier (RFC) has proven to be an exceptional approach for image classification tasks. MobileNetV2's depthwise separable convolutions enable efficient feature extraction, ensuring high representational power while maintaining computational efficiency. The Random Forest Classifier leverages this extracted feature set effectively, providing high prediction accuracy and robustness. The model's performance metrics speak for themselves: achieving 99.02% accuracy, precision, recall, and F1-score is a testament to its reliability and efficiency. These results signify a significant improvement over traditional Logistic Regression Classifier, which, while effective, does not match the superior capabilities of the proposed model. The application of advanced deep learning architecture in conjunction with a versatile ensemble learning algorithm underscores the potential of combining modern methodologies for solving complex problems. The study highlights the critical role of

MobileNetV2 in retaining computational efficiency without compromising accuracy, making it suitable for resource-constrained environments. Additionally, Random Forest’s ability to handle large feature spaces while maintaining interpretability enhances the model's usability in real-world scenarios. Overall, this approach demonstrates a compelling blend of accuracy, efficiency, and scalability, setting a strong benchmark for future image classification models.

REFERENCES

[1] Aberger, Julian, Somayeh Shami, Bendikt Häcker, Jesus Pestana, Karim Khodier, and Renato Sarc. "Prototype of AI-powered assistance system for digitalisation of manual waste sorting." Waste Management 194 (2025): 366-378.

[2] Samal, Choudhury Gyanaranjan, Dipti Ranjan Biswal, Gaurav Udgata, and Sujit Kumar Pradhan. "Estimation, Classification, and Prediction of Construction and Demolition Waste Using Machine Learning for Sustainable Waste Management: A Critical Review." Construction Materials 5, no. 1 (2025): 10.

[3] Li, Lingbo, Runpu Wang, Miaojie Zou, Fusen Guo, and Yuheng Ren. "Enhanced ResNet-50 for garbage classification: Feature fusion and depth-separable convolutions." PloS one 20, no. 1 (2025): e0317999.

[4] Ramos, Edgar, Arminda Guerra Lopes, and Fábio Mendonça. "Application of Machine Learning in Plastic Waste Detection and Classification: A Systematic Review." Processes 12, no. 8 (2024): 1632.

[5] Ahmed Khan, Haroon, Syed Saud Naqvi, Abeer AK Alharbi, Salihah Alotaibi, and Mohammed Alkhathami. "Enhancing trash classification in smart cities using federated deep learning." Scientific Reports 14, no. 1 (2024): 11816.

[6] Ahmed, Abduselam, Fanuel Petros, Tomas Yemane, Farid Flitti, and Yassine Benachour. "Performance Evaluation of Deep Learning Models for Real-Time Trash Classification on Embedded Devices." In 2024 7th International Conference on Signal Processing and Information Security (ICSPIS), pp. 1-6. IEEE, 2024.

[7] Sayem, Faizul Rakib, Md Sakib Bin Islam, Mansura Naznine, Mohammad Nashbat, Mazhar Hasan-Zia, Ali K. Ansaruddin Kunju, Amith Khandakar et al. "Enhancing waste sorting and recycling efficiency: robust deep learning-based approach for classification and detection." Neural Computing and Applications (2024): 1-17.

[8] Adharsh, C. S., Jubaira Mammoo, P. S. Afthab, and Afroos Shahana. "Deep Learning Approaches for Waste Classification." In 2024 International Conference on Advancements in Power, Communication and Intelligent Systems (APCI), pp. 1-7. IEEE, 2024.

[9] Jayaraman, Vaishnavi, and Arun Raj Lakshminarayanan. "MSW-Net: A hierarchical stacking Model for automated municipal solid waste classification." Journal of the Air & Waste Management Association just-accepted (2024).

[10] Smith, Rory Cornelius, Andrew Paul Barnes, Jingjing Wang, Simon Dooley, Christopher Rowlatt, and Thomas Rodding Kjeldsen. "CCTV image-based classification of blocked trash screens." Journal of Flood Risk Management 18, no. 1 (2025): e13038.