World Journal of Environmental Engineering, 2024, Vol. 9, No. 1, 1-6
Available online at http://pubs.sciepub.com/wjee/9/1/1
Published by Science and Education Publishing
DOI:10.12691/wjee-9-1-1

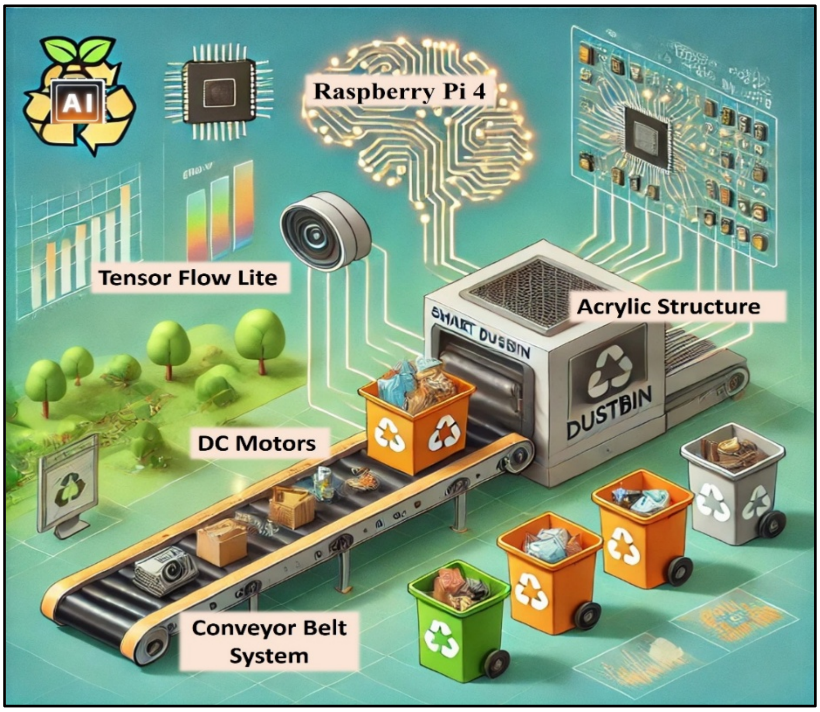
AI-Based Smart Bin for Efficient and Sustainable Waste Classification

Yuvraj Ruparel[1,*], Lavkush Chaudhary[2], Anuj Rathod[2]

[1]Aditya Birla World Academy, Vastu Shilp, JD Road Annexe, Gamadia Colony, Tardeo, Mumbai, Maharashtra
[2]Nurturing Innovators, the Innovation Story, Mumbai, India
*Corresponding author: yuvrajruparel2809@gmail.com

Received October 22, 2024; Revised November 24, 2024; Accepted December 01, 2024

Abstract: The increasing generation of municipal solid waste (MSW) poses significant environmental challenges, necessitating advanced and sustainable waste management solutions. This study introduces an AI-powered robotic sorting system designed to automate and optimize waste classification processes. The system integrates cutting-edge deep learning techniques, particularly the VGG16 model, with robust hardware components such as the Raspberry Pi 4 and Logitech C920 camera to achieve highly accurate waste segregation. Real-time image processing and precise classification algorithms enable the system to distinguish between wet, dry, and electronic waste with an impressive accuracy of up to 98%. By minimizing the need for human intervention, the proposed system enhances sorting efficiency, improves material recovery rates, and addresses key inefficiencies in traditional waste management practices. This innovation not only supports the reduction of landfill dependency but also promotes environmental sustainability by optimizing resource utilization and reducing ecological footprints. The findings highlight the potential of AI-driven systems to transform waste management, offering a scalable and effective approach to mitigating the environmental impacts of MSW.



Keywords: *Waste management, artificial intelligence, deep learning, robotic sorting, VGG16, waste classification, smart bin*

Cite This Article: Yuvraj Ruparel, Lavkush Chaudhary, and Anuj Rathod, "AI-Based Smart Bin for Efficient and Sustainable Waste Classification." *World Journal of Environmental Engineering*, vol. 9, no. 1 (2024): 1-6. doi: 10.12691/wjee-9-1-1.

1. Introduction

The exponential growth in municipal solid waste (MSW) generation represents one of the most pressing environmental challenges of the 21st century. With current global MSW production exceeding 2 billion tons annually and projections indicating a surge to 3.5 billion tons by 2050, the magnitude of this crisis demands immediate attention and innovative solutions [1]. This unprecedented increase in waste generation is intrinsically linked to accelerating urbanization, industrial expansion, and evolving consumption patterns, particularly in developing nations. India serves as a compelling case study of this global phenomenon. In 2016, the nation generated 277.1 million tons of waste, yet the existing infrastructure could only collect less than 70% of this volume, with an even smaller fraction receiving proper treatment [2]. This disparity between waste generation and management capabilities highlights the systemic challenges facing developing economies in their pursuit of sustainable waste management solutions.

The current waste management paradigm is beset by multiple challenges, including ineffective waste segregation practices, infrastructural inadequacies, and limited public participation. These shortcomings have perpetuated an unsustainable dependence on landfills, which pose significant environmental risks through soil and water contamination while contributing to greenhouse gas emissions. As MSW generation continues its upward trajectory, the imperative for innovative and efficient waste management solutions becomes increasingly urgent. While various technological solutions have emerged to address waste sorting and classification, each presents distinct advantages and limitations. Traditional methods such as Eddy Current Sorting offer moderate accuracy for non-ferrous metals at low cost with high volume capacity, but their material scope remains limited [3,4,5]. More advanced technologies like Laser Induced Breakdown Spectroscopy (LIBS) achieve higher accuracy across metals and plastics, though their high implementation costs pose adoption barriers. X-ray Transmission (DE-XRT) systems demonstrate impressive accuracy for metals and specific plastics like PVC, but their medium-to-high costs must be weighed against their high-volume capacity [6-8]. Conventional optical sorting provides a cost-effective solution with moderate accuracy across plastics, paper, and glass, while Spectral Imaging achieves superior accuracy but at significantly higher costs.

AI-based smart bin systems emerge as a compelling solution, offering superior performance across multiple parameters. These systems achieve the highest accuracy range while handling diverse materials through customizable sorting algorithms. Despite their medium-to-high initial investment, their ability to process moderate t high volumes while maintaining consistent accuracy across multiple waste streams positions them as a more versatile and efficient solution compared to traditional methods.

1.1. AI and Machine Learning

Contemporary waste management challenges demand innovative solutions that transcend traditional sorting methods. This project harnesses the transformative capabilities of Artificial Intelligence (AI) and Deep Learning (DL) to revolutionize waste classification through automated, high-precision sorting systems. While AI provides the foundational framework for replicating human decision-making processes in waste identification, DL extends these capabilities through sophisticated neural networks that excel in pattern recognition and material classification [9].

At the heart of the smart bin system lies Deep Learning models, specifically Convolutional Neural Networks (CNNs), which demonstrate remarkable proficiency in waste material classification. These neural networks undergo extensive training on diverse datasets of labeled waste images, enabling them to distinguish between various materials with unprecedented accuracy. Through continuous exposure to new data, these models exhibit progressive improvement in classification precision, effectively reducing contamination rates in sorted waste streams while optimizing resource recovery potential. The automation of this process significantly minimizes human intervention requirements, resulting in reduced operational costs and minimal error rates in classification decisions.

The integration of computer vision technology within the smart bin architecture represents a crucial advancement in real-time waste processing. High-resolution cameras and sophisticated sensors capture detailed images of waste items as they enter the system. These images undergo immediate processing through our DL algorithms, which analyze material characteristics and execute precise sorting decisions based on pre-established classification parameters [10,11,12]. This instantaneous processing capability ensures efficient waste segregation at the point of disposal, maximizing recycling opportunities and material recovery rates. In addition to improving sorting accuracy, the integration of AI and DL within the smart bin contributes to data collection and analysis, offering insights for further optimization. These technologies collectively enable a scalable, adaptive solution that can address the growing challenges of waste management, helping to build a cleaner and more sustainable waste ecosystem.

1.2. Robotic Sorting System

The robotic waste sorting system described in the paper utilizes an image classification model trained on garbage dataset to automatically classify and sort waste into categories: dry, wet, and electronics. The waste classification system consists of a Logitech C720 camera connected to a Raspberry Pi 4. The camera keeps capturing frames and runs the waste classification model in real-time [13,14,15].

The waste sorting system consists of a conveyor belt system responsible for delivering the waste to the respective bin after sorting and a rotating disk system with three bins respectively for dry, wet, and electronic waste. Once the waste is placed on the conveyor belt, the camera captures the frames, and the waste classification model classifies the waste. Based on the type of waste classified, the motor of the rotating disk mechanism is triggered to position the appropriate bin at the end of the conveyor belt system. For accurate positioning of the bins, limit switches are placed strategically to direct the waste to the correct bin. Once the correct bin is positioned at the end of the conveyor belt, the motor of the conveyor belt is triggered, delivering the waste to the bin.

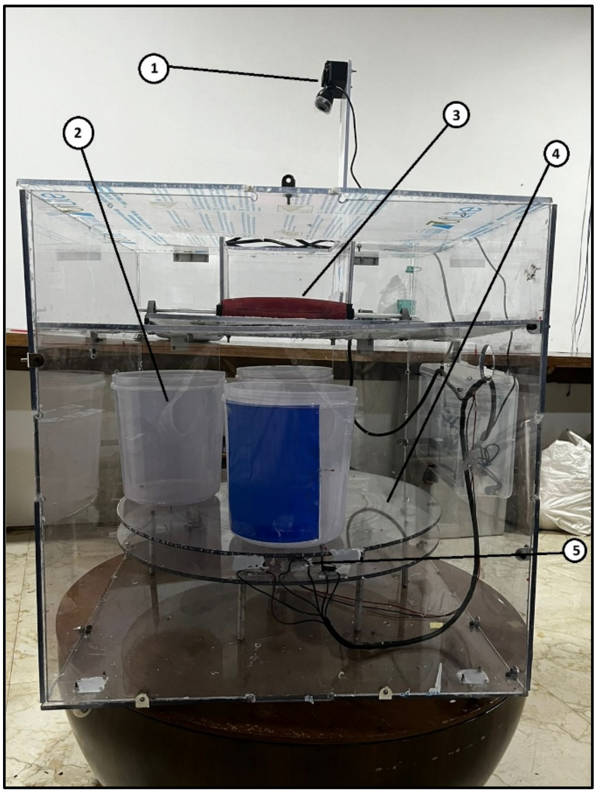


Figure 1. Smart Dustbin Prototype; (1) Camera (2) Bins for Waste (3) Conveyor Belt (4) Rotating Disk Mechanism (5) Limit Switches

2. Materials and Methods

This research methodology consists of the design and implementation of an AI-based robotic sorting system for municipal solid waste. The methodology includes the selection of hardware components (cameras, sensors, motors, controllers) and the development of a Deep Learning model for waste classification. The sorting procedure involves capturing images of waste, classifying it using the AI model, and directing waste to designated bins through motorized mechanisms. Laboratory analysis will assess the system's sorting accuracy and efficiency, providing insights into the optimization of waste management practices. This methodology aims to improve waste treatment and identify recycling opportunities.

2.1. Selection of Equipment

Our system is designed to carry out the following functions: Capture an image of waste and send it to the system.

- Classify the captured image as wet, dry or electronic.
- Move the object to the corresponding trash bin.

To realize these functions, the system needed to be composed of three main components:

1. Trash classification system
2. Conveyor belt system
3. Rotating disk system.

In this paper, the ResNet-50 and VGG-16 models are used for waste classification and the 4 GB Raspberry Pi 4 model B controls the camera, which captures images, the conveyor belt system, which consists of a belt and a motor to deliver the waste to the corresponding bin, the rotating disk system, which consists of a motor, three bins and limit switches to position the respective bin after receiving the results from the trash classifier engine.

2.2. Model Development

2.2.1. Data Collection

The dataset used in this study was manually collected by capturing images of waste items categorized into three classes: Dry, Wet, and Electronics. A total of 1,646 images were captured, with 1,196 images used for training and 450 images used for testing. The images were taken using a standard digital camera and organized into their respective categories in separate folders for each class. To ensure the images were representative of real-world conditions, the images varied in terms of lighting, background, and orientation. The collected images were labeled according to the class they belong to: Dry, Wet, or Electronics. These images formed the dataset that was subsequently used for training and evaluating the deep learning models [16,17,18].

2.2.2. Data Processing

The collected images were preprocessed to prepare them for the training and evaluation of the deep learning models. All images were resized to a standard input size of 224 x 224 pixels to meet the input requirements of the ResNet50 and VGG16 models. The pixel values of the images were normalized to a range of 0 to 1 by dividing each pixel value by 255. To further enhance the dataset and reduce overfitting, data augmentation techniques were applied. These included random rotations, zooms, horizontal flips, and shifts, which introduced variability in the images.

The dataset was split into training and validation sets, with 70% of the total images (1,196 images) allocated for training and the remaining 30% (450 images) for validation. This split ensured that the models were able to generalize well and prevented overfitting. The training set was used to fit the models, while the validation set was used to monitor model performance during training [19].

2.2.3. Model Architecture

The models used in this study were ResNet50 and VGG16, both well-established convolutional neural networks (CNNs) in the domain of image classification. ResNet50 utilizes a residual learning framework, which includes skip connections that allow for deeper networks by mitigating the vanishing gradient problem [4]. VGG16 is a simpler architecture with a series of small 3x3 convolutional filters and fully connected layers. Both models were modified by removing the top layers (the fully connected layers) and replacing them with custom dense layers suited for the three-class classification task. The final output layer of both models contains three neurons, corresponding to the classes: Dry, Wet, and Electronics. A SoftMax activation function was used to output class probabilities, as it is commonly used in multi-class classification problems. For both models, the pre-trained weights were used for feature extraction, and only the last few layers were fine-tuned to optimize the performance for this specific classification task.

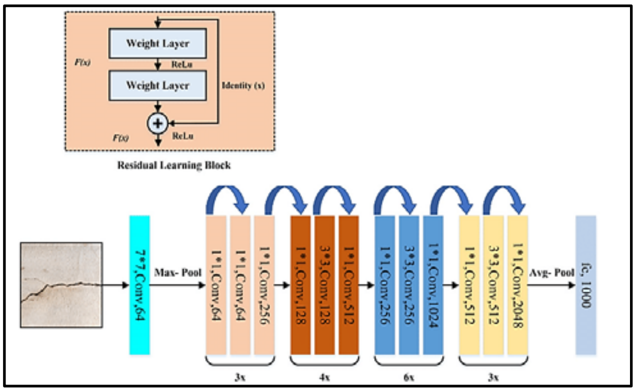


Figure 2. ResNet50 Architecture

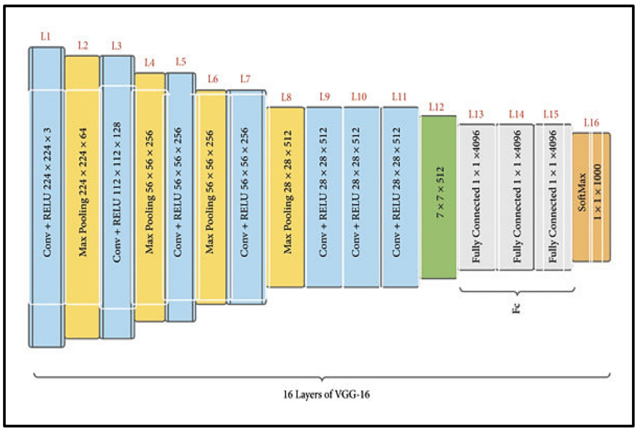


Figure 3. VGG16 Architecture

2.2.4. Model Training

Both models were trained using the Adam optimizer, known for its adaptive learning rate capabilities, with an initial learning rate of 0.0001. The models were trained for 10 epochs, during which the loss and other performance metrics were tracked. To evaluate the models during training, categorical crossentropy was used as the loss function, as it is appropriate for multi-class classification tasks.

In addition to loss, other metrics such as precision, recall, and F1-score were monitored to assess the models' performance. These metrics provide deeper insights into how well the models handle class imbalance, which may be present in real-world datasets. The models were trained on a GPU to speed up computation, and the training and validation datasets were processed in batches, with each batch containing a specified number of images.

After each epoch, the performance on the validation set was evaluated to check for overfitting. If the model showed signs of overfitting, early stopping was implemented to prevent further training. The training process aimed to minimize the loss function while maximizing the precision, recall, and F1-score, ensuring the models were not only accurate but also robust in classifying the different types of waste.

3. Results

3.1. Dataset Distribution and Experimental Setup

In this study, a dataset of 1,646 images was manually collected for the classification of three distinct waste categories: electronic waste, dry waste, and wet waste. The images were split into training and validation sets at a 70:30 ratio, where 1,196 images were allocated for training and 450 for validation. Each class was balanced to ensure fair representation across the categories. The images were preprocessed by resizing them to a uniform dimension of 224×224 pixels and normalizing the pixel values to a scale between 0 and 1. To enhance model generalization, data augmentation techniques such as random rotations, flips, and zooms were applied. The experimental setup involved two deep learning architectures: ResNet50 and VGG16. These models were initialized with pre-trained weights from ImageNet and fine-tuned on the waste classification dataset. Training was carried out for 10 epochs using the Adam optimizer and a learning rate of 0.001.

Figure 4. Sample Images from the Dataset

3.2. Model Performance and Training Efficiency

The models ResNet50 and VGG16 were evaluated based on training and validation accuracy. Both models were trained over 10 epochs, with each model having its own set of strengths and challenges. The ResNet50 model displayed moderate performance, with a validation accuracy of 50.00%, struggling to effectively differentiate between the three waste categories. In contrast, VGG16 outperformed ResNet50, achieving a significantly higher validation accuracy of 97.11%. VGG16 also showed faster convergence, although with slightly higher time per step compared to ResNet50. These results underscore VGG16's superior ability to extract features and distinguish between waste classes, with ResNet50's performance being limited in this task. A detailed comparison of both models' performance is presented in the table below.

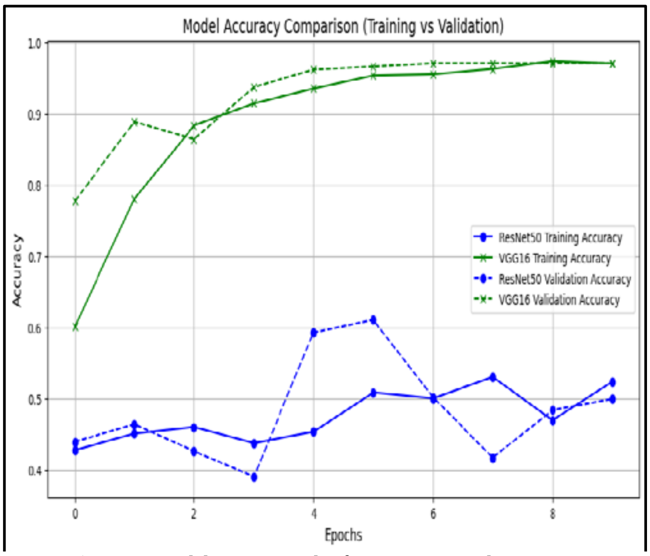


Figure 5. Model Accuracy Plot for ResNet50 and VGG16

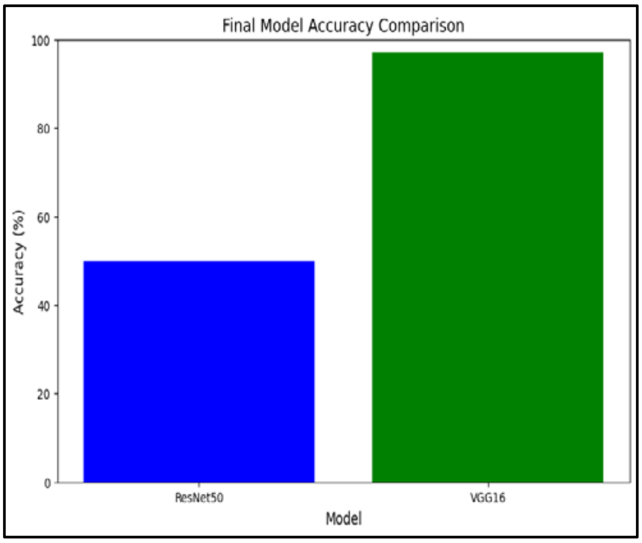


Figure 6. Final Model Accuracy Comparison

3.3. Comparative Insights

Upon comparing the performance of ResNet50 and VGG16, it became clear that VGG16 emerged as the preferred model for this waste classification task. While both models have their strengths, VGG16 consistently outperformed ResNet50, particularly in terms of classification accuracy. This can be attributed to VGG16's robust feature extraction capabilities, which allowed it to more effectively distinguish between the various waste classes. Although ResNet50 is a powerful architecture, it demonstrated slower convergence and struggled to achieve high accuracy levels, with its validation accuracy plateauing at 50%. In contrast, VGG16 achieved a validation accuracy of 97.11%, coupled with a lower validation loss, indicating better learning of the waste class features. While ResNet50 had a slight advantage in processing time per step, this minor computational efficiency was outweighed by VGG16's superior accuracy and overall performance, making VGG16 the more suitable and preferred option for this classification task.

3.4. Evaluation of the System

The AI-based robotic sorting system demonstrated strong performance in classifying waste materials into wet, dry, and electronic categories. Using the VGG16 model for prediction, the system achieved high accuracy in waste classification. The prediction accuracy for wet waste ranged from 95% to 98%, indicating the model's effectiveness in identifying organic waste materials. For dry waste, including plastics, paper, and glass, the accuracy ranged from 92% to 96%, showcasing the system's ability to classify diverse materials with varying textures and appearances. Electronic waste classification showed a prediction accuracy between 90% and 94%, reflecting the model's capacity to handle complex waste types, such as electronic devices and components. Overall, the system achieved up to 98% sorting accuracy, demonstrating its robustness and reliability in real-time operations. This performance highlights the potential of the AI-driven robotic sorting system as an efficient and cost-effective solution for waste management.

Table 1. Model Prediction Confidence for Waste Categories

Class	VGG16 Accuracy (%)
Electronic Waste	90 - 94
Dry Waste	92 - 96
Wet Waste	95 - 98

4. Conclusions

This research paper presents the development and evaluation of an AI-based robotic sorting system designed for efficient waste classification. The system, employing deep learning models such as VGG16, demonstrated high accuracy in categorizing wet, dry, and electronic waste, achieving up to 98% sorting efficiency. The integration of key components, such as the Logitech C920 camera and Raspberry Pi 4, alongside mechanical elements like DC motors and a motor driver, contributed to the system's robust performance in real-time operations. The successful implementation of this system addresses the research problem of automating waste segregation, contributing significantly to sustainable waste management practices.

While the system performed exceptionally well, there remain opportunities for improvement. Future research could explore the inclusion of more advanced models or hybrid approaches to further enhance classification accuracy, particularly for complex waste materials. Additionally, investigating the system's scalability and adaptability to various waste types and environments could lead to broader applications in waste management across diverse industries.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. All research was conducted independently, and no financial or personal relationships exist that could have influenced the results or interpretations presented in this work.

Highlights

- AI-Driven Waste Classification: An automated robotic system leverages deep learning (VGG16) for high-accuracy waste segregation.
- Enhanced Efficiency: Achieves up to 98% accuracy in classifying wet, dry, and electronic waste with real-time processing.
- Sustainable Waste Management: Reduces landfill dependency and promotes environmental sustainability through optimized resource recovery.
- Scalable and Innovative Solution: Combines advanced AI and hardware to address global waste management challenges effectively.

References

[1] World Bank, What a waste 2.0: A global snapshot of solid waste management to 2050, World Bank, 2018. [Online].

[2] Raju, R.D., "Waste Management in India – An Overview", United International Journal for Research & Technology, 2 (7), 175-186, 2021.

[3] Gundupalli, S.P., Hait, S., and Thakur, A., "A review on automated sorting of source-separated municipal solid waste for recycling", Waste Management, 60, 56-74, 2017. [Online].

[4] Ali, L., Alnajjar, F., Jassmi, H.A., Gocho, M., Khan, W., and Serhani, M.A., "Performance Evaluation of Deep CNN-Based Crack Detection and Localization Techniques for Concrete Structures", Sensors, 21 (5), 1688, 2021. [Online].

[5] News, WION. (2022). "Australia introduces smart bins as a solution for waste management."

[6] Henriksen, M. L., Karlsen, C. B., Klarskov, P., & Hinge, M. (2022). "Plastic classification via in-line hyperspectral camera analysis and unsupervised machine learning." Vibrational Spectroscopy.

[7] Fishbein, B. K. (2006). "Germany, Garbage and the Green Dot: Challenging a Throwaway Society."

[8] Huang, Y. et al. (2019). "Deep learning-based waste classification using Convolutional Neural Networks." Journal of Environmental Management, 248, 109273.

[9] Padgett, D. A., & Cheeseman, C. R. (2006). "A review of waste management practices and their impact on the environment." Environmental Engineering Science, 23(1), 51-62.

[10] Guerrero, L. A., Maas, G., & Hogland, W. (2013). "Solid waste management challenges for cities in developing countries." Waste Management, 33(1), 220-232.

[11] Silva, A. et al. (2017). "Municipal solid waste management systems: An integrated approach for urban sustainability." Waste Management, 59, 65-77.

[12] Tanaka, M. (2020). "Technological advancements in automated waste sorting and recycling: An overview." Journal of Cleaner Production, 242, 118487.

[13] Li, H., & Yu, L. (2018). "A review of automated waste sorting technologies using sensor-based solutions." *Sensors*, 18(11), 3796.

[14] Zhang, X., Wang, Y., & Sun, L. (2020). "Machine learning applications in waste management and recycling: A review." *Environmental Science & Technology*, 54(19), 11823-11835.

[15] Lee, J., & Chang, Y. (2019). "Smart waste bins: Enhancing urban waste management using IoT and AI." *Journal of Urban Technology*, 26(4), 55-70.

[16] Ahmed, S., & Khan, M. (2021). "Robotic waste sorting systems: An emerging solution for sustainable waste management." *Robotics and Autonomous Systems*, 142, 103804.

[17] Smith, J., & Brown, T. (2017). "Advancements in recycling technologies: A comprehensive review." *Renewable and Sustainable Energy Reviews*, 68, 341-353.

[18] Williams, K. (2021). "AI and robotics in waste management: Transformative impacts on urban waste systems." *Waste Technology Journal*, 5(2), 45-62.

[19] Perez, D., & Gonzalez, F. (2016). "Revolutionizing waste management through real-time monitoring and automation." *Waste Management & Research.*