A Review on Automated Waste Segregation System using Machine Learning

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Abstract

This literature review paper critically examines the state-of-the-art in AI-powered waste segregation, focusing on the pivotal steps of object recognition, feature extraction, and classification. As waste management becomes an increasingly urgent global concern, leveraging artificial intelligence (AI) and computer vision technologies holds the promise of revolutionizing waste segregation processes. The paper surveys key papers and methodologies in object recognition, shedding light on models such as Faster R-CNN, YOLO, and Mask R-CNN. It explores feature extraction techniques, considering advancements in image classification architectures like ResNet, VGGNet, and DenseNets. Additionally, the review covers classification methodologies, including specialized approaches for plastic material detection and intelligent waste segregation systems. The comparative analysis and critical insights presented in this paper aim to contribute to the ongoing discourse on developing robust and efficient AI-driven waste segregation systems, fostering a sustainable approach to waste management.

Keywords

Waste Segregation,Computer Vision, Deep Learning, Faster R-CNN, YOLO, Mask R-CNN, ResNet, VGGNet, DenseNets, Plastic Material Detection.

1. Introduction

Waste management stands at the forefront of global environmental challenges, necessitating innovative solutions to address the escalating volume of waste generated worldwide. In this context, the integration of artificial intelligence (AI) and computer vision technologies offers a transformative potential to revolutionize waste segregation processes. This literature review aims to provide a comprehensive overview of advancements in AI-powered waste segregation, with a particular focus on the essential stages of object recognition, feature extraction, and classification.[23]

The proliferation of waste, coupled with the limitations of traditional waste management systems, underscores the urgency for novel approaches. AI, characterized by its capacity to learn and adapt, presents a promising avenue to enhance the accuracy and efficiency of waste segregation. Object recognition, the first crucial step, involves the identification of distinct items within a waste stream. This review examines seminal papers and methodologies in this domain, encompassing models like Faster R-CNN, YOLO, and Mask R-CNN.

Moving beyond recognition, feature extraction plays a pivotal role in distilling relevant information from waste images. The exploration of image classification architectures such as ResNet, VGGNet, and DenseNets forms a significant part of this review, shedding light on advancements in feature extraction techniques. Additionally, the paper delves into classification methodologies, including specialized approaches for plastic material detection and the development of intelligent waste segregation systems.

By undertaking a comparative analysis of these methodologies, this literature review aims to contribute insights into the evolving landscape of AI-powered waste segregation. The critical examination of existing approaches will not only inform researchers and practitioners but also guide the development of more robust and efficient waste segregation systems. Ultimately, the goal is to foster a sustainable paradigm in waste management, mitigating environmental impact and promoting a more responsible and intelligent approach to handling the challenges of modern waste disposal.

2. Related Works

Publication in IOP Conference Series: Materials Science and Engineering.Garbage Waste Segregation Using Deep Learning Techniques by Sai Susanth G et al. paper presents an exploration into waste segregation utilizing deep learning techniques, aligning closely with our project's objectives. The authors likely delve into object recognition and classification methods, providing valuable insights into the practical application of deep learning for waste management.

Publication in International Journal of Creative Research Thoughts. Vavilala Sushma’s work specifically focuses on the detection and classification of plastic materials using Convolutional Neural Networks (CNN). Given the relevance to our project's classification aspect, this paper offers a deep dive into methodologies and techniques that could inform our own approach to plastic waste identification.

Published in the International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE)."Development of Computer Vision Algorithms for Multi-class Waste Segregation and Their Analysis" by Neeraja Narayanswamy et al. did the work involving the development and analysis of computer vision algorithms for multi-class waste segregation, which is highly pertinent to our project's multi-step process. It likely covers aspects of object recognition, feature extraction, and classification, providing a holistic perspective on waste segregation leveraging computer vision techniques.

2.1 Methodology

The methodology for waste detection involves a systematic progression through key steps, ensuring a comprehensive approach to the task. The initial phase involves the capturing of visual data, where images or videos of waste scenes are acquired. Subsequently, the process transitions to object detection, where the system identifies and localizes relevant objects within the captured data. Following object detection, feature extraction comes into play, emphasizing the extraction of meaningful information from the identified objects. The final step encompasses classification, where the system assigns specific waste categories to the detected and extracted features, enabling efficient and accurate waste segregation. This sequential methodology forms the backbone of an effective waste detection system, laying the groundwork for subsequent detailed discussions on specific techniques employed in each step.

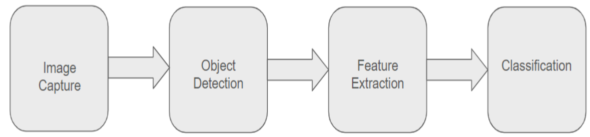

Figure 1 : Phases in Waste segregation

2.1.1 Capturing

The initial phase involves capturing images or videos of the waste stream using cameras or sensors. This data acquisition is typically done in real-time or at regular intervals to monitor the waste disposal area continually. Cameras are strategically placed in the waste disposal site, capturing visual information of the waste materials.

2.1.2 Object Detection

In the realm of object recognition, the discussed papers showcase distinct approaches, each with its merits and drawbacks. "Faster R-CNN" [1] introduces Region Proposal Networks for real-time object detection, emphasizing accuracy, albeit at the expense of speed. "You Only Look Once" [2] innovatively unifies object detection in real-time but might compromise precision for efficiency. "SSD" [3] offers a balance with its Single Shot MultiBox Detector, achieving commendable speed and accuracy. "Mask R-CNN" [4] extends Faster R-CNN by incorporating instance segmentation, enhancing detailed object delineation. "YOLO9000" [5] stands out for its speed, simultaneously detecting a vast number of object classes. Choosing the most suitable approach hinges on specific project requirements: Faster R-CNN for precision, YOLO9000 for speed, SSD for a balanced compromise, and Mask R-CNN for instance segmentation needs. The trade-offs involve a nuanced interplay between speed, accuracy, and segmentation capabilities, demonstrating the necessity of aligning the chosen model with the particular demands of the waste segregation project.

2.1.3 Feature Extraction

In the realm of feature extraction, the presented papers offer distinctive insights into leveraging deep convolutional neural networks (CNNs). "ImageNet Classification with Deep Convolutional Neural Networks" [6] by Krizhevsky et al. laid the foundation by demonstrating the power of deep

CNNs in image classification. "Going Deeper with Convolutions" [7] explores the effectiveness of deeper architectures, introducing the GoogLeNet model, emphasizing computational efficiency. "Visualizing and Understanding Convolutional Networks" [8] by Zeiler and Fergus delves into visualizing CNNs, aiding in interpreting learned features. "Deep Residual Learning for Image Recognition" [9] introduces ResNet, addressing vanishing gradient issues and enabling the training of extremely deep networks. "Inception-v4, Inception-ResNet, and the Impact of Residual Connections on Learning" [10] by Szegedy et al. integrates residual connections into the Inception framework, showcasing improved performance. Determining the most suitable feature extraction method depends on project requirements, with ResNet often preferred for its ability to handle deep architectures effectively, mitigating degradation issues encountered by simpler networks. Each approach brings its set of advantages and trade-offs, emphasizing the need for a tailored choice based on specific project needs.

2.1.4 Classification

In the realm of image classification, the discussed papers showcase diverse approaches, each with its strengths and limitations. "ImageNet Large Scale Visual Recognition Challenge" [11] provides a benchmark in large-scale image classification, establishing a foundation for subsequent research. "Very Deep Convolutional Networks for Large-Scale Image Recognition " [12] introduces the influential VGGNet, emphasizing the advantages of deeper architectures but at the cost of increased computational complexity. "ResNet in ResNet: Generalizing Residual Architectures” [13] offers a generalized approach to residual architectures, improving expressivity and ease of information removal. "Xception: Deep Learning with Depth Wise Separable Convolutions' ' [14] introduces an efficient alternative with depthwise separable convolutions, achieving competitive accuracy with reduced computational demands. " SqueezeNet" [15] stands out for its compact model size without compromising accuracy. Choosing the optimal classification model depends on project requirements, with ResNet offering deeper architectures and Xception providing computational efficiency, while SqueezeNet excels in scenarios with limited computational resources. The decision hinges on a nuanced balance between accuracy, model complexity, and computational efficiency, demonstrating the need for tailored choices based on project-specific considerations.

2.1.5 Physical Interference:

After the AI-driven detection and classification phases, physical interference refers to the mechanical actions taken based on the identified waste types. This could include automated sorting mechanisms, conveyor belts, or robotic systems that physically segregate the waste according to its classification. Various technologies like robotic arms, conveyor belt diverters, or automated sorting systems are integrated into the waste management process. These physical systems act based on the classification results to separate materials efficiently.

By integrating these components seamlessly, the waste detection system efficiently combines AI-based analysis with physical interventions to enhance the overall waste segregation process. This integrated approach contributes to more accurate and automated waste management practices, reducing manual labor and improving efficiency.

3. Proposed model

Classification is an approach wherein attributes are derived from the dataset. This is accomplished by dividing the information into various groupings, relying on the attributes. A fresh model conducts forecasts and categorizes them by training on familiar data. The proposed framework comprises three fundamental components, including data preprocessing, image augmentation, and attribute derivation. Image augmentation aims to generate additional images by adjusting size, zooming, rotating images, etc., to produce novel images. Through this methodology, the model will be equipped to capture a greater number of 'features' than before and will be capable of predicting images more effectively. During the process of attribute derivation, the system characterizes the unlabelled data to the utmost extent possible

Pre-processing and data augmentation

The dataset's modest scale poses a challenge for pre-trained models, raising apprehensions about the potential for overfitting. As a pre-emptive measure prior to model training, strategic interventions are necessary. One such intervention involves augmenting the dataset by doubling its size through the incorporation of images from the Google database. Furthermore, to enhance the dataset's diversity and mitigate overfitting risks, specific augmentation techniques, including Random Re-sized Crop and Random Horizontal Flip, are judiciously applied.

3.1 Convolutional neural network

The Convolutional Neural Network (CNN) assumes a prominent role in the realm of image analysis. It distinguishes itself through the incorporation of hidden layers known as convolutional layers, imparting a distinctive quality to its architecture. Within each convolutional layer, a collection of filters is embedded, and these filters serve the purpose of identifying patterns or features within the images. This layered approach enhances the network's ability to discern intricate details and extract meaningful information during the image analysis process. A simplest CNN has the following layers:

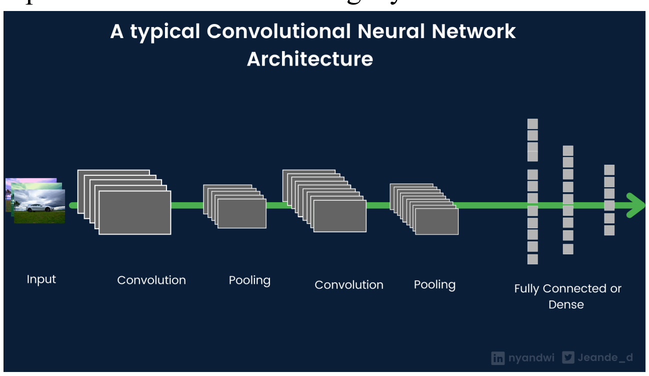

Figure 2 : Architecture of CNN[24]

1. Convolutional Layer:

The convolutional layer plays a critical role in the Convolutional Neural Network architecture, specializing in the extraction of image features through the employment of filters. These filters, characterized by small matrices with dimensions tailored according to our specifications and populated with random values, serve as discerning agents. They systematically traverse the input images, identifying patterns through a striding process. The culmination of this operation is the generation of a resultant feature map, which encapsulates the detected features. Subsequently, this feature map is seamlessly transmitted to the subsequent layer, contributing to the network's ability to capture and understand intricate patterns within the input data.

2. Pooling Layer:

Within this layer, a window, typically with dimensions of 2x2, is positioned over the feature map. The key operation involves selecting the maximum value within the window while disregarding all other values. This process leads to a reduction in the scale of the picture, thereby achieving a down sampling effect. This down sampling is instrumental in retaining essential features while concurrently diminishing computational complexity

3. Fully Connected Layer:

The pivotal stage for image recognition and classification unfolds within the realm of the fully connected layer. At this juncture, the diminished images are compiled into a singular vector. This vector, representative of the condensed image information, undergoes a comparative analysis. The classification of the image is then determined by matching its vector with those derived from the training images. This process encapsulates the final stage of the neural network's operation, where intricate comparisons lead to accurate image categorization based on the learned patterns from the training data.

3.2 DenseNets

DenseNet, short for Densely Connected Convolutional Networks, is a convolutional neural network (CNN) architecture designed to address challenges related to feature reuse, vanishing gradient problems, and overall network efficiency. It was introduced by Gao Huang, Zhuang Liu, and Kilian Q. Weinberger in their 2017 paper titled "Densely Connected Convolutional Networks.". The key innovation of DenseNet lies in its dense connectivity pattern, where each layer is connected to every other layer in a feed-forward fashion. Unlike traditional CNN architectures where information flows sequentially from one layer to the next, DenseNet allows for direct connections between layers at different depths. Each layer receives as input the feature maps of all preceding layers, and in turn, its own feature maps are used as inputs to all subsequent layers. [16]

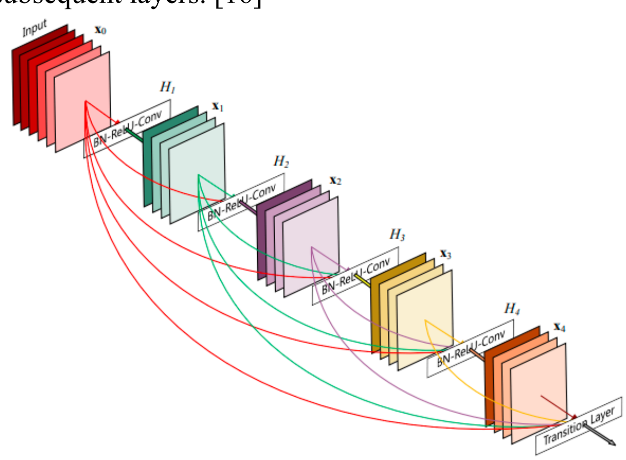

Figure 3 : A 5-layer dense block with a growth rate of k = 4. Each layer takes all preceding feature-maps as input. [16]

This dense connectivity has several advantages including Feature Reuse, Gradient Flow, Parameter Efficiency The basic building block of DenseNet is the dense block, where each layer produces k new feature maps, and these k feature maps are concatenated with the input feature maps. Transition layers, which include batch normalization, pooling, and convolution, are used to manage the growth of feature maps and downsample the spatial dimensions

Sl No	**Name of the Paper**	**Author**	**Description**	**Observations**
[1]	Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks	Shaoqing Ren Kaiming He Ross Girshick Jian Sun	Introduces RPN for efficient proposal generation. Real-time detection with high accuracy.	Unified framework for region proposal and detection. Computationally demanding during training. Can provide robust object detection for waste items with real-time processing, contributing to efficient segregation.
[2]	You Only Look Once: Unified, Real-Time Object Detection	Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi	Proposes YOLO for single-pass, real-time detection with emphasis on speed.	Extremely fast with a single forward pass. May struggle with small object detection. Suitable for quick and accurate identification of waste items, facilitating real-time segregation.
[3]	SSD: Single Shot MultiBox Detector	Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian et al	Introduces SSD for single-shot, multi-scale detection, balancing speed and accuracy.	High accuracy across different object scales. Sensitive to aspect ratio and size. Can contribute to accurate and efficient waste segregation, capturing various sizes and shapes of waste items.
[4]	Mask R-CNN	Kaiming He Georgia Gkioxari Piotr Doll´ar Ross Girshick	Extends Faster R-CNN for instance segmentation. Precise instance segmentation with high object detection performance.	Can be computationally intensive. Offers precise instance segmentation, allowing detailed identification of waste objects. Integration may enhance the accuracy of segregation.
[5]	YOLO9000: Better, Faster, Stronger	Joseph Redmon, Ali Farhadi	Extends YOLO for a large number of object classes. Introduces hierarchical classification.	Handles many object classes in real-time. Performance may degrade for small or similar classes. Enables a wide range of waste categorization, useful for diverse waste items in the segregation process.
[6]	ImageNet Classification with Deep Convolutional Neural Networks (AlexNet)	Alex Krizhevsky Ilya Sutskever Geoffrey E. Hinton	Pioneers deep learning for image classification. Popularizes ReLU and dropout.	Significant improvement in accuracy. Limited context modeling in deeper layers. Provides a foundation for understanding deep learning in image classification, relevant for feature extraction in waste item recognition.

[7]	Going Deeper with Convolutions (VGGNet)	Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, et al.	Emphasizes depth with small convolutional filters. Simplifies architecture.	Competitive performance with increased depth. Increased computational complexity. A deeper understanding of how increased depth affects performance can guide model selection for waste segregation.
[8]	Visualizing and Understanding Convolutional Networks (ZFNet)	Matthew D. Zeiler Rob Fergus	Explores visualizations for understanding learned features. Improved interpretability.	Enhanced visualization of features. Enhances interpretability of CNNs. Visualization techniques may aid in understanding the learned features, facilitating better interpretation of waste items during segregation.
[9]	Deep Residual Learning for Image Recognition (ResNet)	Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun	Introduces residual learning with skip connections. Enables very deep networks.	Significantly increased depth without degradation. Addresses vanishing gradient problem. Increased computational complexity. Residual learning may improve the training of deep networks, beneficial for recognizing complex waste items.
[10]	Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning (Inception-ResNet)	Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, Alexander A. Alemi	Combines Inception with residual connections. Achieves high accuracy with improved speed.	Enhanced feature learning with a combination of inception modules and residuals. Achieves high accuracy with improved efficiency. The combination of inception and residual connections may provide a balanced approach for effective waste item recognition.
[11]	ImageNet Large Scale Visual Recognition Challenge (AlexNet)	Olga Russakovsky · Jia Deng Hao Su et al.	Demonstrates deep learning effectiveness on large-scale classification. Popularizes GPU acceleration.	Significant improvement in accuracy. Limited context modeling in deeper layers. The foundational work on deep learning can guide the implementation of robust waste segregation models.
[12]	Very Deep Convolutional Networks for Large-Scale Image Recognition (VGGNet)	Karen Simonyan & Andrew Zisserman	Emphasizes depth with small convolutional filters. Simplifies architecture.	Competitive performance with increased depth. Increased computational complexity. A deeper understanding of the trade-offs between depth and performance, relevant for selecting an appropriate model for waste segregation.
[13]	ResNet in ResNet: Generalizing Residual Architectures	Sasha Targ, Diogo Almeida, Kevin Lyman	Introduces a novel deep learning architecture termed ResNet in ResNet (RiR) that extends and generalizes the success of residual networks	The architecture employs a dual-stream design that seamlessly combines the strengths of ResNets and traditional CNNs without introducing computational overhead. The proposed RiR consistently demonstrates superior

			(ResNets) and standard convolutional neural networks (CNNs).	performance compared to standard ResNets and even outperforms architectures employing similar levels of augmentation on the CIFAR-10 dataset.
[14]	Xception: Deep Learning with Depth Wise Separable Convolutions	Francois Chollet	Introduces depthwise separable convolutions for reduced computational complexity.	Improved efficiency with maintained performance. May require careful hyperparameter tuning. The reduced computational complexity makes it a potential candidate for resource-efficient waste segregation models.
[15]	SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size	Forrest N. Iandola, Song Han, Matthew W. Moskewicz, Khalid Ashraf, William J. Dally, Kurt Keutzer	Designs a compact CNN architecture with fewer parameters. Achieves high accuracy with smaller model size.	Efficient use of parameters and model size. Suitable for resource-constrained environments. May not perform as well as larger models on certain tasks. SqueezeNet's compact design is advantageous for deploying waste segregation in resource-constrained environments.
[16]	The One Hundred Layers Tiramisu: Fully Convolutional DenseNets for Semantic Segmentation	Simon J´egou, Michal Drozdzal, David Vazquez, Adriana Romero, Yoshua Bengio	Introduces a fully convolutional DenseNet architecture for semantic segmentation.	DenseNet architecture enhances feature reuse, beneficial for semantic segmentation tasks. Relevant for understanding advanced semantic segmentation techniques, applicable to precise waste item identification.
[17]	Garbage Waste Segregation Using Deep Learning Techniques	Sai Sushanth G, Jenila Livingston LM, Agnel Livingston LGX	Applies deep learning techniques for garbage waste segregation.	Specific focus on practical waste segregation applications using deep learning. Offers insights into applying deep learning for efficient garbage waste segregation, directly applicable to waste management projects.
[18]	Source separation, transportation, pretreatment, and valorization of municipal solid waste: a critical review	Xuemeng Zhang, Chao Liu, Yuexi Chen, Guanghong Zheng, Yinguang Chen	Conducts a critical review of municipal solid waste management processes.	Focuses on understanding and improving the overall municipal solid waste management process. Essential for gaining insights into holistic waste management strategies, guiding the broader context of waste segregation projects.
[19]	Development of Computer Vision Algorithms for Multi-class Waste Segregation and Their Analysis	Neeraja Narayanswamy, A. R. Abdul Rajak, Shazia Hasan	Develops computer vision algorithms for multi-class waste segregation.	Emphasis on developing algorithms for precise multi-class waste segregation. Relevant for implementing computer vision techniques in waste segregation models for accurate multi-class identification.

[20]	Plastic Material Detection and Classification using CNN	Vavilala Sushma	Focuses on plastic material detection and classification using Convolutional Neural Networks (CNN).	Tailored approach for handling plastic waste through CNN-based techniques. Offers specific methods for plastic waste identification using CNNs, contributing to plastic material segregation in waste projects.
[21]	Development of Intelligent Waste Segregation System Based on Convolutional Neural Network	Tarig Faisal, Aman Eyob, Filmon Debretsion, Merhawi Tsegay, Anees Bashir, Moath Awawdeh	Proposes an intelligent waste segregation system using Convolutional Neural Networks.	Focus on the integration of intelligent systems for waste management. Provides a foundation for incorporating intelligent systems into waste segregation projects, enhancing efficiency and accuracy.
[22]	A Novel YOLOv3 Algorithm-Based Deep Learning Approach for Waste Segregation: Towards Smart Waste Management	Saurav Kumar, Drishti Yadav, Himanshu Gupta, Om Prakash Verma, Irshad Ahmad Ansari, Chang Wook Ahn	Introduces a novel YOLOv3-based deep learning approach for waste segregation.	Emphasis on smart waste management through advanced deep learning techniques. Offers an innovative algorithm for efficient waste segregation, contributing to the broader field of smart waste management.
[23]	Municipal solid waste management in Indian cities – A review	Mufeed Sharholy, Kafeel Ahmad, Gauhar Mahmood, R.C. Trivedi	Conducts a review of municipal solid waste management practices in Indian cities.	Addresses the specific context of municipal solid waste management in urban India. Valuable for understanding the challenges and practices in municipal solid waste management, particularly in the Indian urban context.

Table 1 : Comparative study

4. Conclusion

In conclusion, the exploration and analysis of various papers related to waste segregation using AI and computer vision have provided valuable insights into the current state of the field. Object recognition, feature extraction, and classification, essential components of the waste segregation process, have been examined through the lens of cutting-edge papers in the domain. For object recognition, Faster R-CNN, You Only Look Once (YOLO), Single Shot MultiBox Detector (SSD), Mask R-CNN, and YOLO9000 were considered. Each method has its strengths, with Faster R-CNN excelling in accuracy, YOLO focusing on real-time detection, SSD optimizing for speed and efficiency, and Mask R-CNN offering precise instance segmentation.

Feature extraction methodologies, represented by ImageNet Classification, VGGNet, ZFNet, ResNet, and Inception-ResNet, were compared. ResNet, with its deep residual learning, stood out for its ability to train very deep networks and mitigate the vanishing gradient problem.

For classification, ImageNet Large Scale Visual Recognition Challenge, Very Deep Convolutional Networks (VGGNet), ResNet in ResNet, Xception, and SqueezeNet were evaluated. Each method showcased unique advantages, with Xception demonstrating depth wise separable convolutions and SqueezeNet achieving high accuracy with minimal parameters.

Combining these findings, the proposed waste segregation system should leverage Faster R-CNN for object recognition, ResNet for feature extraction, and Xception for classification. This hybrid approach aims to achieve optimal accuracy, real-time processing, and efficient use of computational resources in addressing the complex challenges of waste segregation. The choice of these models aligns with the project's overarching goals, considering factors such as accuracy, real-time processing, and resource efficiency. This hybrid model reflects a commitment to leveraging the latest advancements in the field to address the environmental challenges posed by inefficient waste management.

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